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A hybrid of clustering and meta-heuristic algorithms to solve a *p*-mobile hub location–allocation problem with the depreciation cost of hub facilities

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ABSTRACT

Hubs act as intermediate points for the transfer of materials in the transportation system. In this study, a novel *p*-mobile hub location–allocation problem is developed. Hub facilities can be transferred to other hubs for the next period. Implementation of mobile hubs can reduce the costs of opening and closing the hubs, particularly in an environment with rapidly changing demands. On the other hand, the movement of facilities reduces lifespan and adds relevant costs. The depreciation cost and lifespan of hub facilities must be considered and the number of movements of the hub's facilities must be assumed to be limited. Three objective functions are considered to minimize costs, noise pollutions, and the harassment caused by the establishment of a hub for people, a new objective that locates hubs in less populated areas. A multi-objective mixed-integer non-linear programming (MINLP) model is developed. To solve the proposed model, four meta-heuristic algorithms, namely multi-objective particle swarm optimization (MOPSO), a non-dominated sorting genetic algorithm (NSGA-II), a hybrid of *k*-medoids as a famous clustering algorithm and NSGA-II (KNSGA-II), and a hybrid of *K*-medoids and MOPSO (KMOPSO) are implemented. The results indicate that KNSGA-II is superior to other algorithms. Also, a case study in Iran is implemented and the related results are analyzed.

1. Introduction

A hub location problem (HLP) is one of the well-known problems in the location theory. Hubs act as middle nodes to reduce the cost of movements and air pollution between origin and destination nodes. In a hub network system, a flow between two origin–destination nodes is transferred through hub nodes instead of direct transferring. Applications of hub systems include but not limited to airline transportation industries (Vasconcelos et al., 2011; Vidović et al., 2011; Karimi and Bashiri, 2011), emergency services (Berman et al., 2007), and other applications (Ishfaq and Sox, 2012; Çetiner et al., 2010). The HLP was introduced by O'kelly (1986) for the first time and then many researchers have investigated this problem under several assumptions. O'kelly (1987) presented a quadratic mathematical model. A hub covering problem was introduced by Campbell (1994). Kara and Tansel (2003) and Wagner (2008) presented a new model for hub covering problems. *p*-HLPs are a particular form of hub systems, in which *p* nodes are selected as hubs and the other nodes are allocated to them. A *p*-HLP determines *p*-hub locations, in which start–end non-hub nodes can be covered by a pair of hubs. It is assumed that the hubs are fully connected. There is no direct connection between non-hub nodes. Flows are transferred through hubs. There are different types of *p*-HLPs, which can categorize as single/multiple allocation HLP and *p*-hub median/center/covering location problems (Farahani et al., 2013).

Uncertainty is an integral part of real-world problems. Many researchers in the various field have proposed different approaches to deal with it (Eskandari-Khanghahi et al., 2018; Mousavi et al., 2015, Haghjoo et al., 2020). Some studies have developed stochastic or fuzzy models to deal with uncertainty. Regarding *p*-HLPs, Mohammadi et al. (2013) presented a new stochastic bi-objective model under uncertainty and risk. Their main objectives were to minimize the maximum transportation time and total investment costs. Also, they used an imperialist competitive algorithm (ICA) to solve the model. Mohammadi et al. (2014) proposed a mixed possibilistic–stochastic approach to deal with

Abbreviations: ID, Virtual unique hub identification code; GA, Genetic algorithm; HLP, Hub location problem; KMOPSO, Hybrid of *k*-medoids and MOPSO; KNSGA-II, Hybrid of *k*-medoids and NSGA-II; MOPSO, Multi-objective particle swarm optimization; MINLP, Mixed-integer non-linear programming; NDS, Non-dominated solutions; NSGA-II, Non-dominated sorting genetic algorithm; POS, Pareto-optimal solutions; ICA, Imperialist competitive algorithm; SA, Simulated annealing

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uncertainty in a sustainable HLP with an environmental-based cost objective for air and noise pollution. Mohammadi et al. (2016) developed a game-based meta-heuristic algorithm to investigate the effect of delivery service requirement on a hubs system, in which a fuzzy queuing method is implemented to model the uncertainties. Qin and Gao (2017) developed a new incapacitated *p*-HLP under uncertainty in the flows between non-hub nodes. Sadeghi et al. (2018) proposed a *p*-HLP in a degradable transportation system.

Rahimi et al. (2019) proposed a multi-objective *p*-HLP, which minimizes the costs while it maximizes the flow between a pair of nodes and minimizes transportation times. They proposed a robust-possibilistic programming model to deal with the uncertainties in the system. Mohammadi et al. (2019) proposed a self-adaptive NSGA-II for solving a reliable *p*-HLP, which deal with disasters such as an earthquake or terrorist attacks. Zhalechian et al. (2017a) discussed a new multi-objective mathematical model for the *p*-HLP with environmental aspects of noise pollution. A two-phase approach is proposed including a fuzzy ME measure and fuzzy interactive approaches. Zhalechian et al. (2017b) proposed a multi-objective *p*-HLP considering social aspects, responsiveness, and economic under uncertainties and developed a self-adaptive differential evolution (DE) for solving their problem.

Another way to deal with uncertainties in location problems is to implement a dynamic facility location (Ghiani et al., 2007). Dynamic location problems are looking for the relocation of the existing facilities to reduce the total cost in different periods. For example, Melo et al. (2006) developed a supply chain network modeling framework considering a dynamic planning horizon, in which some extensions (e.g., facility configuration and external supply of materials) are considered on the supply chain structure to cope with the relocation of facilities. The existing facilities are partially or completely relocated. Partial relocation enables a facility to operate again. Complete relocation means a facility never can be reopened if the previous location is closed. Respectively, in a HLP, dynamic hub location can be used for adapting to the changes in non-hubs flow and reducing the costs. In a classical dynamic HLP, opening and closing hubs are considered in different periods, while moving the hub facilities between different nodes in different periods is the objective of novel dynamic HLPs. Mobile facilities have different applications, such as mobile fire stations and portable cellphone facilities (Bashiri et al., 2018).

Miller et al. (2007) developed a dynamic facility location model with increasing demand assumptions in the future, which forces a firm to establish a new facility or relocate old ones. Taghipourian et al. (2012) developed a multi-period virtual HLP to minimize transportation costs, in which hubs can be open or close during periods. A dynamic (i.e., multi-period) model is developed by Ghaderi and Jabalameli (2013) to design the facility location-network with a budget constraint. A mobile facility location problem (MFLP) is formulated by Halper et al. (2015). An existing facility can be moved over periods and allocated clients to that facility can be renewed to minimize the total travel cost. Then a local search heuristic method was developed for solving it. Jena et al. (2016) proposed a model for a complex multi-period facility location and assumed that facilities can partially close and reopen. Alumur et al. (2016) presented a multi-period hub location framework, in which capacity was gradually expanded over time. Correia et al. (2018) focused on multi-period stochastic capacitated multiple allocation HLP with uncertain flows. They assumed that hubs have modular capacities.

A mobile HLP (MHLP) provides the infrastructure to transport facilities in different periods instead of opening and closing them to reduce the total costs of the system. This infrastructure is considered as pathways between some nodes that allow a mobile facility to move between these nodes (Bashiri et al., 2018). In this study, a *p*-mobile HLP is developed. A schematic representation of a *p*-mobile HLP, as developed in Bashiri et al. (2018), is shown in Fig. 1. In an MHLP, facilities can be classified into two categories. Mobile facilities that can be relocated to other nodes without any establishment costs. Immobile facilities that are fixed in their locations and can be closed and reopened.

Since a HLP belongs to the class of NP-hard problems, some studies tried to find the approximate solution using heuristic algorithms. The nearest distance heuristic algorithm is proposed by Ebery et al. (2000). Two decomposition methods based on branch-and-cut are proposed by Rodriguez-Martin and Salazar-Gonzalez (2008). A branch-and-price algorithm is proposed by Catanzaro et al. (2011). Danach et al. (2019) proposed a Lagrangian relaxation and a hyper-heuristic approach for solving the capacitated HLP.

1.1. Related works

Many studies have used meta-heuristic algorithms. Ebrahimi-Zade et al. (2016) presented a new model by considering the covering radius as a decision variable and validated their model through a real-world case study. They proposed a genetic algorithm (GA) with dynamic stopping criteria and an immigration operator that is more efficient compared to the original GA. Yang et al. (2013) solved an HLP using a GA. Mohammadi et al. (2014) proposed an ICA and SA. Yang and Liu (2015) extended the hybrid tabu search based on a new parametric decomposition. A hybrid ICA and a hybrid DE are developed by Zhalechian et al. (2017a). Atta and Sen (2020) solved a multiple *p*-HLP using a DE. Ghaffarinasab and Kara (2019) proposed benders decomposition methods to solve different classes of the HLP. Bashiri et al. (2018) proposed GA and SA algorithms. Khodemani-Yazdi et al. (2019) proposed a game theory with variable neighborhood fuzzy invasive weed optimization (GVIWO) and compared its performance against NSGA-II and hybrid SA. In this study, the NSGA-II and MOPSO are chosen to solve the problem because of their high efficiency in solving similar problems (e.g., Rabbani et al., 2018b; Tirkolaee et al., 2019; Hasani Goodarzi et al., 2020).

