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RESEARCH ARTICLE

A biobjective home health care logistics considering the working time and route balancing: a self-adaptive social engineering optimizer

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Abstract

Home health care (HHC) logistics have become a hot research topic in recent years due to the importance of HHC services for the care of ageing population. The logistics of HHC services as a routing and scheduling problem can be defined as the HHC problem (HHCP) academically including a set of service centers and a large number of patients distributed in a specific geographic environment to provide various HHC services. The main challenge is to provide a valid plan for the caregivers, who include nurses, therapists, and doctors, with regard to different difficulties, such as the time windows of availability for patients, scheduling of the caregivers, working time balancing, the time and cost of the services, routing of the caregivers, and route balancing for their routes. This study establishes a biobjective optimization model that minimizes (i) the total service time and (ii) the total costs of HHC services to meet the aforementioned limitations for the first time. To the best of the authors' knowledge, this research is the first of its kind to optimize the time and cost of HHC services by considering the route balancing. Since the model of the developed HHCP is complex and classified as NP-hard, efficient metaheuristic algorithms are applied to solve the problem. Another innovation is the development of a new self-adaptive metaheuristic as an improvement to the social engineering optimizer (SEO), so-called ISEO. An extensive analysis is done to show the high performance of ISEO in comparison with itself and two well-known metaheuristics, i.e. FireFly algorithm and Artificial Bee Colony algorithm. Finally, the results confirm the applicability of new suppositions of the model and further development and investigation of the ISEO more broadly.

Keywords: home health care (HHC); HHC services; HHC problem; service time; route balancing; metaheuristic algorithms

1. Introduction

Home health care (HHC) is a set of logistics activities for visiting, curing, and supporting the old and elderly patients at their home (Decerle, Grunder, El Hassani, & Barakat, 2019). The HHC services provide a wide range of health services as the informal care with regard to the convenience of the patients and are usually more economical and efficient than the formal services provided at a hospital. Furthermore, the HHC services are highly recommended for patients with chronic illnesses, who require an on-time service from a health system (Fathollahi-Fard, Hajiaghaei-Keshteli, & Mirjalili, 2020a). In this regard, various sorts of the care are carried out depending on the need of the patients. The caregivers to provide the HHC services are composed

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of nurses, doctors, and therapists, who provide the full range of care required, such as personal cleaning, injections, bandage, and much more (Moussavi, Mahdjoub, & Grunder, 2019). Therefore, the HHC services have been grown in response to the needs of the patients at the community level (Abdellatif *et al.*, 2019). One of the reasons for this rapid growth is the demonstration of the HHC efficacy and performance when faced with different patient needs, which have been proven to increase the efficiency of the HHC services (Bahadori-Chinibelagh, Fathollahi-Fard, & Hajiaghaei-Keshteli, 2019; Shi, Boudouh, & Grunder, 2019).

The logistics operations of these services, such as visiting patients by a set of caregivers, drug delivery, medical equipment, and especially the scheduling and routing of the caregivers, motivate an optimization problem so-called the home health care problem (HHCP). The HHCP is classically an extension to the vehicle routing problem with time windows (VRPTW; Shi, Boudouh, & Grunder, 2017; Shi, Boudouh, Grunder, & Wang, 2018). This development aims to make the scheduling and routing decisions for the caregivers to create a valid plan that is complex due to different difficulties such as the time windows of availability for patients, scheduling of the caregivers, working time balancing, the time and cost of the services, routing of the caregivers, and route balancing for their routes. This study proposes a biobjective optimization model that minimizes (i) the total service time and (ii) the total costs of HHC services simultaneously with regard to the aforementioned limitations for the first time. Due to the complexity of the model in large-scaled networks, a new improvement to the social engineering optimizer (SEO; Fathollahi-Fard, Hajiaghaei-Keshteli, & Tavakkoli-Moghaddam, 2018a) is developed and compared with its general idea and with two well-known metaheuristics, i.e. FireFly algorithm (FFA) and Artificial Bee Colony (ABC) algorithm.

Therefore, the main highlights of this paper are as follows:

- A biobjective HHC routing and scheduling problem with time windows is introduced to minimize the total cost and the service time.
- Simultaneous consideration of the route balancing, service time, and working time balancing is contributed to the literature for the first time.
- A new improvement to the SEO, called improved SEO (ISEO), is developed.

This paper unfolds as follows: Section 2 presents the literature review in a comprehensive survey with an identification of literature gaps. Section 3 introduces the proposed HHCP and its model. Section 4 explains our development on the SOE with its mathematics and implementation on our HHCP. Next, Section 5 contains a numerical example, the results of the metaheuristic algorithms, the trade-off among the total time of operations and the total cost of the HHC services, a comparison according to the Pareto optimal analyses, and sensitivity analyses of the offered model, along with the practical insights. Finally, Section 6 provides the conclusions and future research avenues.

2. Literature Review

Here, the literature of HHCP is reviewed as follows: To the best of our knowledge, the study of Begur, Miller, and Weaver (1997) is the earliest study. They suggested a decision support system (DSS) as a tool that would allow the managers of HHC services to manage their caregivers efficiently and effectively and then utilized the suggested DDS for the scheduling and routing decisions of 10 000 HHC organizations across the United States. Hence, the University of Alabama's Productivity Center and the Visiting Nurses Association extended a spatial DSS (SDSS) to investigate their problem in a joint project. Later, Cheng and Rich (1998) formulated for the first time a mixed-integer linear programming (MILP) model for the scheduling and routing decisions in an HHCP. As an extension to the VRP, each patient must be visited by a single "feasible" caregiver like a vehicle in the VRP. Since their problem was NP-hard, a parallel tour-building heuristic was extended for finding an optimal solution.

In another important paper, Bertels and Fahle (2006) extended a hybrid setup for a mixed scenario-based HHCP with various heuristics. Additionally, an MILP was established to minimize the transportation costs and to maximize the satisfaction of patients and caregivers. A combination of constraint programming, linear programming, and metaheuristic algorithms for the HHCP was utilized. Akjiratikarl, Yenradee, and Drake (2007) designed a particle swarm optimization (PSO) algorithm based on the collaborative scheduling algorithm to solve a scheduling of HHCP. They validated this model using a real data set in the UK. Their objective was the minimization of the total distance traveled by all caregivers while satisfying the capacity of the vehicle and the time window constraints. In addition, Trautsamwieser, Gronalt, and Hirsch (2011) introduced a variable neighborhood search (VNS)-based heuristic for the daily planning of HHC services; their objective was to minimize the sum of driving times, waiting times, and the dissatisfaction levels of patients and caregivers. They used three numerical examples with real-life data from Austria. Later, another important study was done by Mascolo and Gouin (2013), who formulated a generic simulation model to evaluate the efficiency of sterilization services in the HHCP. Their model can be utilized for testing changes in the organization of a given sterilization service to enhance its efficiency. Hence, a case study is provided to validate the model. Torres-Ramos, Alfonso-Lizarazo, Reyes-Rubiano, and Quintero-Araújo (2014) built a mathematical model for the HHCP with multiple treatments and time windows. According to the cost and quality implications, an MILP model was provided for the planning of the periodic schedule of medical caregivers and the route planning for patient visits with workload and attention capacity constraints.

Due to the high complexity of HHCPs, recent studies have mainly focused on the high-performance heuristics and metaheuristics. For example, Hiermann, Prandtstetter, Rendl, Puchinger, and Raidl (2015) suggested several metaheuristic algorithms, including VNS, memetic algorithm (MA), scatter search (SS), and simulated annealing (SA) algorithm, in order to solve a multimodal scheduling of HHCP. Their model aims to assign caregivers to the patients and to determine efficient multimodal tours considering the satisfaction of both patients and caregivers. Braekers, Hartl, Parragh, and Tricoire (2016) extended a new biobjective model for the HHCP to minimize the operating cost and to maximize the service level for a multi-depot network. The concepts of the hard time windows, client preferences on visit times and caregivers, and travel costs depending on the types of transportation systems are considered. To solve the model and to find the optimal solutions, the authors utilized a metaheuristic algorithm based on a multidirectional local search. Shi *et al.* (2017) proposed a fuzzy chance constraint programming for an HHCP with time windows and fuzzy demand. Besides, a new hybrid genetic algorithm with stochastic simulation was introduced. Sinthamrongruk, Dahal, Satiya, Vudhironarit, and Yodmongkol (2017) offered two sorts of adaptive local search-based genetic algorithms to solve an HHCP with the goal of total cost minimization. The immigrant scheme was combined with GAs to enhance their efficiency.