Some studies proposed heuristic algorithms based on the nearest distance or clustering (Ebery et al., 2000; Sung and Jin, 2001; Wagner, 2007; Sohn and Park, 1998). To generate high-quality initial solutions in this study, the clustering of nodes using the k-medoids method is proposed. k-medoids is one of the two most famous algorithms for clustering data, the other one is *k*-means. These algorithms separate data to *k* different groups, attempting to minimize the distance between nodes in each group. *k*-medoids is less sensitive to the outlier data. Also, using dissimilarities between nodes makes *k*-medoids robust in comparison with k-means which uses the sum of distance as the cost function. These algorithms are heavily affected by their initial solutions and consequently generate different outputs. Although, in general, this feature can be a weakness, here this can be useful since it can generate a set of different initial solutions for use by meta-heuristic algorithms. Here, a hybrid of NSGA-II and MOPSO with k-medoids, namely KNSGA-II and KMOPSO, is developed. K-medoids is used to generate initial solutions of NSGA-II and MOPSO. The performance of KNSGA-II and KMOPSO is compared to that of MOPSO and NSGA-II, and the best algorithm is elicited.

Based on our best knowledge, there are a few studies that have investigated mobile facilities. One application of these facilities is in HLPs, which has never been considered until Bashiri et al. (2018) studied this issue. In this study, some aspects of *p*-mobile HLPs are covered that have been neglected in the previous studies. Therefore, a multi-objective formulation of a *p*-mobile HLP is developed to minimize noise pollution alongside the minimization of total costs. Also, a new objective is proposed to measure the population around a hub and choose a node as a hub with as less population as possible around it. Mobile facilities have a depreciation cost and their movements are limited in the real world, which are addressed and modeled here. These assumptions are considered to make the model more realistic. Also, a hybrid of k-medoids and two meta-heuristics is developed to efficiently solve large-size problems. The important features of this study and the most relevant studies are in Table 1.

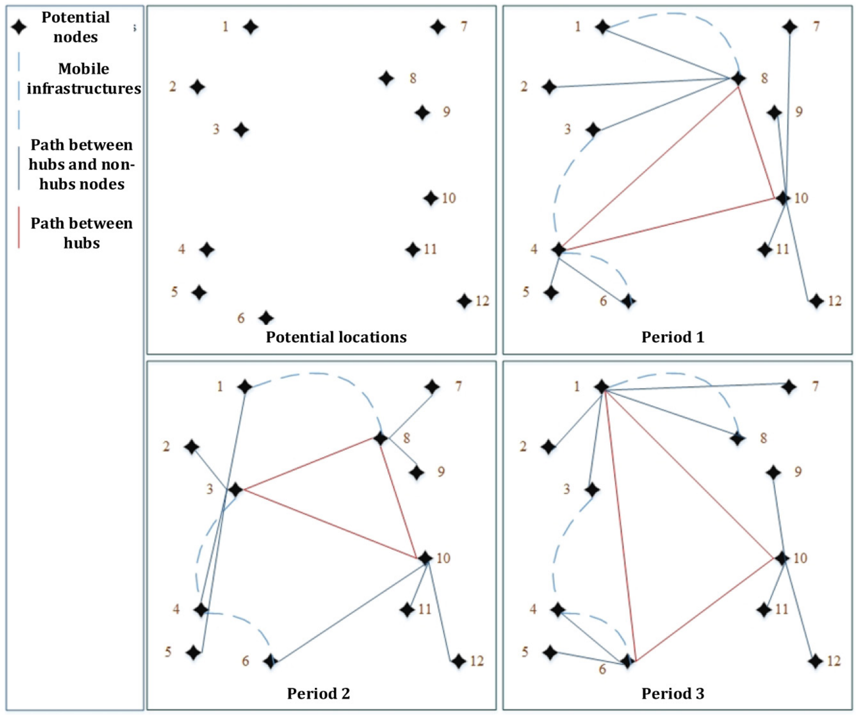

Fig. 1. Schematic view of the p-mobile HLP (Bashiri et al., 2018).

Table 1
Prominent feature of this study and the most relevant studies.

Study	Meta-heuristic algorithm	Multi-period	Mobile facilities	Mobility infrastructure	Allocation type	Covering radius	Depreciation cost	Limited mobile facility movements	Social objective
Mohammadi et al. (2013)	MOICA, NSGA-II, PAES				Single	✓			
Mohammadi et al. (2014)	MOSA, MOICA	✓			Single	✓			
Halper et al. (2015)		✓	✓		Single				
Ebrahimi-Zade et al. (2016)	GA	✓			Single	✓			
Jena et al. (2016)		✓			Single				
Zhalechian et al. (2017a)	HDE, HICA				Single				
Bashiri et al. (2018)	GA, SA	✓	✓	✓	Single				
This study	NSGA-II, MOPSO	✓	✓	✓	Single		✓	✓	✓

1.2. This study's contributions and structure

To sum up, the main contributions of this study are as follows:

- Extending a model for solving a p-mobile HLP by considering depreciation.
- Considering the depreciation cost of hub facilities and hubs lifespan.
- Considering the predefined mobile facility movements for mobile facilities.
- Considering a new population-based objective (i.e., social factor), which aims to establish hubs in the less populated zones of the city.
- Proposing a hybrid of k-medoids and NSGA-II and hybrid of k-medoids and MOPSO to solve the problem and comparing their performance with NSGA-II and MOPSO.

The rest of this study is arranged as follows. Section 2 provides a problem description and a multi-objective p-mobile HLP model. To solve the problem, Section 3 proposes meta-heuristic algorithms to efficiently solving the problem. Section 4 provides some experimental examples and a comparison study of these meta-heuristic algorithms. Finally, Section 5 concludes our study and mentions important results and future opportunities.

2. Problem description and mathematical model

2.1. Problem definition and assumptions

In a hub network system, a HLP locates some nodes as hubs. Other nodes are connected just to one hub node. Additionally, all hub nodes are connected. A flow from an origin node moves to a hub node and if needed moves to another hub node to reach its destination. In this section, a p-mobile HLP optimization model is extended, which for the first time proposed by Bashiri et al. (2018). A multi-period HLP is proposed, where the facilities of a hub can be transferred to other hubs at the start of each period if the mobile infrastructure was established between those two nodes. Three objectives have been considered in this study: minimizing the total costs, minimizing the noise pollution, and minimizing the population around hubs. Since the facilities depreciated by moving from one node to another, the depreciation cost is considered. Regarding the above features, the following assumptions are considered:

1. Mobile facilities are established in the first period and cannot change during the subsequent periods.
2. Hub facilities can be mobile or immobile. However, the number of hubs is predefined and is equal to p.
3. The lifespan of hub facilities is limited to predefined periods Ls.
4. If the transportation time of flow between two hubs exceeds its available time window, the cost of the violation is considered.
5. Discount factor α is considered for inter-hub transporting time and cost.
6. The hub network is fully interconnected.
7. If a mobile infrastructure (railway) exists, then the location of the hub can be changed.
8. The maximum number of non-hub nodes that can be allocated to hub nodes is limited and predefined.
9. The number of mobile hub movements is limited and predefined.
10. All parameters are deterministic.

2.2. Depreciation cost calculation

There are different methods for calculating depreciation cost including straight-line, declining balance, units/volume of production, and the sum of years' digits. Due to different volumes of a hub activity in each period, because there are different allocated non-hub nodes, the volume of production method is used for calculating the depreciation cost. If the hub use only for a period, and a new hub establishes in the next period, then there is no need to consider the depreciation cost. However, for mobile hubs and hubs established in the previous periods, the impact of this cost must be considered.

Accordingly, the total input flow to each hub is considered as production volume. The input flows use hub facilities and causes exhaustion, where the effect is modeled as depreciation cost. Moreover, the depreciation of facilities in previous periods affects the depreciation of subsequent periods. Therefore, the depreciation cost of hub facilities in period p that have been active for the past p periods is computed by:

$$dc_h^p = (\sum_{t=1}^{p-1} \psi F_h^t + F_h^p)\xi \tag{1}$$

where dc_h^p indicates the depreciation cost of hub h in period p. F_h^t indicates the total amount of input flow to hub h in period t, ψ $(0 < \psi < 1)$ indicates the effect of the previous periods flows on the current period p. ξ indicates the cost of a flow unit in depreciation costs. Eq. (1) expresses that the depreciation cost of a hub at a period depends on the input flow of that period and flows in the previous periods. It depends on previous periods because the more hub facilities are used in previous periods, the more it is depreciated and the more costs are incurred. Therefore, it is necessary to consider the current of the previous periods in addition to the currents of that period in the cost of each period.

2.3. Noise pollution calculation

According to Mohammadi et al. (2014) and Zhalechian et al. (2017a), the noise pollution in each node is formulated by:

$$np_n^p(F_h^p) = \phi\left[\exp\left(\tau\left(\left(10\log_{10}\left(v_n^p + mvo_n\right) + 33\log_{10}\left(ts_n + 4 + \frac{500}{ts_n}\right) + 10\log_{10}\left(1 + \frac{5(\frac{100v_n^p}{v_n^p+mvo_n})}{ts_n}\right) - 26.6\right)\right) - th_n\right) - 1\right] \tag{2}$$

$$v_n^p = \frac{F_h^p}{Cv} \tag{3}$$

where v_n^p indicates the hourly flow of vehicles (i.e., number of the vehicles) at node n in period p, mvo_n indicates the average number of vehicles flowing hourly at node n, ts_n indicates the total hourly mean traffic speed m/h at node n, th_n indicates the threshold of the acceptable noise in node n. Note that for sound levels lower than th_n, the noise cost is zero and measured in dB(A), ϕ and τ are two constant coefficients. Cv indicates the capacity of vehicles used for transporting the flow between nodes. Vehicles are considered homogeneous with the same capacity, and F_h^p indicates the total amount of input flow directed to node n in period p (Zhalechian et al., 2017a).

2.4. Proposed mathematical model

Here, the mathematical model of the problem is developed. The main differences between the current model and existing models are that, in this study, the depreciation cost of hub facilities, hubs lifespan, and the predefined mobile facility movement for mobile facilities are considered. The notation is in Table 2 and the proposed model is in Eqs. (4)–(27).

$$\begin{aligned}\text{Min } Z_1 = & \sum_{p=1}^{P}\sum_{l=1}^{N}\sum_{n=1}^{N}\sum_{m=1}^{N} Utc_{l,n}^p f_{l,m}^p X_{l,n}^p \\ & + \sum_{p=1}^{P}\sum_{l=1}^{N}\sum_{n=1}^{N}\sum_{o=1}^{N}\sum_{m=1}^{N} \alpha Utc_{n,o}^p f_{l,m}^p Y_{l,n,o,m}^p \\ & + \sum_{p=1}^{P}\sum_{l=1}^{N}\sum_{o=1}^{N}\sum_{m=1}^{N} Utc_{o,m}^p f_{l,m}^p X_{m,o}^p + \sum_{l=1}^{N}\sum_{n=1}^{N} Cer_{l,n} V_{l,n} + \sum_{p=1}^{P}\sum_{n=1}^{N} Ceh_n^p W1_n^p + \\ & \sum_{p=1}^{P}\sum_{l=1}^{N}\sum_{n=1}^{N} Tcm_{l,n}^p W2_{l,n}^p + \sum_{h=1}^{H}\sum_{p=1}^{P}(\sum_{n=1}^{N}\sum_{p'=1}^{p-1} \psi F_n^{p'} Q_{h,n}^{p'} + \sum_{n=1}^{N} F_n^p Q_{h,n}^p)\xi\end{aligned} \tag{4}$$

$$\text{Min} Z_2 = \sum_{p=1}^{P}\sum_{n=1}^{N} np_n^p(F_n^p) X_{n,n}^p \tag{5}$$

$$\text{Min} Z_3 = \sum_{p=1}^{P}\sum_{n=1}^{N} Pop_n X_{n,n}^p \tag{6}$$

$s.t.$

$$\sum_{n=1}^{N} X_{n,n}^P = \pi \qquad \forall p \tag{7}$$

$$\sum_{n=1}^{N} X_{l,n}^p = 1 \qquad \forall p, l \tag{8}$$

$$X_{l,n}^p \leq X_{n,n}^p \qquad \forall p, l, n \tag{9}$$

$$X_p^{l,n} W3_p^n \sum_{l=1}^{N} W2_{l,n}^p \qquad \forall p, n \tag{10}$$

$$W2_{l,n}^p = 0 \qquad \forall p = 1, l, n \tag{11}$$

$$W2_{n,l}^p \leq X_{n,n}^{p-1} \qquad \forall p \geq 2, l, n, l \neq n \tag{12}$$

$$W2_{l,n}^p \leq V_{l,n} \qquad \forall p, l, n, l \neq n \tag{13}$$

$$Y_{l,n,o,m}^p = X_{l,n}^p X_{m,o}^p \qquad \forall p, l, n, o, m \tag{14}$$

$$W1_n^p = W3_n^p + U_n^{p,p-1} \qquad \forall p, n \tag{15}$$

$$U_n^{p,p-1} = W3_n^p W3_n^{p-1} \qquad \forall p, n \tag{16}$$

Table 2
Notation.

Notation	Description
Sets:	
l, n, m, o	All nodes ($\in \{1, 2, \dots, N\}$)
p, p	All periods ($' \in \{1, 2, \dots, P\}$)
h	Auxiliary set for all hubs ($\in \{1, 2, \dots, H\}$)
Parameters:	
α	Discount rate for flows between hub nodes
π	Number of hubs that must be established in each period
$f^p_{l,n}$	Flow that must transport from node l to n in period p
$Utc^p_{l,n}$	Unit transportation cost of flow between nodes l and n in period p
$Cer_{l,n}$	Fixed cost of establishing a railway between nodes l and n
Ceh^p_n	Fixed cost of establishing node n as a hub in period p
$Tcm^p_{l,n}$	Cost of transferring mobile hub from node l to node n in period p
$D_{l,n}$	Distance between nodes l and n
La_n	Maximum number of non-hub that can be allocated to hub n
Lmv	Maximum number of mobile hub movements
Ls	Maximum lifespan of hubs
Pop_n	Population around node n
Decision Variables:	
$X^p_{l,n}$	1 if node l allocated to hub n in period p; 0, otherwise. Also, $X^p_{n,n} = 1$ if node n acts as a hub in period p; 0, otherwise
$Y^p_{l,n,o,m}$	1 if flow between nodes l and m is transported through hubs n and o in period p; 0, otherwise
$V_{l,n}$	1 if a railway is established between nodes l and n; 0, otherwise
$W1^p_n$	1 if a hub is established in node n in period p; 0, otherwise
$W2^p_{l,n}$	1 if hub l is moved to node n in period p; 0, otherwise
$W3^p_n$	1 if node n is treated as an immobile hub in period p; 0, otherwise
$U^{p,p-1}_n$	1 if hub n remains as a hub in two consecutive periods; 0, otherwise
$Q^p_{h,n}$	1 if hub h is in node n in period p (auxiliary variable); 0, otherwise
S^p_h	1 if hub h became inactive in period p or previous one (auxiliary variable); 0, otherwise
$F^p_n \in R^+$	Auxiliary variable that determines total income flow to node n in period p

$$W3^p_n + \sum_{l=1}^{N} W2^p_{n,l} \le 1 \qquad \forall p, n \qquad (17)$$

$$\sum_{l=1}^{N} X^p_{l,n} \le La_n \qquad \forall p, n \qquad (18)$$

$$F^p_n = \sum_{l=1}^{N}\sum_{o=1}^{N}\sum_{m=1}^{N} f^p_{l,m} Y^p_{l,n,o,m} + \sum_{l=1}^{N}\sum_{o=1}^{N}\sum_{m=1}^{N} f^p_{l,m} Y^p_{l,o,n,m} \qquad \forall p, n \qquad (19)$$

$$\sum_{n=1}^{N} Q^p_{h,n} + S^p_h \le 1 \qquad \forall p, h \qquad (20)$$

$$Q^p_{h,n} = \sum_{l=1}^{N} Q^{p-1}_{h,l} W2^p_{l,n} + Q^{p-1}_{h,n} U^{p,p-1}_n \qquad \forall p \ge 2, h, n \qquad (21)$$

$$\sum_{h}^{H} Q^p_{h,n} = X^p_{n,n} \qquad \forall p, n \qquad (22)$$

$$S^p_h \ge \sum_{n=1}^{N} (1 - Q^p_{h,n}) Q^{p-1}_{h,n} \qquad \forall p \ge 2, h \qquad (23)$$

$$S^p_h = 0 \qquad \forall p = 1, h \qquad (24)$$

$$S^p_h \ge S^{p-1}_h \qquad \forall p \ge 2, h \qquad (25)$$

$$\sum_{p=1}^{n}\sum_{n=1}^{N} Q^p_{h,n} \le Ls \qquad \forall h \qquad (26)$$

$$\sum_{p=2}^{P}\sum_{n=1}^{N} Q^p_{h,n}(1 - Q^{p-1}_{h,n}) \le Lmv \qquad \forall h \qquad (27)$$

In this model, Objective 1, expressed in Eq. (4), minimizes total costs including cost of transferring flow from origin non-hub nodes to their hub nodes, transferring flow from the hubs of origin non-hub nodes to hubs of destination non-hub nodes, transferring flow from destination hubs to destination non-hub nodes, establishing railway between two nodes, establishing hubs, transferring mobile hubs facilities from a node to another, and depreciating facilities. Objective 2, expressed in Eq. (5), minimizes the noise pollution, and objective 3, expressed in Eq. (6), minimizes the social impact of establishing hubs. This objective tries to establish hubs in the less populated zones.

Constraints of the model are expressed in Eqs. (7) to (27). Eq. (7) guarantees that the number of established hubs must be equal to a predefined π number in each period. Eq. (8) guarantees that, in each period, each hub must be established in a node. Eq. (9) guarantees that any non-hub node must be connected to a hub node. Eq. (10) expresses that a hub can be transferred from other hubs or newly established in at the start of each period. Eq. (11) ensures that there is no hub movement in period one (all required hubs for period one must be established). Eq. (12) ensures that a hub can be established by moving facilities of a node if that node is operated as a hub in the previous period. Eq. (13) guarantees that if there is a railway between two nodes, then hub facilities can be moved between them. Eq. (14) indicates the path between every pair of two nodes; it expresses that flow from an origin node to a destination node is moved by moving from which two hubs. Eqs. (15) and (16) are used for distinguishing hub establishment. In each period, a hub is newly established if that hub is established as an immobile hub. Eq. (17) states that, at each period, a node is hub either if hub facilities are moved from another nodes or if it is established. Eq. (18) limits the maximum number of non-hubs that can be allocated to a hub at each period. Eq. (19) calculates the total input flow to a hub at each period.