Recently, Decerle, Grunder, El Hassani, and Barakat (2018) formulated an MILP model for the HHCP with hard and soft time windows and synchronization constraints. Additionally, an MA was developed with the supposition of two new crossover operators based on the multiobjective optimization concept. A real case study in France was also considered to have a large-scaled instance. A Lagrangian relaxation-based algorithm was developed by Fathollahi-Fard, Hajiaghaei-Keshteli, and Tavakkoli-Moghaddam (2018b) to address a single depot and single objective HHCP with time windows and route balancing. Nasir and Dang (2018) extended another MILP to model an HHCP with the joint of patient and caregiver considering the dynamic arrival and departure of patients. Besides, two heuristic approaches based on the VNS were compared with the exact solution. Liu, Yang, Su, and Xu (2018) designed a new biobjective approach for an HHCP. An MILP model was formulated with the aims of maximizing the patients' satisfaction and minimizing the total cost. Due to the high complexity of large-scaled samples, three heuristic methods for generating Pareto-based solutions were considered. With regard to the concept of network design for the HHCP, Khodaparasti, Bruni, Beraldi, Maleki, and Jahedi (2018) offered a multiperiod, location, and allocation model under uncertainty. The model was applied to a real case study for the nursing home planning network in Shiraz city, Iran. Martinez, Espinouse, and Di Mascolo (2018) developed an HHCP with fixed services, and utilized the graph theory to address them. Furthermore, a branch-price-cut algorithm was presented to solve the model to minimize the number of caregivers needed to provide all the services. The concept of green HHCP was first contributed by Fathollahi-Fard, Hajiaghaei-Keshteli, and Tavakkoli-Moghaddam (2018c), who propose a single depot and biobjective HHCP with time windows and route balancing. They developed four heuristics as well as a hybrid algorithm of SA and salp swarm algorithm (SSA) to find an interaction between the total cost and green emissions of the logistics activities in view of Pareto-based metrics.

More recently, Haddadene, Roufaida, Labadie, and Prodhon (2019) suggested a multiobjective approach to the optimization of the HHCP, minimizing the caregivers' travel costs and maximizing the patients' preferences. Szander, Ros-McDonnell, and de la Fuente (2019) formulated an MILP model related to the routing and delivery of HHC services, in which there is the possibility of utilizing electric bicycles instead of the combination of walking and public transport. The objective functions were to minimize transportation costs and maximize the flexibility of the services. Mousavi *et al.* (2019) proposed a metaheuristic approach based on decomposition to model an integrated worker assignment and VRPTW. In this regard, human resource planning for an HHCP was designed. To solve the model, the *Gurobi* MILP solver was proposed. Fathollahi-Fard, Govindan, Hajiaghaei-Keshteli, and Ahmadi (2019a) developed a multiperiod location-allocation-routing model for the green HHCP. New modifications of SA were tackled to address their biobjective model. Decerle *et al.* (2019) introduced a new hybrid of MA and ant colony optimization (ACO) algorithm to solve the HHCP with time windows, synchronizations, and working time balancing of the caregivers. They considered three objective functions to minimize the total working time of the caregivers, to maximize the service quality, and to minimize the maximal working time difference between auxiliary of the caregivers. Grenouilleau, Legrain, Lahrichi, and Rousseau (2019) presented a set of partitioning heuristic approaches for the HHCP with minimizing the travel time and maximizing the continuity of care. Moreover, several new VNS operators to find the optimal solutions were presented. Bahadori-Chinibelagh *et al.* (2019) proposed two heuristics for a multidepot HHCP with time windows and travel balancing.

Fathollahi-Fard *et al.* (2020a) designed three new heuristic methods, a hybrid metaheuristic algorithm based on VNS and SA, and a lower bound according to the Lagrangian relaxation theory, to solve a single depot and period HHCP. Manavizadeh, Farrokhi-Asl, and Beiraghdar (2020) developed a mathematical model for multiple services of HHCP. The SA based on the real condition of the caregivers and vehicles to find the optimal solutions was extended. Last but not least, Fathollahi-Fard, Ahmadi, Goodarzian, and Cheikhrouhou (2020b) developed a biobjective multiperiod HHCP with patient satisfaction. The Jimenez's method based on the triangular fuzzy numbers was first used to model the HHCP. An adaptive memory SEO was employed to solve the large-scaled instances.

To identify the literature gaps, the papers are classified in view of five main criteria, as follows. The number of depot(s), period(s), the type of objectives including the cost, the service time, satisfaction, and green emissions, as well as the type of the constraints, including time windows, working time balancing of the caregivers, route balancing, and synchronizations in addition to the solution algorithm, are utilized. In this regard, this classification of the HHCP studies is given in Table 1.

As can be concluded from Table 1, we make the following observations:

- The majority of the studies (around 80%) involve a single depot and period HHCP, with the minimization of the total cost.
- The main constraint in most papers is the time windows.
- Only five studies contributed to the route balancing (Fathollahi-Fard, Hajiaghaei-Keshteli, & Tavakkoli-Moghaddam, 2018b, 2018c; Bahadori-Chinibelagh *et al.*, 2019; Fathollahi-Fard *et al.*, 2019a, 2020a). However, none of them has considered the travel cost and service time simultaneously.
- Only two papers are simultaneously multidepot, multiperiod, and multiobjective HHCPs (Fathollahi-Fard *et al.*, 2019a, 2020b). In addition to these contributions, this study considered the service time for the first time.
- The simultaneous consideration of the route balancing and working time balancing of the caregivers is studied in the present paper for the first time.
- Due to the high complexity of HHCPs, heuristics and metaheuristics are popular in the literature. However, there is no study to apply ABC, FFA, and SEO as well as a new improvement to the SEO simultaneously.

Generally speaking, this study proposes a biobjective HHCP with simultaneous consideration of service time, working time, and route balancing for the first time. In addition to this novelty, this study develops a new improvement to the SEO, which is novel in comparison with other developments on this metaheuristic (Fathollahi-Fard, Ranjbar-Bourani, Cheikhrouhou, & Hajiaghaei-Keshteli, 2019b; Fathollahi-Fard *et al.*, 2020b).

3. Proposed HHCP

The section provides a detailed and exhaustive view about the link between the concept of HHC services with time windows, route balancing, and a biobjective optimization model. The statement of the proposed HHCP is first illustrated and consequently, assumptions, notations, and the mathematical model are exposed to the HHCP comprehensively.

Table 1: The summary of the literature review.

Reference	Number of depots		Number of periods		Type of the objectives				Type of the constraints				Solution
	Single depot	Multidepot	Single period	Multiperiod	Cost	Service time	Satisfaction	Green emissions	Time windows	Worker time balancing	Route balancing	Synchronizations	
Begur, Miller, and Weaver (1997)	*	-	*	-	*	-	-	-	-	-	-	-	Exact solver
Cheng and Rich (1998)	*	-	*	-	*	-	-	-	-	-	-	-	Heuristic
Bertels and Fahle (2006)	*	-	*	-	*	-	*	-	-	-	-	-	Heuristic
Akjiratikarl, Yenradee, and Drake (2007)	*	-	*	-	*	-	-	-	*	-	-	-	PSO
Trautsamwieser, Gronalt, and Hirsch (2011)	*	-	*	-	-	*	*	-	*	-	-	-	VNS
Mascolo and Gouin (2013)	*	-	*	-	*	-	-	-	-	-	-	-	Simulation
Torres-Ramos *et al.* (2014)	*	-	*	-	*	-	*	-	*	*	-	-	ε-constraint method
Hiermann *et al.* (2015)	-	*	*	-	*	-	-	-	-	-	-	-	VNS, MA, SS, and SA
Braekers *et al.* (2016)	-	*	*	-	*	-	*	-	*	-	-	-	Simulation
Shi, Boudouh, and Grunder (2017)	*	-	*	-	*	-	-	-	*	-	-	-	Hybrid GA
Sinthamrongruk *et al.* (2017)	*	-	*	-	*	-	-	-	-	-	-	-	Hybrid GAs
Decerle *et al.* (2018)	*	-	*	-	*	-	*	-	*	-	-	*	MA
Fathollahi-Fard, Hajiaghaei-Keshteli, and Tavakkoli-Moghaddam (2018c)	*	-	*	-	*	-	-	*	*	-	*	-	Heuristics and hybrid of SA and SSA
Nasir and Dang (2018)	-	*	*	-	*	-	-	-	*	-	-	-	VNS
Liu *et al.* (2018)	*	-	-	*	*	-	*	-	*	-	-	-	Heuristic
Khodaparasti *et al.* (2018)	*	-	-	*	*	-	-	-	-	-	-	-	GA, VNS, and SA
Martinez, Espinouse, and Di Mascolo (2018)	*	-	-	*	*	-	-	-	-	-	-	-	Branch-price-cut method
Shi *et al.* (2018)	*	-	*	-	*	-	-	-	*	-	-	-	GA, SA, and Bat algorithm
Fathollahi-Fard, Hajiaghaei-Keshteli, and Tavakkoli-Moghaddam (2018b)	*	-	*	-	*	-	-	-	*	-	*	-	Lagrangian relaxation
Haddadene *et al.* (2019)	*	-	*	-	*	-	*	-	-	-	-	-	GA
Mousavi *et al.* (2019)	*	-	-	*	*	-	-	-	*	-	-	-	Heuristics
Bahadori-Chinibelagh, Fathollahi-Fard, and Hajiaghaei-Keshteli (2019)	*	-	-	*	*	-	-	-	*	-	*	-	Heuristic
Fathollahi-Fard *et al.* (2019a)	-	*	-	*	*	-	-	*	*	-	*	-	SAs
Szander *et al.* (2019))	-	*	*	-	*	-	-	-	*	-	-	-	Exact solver
Decerle *et al.* (2019)	*	-	*	-	*	-	-	-	*	-	*	*	Hybrid MA-ACO
Shi, Boudouh, and Grunder (2019)	*	-	*	-	*	-	-	-	*	-	-	-	SA and VNS
Fathollahi-Fard *et al.* (2020a)	*	-	*	-	*	-	-	-	*	-	*	-	Heuristics and Hybrid of VNS and SA
Grenouilleau *et al.* (2019)	*	-	-	*	-	*	*	-	*	*	-	-	Metaheuristic algorithms
Manavizadeh, Farrokhi-Asl, and Beiraghdar (2020)	*	-	*	-	*	-	-	-	*	-	-	-	SA
Fathollahi-Fard *et al.* (2020b)	-	*	-	*	*	-	*	-	*	-	-	-	SEO and AMSEO
Our study	-	*	-	*	*	*	-	-	*	*	*	-	SEO, FFA, ABC, and a new improved SEO