An auxiliary set and two auxiliary variables are used to model the lifespan of hubs, the number of mobile hub movements, and depreciation costs in Eqs. (20) to (27). A virtual unique identification code (ID)

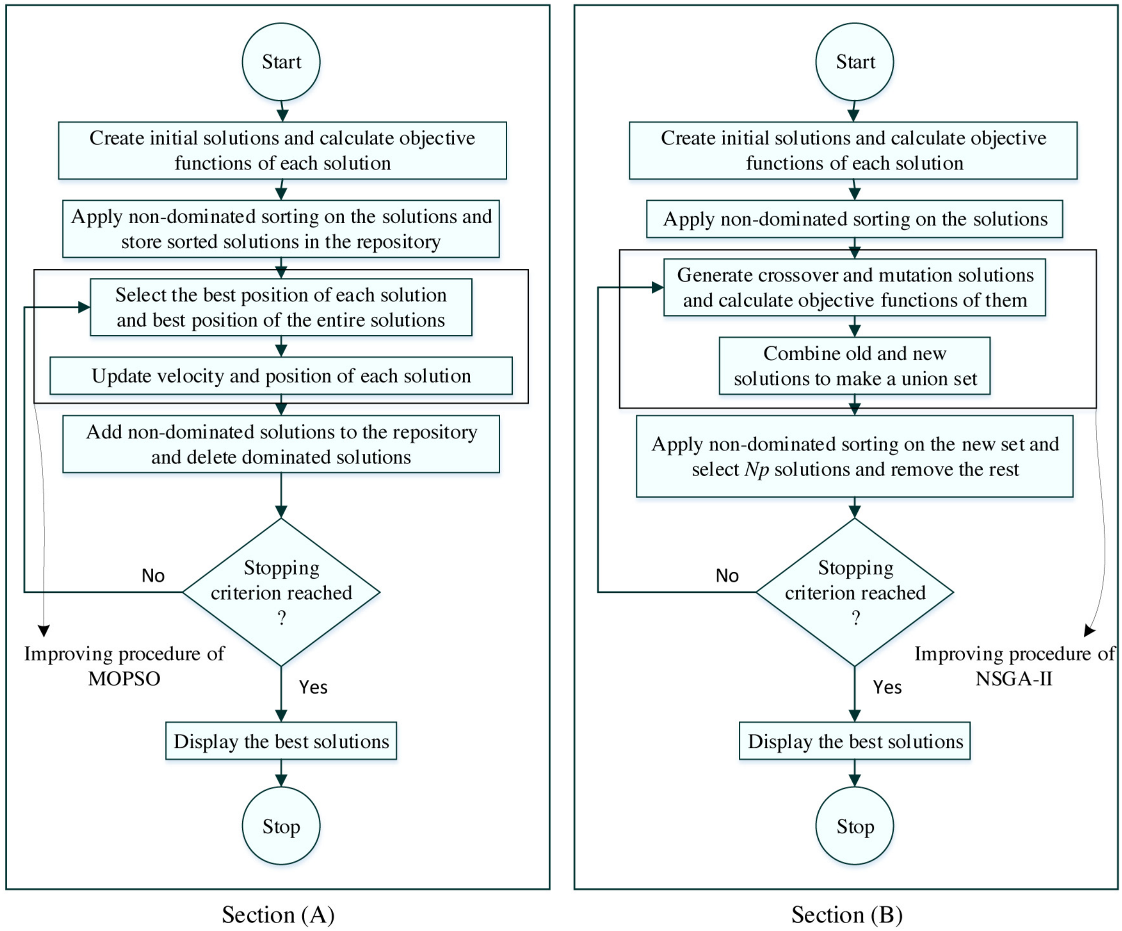

Fig. 2. Flowchart of (A) MOPSO and (B) NSGA-II.

is assigned to each newly constructed hub. Using this ID, it is possible to track the status of hubs in all periods. Eq. (20) guarantees that any ID can only be assigned to a particular hub. Eq. (21) tracks the movements of a particular hub ID. A hub with ID h is in node n at period p if that hub with ID h is moved from another node to node n or a new hub is established. In the case of establishing a new hub for a period, ID h is assigned to that node for the first time. Eq. (22) guarantees that each node that acts as a hub at a period must have an ID that identifies its hub. Eq. (23) identifies the activity (exhaustion) status of hubs: either active or inactive in each period. An inactive hub is a hub that was used for some periods and will never be used in future periods Eq. (24) says that there is no inactive (exhaust) hub in period one. Eq. (25) guarantees that a hub will remain inactive in all the subsequent periods if it is inactive in a period. Eq. (26) guarantees that the lifespan of hubs is limited. Eq. (27) guarantees that the maximum number of mobile hub movements is limited.

3. Solution methodology

HLPs are considered as NP-hard, meaning that it is impracticable to obtain an optimal solution of large-sized instances in a reasonable time (Skorin-Kapov and Skorin-Kapov, 1994; Hörhammer, 2014; Kara, 1999). Moreover, the non-linear nature of Eqs. (4), (5), (6), (14), (16), (21), (23), and (27), makes the model more difficult to solve. Nowadays, meta-heuristics are widely used to deal with NP-hard problems (Salehi and Tavakkoli-Moghaddam, 2009; Triki and Al-Hinai, 2016; Jamili et al., 2012; Shirvani, 2020; Rabbani et al., 2018a). In this study, two well-known meta-heuristic algorithms, namely MOPSO and NSGAiII, are implemented to solve the problem. MOPSO is rarely seen in the related literature. NSGA-II is well performed in the literature of HLPs.

MOPSO and NSGA-II are population-based algorithms meaning that they work with a set of solutions instead of a single solution at each iteration. As it is shown in Fig. 2, They start with a set of initial random solutions, then, in each iteration, they improve the solutions of the previous iteration based on their philosophy (see Sections 3.2 and 3.3). They iterate and try to improve the solutions until they reach the stopping criterion. In this study, the stopping criterion is the number of iteration. To improve the quality of solutions provided by meta-heuristic algorithms, some researchers proposed to generate initial solutions using heuristic algorithms, particularly for the HLP based on the nearest distance or clustering (Ebery et al., 2000; Sung and Jin, 2001; Wagner, 2007; Sohn and Park, 1998). k-medoids is a famous algorithm for clustering data based on their features. Therefore, an algorithm based on k-medoids is developed to generate the initial set of solutions using the k-medoids algorithm instead of generating random solutions (see Section 3.4).

In multi-objective problems, where there is no single global solution that optimizes all objectives simultaneously, the concept of the Pareto-optimal solution (POS) set is applied (Mock, 2011; Baumgartner et al., 2004). POS is defined as a solution that the value of an objective cannot be improved without worsening at least another one. Non-dominated sorting is implemented in these algorithms to categorize the solutions in a population into several fronts of non-dominated solutions (NDS) regarding the dominance relation in the objective space. Then, for sorting the solutions within each front, the crowd-distance operator is implemented. The procedures of both algorithms are in Fig. 2.

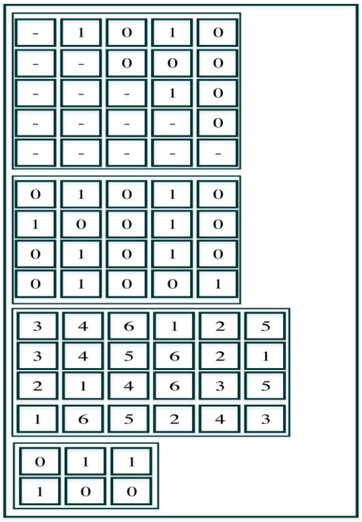

Fig. 3. Example of the proposed encoding way of the given problem.

In the following, first, the problem is decoded, then, the MOPSO and NSGA-II improving procedures are described. After that, an algorithm based on k-medoids is developed for generating the initial set of solutions. Finally, the parameters of these algorithms are tuned.

3.1. Encoding the problem

The performance of evolutionary algorithms is heavily influenced by the encoded way of the problem. Encoding is an expression of the problem in an understandable way for the algorithm. In this regard, a structure containing four arrays is used to encode the solution (Fig. 3). A $L{*}L$ binary array represents the status of an established railway between two nodes. Because an upper triangular matrix can represent the status of railways, the related part of this array is considered as shown in Fig. 3. A $P{*}L$ binary array represents if a node is selected as a hub for a period. This array is repaired before objective functions calculation to contains only π hubs. A $P{*}(L+\pi-1)$ integer array represents the allocation status of non-hubs to hubs. $(\pi-1)$ is the number of needed separators to separate between non-hubs assigned to each hub. A separator number (greater than L) is considered to separate allocated non-hub nodes to hubs. Therefore, all nodes come before a separator are allocated to the related hubs. Nodes before the first separator are allocated to hub 1, and so on. A $\pi{*}(P-1)$ binary array presents whether a hub has been built or moved from the previous period — the status of period 1 is known (all hub has been built); therefore, it should be determined for $(P-1)$ periods. An example of this encoding structure is illustrated in Fig. 3. In this example, it is assumed that $l=5, p=4$, and $\pi=2$. Array 1 indicates that railways are established between nodes 1 and 2, nodes 1 and 3, and nodes 3 and 4; therefore, the facilities of hubs can be transferred between these nodes respectively. The first row of array 2 indicates that nodes 2 and 4 are established as hubs in period 1 (i.e., same for other periods). The first row of array 3 indicates that node 3 is allocated to the first hub (i.e., node 2); since node 4 is a hub, then it cannot be allocated to another hub and is ignored in this array (it is allocated to itself); the value 6 in this array is a separator, then, nodes 1 and 5 are allocated to the second hub (i.e., node 4) because they are before the second separator and after the first separator. This procedure is applied for all other periods. The first column of array 4 indicates that the first hub (node 2) is a new hub and the second hub (node 4) is moved from the previous period. It should be noted that with this encoding all the constraints of the problem are met.