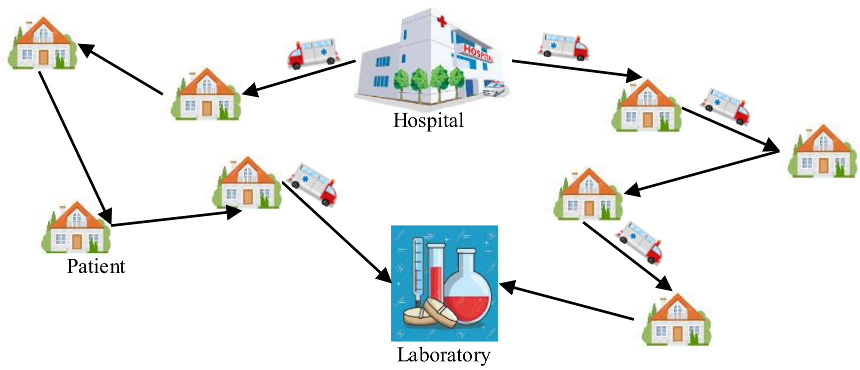


Figure 1: The framework of HHCP with one service center, two caregivers, and eight patients.

3.1 Problem statement

The framework of the proposed HHCP is given in Fig. 1. In this paper, different HHC services with respect to three types of caregivers, namely doctors (DO), nurses (NU), and therapists (TH), in different time windows for the planning horizon H, are assumed. Indeed, the model is defined as a directed graph $G = (N, A)$, where N stands for the set of nodes, including the sets of patients i and j and service center sc, and shows the set of directed arcs $A = \{(i, j)i, j \in N, i \neq j\}$, that is, joining pairs of nodes. Then, we consider a city or a geographical zone by P patients distributed all over the city with the distance of D_{ij} in the suggested HHCP. Each service center ($sc \epsilon SC$) is served by the type of caregivers ($p \epsilon P$) required. In this model, two sorts of service centers (sc) called the hospital and the laboratory are considered to provide special services to patients. Besides, each patient i has a demand for visits based on the sort of caregivers and service centers that these visits are performed based on the patient and the types of caregivers according to the specific time window on the days. In this regard, based on the service time on each day, a time limitation exists ($\underline{\nabla}_{id}$ and $\overline{\nabla}_{id}$). Each patient also has a starting time ($\underline{\psi}_i^d$) and an ending time ($\bar{\psi}_i^d$) to be visited by the caregiver. Also, a caregiver starts from their service centers to visit the patients and returns back to the same service center; so, they have a maximum working time per day (MW) to do the working time balancing. Additionally, travel times vary based on the type of caregivers. For instance, doctors utilize private transport that is faster than the public transport by which nurses and therapists are mobilized, with the transportation cost (TC_{ij}). It takes α_{ij} the time to travel from patient i to patient j. Also, there is a specified service time for patient i by caregivers (ST_{id}). To perform the route balancing, a maximum allowable distance (MS) is considered for each route and if the vehicle does not meet this constraint, a penalty value for the overall allowable distance is assumed (PEN). In this model, four types of services, namely domicile, blood anticoagulation, chronic care, and palliative care, are considered to be special services provided to the patients. Then, according to this HHCP, the HHC companies are able to serve patients with the lowest costs in a specific time window.

3.2 Assumptions

The following assumptions for the offered HHCP are made:

- A set of nodes involving of service centers (i.e. hospital and laboratory) and patients' homes is considered.
- The model is multidepot (i.e. a set of hospitals and laboratories) and multiperiod (i.e. a set of days).
- The model contributes to optimizing the total service time and the cost.
- Each route starts from the hospital and ends at the laboratory.
- Each patient is visited only once.
- The types of caregivers and services are identified based on the type of illness of patients.
- Each vehicle visits each node only once per route.
- There is no direct link between service centers.
- The maximum working time for each patient is predefined/estimated by the caregiver, to do the working time balancing.
- A time window exists for the available vehicles and patients at a specified time.
- For each vehicle's route, a maximum desired distance is allowable. Otherwise, it gets a penalty value for the overall distance.

3.3 Notations

The notations of HHCP including a set of indices, parameters, and decision variables are as follows:

Indices:	
i, j	Indices of patients, $i, j \in N$
p	Index of caregivers, $p \in \{1, 2, \ldots, P\}$
sc	Index of service centers, $sc \in \{1, 2, \ldots, SC\}$
d	Index of days, $d \in \{1, 2, \ldots, D\}$
v	Index of vehicles, $v \in \{1, 2, \ldots, V\}$
Parameters:	
$\underline{\psi}_i^d$	Starting time of the time window for patient i on the day d
$\overline{\psi}_i^d$	Ending time of the time window for patient i on the day d
$\underline{\nabla}_{id}$	The earliest allowed service time for the patient i on the day d
$\overline{\nabla}_{id}$	The latest allowed service time for the patient i on the day d
TC	Transportation cost per unit of distance
ST_{id}	The estimated service time for the patient i on the day d
α_{ij}	Traveling time from patient i to patient j
D_{ij}	The distance from patient i to patient j
$\beta_i^{p,sc}$	Required working time for patient i by caregiver p working at the service center sc
$\kappa_{DO,d}^{sc}$	1, if the doctors DO in the service center sc are available on the day d. Otherwise, 0.
$\kappa_{NU,d}^{sc}$	1, if the nurses NU in the service center sc are available on the day d. Otherwise, 0.

$\kappa^{sc}_{TH,d}$	1, if the therapists TH in the service center sc are available on the day d. Otherwise, 0.
$HS_{i,d,DO,NH,TH}$	1, if the patient i on the day d needs one of HHC services by doctors DO, nurses NU, and therapists TH. Otherwise, 0.
δ^{DO}_{isc}	The number of required visits to the patient i from doctors DO for service centers sc
γ^{NU}_{isc}	The number of required visits to the patient i from nurses NU for service centers sc
λ^{TH}_{isc}	The number of required visits to the patient i from therapists TH for service centers sc
MT	Maximum time length of each tour
MW	Maximum working time in each day for the caregiver
MS	Maximum allowable distance of each vehicle
PEN	Penalty value for the overall distance from the maximum allowable distance of each vehicle
M	A big number
H	Planning horizon
Decision variable:	
$\vartheta^{pd}_{ij,sc}$	1, if the caregiver member p working at service center sc visits patient i and then patient j on the day d; otherwise, 0.
$Z_{i,sc}$	1, if patient i is assigned to the service center sc; otherwise, 0.
σ_i^{pd}	Arrival time of caregiver p at patient i's home on the day d
π_{ijvd}	1 if vehicle v goes directly from patient i to patient j on the day d; otherwise, 0.
B_{ivd}	The time of beginning service for patient i by vehicle v on the day d.
O_{vd}	The overall distance from allowable distance for vehicle v on the day d

3.4 Formulation

Based on the aforementioned problem definition and notations, a biobjective MILP is proposed:

$$Z1 = \min\left(\sum_{i\in N}\sum_{j\in N}\sum_{p\in P}\sum_{d\in D}\sum_{sc\in\{DO,NU,TH\}\in SC} \times \vartheta^{pd}_{ij,sc}\left(\alpha_{ij} + \left(\beta^{psc}_j \times \left(\kappa^{sc}_{TH,d} + \kappa^{sc}_{NU,d} + \kappa^{sc}_{DO,d}\right)\right)\right)\right) \tag{1}$$

$$Z2 = \min\left(\sum_{i\in N}\sum_{j\in N}\sum_{v\in V}\sum_{d\in D}\left(TC \times D_{ij} \times \pi_{ijvd}\right) + \sum_{v\in V}\sum_{d\in D} PEN \times O_{vd}\right) \tag{2}$$

s.t.

$$\sum_{j\in N}\sum_{sc\in SC}\vartheta^{pd}_{ij,sc} \times \beta^{psc}_i \le MW\ \forall i\in N, \forall p\in P, \forall d\in D \tag{3}$$

$$\sum_{j\in N}\vartheta^{pd}_{ij,sc} - \sum_{j\in N}\vartheta^{pd}_{ji,sc} = 0\ \forall i\in N, \forall p\in P, \forall d\in D, sc\in SC \tag{4}$$

$$\sum_{sc\in N} Z_{i,sc} = 1\ \forall i\in N \tag{5}$$

$$\sum_{j\in N}\vartheta^{pd}_{ij,sc} = Z_{i,sc}\ \forall i\in N, \forall p\in P, \forall d\in D, sc\in SC \tag{6}$$

$$\sum_{i\in N}\vartheta^{pd}_{ij,sc} = HS_{j,d,DO,NH,TH} \times Z_{j,sc}\left(\kappa^{sc}_{TH,d} + \kappa^{sc}_{NU,d} + \kappa^{sc}_{DO,d}\right), \forall p\in P, \forall d\in D, sc\in SC \tag{7}$$

$$\sum_{j\in N}\vartheta^{pd}_{jj,sc} = 0\ \forall p\in P, \forall d\in D, sc\in SC \tag{8}$$

$$\sum_{p\in P}\sum_{sc\in SC}\sum_{j\in N}\vartheta^{pd}_{ij,sc} = 1\ \forall i\in N, \forall d\in D \tag{9}$$

$$\sum_{i\in N}\vartheta^{pd}_{ii,sc} = 0\ \forall i\in N, \forall p\in P, \forall d\in D, sc\in SC \tag{10}$$

$$\sum_{j\in N}\sum_{d\in D}\sum_{p\in DO}\vartheta^{pd}_{ij,sc}\kappa^{sc}_{DO,d} \ge \delta^{DO}_{isc}\ \forall i\in N, \forall sc\in SC \tag{11}$$

$$\sum_{j\in N}\sum_{d\in D}\sum_{p\in NU}\vartheta^{pd}_{ij,sc}\kappa^{sc}_{NU,d} \ge \gamma^{NU}_{isc}\ \forall i\in N, \forall sc\in SC \tag{12}$$

$$\sum_{j\in N}\sum_{d\in D}\sum_{p\in TH}\vartheta^{pd}_{ij,sc}\kappa^{sc}_{TH,d} \ge \lambda^{TH}_{isc}\ \forall i\in N, \forall sc\in SC \tag{13}$$

$$O_{vd} \ge \left(\sum_{i\in N}\sum_{j\in N}\pi_{ijvd} \times D_{ij}\right) - MS\ \forall v\in V,\ \forall d\in D \tag{14}$$

$$\underline{\psi}^d_i \le \sigma_i^{pd} \le \overline{\psi}^d_i \forall i\in N, \forall p\in P, \forall d\in D \tag{15}$$

$$\sigma_i^{pd} + \sum_{sc\in SC}\beta^{psc}_i + \alpha_{ij} \le \sigma_j^{pd} + M\left(1 - \vartheta^{pd}_{ij,sc}\right)\ \forall i, j\in N, i\ne j, \forall p\in P, \forall d\in D, \forall sc\in SC \tag{16}$$

$$\sum_{i\in N}\sum_{j\in N}\pi_{ijvd} = \sum_{i\in N}\sum_{j\in N}\vartheta^{pd}_{ij,sc}\ \ \forall p\in P, \forall d\in D, \forall sc\in SC, \forall v\in V \tag{17}$$

$$\sum_{v\in V}\pi_{ijvd} = \sum_{sc\in N}\sum_{p\in P}\vartheta^{pd}_{ij,sc}\ \forall i\in N, \forall j\in N, \forall d\in D \tag{18}$$

$$\sum_{v\in V}\pi_{ijvd} = 1 \forall i\in N, \forall j\in N, \forall d\in D \tag{19}$$

$$B_{ivd} + \alpha_{ij} + ST_{id} \le B_{jvd} + M\left(1 - \pi_{ijvd}\right)\ \forall i\in N, \forall j\in N, \forall p\in P, \forall v\in V, \forall d\in D \tag{20}$$

$$\underline{\nabla}_{id} \le B_{ivd} \le \overline{\nabla}_{id}\ \forall i\in N, \forall v\in V, \forall d\in D \tag{21}$$

$$\sum_{i\in N}\sum_{j\in N}\pi_{ijvd}\left(\alpha_{ij} + ST_{id}\right) \le MT\ \forall p\in P, \forall v\in V, \forall d\in D \tag{22}$$

$$\pi_{ijvd}, \vartheta^{pd}_{ij,sc}, Z_{i,sc} \in \{0,1\},\ \forall i\in N, j\in N, \forall p\in P, \forall d\in D, \forall v\in V,\ \forall sc\in SC \tag{23}$$

$$O_{vd}, \sigma_i^{pd}, B_{ivd} \ge 0\quad \forall i\in N, j\in N, \forall p\in P, \forall d\in D, \forall v\in V \tag{24}$$

The first objective function manifests the minimization of the total time of HHC services based on the travelling and working times, as given in equation (1). The second objective function displays the minimization of the total cost. As given in equation (2), the first part is the transportation cost per unit of distance for visiting the patients. The last part is the penalty value for the overall distance from the maximum allowable distance for each vehicle.

With regard to the working time limitation, the term $\sum_{j\in N}\vartheta^{pd}_{ij,\ sc}(\sum_{sc\in SC}\beta^{psc}_i)$ shows the time required for patient i by caregiver p at the service centers, which should be less than or equal to cure working per day MW for each caregiver, as given in equation (3). Equation (4) confirms that each caregiver visits each patient only once. As the model is a multidepot HHCP, equation (5) ensures that each patient is supported by one service center. Equation (6) satisfies that the caregiver is able to support the patient i assigned to service center sc, if the caregiver is the member of this service center. Each patient demands a caregiver on each day, which may be a doctor, nurse, or a therapist, as given in equation (7). Equations (8) and (10) confirm that there is no way from a patient to itself. Equation (9) ensures that the demand of each patient on each day should be met. In addition, to satisfy different types of HHC services for patients, the right-hand sides of equations (11)–(13) indicate the number of required visits by patient i from different types of caregivers in each service center, which should be equal or bigger than the corresponding number of visits. Equation (14) computes the overall distance from an ideal one for each vehicle to visit the patients. Equation (15) satisfies the on-time services, where the arrival time of caregiver p at patient i's home on the day d, i.e. σ_i^{pd}, should be within the given time window $[\underline{\psi}_i^d, \overline{\psi}_i^d]$. Equation (16) satisfies the time window per each patient each day according to the caregiver's arrival time and leave time for each patient. To be more precise, if caregiver p goes from patient i's home to patient j's home, i.e. $\vartheta_{ij,\ sc}^{pd} = 1$, then the sum of (i) required treatment time σ_i^{pd} for patient i, (ii) arrival time at patient i's home, i.e. $\sum_{sc \in SC} \beta_i^{psc}$, and (iii) α_{ij} is the travel time from patient i to patient j, which must be less than or equal to the arrival time at patient j's home. Mathematically, $\sigma_i^{pd} + \sum_{sc \in SC} \beta_i^{psc} + \alpha_{ij} \le \sigma_j^{pd}$. Otherwise ($\vartheta_{ij,\ sc}^{pd} = 0$), the constraint turns to a redundant constraint $\sigma_i^{pd} + \sum_{sc \in SC} \beta_i^{psc} + \alpha_{ij} \le \sigma_j^{pd} + M$. Since M is a sufficiently large positive number, the constraint does not let get values for these variables. Equation (17) confirms that each caregiver should be assigned to one vehicle on each day. Equation (18) ensures that the route of the vehicles is exactly the same as the route of the caregivers. Equation (19) shows that each patient should be visited by only one vehicle on each day. Equations (20) and (21) show the time limitations for each vehicle to do the patients' services. Equation (22) limits the working time of vehicles on each day to be not more than a desired value. Equation (23) guarantees the feasible values for the binary variables and equation (24) shows the feasibility of continuous variables.

In conclusion, as far as we know, no study has applied the introduced model yet. The proposed model optimizes the time and cost of HHC services simultaneously in addition to different real-world suppositions for HHC companies, such as the route balancing, working time balancing, and time windows for availability of patients and caregivers in addition to different types of caregivers like doctors, nurses, and therapists. This model, as an extension to the classical VRPTW, is obviously NP-hard. Therefore, different metaheuristics in addition to the exact solver are applied to solve it.

4. Solution Method

This study uses an exact method for multiobjective optimization called ε-constraint method (Haimes, Ladson, & Wismer, 1971). Since we have no novelty in this algorithm, the description of this method is provided in the appendix A1. This algorithm like our metaheuristics is structured by the concept of multiobjective optimization (Goodarzian & Hosseini-nasab, 2019). The definition of the multiobjective evaluation is given in the appendix A2. With regard to this assessment, some metrics must be used. Here, the number of Pareto solutions (NPS), mean ideal distance (MID), spread of non-dominance solution (SNS), and maximum spread (MS) are four well-known metrics in this field (Fathollahi-Fard *et al.*, 2018c, 2019a; Sahebjamnia, Goodarzian, & Hajiaghaei-Keshteli, 2020).

In this section, we first illustrate the solution representation to show the encoding plan for the metaheuristics. It goes without saying that this paper employs three nature-inspired and swarm intelligence-based metaheuristic algorithms, i.e. SEO (Fathollahi-Fard *et al.*, 2018a), FFA (Yang, 2010), and ABC (Karaboga, 2005) algorithms that are known to be powerful tools for solving optimization problems. An important feature of these algorithms, which distinguishes them from similar optimization algorithms, is their excellent performance in finding efficient solutions for multiobjective optimization problems (Zhao, Liu, Zhou, Guo, & Qi, 2018; Guo, Zhou, Liu, & Qi, 2019). Such an important feature makes the employed algorithms as the ideal choice for solving our suggested HHCP. Therefore, we provided the multiobjective version of SEO (MOSEO), FFA (MOFFA), and ABC (MOABC) accordingly. It should be noted that the details of these algorithms are provided in the appendix A3, A4, and A5 for the MOSEO (Fathollahi-Fard *et al.*, 2019b, 2020b; Goodarzian *et al.*, 2020b), MOFFA (Dekhici, Redjem, Belkadi, & El Mhamedi, 2019), and MOABC (Gergin, Tunçbilek, & Esnaf, 2019) algorithms, respectively. Finally, the proposed self-adaptive SEO as one of the main novelties of this study is illustrated at the end of this section.