3.2. MOPSO improving procedure

This algorithm is developed by Coello et al. (2004). In this algorithm, a swarm (a set of solutions) is made of particles (solutions). The intelligence of the group is the basis of this algorithm. It means that each particle knows its prior best position and best position of the entire swarm. Each particle moves at a certain velocity in the feasible space of the problem to produce new solutions. Eqs. (29) and (30) are used to update the velocity and position of each particle.

$$S_p(i)=\omega S_p(i-1)+C_p r_1\left(x_p^{best}(i)-x_p(i)\right)+C_g r_2(x_g^{best}(i)-x_p(i)) \tag{28}$$

$$x_p(i)=x_p(i-1)+S_p(i) \tag{29}$$

where, $S_p(i)$ and $x_p(i)$ are velocity and position of particle p at iteration i. $x_p^{best}(i)$ and $x_g^{best}(i)$ are the best experience of the particle and entire swarm at iteration i, respectively. ω, C_p and C_g are the inertia factor, personal and global learning coefficients. r_1 and r_2 are two random numbers between 0 and 1. In Fig. 2b, a flowchart of this algorithm is illustrated.

3.3. NSGA-II improving procedure

This algorithm developed by Srinivas and Deb (1994) is one of the most well-known and widely used algorithm to solve multi-objective discrete problems. In GA, a population is made by individuals that have their chromosomes. Each chromosome represents a solution. The population then changes by creating new children and deteriorating weak individuals. To achieve better solutions and explore completely the feasible space of the problem, crossover and mutation operators are implemented to create new children. A crossover operator is implemented to generate new children out of two selective parents and improve the parents' solutions. For applying this operator, the parents are selected randomly. A mutation operator is implemented to guarantee the diversity of solutions and prevent the search process from falling into a local optimum. For applying this operator, a parent is selected randomly. Then, the mutation operator is applied to this parent to generate a new child. In Fig. 2b, a flowchart of this algorithm is illustrated.

Crossover operator: According to the structure of the encoded problem (i.e., chromosome), which is made of several arrays, a single-point crossover technique is applied to them separately. In this technique, a random point is selected; using this point, the selected parents are divided into two sections. Then, the first child is generated by sticking the second part of Parent 2 to the first part of Parent 1, and the second child is generated by sticking the second part of Parent 1 to the first part of Parent 2. An example of this operator on array 3 is illustrated in Fig. 4a.

Mutation operator: Based on the structure of the chromosome, two columns of each array are exchanged randomly. An example of this operator is illustrated in Fig. 4b.

3.4. Initial solutions based on the k-medoids algorithm

Generally, the k-medoids algorithm is used by machine learning techniques to clusters data into some groups based on the nearest distances of these data. By considering nodes' coordinates as k-medoids criteria and p as k (i.e., number of clusters), it is possible to cluster the nodes into p clusters. This algorithm starts with selecting k random nodes as the center of clusters and allocating the other nodes to one of them in a way that the dissimilarities between selected center and node minimize. Then, the sum of dissimilarities within each cluster is calculated as its cost function. Then, a new random center is selected and this procedure is applied to minimize the sum of cost functions. After running this algorithm on nodes data, the node with the minimum Sh, which is calculated as Eq. (31), is chosen as a hub.

$$Sh_k=\sum_{i}^{C_k} d_{ik}\left(\sum_{j}^{I} f_{ij}+f_{ji}\right) \qquad \forall k\in C_k \tag{30}$$

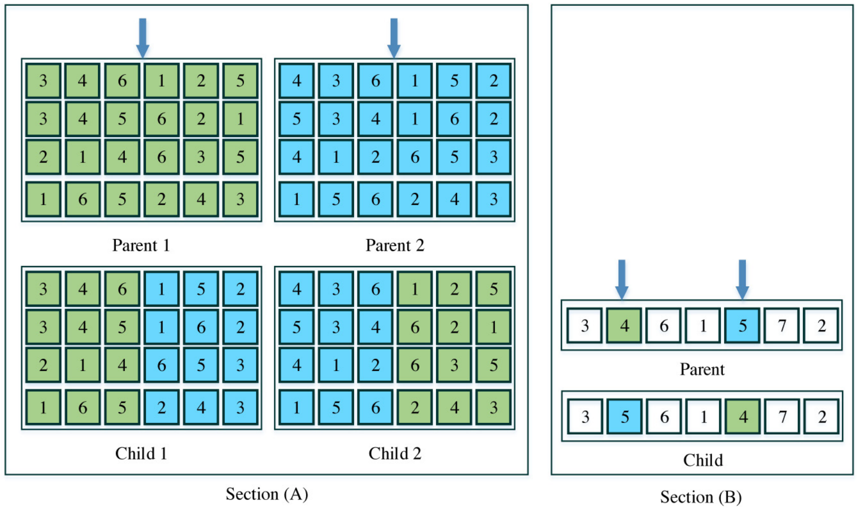

Fig. 4. Example of (A) crossover and (B) mutation operators on array 3.

where C_k is the set of all nodes in the cluster.

For the hybridization of k-medoids and proposed meta-heuristic algorithms, we developed them in a way that the initial population is generated using k-medoids instead of a random generator. The steps of this algorithm are detailed as follows:

a. For period 1: form the clusters of nodes and use Eq. (31) to identify the hubs
b. For the other periods:
   b.a. Determine the number of periods in which a hub is established (N_p)
   b.b. If $N_p \leq Ls$ establish that node as a hub for the current period
   b.c. Else, establish a new hub using Eq. (31)

3.5. Parameters tuning

Tuning parameters of meta-heuristic algorithms are of great importance due to their direct influence on the efficiency of the algorithm (Eiben and Smit, 2011). The design of experiments (DOE) technique is usually used to tune the parameters of each algorithm. Performing all experiments is time-consuming. A very widely used method to reduce the number of required experiments and to obtain valid results on DOE is the Taguchi method (Taguchi, 1986), that succeeds to reduce the number of experiments with no effect on the validity of the final results. The Taguchi method as a strong tool for the DOE is used for tuning the parameters of the proposed algorithms. For this, a three-level Taguchi experiment is implemented to examine the impact of the main MOPSO's parameters (i.e., number of iterations (Max_i), repository size (N_r), swarm size (N_p), inertia weight (ω), global learning coefficient (C_g) and personal learning coefficient (C_p)) and NSGA-II's parameters (i.e., number of iterations (Max_i), population size (N_p), crossover and mutation rates (C_i and M_i)). Objective one is considered as the Taguchi's design response. The results of implementing this method on a problem instance with 50 nodes and 10 periods and 5 hubs (i.e., a medium-scale problem) are analyzed by Minitab software. The results of these analyses are illustrated in Figs. 5 and 6. Also, the best value of these parameters is illustrated in Table 3.

Table 3
Parameter setting of the proposed algorithms based on the Taguchi method.

Algorithm	Parameter							
	N_p	Max_i	N_r	ω	C_p	C_g	C_i	M_i
MOPSO	50	75	75	0.6	1.5	1.0	–	–
NSGA-II	75	150	–	–	–	–	0.6	0.1

4. Experimental results

In this section, the performance of algorithms is analyzed and the model is applied to a case study. It is worth noting the validation of the proposed mathematical model is checked by solving a simple instance and considering the first objective. In this regard, a random instance (having 5 nodes and 3 periods) is randomly generated and solved using GAMS software version 24.1.3. To evaluate the performance of the proposed algorithms and compare the results, numerical experiments are illustrated. MATLAB R2017a software on a personal computer is used to code the algorithms. Concerning the inexistence instances for benchmarking in the literature, three types of random problem instances, including small-, medium- and large-sized problems are randomly generated and used to measure the performance of these algorithms. All codes and generated samples are available upon request.

4.1. Performance measurement of the proposed algorithms

In this section, first, the domination metric is used to elicit the superior algorithms. The domination metric indicates a percent of non-dominated solutions, among all solutions provided by all algorithms, that belongs to each algorithm. The results of this metric are shown in Fig. 7, and relevant data are in Appendix A. This metric is related to the quality of solutions provided by an algorithm. An algorithm with low performance in this metric cannot be a suitable one because its solutions are dominated by other algorithms. As Fig. 7 shows, POS of the KNSGA-II and KMOPSO dominates all others, which reflects their superiority. Accordingly, it can be seen that NSGA-II and MOPSO cannot produce high-quality solutions in comparison with KNSGA-II and KMOPSO. Therefore, NSGA-II and MOPSO cannot be used for solving the proposed problem.

The domination metric shows that both KNSGA-II and KMOPSO are qualified. KNSGA-II and KMOPSO algorithms are examined to determine their strengths and weaknesses and elicit the best one. There are several criteria in the literature for evaluating the strengths and weaknesses of multi-objective algorithms. Among them, four criteria including execution time, quantity, spacing, diversity, and hypervolume metrics are employed, which are used in several studies (Rabbani et al., 2018b; Mohammadi et al., 2016).

Quantity metric: This metric assesses the number of returned POS of each algorithm for each instance. A higher value of this metric is

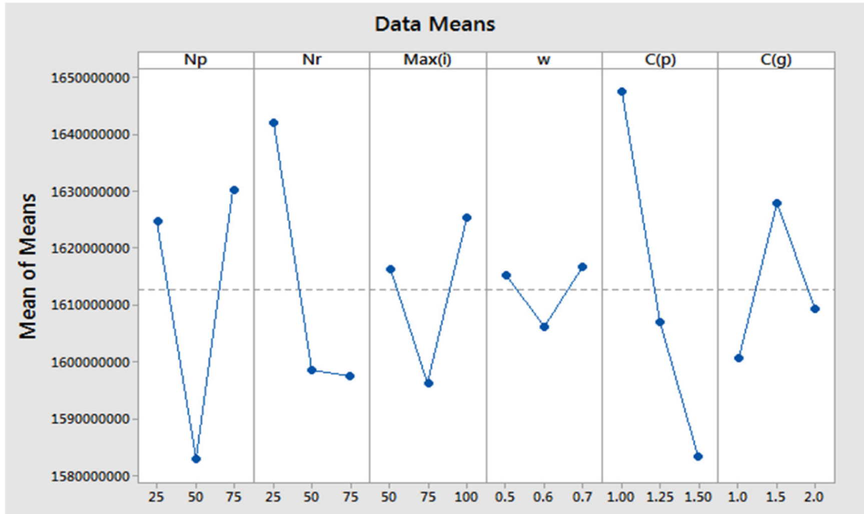

Fig. 5. Analysis diagrams of the MOPSO parameters tuning based on the Taguchi method.