4.1 Solution representation

To solve an optimization model by metaheuristics, we need an encoding scheme to handle the constraints of the model and to compute the objectives. As all applied metaheuristics in this study have continuous mechanisms, a two-stage method called Random-Key (RK) is used (Snyder & Daskin, 2006). The RK transforms an infeasible solution into a feasible one (Deivika *et al.*, 2014; Guo, Zhou, Liu, & Qi, 2020).

Here, a numerical example for one day to show the solution representation is defined. First, consider that there are 10 patients and we want to assign them to 3 service centers. For each patient, the metaheuristic generates a random number between 0 and 3. If this number is between 0 and 1, the patient would be assigned to the first service center. If the value is between 1 and 2, the second service center is considered, and if the value is between 2 and 3, then the third service center is considered. This example is provided and shown in Fig. 2. As an instance, the second, fourth, fifth, and sixth patients are allocated to the first service center.

On this day (this period), there are four caregivers who are available to do the HHC services. We have two different cars and want to assign a vehicle to each caregiver. The first caregiver is a doctor, the second and third caregivers are nurses, and the last caregiver is a therapist. As given in Fig. 3, with regard to the two types of vehicles, the metaheuristic generates the random numbers between 0 and 2. The caregiver who gets a value between 1 and 2 would be assigned to the second vehicle. The rest would be assigned to the first vehicle. As shown in Fig. 3, except for the fourth caregiver, all caregivers use the second vehicle.

Finally, we want to generate the routes of each caregiver. Once again, similar to the procedure in Fig. 2, for each patient, this time, random numbers using the probability distribution function $U(0, 1)$ are generated. Now, based on the classifications of patients in Fig. 2, the sequence of patients in Fig. 4 is considered.

Let us assume that among four patients allocated to the first service center, where their sequence is 3, 10, 2, and 1, respectively, the second and fourth patients need a doctor and the fifth and sixth patients require a nurse. In this regard, the route of the first caregiver is started from the second patient to the fourth patient. The second caregiver's route is started from the sixth patient to the fifth patient. Other routes for the third and fourth caregivers are generated in a similar way. After that, the objectives will be calculated based on this solution representation.

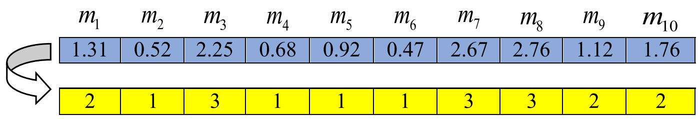


Figure 2: The patients' assignment to the service centers.

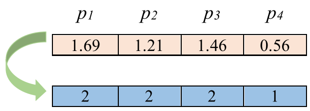


Figure 3: Allocation of vehicles to the caregivers.

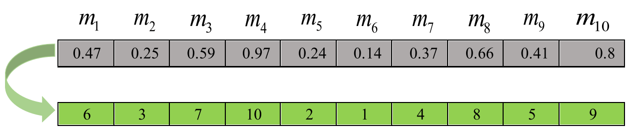


Figure 4: Routing decisions to assign the caregivers to the patients.

4.2 Improved self-adaptive SEO

Due to the novel contributions of the SEO in the area of metaheuristic studies, there are plenty of recent research papers that contributed to the further development and application of SEO (Fathollahi-Fard *et al.*, 2019b, 2020b; Baliarsingh, Ding, Vipsita, & Bakshi, 2019; Zhang *et al.*, 2019; Goodarzian *et al.*, 2020a). This study proposes a self-adaptive metaheuristic as a novel improvement to this algorithm called ISEO, to address the drawbacks of this recently proposed SEO. Based on the literature and the recent advances in relation to this algorithm, it suffers from premature convergence, which makes it less suitable for solving real-world problems. To tackle these issues, we suggested an ISEO with a new adjustment operator to improve its performance in terms of Pareto-based solutions, search accuracy, convergence speed, and computational time, wherein the position updating of SEO is modified to reconsider the previous solutions in addition to the best solution obtained thus far. Another main difference between our proposed approach and the original SEO is that the developed ISEO is a population-based algorithm while the original SEO is a single-point algorithm.

Most notably, the ISEO shows benefits from high Pareto optimal solutions, low computational time, and fast convergence speed that helps this algorithm to outperform SEO. In fact, the main reason for the use of the ISEO for our practical HHCP is to have features such as high convergence speed and lower computational time. Hence, an adjusting operator is added to the SEO algorithm. The aim of the new operator is to achieve a better balance between the exploration and exploitation phases. It goes without saying that the proposed ISEO is a population-based algorithm that is useful to provide a balance between the intensification and diversification phases. Since the original SEO was a single-point algorithm, it is difficult to manage these phases. Therefore, as one of the main novelties of this paper, following describes the process of ISEO algorithm.

4.2.1 *The number of attackers and defenders*

As mentioned earlier, there are two different search factors that include the attacker and the defender. In this new improvement, we transform this single-point metaheuristic into a population-based one. The number of attackers and defenders constitute the population considered in this search space. The number of attackers is randomly selected from 65% to 90% of the total population. In this regard, a self-adaptive strategy is utilized to propose ISEO. To this end, the number of attackers obtained from equation (25) is

$$N_a = \ floor\left[(0.9 - rand \times \ 0.25) \times N\right], \tag{25}$$

where $rand$ is a random number between 0 and 1. Meanwhile, $floor(0)$ shows a real number as an integer. The number of defenders (N_d) as complementary between (N) and (N_a) is calculated as per equation (26):

$$N_d = \ N - N_a. \tag{26}$$

Therefore, the total population of (M) is formed by elements of N and is divided into two subgroups G and Q. Therefore, G and Q sizes are controlled by a predetermined constant ρ ratio. The group of G is a set of attackers $G \ = \{G_1,\ G_2,\ \ldots,\ G_{N_a}\}$. Meanwhile, the group of Q includes defenders $Q \ = \{Q_1,\ Q_2,\ \ldots,\ Q_{N_d}\}$, wherein $M \ = \{M_1,\ M_2,\ \ldots,\ M_N\}$. So, then we have

$$M = m_1 = G_1\ ,\ M_2 = G_2\ , \ldots,\ M_{N_a} = G_{N_a}\ ,\ M_{N_a+1} = Q_1,$$
$$M_{N_a+2} = Q_2\ , \ldots,\ M_N = Q_{N_d}.$$

4.2.2 *Defender and attacker evaluation criteria*

In this way, each defender and attacker has one weight W_a and W_d, respectively. This indicates the quality of the solution for the defender d and the attacker a of the population (M). Therefore, equations (27) and (28) are used to calculate the weight of each attacker and defender:

$$W_a = \frac{K\ (M_a) - worst_m}{best_m - worst_m} \tag{27}$$

$$W_d = \frac{K\ (M_d) - worst_m}{best_m - worst_m} \tag{28}$$

where $K(M_a)$ and $K(M_d)$ are capabilities, which are obtained by evaluating the attacker's and defender's positions, respectively, and in accordance with the objective function $K(0)$. The values of $worst_m$ and $best_m$ are defined in line with equations (29) and (30):

$$bes\ t_m = \min_{i\in(1,2,\ldots,M)} \ (K\ (M_i)) \tag{29}$$

$$wors\ t_m = \max_{i\in(1,2,\ldots,M)} \ (K\ (M_i)). \tag{30}$$

4.2.3 *Adjustment operator*

This improved algorithm is developed by an adjustment operator to enhance its efficiency in terms of search accuracy and running time. This operator is used to make a novel generation of this population-based algorithm. The size of this part is equal to the size of G and Q. This operator creates a novel division according to the best person and other random people from G and Q. Also, we assume that $Y_{o,\ j}^{t+1}$, the value of the element j, is the number of individuals o; then, $Y_{o,\ j}^{t+1}$ is generated based on equation (31):

$$Y_{o,j}^{t+1} = \begin{cases} Y_{\text{best},j}^{t}\ rand\ \le \rho \\ Y_{r3,j}^{t}\ rand\ > \rho, \end{cases} \tag{31}$$

For $(i=1; i<M_d+1;)$
For $(j=1;\ j<n+1;)$
$$d_{i,j}^0 = p_j^{low} + rand(0,1).\left(p_j^{high} - p_j^{low}\right)$$
End for
End fore
For *(k=1;i<M_a+1;k++)*
For *(j=1; j<n+1; k++)*
$$a_{k,j}^0 = p_j^{low} + rand(0,1).\left(p_j^{high} - p_j^{low}\right)$$
End for
End for

Figure 5: The pseudocode for initialization.

where r is a random number achieved from equation (32), where *rand* is a random number with a uniform distribution and δ is a fixed value (equals to 1.2). Also, t is the number of iterations.

$$r = rand \times \delta \tag{32}$$

In equation (32), parts of the newly created person are updated according to equation (33). If the number of other random numbers created is greater than the adjustment rate, the adjustment rate is equal to the fixed partition. In equation (34), d_y is a local search and represents the training and retraining of the defender and the attacker in this algorithm. μ is an element that controls the penetration of d_y in the updating process.

$$Y_{o,j}^{t+1} = Y_{o,j}^{t+1} + \mu\,(dL_y - 0.5) \tag{33}$$

$$dy = RT\,(Y_o^t) \tag{34}$$

4.2.4 *Main loop*

The computations of the solicited algorithm as its main loop are as follows:

Step 1: Given M as the number of members of the m-dimensional set, the number of defenders M_d, and the number of attackers M_a in the total population, we have

$$N_a = floor\,[(0.9 - rand \times 0.25) \times N] \tag{35}$$

$$N_d = N - N_a, \tag{36}$$

where *rand* is a random number between $[0, 1]$. Meanwhile, $floor(0)$ shows a real number.

Step 2: Initialization is random for the defender (equation 37), the attacker (equation 38), and for the set of members (equation 39). An initialized pseudocode is presented in Fig. 5.

$$Q = \{Q_1, Q_2, \ldots, Q_{N_d}\} \tag{37}$$

$$G = \{G_1, G_2, \ldots, G_{N_a}\} \tag{38}$$

$$M = m_1 = G_1,\ M_2 = G_2, \ldots,\ M_{N_a} = G_{N_a},\ M_{N_a+1} = Q_1,$$
$$M_{N_a+2} = Q_2, \ldots,\ M_N = Q_{N_d} \tag{39}$$

Step 3: At this stage, we intend to demonstrate the defenders' and the attackers' training and retraining. In this way, the attacker chooses the most influential trait. For this purpose, α% of the traits are selected randomly and repeated directly in the same trait in the defender. The number of traits for training is indicated in equation (40):

$$N_{Train} = round\,\{\propto .nVar\}, \tag{40}$$

For $(a=1;\ a<M+1;)$
For $(d=1;\ d<M+1;)$
$$W_a = \frac{K(M_a) - worst_m}{best_m - worst_m}$$
$$W_d = \frac{K(M_d) - worst_m}{best_m - worst_m}$$
$$wherebest_m = \max_{i\in(1,2,\ldots,M)}(K(M_i))$$
and
$$\min_{i\in(1,2,\ldots,M)}(K(M_i))$$
End for
End for

Figure 6: The pseudocode for calculating the weight of each attacker and defender.

For *i=1 to num Q* ***do***
Scale=max Step Size(Iter)
*Step Size=exprnd (2*Max Iter)*
DeltaY=RT (Step Size, Dim)
For *j=1 to Dim* ***do***
If *rand ≥ partition,* ***then***
Q(i, j)=Best(j)
Else
*r_4=round (num Q * rand + 0.5)*
Q(i. j)=Population(r_4, j)
If *rand>BAR,* ***then***
Q(i. j)= Q(i. j)+scale(delta Y(j)-0.5)*
End if
End if
End for
End for

Figure 7: The pseudocode for the adjustment operator.

where α% represents the chosen characteristics and $nVar$ is the total number of traits in the person. Therefore, N_{Train} is the number of traits that are randomly tested in a defender.

Step 4: Calculate the weight of each defender and attacker from the population N, which is expressed in the pseudocode in Fig. 6.

Step 5: In order to carry out an attack, this algorithm proposes four various techniques, including obtaining, phishing, diversion theft, and pretext. For details regarding their mathematics, readers are referred to Fathollahi-Fard *et al.* (2018a).

Step 6: This improved algorithm is developed with an adjustment operator to enhance its efficiency in terms of search accuracy and running time. In the following, we will express its pseudocode in Fig. 7.

Step 7: In this step, the attacker finally defeats the defender and the defender is randomly replaced by a new one.

Step 8: If the stop criteria are met, the process ends; otherwise, we will go back to step 3.

In conclusion, our proposed ISEO is summarized in a flowchart and a pseudocode as shown in Figs 8 and 9, respectively.

5. Experiments and Results

Here, the experiment results to evaluate the efficiency and performance of the ISEO algorithm are compared with the outcomes of other metaheuristic algorithms including the original MOSEO, MOFFA, and MOABC. In addition, all algorithms

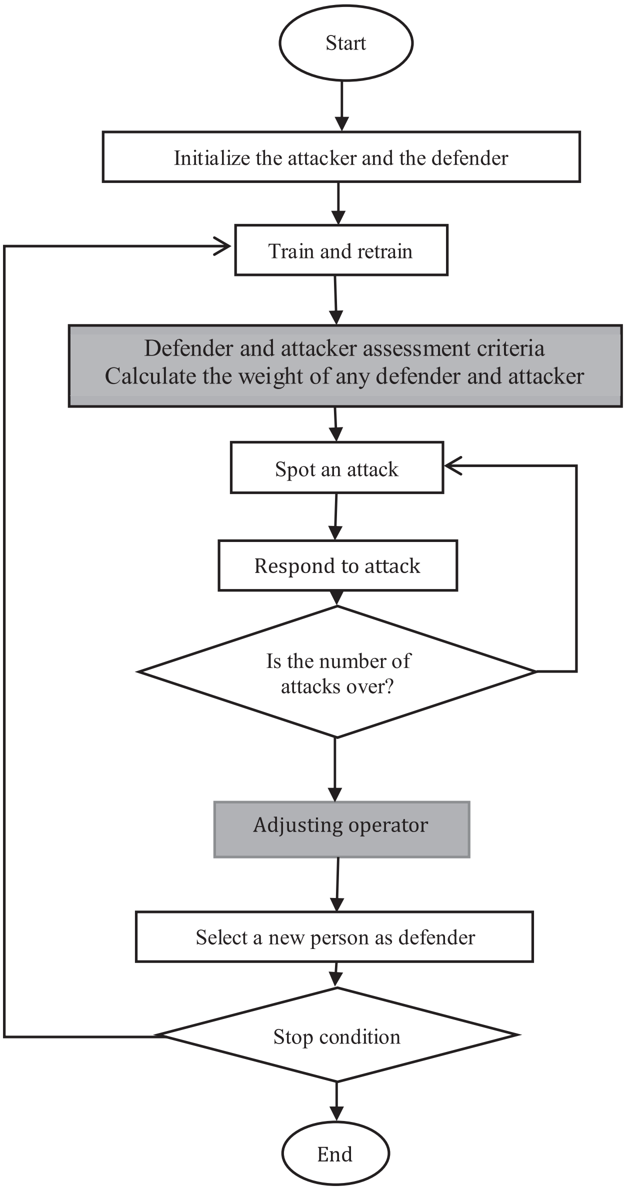


Figure 8: The flowchart of the proposed ISEO.

were run 25 times to obtain statistically significant outcomes. In this section, we first set the algorithms and simulated test studies. Then, the validation of both the model and the algorithms is explained. An executive analysis and comparison among the algorithms are performed. Finally, some sensitivities and practical solutions of the model are presented. Notably, all the tests were implemented on the computer at 2.50 GHz, 6.00 GB of RAM. Besides, the MATLAB R2020b software was used for the implementation of the metaheuristic algorithms, as well as the GAMS 24. 1. 3 was utilized for the ε-constraint method.

5.1 Data setting

Data setting in this paper includes two main parts: data generation for the proposed model and the tuning of the algorithms' parameters.

5.1.1 *Simulated test studies*

Due to the novelty of our proposed model, no benchmark data are available for our model. Therefore, an approach is needed to design the test problems. Then, 20 test problems were designed and introduced: five problems at the small size (SP1 to SP5), medium size (MP6 to MP10), large size (LP11 to LP15), and extra-large size (EP16 to EP20) as the very large-scaled instances. Table 2 shows the size of the problems. It should be noted that the simulated test studies are varied from 2 days to 2 weeks. Besides, the distribution of parameters is presented in Table 3. In this regard, the range of parameters is taken from recent simulated test studies, as given in the literature (Fathollahi-Fard *et al.*, 2018b, 2018c, 2019a, 2020a, 2020b; Bahadori-Chinibelagh *et al.*, 2019; Fakhrzad & Goodarzian, 2019).

5.1.2 *Tuning of algorithms' parameters*

First, to have an unbiased comparison, the parameters of the presented algorithms must be tuned (Devika, Jafarian, & Nourbakhsh, 2014; Li, Sang, Pan, Duan, & Gao, 2017; Nguyen & Vo 2019). To this end, this study uses the Taguchi method (Kackar, 1985) to design the experiments of the algorithms' tuning. To have a fair comparison, in all algorithms, the population size and the maximum number of iterations were set to 25 and 50, respectively (Fathollahi-Fard, Hajiaghaei-Keshteli, Tian, & Li, 2020c; Goodarzian, Hosseini-Nasab, & Fakhrzad, 2020c). For the SEO, as a single solution technique, the maximum number of iterations is 600. Other parameters have been tuned by the Taguchi method.

Since the proposed HHCP is a biobjective optimization model, a metric to evaluate the objective functions is created, so-called MCOV (Fathollahi-Fard *et al.*, 2019a). This metric is a fraction of MID metric to study the convergence and MS to measure the diversity of the algorithms' solutions. In this regard, MCOV is formulated as follows:

$$\mathrm{MCOV} = \frac{MID}{MS}, \tag{41}$$

where a lower value of MCOV brings a better capability of the metaheuristic (Hou, Wu, Zhou, & Li, 2015; Guo *et al.*, 2019). Then, for each metaheuristic, the candidate levels for the parameters are studied with regard to previous works (Fathollahi-Fard *et al.*, 2020b; Goodarzian, Shishebori, Nasseri, & Dadvar, 2020a; Goodarzian, Hosseini-Nasab, Muñuzuri, & Fakhrzad, 2020b) and our tests on the performance of the algorithms. The candidate values of the algorithms' parameters are given in Table 4.

The main advantage of the Taguchi design experiment method is to reduce the number of total experiments. For example, for FFA, if we use a full factorial method, the total experiments are $3 \times 3 \times 3 = 27$. However, Taguchi with the use of orthogonal arrays reduces the tests. For FFA, Taguchi suggests L9 that uses 9 selected tests among 27 possible ones. Similarly, this orthogonal array is also used for other algorithms as they have a similar number of parameters and levels. For each test, the value of MCOV is calculated and for each level, the average value of MCOV is computed. Finally, the best values of these parameters are given in Table 5.