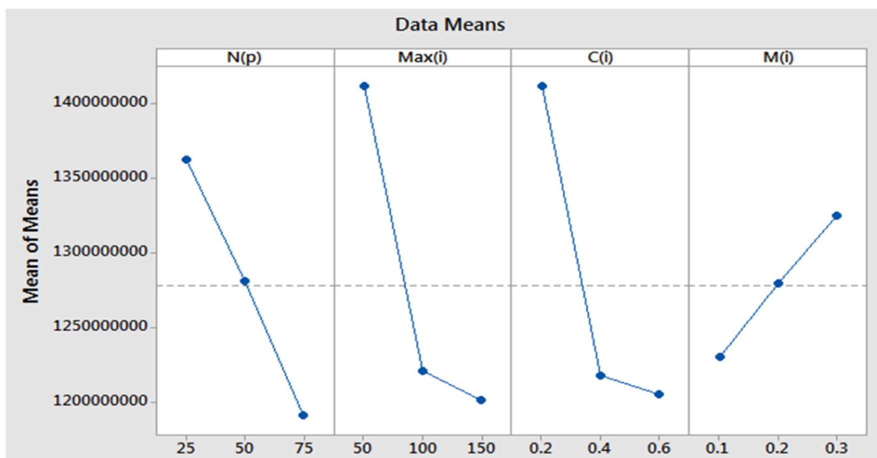

Fig. 6. Analysis diagrams of the NSGA-II parameters tuning based on the Taguchi method.

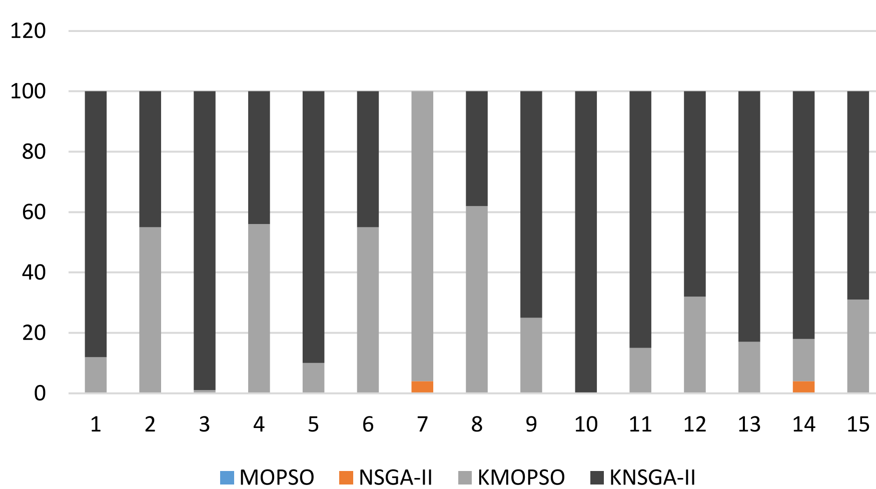

Fig. 7. Comparison of algorithms based on the domination metric.

preferred because the algorithm can be more converged towards the real Pareto front.

Spacing metric: The information about the distribution of NDS is given by this metric (Suo et al., 2017). The spacing metric is computed by Eqs. (31) and (32).

$$Spacing = \sqrt{\frac{1}{J-1}\sum_{j=1}^{J}(z_i - \bar{z})^2} \quad (31)$$

Table 4
Evaluation of KNSGA-II and KMOPSO in terms of hypervolume metric.

Instance	KNSGA-II	KMOPSO
1	3.7E+07	1.7E+07
2	1.1E+08	7.3E+07
3	4.8E+08	2.5E+08
4	2.7E+09	2.3E+09
5	2.7E+09	1.9E+09
6	9.3E+08	4.1E+09
7	2.5E+08	8.9E+08
8	2.9E+09	7.8E+09
9	1.2E+10	6.6E+09
10	2.1E+10	8.8E+09
11	3.3E+10	1.2E+10
12	2.1E+10	1E+10
13	8E+09	6.3E+09
14	4.1E+10	2.1E+10
15	3.3E+10	2.5E+10
Average	1.19E+10	7.14E+09

$$z_j = \min_{i=1}^{I}\left(\sum_{k=1}^{K}\left|obj_k^i - obj_k^j\right|\right) \tag{32}$$

where J denotes the number of NDS, z_j denotes the minimum distance of POS j from other solutions, $\overline{z}$ denotes the mean of z_j for all NDS, and obj_k^i denotes the value of objective $k \in \{1,2,3\}$ for solution i.

Diversity metric: This metric is defined as the maximum Euclidean distance between NDS. Whenever this metric increases, it means that it explores better solution space; hence the algorithm with the higher value of this metric acts better.

Hypervolume metric: This metric measures the size of the objective function space covered by the non-dominated solutions of an algorithm (Zitzler et al., 2007). An algorithm with a larger hypervolume is preferred because it shows a wider range of non-dominated solutions. To calculate this metric, the anti-ideal point (the worst solution of each objective) is considered as the reference point. The volume between the Pareto front obtained from solutions of an algorithm and the reference point is a hypervolume of the algorithm (Halim et al., 2020).

The obtained experimental results of applying these algorithms to solve different types of instances are illustrated in Figs. 8–11 for comparing their performance based on the proposed criteria. Also, the details of these instances are reported for execution time, quantity, spacing, and diversity metrics in Appendix A. Based on these experiments, KNSGA-II is weaker in generating diverse solutions. However, KNSGA-II is superior to the KMOPSO in other metrics. Since the main iterations (improving process) of KNSGA-II and MOPSO algorithms are similar to that of NSGA-II and MOPSO, the obtained results are similar to the results of NSGA-II and MOPSO showed by Rabbani et al. (2018b,c). To sum up, KNSGA-II is superior to KMOPSO regarding the domination metric (Fig. 7). KNSGA-II is better regarding quantity and spacing metrics. The execution time of KNSGA-II is less than the execution time of KMOPSO, as shown in Fig. 11. Table 4 provides a hypervolume metric for KNSGA-II and KMOPSO. This metric clearly shows the superiority of KNSGA-II over KMPSO in most instances. However, KMPSO dominates KNSGA-II in instances 6, 7, and 8. For selecting an efficient algorithm based on these criteria, a two-sample t-test is implemented and the results are shown in Table 5, which statistically proves that KNSGA-II is better than KMOPSO regarding quantity and spacing metrics. MOPSO is better regarding the diversity metric. Therefore, we can conclude that KNSGA-II is superior in the whole view.

4.2. Effect of depreciation costs on the optimal solutions

To analyze the effect of the depreciation cost, problem instance number 2 is solved using KNSGA-II when depreciation cost is (or is not) considered. For this, the problem is first solved by considering the depreciation cost and then after finding the near-optimal solution, the objective is calculated without considering the depreciation cost for that solution. Note that in this instance, $Lmv = 2$ and $Ls = 5$. The near-optimal solution regarding objective 1 is shown in Table 6.

The first and second columns provide periods and hub nodes in each period, respectively. For example, in period 1, nodes 5, 6, and 15 are hubs. The third column gives which hub facilities are moved at the end of that period. For example, hub 5 facilities are moved to the next period; however, they remain in node 5. Hub 6 is completely closed (as can be seen, a new hub at node 8 is established in Period 2). Hub 15 facilities are moved to the next period and also moved to a new hub location (i.e., node 20). The fourth column shows which non-hub nodes are allocated to each hub at each period. For example, nodes 12, 3, 7, 16, 9, 13, and 17 are allocated to the hub at node 5. Column 5 provides hubs that are equipped with mobile infrastructure. Mobile infrastructures are established between nodes 15 and 20 and nodes 11 and 18. Column 6 provides total costs when depreciation cost is not considered. Column 7 gives total costs when depreciation cost is considered for the solution that solution. The last column provides the percent of underestimate costs. It can be seen that if the depreciation cost is not considered for solving a multi-period HLAP, the cost is underestimated by 0.52%.

Moreover, the percent of change in the costs of some other instances when depreciation cost is (or is not) considered are in Fig. 12. For this, once, the instances are solved when the depreciation cost is considered and once, they are solved without considering the depreciation cost. Then, the percent of the difference between them is calculated and shown. Fig. 12 provides the percent of the underestimated cost for each test instance. For example, underestimated costs for instances 2 and 4 are 0.52% and 11.08%, respectively. This shows that not considering the depreciation cost leads to the underestimation of costs and consequently sub-optimality. According to the importance of depreciation costs, it is necessary to consider such costs in the modeling of multi-period problems to find the optimal location of hubs and their nodes' allocation.

4.3. Case study

Given the immense cost of energy supplies in Iran, the government has made a multi-step plan for removing the subsidies, which was accompanied by a 4-fold increase in fuel costs in the first phase; however, it has caused a significant increase in transportation costs (Ebrahimi-Zade et al., 2016). Due to a continuous increase in costs and excessive inflation, a shipping company, that transports goods between 11 provinces in Iran, decides to plan for the next 10 periods. The number of hubs in each period, the discount rate, Lmv, and Ls are set to 3, 0.4, 3 and 5, respectively. According to the longevity of the facilities used in the hubs, the company decides to reuse or transfer them to the new hubs in the subsequent periods. The relocation of these facilities requires special infrastructure, like railways preparation to carry high weight facilities. Other parameters of this problem are also available upon request.

The solution produced for the case study shows, for example, that in period 1, nodes 1, 5, 10, and 11 are allocated to hub 1 established in node 3; nodes 2 and 6 are allocated to hub 2 established in node 4; and nodes 7 and 8 are allocated to hub 3 established in node 9. The Pareto solutions of the case study are shown in Table 7. This table can help the decision-makers (i.e., managers) to compare the different combinations of objectives for near-optimal solutions. Therefore, they can select a desirable solution. Suppose that we consider a solution that only minimizes objective 1 (i.e., solution 4). Fig. 13 shows the railway infrastructures.

A comparison between the results of the proposed model and the results of solving the case study by Bashiri et al. (2018) is done. The differences between our model and Bashiri et al. (2018) is that they did not consider the depreciation cost and did not limit the maximum number of non-hub nodes that can be allocated to hub nodes. They did

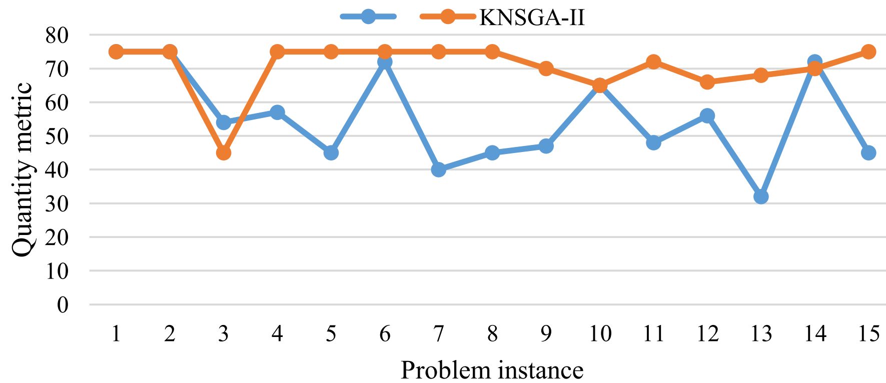

Fig. 8. Evaluation of KNSGA-II and KMOPSO in terms of the quantity metric.

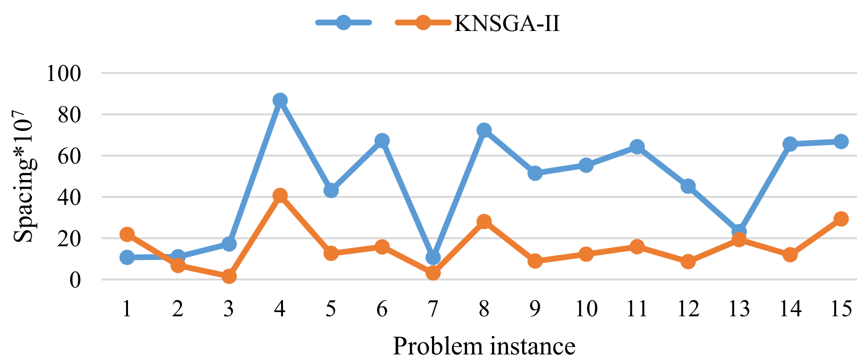

Fig. 9. Evaluation of KNSGA-II and KMOPSO in terms of the spacing metric.

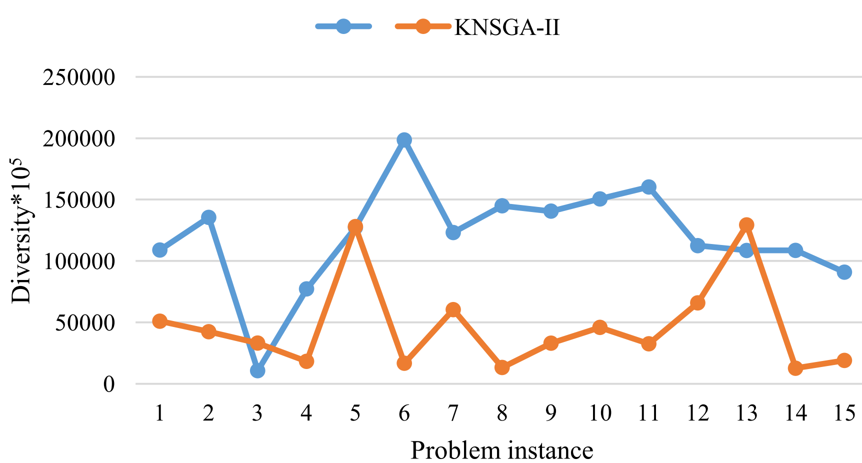

Fig. 10. Evaluation of KNSGA-II and KMOPSO in terms of the diversity metric.

Table 5
Identification of an optimal solution approach using a two-sample *t*-test.

Criterion	Selected algorithm	Mean of results		Two sample t-test	
		KMOPSO	KNSGA-II	Means comparison	P-value
Quantity	KNSGA-II	55.2	70.4	$\mu_{KNSGA-II} \geq \mu_{KMOPSO}$	0.019
Spacing	KNSGA-II	46.03	15.78	$\mu_{KNSGA-II} \leq \mu_{KMOPSO}$	0.031
Diversity	KMOPSO	119 858	46 728	$\mu_{KNSGA-II} \leq \mu_{KMOPSO}$	0.003
Hypervolume	KNSGA-II			$\mu_{KNSGA-II} \geq \mu_{KMOPSO}$	
Execution time	KNSGA-II, KMOPSO	303	224	$\mu_{KNSGA-II} = \mu_{KMOPSO}$	0.169

not limit the number of mobile hub movements. The comparison was made based on the total costs (i.e., the first objective) because Bashiri et al. (2018) only considered the total cost of the solution is 6.43E+10. A comparison of this cost with Table 7 shows that the total cost of Bashiri et al. (2018) is less than the total cost of the proposed model solutions. This is because Bashiri et al. (2018) neglected depreciation costs and real-world limitations that we consider.

The status of hubs at different periods for our proposed solution and that proposed by Bashiri et al. (2018) is in Table 8. Hubs 1 and 2 are established in nodes 3 and 4 in period 1, which remain there for

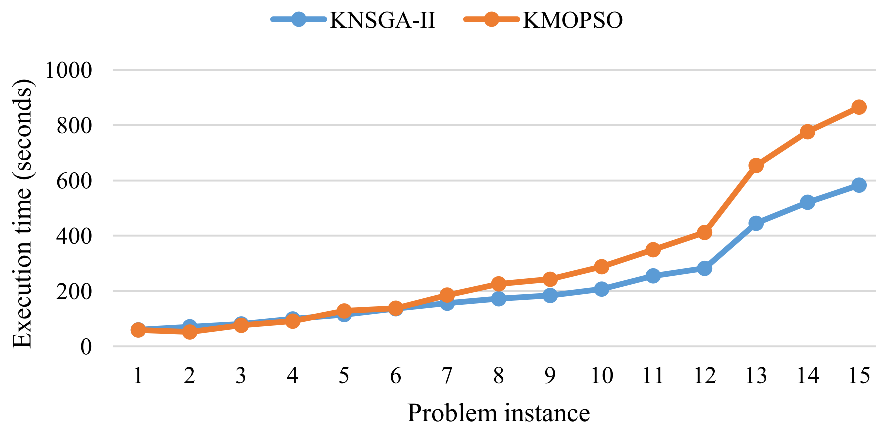

Fig. 11. Evaluation of KNSGA-II and KMOPSO in terms of execution time.

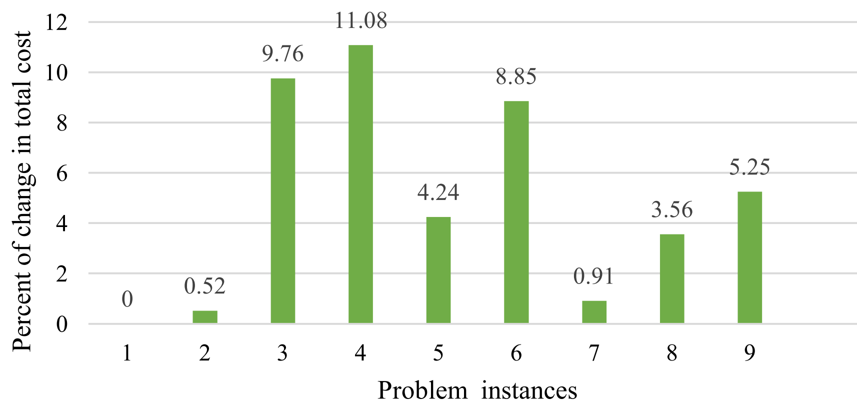

Fig. 12. Comparison of costs with/without considering depreciation.

Table 6
Analyzing of considering/not considering the depreciation cost.

Period	Hub nodes	Hub movement	Non-hub allocation	Mobility infrastructure	Costs: With depreciation	Costs: Without depreciation	Percent of underestimate costs
1	5	5	12, 3, 7, 16, 9, 13, 17				
	6	–	18, 1, 8				
	15	20	11, 19, 20, 2, 4, 10, 14				
2	5	5	9, 2, 14, 17, 3, 18, 7				
	8	8	19, 16, 4, 15				
	20	–	12, 10, 1, 6, 11, 13				
3	5	5	2, 14, 13, 10, 11, 15, 16	(15, 20); (11,18)	390230172	388214256	0.52%
	8	8	7				
	18	18	9, 1, 12, 6, 3, 4, 19, 20, 17				
4	5	5	10, 15, 17				
	8	–	4, 7, 18, 14, 2, 19, 9, 1, 20				
	11	18	3, 6, 16, 13, 12				
5	5	–	12, 4, 15, 10, 1, 3				
	16	–	None				
	18	–	17, 9, 19, 20, 2, 5, 8, 14, 6, 7, 11, 13				

the next three periods. Hub 3 is established in node 9 and is closed for the next period and hub 4 is established in node 10 for period 2. Hub 7 is used for its whole life (i.e., five periods) while hubs 3 and 9 are used only for one period. Hubs 4, 7, and 8 do all of their movement (i.e., three movements) while hubs 3 and 4 do not move at all. Comparing to Bashiri et al. (2018) established 6 different hubs over all periods, our solution establishes 10 hubs. Bashiri et al. (2018) reported a solution to establish hub 4 for 9 periods; however, it may not be possible because the lifespan of facilities is limited and predefined. Therefore, such a solution may not be feasible. Also, depreciation costs are neglected, which underestimated the costs. It is better to replace some facilities even before they finish their lifespan. In contrast, our proposed solution considers these limitations and costs. This leads to a solution that is feasible compared to a solution found in Bashiri et al. (2018). Therefore, the costs are more realistic.