5.2 Validation of the algorithms and model

To validate the proposed model, the results are presented, analysed, and compared. In addition, the validation of metaheuristics is checked by the exact solver. Here, the outputs of the metaheuristics are the average of each objective among all the

Initialize the population of the attackers and defenders;
Create the initial Pareto fronts;
It=1;
For $(i = 1; i < M_d + 1; i + +)$
  For $(j = 1;\ j < n + 1;\ j + +)$
    $d_{i.j}^0 = p_j^{low} + rand(0{,}1).\left(p_j^{high} - p_j^{low}\right)$
  End for
End fore
For *(k=1;i<M_a+1;k++)*
  For *(j=1; j<n+1; k++)*
    $a_{k.j}^0 = p_j^{low} + rand(0.1).\left(p_j^{high} - p_j^{low}\right)$
  End for
End for
    For *(a=1; a<M+1; a++)*
      For *(d=1; d<M+1; d++)*

$W_a = \frac{K(M_a) - worst_m}{best_m - worst_m}$

$W_d = \frac{K(M_d) - worst_m}{best_m - worst_m}$

Where $best_m = \max_{i \in (1.2 \ldots M)} \left(K(M_i)\right)$ *and*

$\min_{i \in (1.2 \ldots M)} \left(K(M_i)\right)$

    End for
      End for
while $It < max_{iter}$
  Do training and retraining;
  $num_{attack} = 1$;
  while $num_{attack} < max_{attack}$
    Spot an attack;
    Check the boundary;
    Respond to attack;
    if the defender dominates the attacker
      Exchange the defender and attacker position;
    End if
    $num_{attack} = num_{attack} + 1$;
  End while
      For $i = 1$ *to num Q* ***do***
        Scale=max Step Size(*Iter*)
        Step Size=exprnd $(2 * max_{iter})$
        $DeltaY = RT(StepSize, Dim)$
        For *j=1 to Dim* ***do***
          If *rand ≥ partition*, ***then***
            $Q(i.j)$*=Best(j)*
          Else
            r_4*=round (num Q * rand + 0.5)*
            $Q(i.j)$*=Population* $(r_{4,}j)$
            If *rand>BAR*, ***then***
              $Q(i.j) = Q(i.j)$*+scale*(delta Y(j)-0.5)*
            End if
          End if
        End for
      End for
  Create a new solution as defender;
  $It = It + 1$;
  Update the Pareto solutions;
End while
Return attackers as the best non-dominated solutions.

Figure 9: The pseudocode of the proposed ISEO.

Table 2: The size of the test problems.

Levels	Size problem	Number of doctors	Number of therapists	Number of nurses	Number of vehicles	Number of service centers	Number of patients	Number of days
Small	SP1	2	2	2	2	3	10	2
	SP2	3	4	3	2	3	25	2
	SP3	4	5	6	3	3	40	4
	SP4	6	7	8	3	4	65	4
	SP5	8	7	8	3	4	80	4
Medium	MP6	8	8	9	3	4	90	7
	MP7	9	9	9	4	4	105	7
	MP8	9	9	9	5	5	125	7
	MP9	10	10	10	5	5	150	7
	MP10	11	11	10	5	6	165	7
Large	LP11	12	12	12	6	6	180	10
	LP12	14	14	15	6	7	200	10
	LP13	16	16	16	7	8	220	10
	LP14	18	18	20	8	8	240	10
	LP15	20	20	22	8	10	260	10
Extra-large	EP16	60	40	40	20	20	460	14
	EP17	120	80	100	80	30	860	14
	EP18	180	120	160	140	40	1260	14
	EP19	240	160	220	200	50	1660	14
	EP20	300	200	280	260	60	1860	14

Table 3: The generated parameters to solve the model.

Parameters	The range of parameters	Parameters	The range of parameters
$\underline{\phi}_{iv}$	$rand\{10, 15, \ldots, 150\}$	$\kappa^{sc}_{TH,d}, \kappa^{sc}_{NU,d}, \kappa^{sc}_{DO,d}$	$rand\{0, 1\}$
$\bar{\phi}_{iv}$	$rand\{100, 15, \ldots, 1500\}$	$\delta^{DO}_{i,sc}$	$rand\{5, 10, \ldots, 80\}$
$\underline{\psi}^{d}_{i}$	$rand\{600, 700, \ldots, 1500\}$	$\gamma^{NU}_{i,sc}$	$rand\{5, 10, \ldots, 80\}$
$\overline{\psi}^{d}_{i}$	$rand\{800, 900, \ldots, 2000\}$	$\lambda^{TH}_{i,sc}$	$rand\{5, 10, \ldots, 80\}$
$\overline{\nabla}_i$	$rand\{40, 50, \ldots, 100\}$	$HS_{i,d,DO,NH,TH}$	$rand\{0, 1\}$
$\underline{\nabla}_i$	$rand\{40, 50, \ldots, 100\}$	$(x_i, y_i),(x_j, y_j)$	$1000 \times (U(0, 1), U(0, 1))$
TC	5	D_{ij}	$\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$
ST_{id}	$rand\{50, 10, \ldots, 250\}$	MW, MT	$rand\{20\,000, 40\,000, \ldots, 80\,000\}$
α_{ij}	$rand\{40, 50, \ldots, 100\}$	M	1000 000
β^{psc}_{i}	$rand\{40, 50, \ldots, 100\}$	PEN	100

Table 4: The candidate levels for the algorithms' parameters.

Algorithm	Parameter	Level 1	Level 2	Level 3
FFA	Light absorption coefficient (LAC)	1	1.2	1.5
	Mutation coefficient (MC)	0.3	0.5	0.7
	Mutation coefficient damping ratio (MCDR)	0.8	0.9	0.99
ABC	The NP size (NP)	40	60	80
	The food sources (FS)	15	20	30
	Maximum search of each bee (MSB)	100	120	140
SEO and ISEO	Rate of collecting data (RCD)	0.1	0.2	0.3
	Rate of connecting attacker (RCA)	0.05	0.08	0.15
	Number of connections (NC)	30	40	50

non-dominated solutions generated by each metaheuristic. Based on this criterion, the algorithms are compared with each other. Finally, the best metaheuristic algorithm is chosen.

The results and details of the presented metaheuristic algorithms are presented in Tables 6 and 7. As the model is a biobjective model, the first objective function (Z1) includes the total time of services. The second objective function (Z2) is the total costs of the HHC services and its penalty value for the route balancing. The computational time (CPU) of the presented metaheuristic algorithms is shown by 'T' in tables.

Table 5: The tuned algorithms' parameters.

Algorithm	Parameter	Best level
FFA	LAC	1.2
	MC	0.3
	MCDR	0.99
ABC	NP	60
	FS	30
	MSB	120
SEO and ISEO	RCD	0.2
	RCA	0.08
	NC	50

ISEO indicates the best results on all of the 20 test functions. These outputs show that ISEO improves the convergence rate of SEO. Additionally, ISEO convergence outperforms other algorithms. Figures 10–12 show the behavior of the stated algorithms according to the convergence, which allows us to better compare them due to the different size problems. Also, Figs 13 and 14 indicate the behavior and CPU time of the ε-constraint approach for different size problems. Note that due to the high complexity of the HHCP, there is no solution for the medium, large, and extra-large-scaled problems based on the exact solver. By means of a comparison with the solutions of the exact solver and metaheuristics, the validation of the results is approved. Most importantly, the convergence of ISEO is more significantly durable than that of the other offered algorithms.

5.3 Executive analyses and comparison of algorithms

To be able to perform a comparison among metaheuristics based on Pareto solutions, four multiobjective assessment metrics, as noted earlier, are studied here; these are NPS, MID, SNS, and MS. For information regarding their mathematics, one can refer to the previous papers (Devika *et al.*, 2014; Fathollahi-Fard *et al.*, 2018c, 2019a; Fakhrzad, Goodarzian, & Golmohammadi, 2019; Fakhrzad & Goodarzian, 2020; Sahebjamnia *et al.*, 2020).

Table 6: The results and CPU times of the suggested algorithms.