Finally, the impact of the previous periods flows on the current period depreciation costs (ψ) is analyzed against total costs. Fig. 14 provides the results. As one can expect, total cost increases when ψ increases. Increase in costs between $\psi = 0.2$ and $\psi = 0.3$, between $\psi = 0.6$ and $\psi = 0.7$, and between $\psi = 0.8$ and $\psi = 0.9$ are more

Table 7
Pareto solutions of the case study.

No.	Objective 1	Objective 2	Objective 3
1	7.85E+10	3.25E+04	9.25E+07
2	7.85E+10	3.21E+04	9.60E+07
3	7.85E+10	3.25E+04	9.46E+07
4	1.57E+11	3.20E+04	8.90E+07
5	1.57E+11	3.21E+04	8.75E+07
6	1.57E+11	3.20E+04	8.73E+07
7	1.57E+11	3.23E+04	7.88E+07
8	1.57E+11	3.65E+04	7.63E+07
9	1.57E+11	3.65E+04	7.69E+07
10	2.35E+11	3.23E+04	7.73E+07
11	2.35E+11	3.21E+04	8.17E+07

Fig. 13. Railway infrastructure.

obvious than between other values of ψ. These are because the impact of ψ becomes more than establishing a new hub. Therefore, a new hub is established instead of using an old hub. For example, as one can see in Table 8, hub 1 and 2 are used for 4 periods.

Finally, the impact of the previous periods flows on the current period depreciation costs (ψ) is analyzed against total costs. Fig. 14 provides the results. As one can expect, total cost increases when ψ increases. Increase in costs between $\psi = 0.2$ and $\psi = 0.3$, between $\psi = 0.6$ and $\psi = 0.7$, and between $\psi = 0.8$ and $\psi = 0.9$ are more obvious than between other values of ψ. These are because the impact

Table 8
Status of hubs in each period.

Hub ID/period	Current study										Bashiri et al. (2018)									
	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10
1	3	3	3	3							3	3	3	3						
2	4	4	4	4							4	4	4	4						
3	9										10									
4		10	6	9	9							9	4	9	9	4	7	7	4	4
5					8	8	9								4	8	9	4	9	9
6					11	11	6								11	11	6	1	6	3
7						4	7	7	4	4										
8								1	6	3										
9								10												
10									9	9										

Table A.1
Domination metric values for the proposed algorithms.

Instance	MOPSO	NSGA-II	KMOPSO	KNSGA-II
1	0	0	12	88
2	0	0	55	45
3	0	0	1	99
4	0	0	56	44
5	0	0	10	90
6	0	0	55	45
7	0	4	96	0
8	0	0	62	38
9	0	0	25	75
10	0	0	0	100
11	0	0	15	85
12	0	0	32	68
13	0	0	17	83
14	0	4	14	82
15	0	0	31	69

of ψ becomes more than establishing a new hub. Therefore, a new hub is established instead of using an old hub. For example, as one can see in Table 8, hubs 1 and 2 are used for four periods.

5. Conclusion

This study investigated a multi-objective p-mobile HLP. Regarding the dynamic environment, where facilities may be used for several periods, it is necessary to pay attention to economic concerns. Two important factors in this regard are the economic longevity of facilities and depreciation costs. Therefore, in this study, for the first time, a p-mobile HLP was proposed to address these concerns. There were different allocated non-hub nodes, and consequently, there were different volumes of a hub activity in each period, the volume of production method is used for calculating the depreciation cost. The proposed model was an extension of the Bashiri et al. (2018) study, which addressed the p-mobile HLP by considering mobile infrastructures for

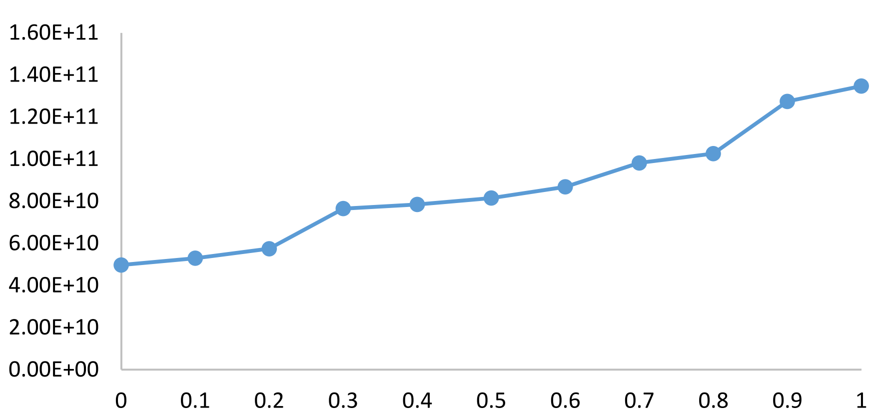

Fig. 14. Impact of ψ on total costs.

Table A.2
Comparison metrics for the problem instances.

No.	Specifications*	KNSGA-II				KMOPSO			
		Quantity	Spacing*10^7	Diversity*10^5	Run time (seconds)	Quantity	Spacing*10^7	Diversity*10^5	Run time (seconds)
1	(12,4,3)	75	21.819	50 924	59.8	75	10.694	108 880	59.2
2	(20,5,3)	75	6.7786	42 347	71	75	11.006	135473.3	52
3	(25,8,5)	45	1.528	33 101	81	54	17.169	10 617	76
4	(30,10,6)	75	40.675	18 224	99	57	86.728	77 220	91
5	(35,12,6)	75	12.646	128 000	115	45	43.073	127 280	128
6	(40,12,5)	75	15.77	16 674	136	72	67.216	198 560	138
7	(50,15,6)	75	3.1744	60 320	156	40	10.649	123 130	185.5
8	(60,15,8)	75	28.049	13 207	172	45	72.261	144 940	226
9	(70,15,8)	70	8.9142	33 006	184	47	51.426	140 580	242.5
10	(80,15,8)	65	12.235	45 872	207	65	55.32	150 527	288
11	(90,15,8)	72	15.8546	32 514	255	48	64.26	160 258	349.5
12	(100,15,8)	66	8.65	65 852	282	56	45.15	112 457	412
13	(120,20,9)	68	19.321	129 351	445	32	23.15	108 524	654
14	(135,20,9)	70	11.975	12 584	521	72	65.554	108 574	776
15	(150,20,10)	75	29.321	18 954	583	45	66.78	90 852	865
	Average	70.4	15.78	46 728	224	55.2	46.03	119 858	303

*Note that in specifications column, (a, b, c) means (number of nodes, number of periods, p), on which the problem size depends.

the movement of hub facilities between nodes. Also, in this study, a new objective (social factor) was proposed to locate the hubs in less populated zones. A hybrid of k-medoids, a clustering algorithm, with two meta-heuristic algorithms (i.e., KNSGA-II and KMOPSO) was developed to solve the presented problem. Numerical results were important two-fold. First, comparing the performance of the algorithms indicated that the hybridization of the clustering algorithm with a meta-heuristic algorithm creates a more qualified solution than pure meta-heuristic algorithms. This because the purpose of both clustering and hub location problems is to cluster the data (i.e., in the hub location, the objective is to locate hubs and allocate non-hub nodes to hubs). KNSGA-II is more efficient than KMOPSO and can be used for real-world situations and for future studies. Second, comparing the results when depreciation costs are/are not considered showed the importance of considering depreciation costs in multi-period location problems. If depreciation costs and hubs longevity are not considered, the solution may be non-optimal.

A limitation of our study is that only the uncertainty of flows between nodes was considered as a multi-period method. However, there are uncertainty inflows between nodes within each period, which we proposed to be considered in future research. Also, we considered that mobile infrastructures must be established in the first period. Research can be conducted to determine the best time for establishing mobile infrastructures based on its maintenance costs.

As a conclusion, some economic factors have been investigated for the first time in this study. The encouraging obtained results suggest considering other financial factors of p-mobile HLP in future studies, such as delay in transportation payments (Hörhammer, 2014), discounted interest rate (Paydar et al., 2020), inflation and risk (Musmanno et al., 2010) . Also, given the importance of involving economic considerations, the generalization of the proposed idea in other multi-period problems dealing with economic lifetime and depreciation, such as vehicle routing-location problems, is recommended for future studies. Also, hybridization of other meta-heuristics (i.e., MOEA by k-medoids or other clustering techniques) for solving the problem is proposed.

CRediT authorship contribution statement

Mahdi Mokhtarzadeh: Conceptualization, Writing - original draft. **Reza Tavakkoli-Moghaddam:** Supervision, Resources, Writing - review & editing. **Chefi Triki:** Project administration, Data collection, Investigation. **Yaser Rahimi:** Visualization, Software.

Declaration of competing interest

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

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Appendix A

See Tables A.1 and A.2

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