Levels	Objective function	FFA	T	ABC	T	SEO	T	ISEO	T
SP1	Z_1	322.5	0.121	367.3	0.176	298.3	0.037	245.1	0.028
	Z_2	243.3		267.5		199.6		167.2	
SP2	Z_1	367.7	0.433	403.5	0.566	315.2	0.042	287.2	0.037
	Z_2	295.5		322.5		210.4		188.3	
SP3	Z_1	401.5	0.664	467.4	0.978	357.4	0.354	310.5	0.275
	Z_2	321.1		378.4		267.3		201.4	
SP4	Z_1	477.2	6.566	510.4	8.455	377.1	3.414	325.6	2.17
	Z_2	355.1		412.5		288.1		225.6	
SP5	Z_1	511.3	10.23	567.3	17.02	423.7	6.01	378.4	3.57
	Z_2	366.5		456.6		312.8		256.8	
MP6	Z_1	588.1	23.67	599.6	31.26	576.2	15.31	510.3	5.51
	Z_2	466.2		489.4		401.5		345.7	
MP7	Z_1	645.2	29.45	678.7	38.56	632.2	25.23	567.5	23.81
	Z_2	499.3		510.2		432.1		398.3	
MP8	Z_1	633.1	78.68	723.2	45.34	677.9	69.1	602.4	33.98
	Z_2	511.1		544.3		455.1		412.7	
MP9	Z_1	755.3	123.1	788.5	156.2	733.45	98.7	656.2	66.3
	Z_2	544.1		591.1		478.1		446.8	
MP10	Z_1	801.3	192.3	822.1	213.2	788.2	187.4	689.3	171.4
	Z_2	599.3		601.2		501.23		488.3	
LP11	Z_1	834.2	289.1	877.2	322.4	812.34	245.6	701.3	195.1
	Z_2	612.2		654.1		543.12		501.5	
LP12	Z_1	901.3	356.7	945.6	398.5	856.24	332.6	823.1	223.5
	Z_2	655.1		734.5		589.12		578.2	
LP13	Z_1	923.1	456.3	1051	415.4	899.28	410.4	877.3	267.4
	Z_2	788.4		803.5		612.27		610.3	
LP14	Z_1	1023	578.3	1145	603.4	934.56	533.1	912.4	289.1
	Z_2	823.4		876.5		678.66		645.3	
LP15	Z_1	1133	656.3	1566	688.5	988.23	627.3	947.2	312.4
	Z_2	899.3		904.5		734.33		699.7	
EP16	Z_1	1344.2	899	1899	907	1123	690.1	995	456
	Z_2	923.5		1125		876.2		768	
EP17	Z_1	1678.3	987.1	2344	1036	1344	720.3	1190	566.5
	Z_2	1023.4		1677		956.4		870.7	
EP18	Z_1	2388.2	1203	2899.7	1566	1567	768	1344	699.3
	Z_2	1788.7		1894		1087		910.2	
EP19	Z_1	2523	1455	3455.4	1789	1987	896	1567	788
	Z_2	2344		2788		1203		988	
EP20	Z_1	3833	1867	3908	1905	2344	1035	1789	987.1
	Z_2	3056.6		3244		1899		1054	

Table 7: The results and CPU times of the ε-constraint approach.

Levels	ε-constraint	T
SP1	122.467	0.021
SP2	137.499	0.032
SP3	178.421	0.154
SP4	188.322	0.864
SP5	201.566	2.045
MP6	245.122	3.024
MP7	-	-
MP8	-	-
MP9	-	-
MP10	-	-
LP11	-	-
LP12	-	-
LP13	-	-
LP14	-	-
LP15	-	-
EP16	-	-
EP17	-	-
EP18	-	-
EP19	-	-
EP20	-	-
$\varepsilon = 0.2$		

According to the stated four evaluation metrics of Pareto optimum analyses, metaheuristic algorithms are compared with each other as given in Table 8. To improve the performance of utilized metaheuristic algorithms, the prior solutions are generated. According to the four metaheuristics involving FFA, ABC, SEO, and ISEO algorithms, their primary solutions are generated with an equal share. Eventually, to promote the reliability of metaheuristic algorithms, the average results for 25 run times are considered during this section. As given in Table 8, it is clear the ISEO metaheuristics are quicker than other metaheuristic algorithms. Thus, the CPU time of ISEO is less than the CPU time of other suggested metaheuristics in different sizes. Therefore, ISEO has a minimum average of computational time (122.655 seconds). The ABC has the maximum rate of this item (195.9976 seconds).

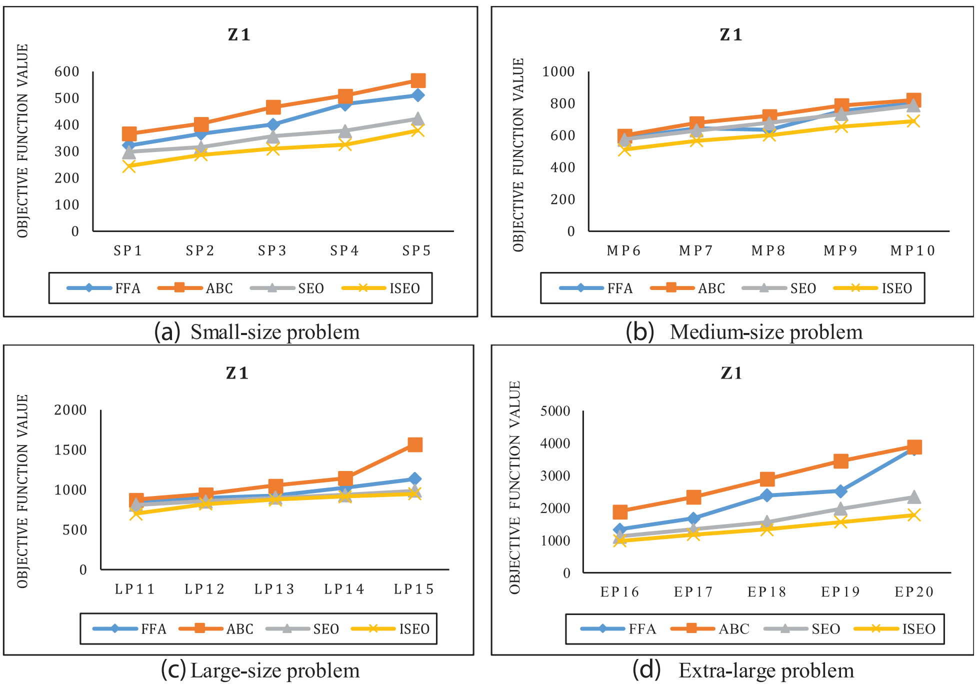
As mentioned earlier, the efficiency of the presented algorithms is examined by the evaluation metrics, including NPS, MID, MS, and SNS as the comparison metrics for the achieved non-dominated solutions under every experiment problem. Then, the outcomes are indicated in Table 8.

Figure 15 indicates two examples of non-dominated solutions of the suggested metaheuristic algorithms, in two experiment problems, e.g. SP2 and LP13. Based on these figures, it can be noticed that ABC records the worst efficiency, while the ISEO overcomes all the algorithms. Generally, the solutions of ISEO and SEO significantly dominate the solutions of ABC and FFA.

To determine the best metaheuristic algorithms, this paper conducts several statistical comparisons between the metaheuristic algorithms according to the Pareto-based analyses taken by a measurement metric. The outcomes presented in Table 8 are transformed into a general metric, i.e. the relative deviation index (RDI), for which the formula is as follows (Fakhrzad, Talebzadeh, & Goodarzian, 2018; Goodarzian *et al.*, 2020b):

$$RDI = \frac{|Alg_{sol} - Best_{sol}|}{Max_{sol} - Min_{sol}} \times 100, \tag{42}$$

where Alg_{sol} is the objective function value achieved by a given measurement metric of the algorithm, and Max_{sol} and Min_{sol} are, respectively, the maximum and minimum values among all values of the algorithms. Also, $Best_{sol}$ is the best solution. In other words, it is one of the Max_{sol} and Min_{sol} based on the nature of the metrics. It is clear that a lower value of RDI indicates a higher



(a) Small-size problem
(b) Medium-size problem
(c) Large-size problem
(d) Extra-large problem

Figure 10: The results of the first objective function.

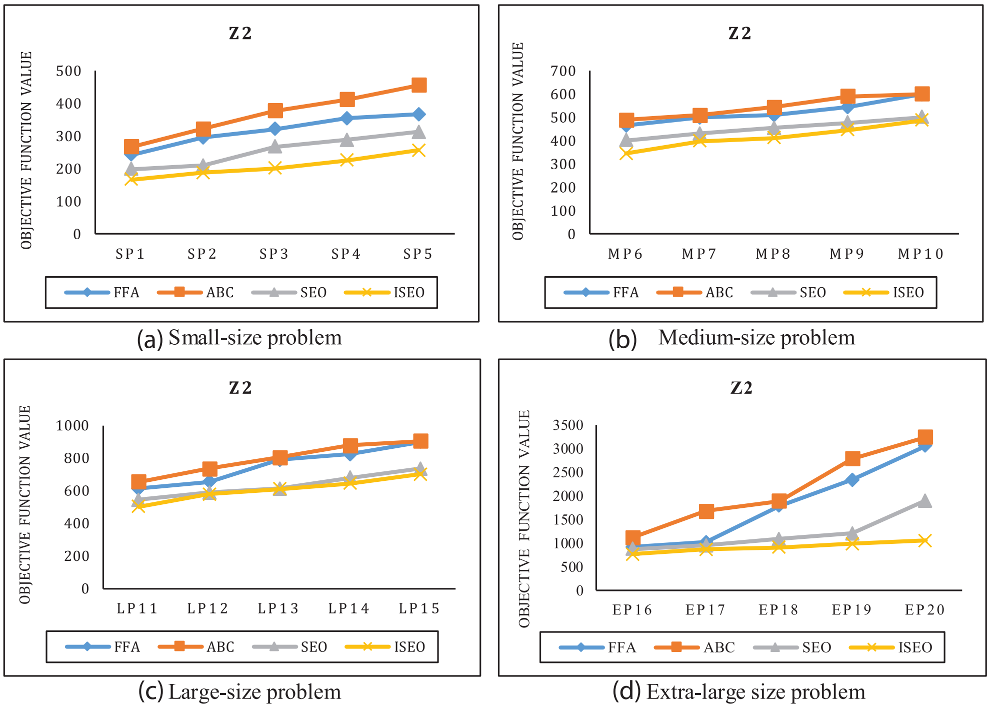


Figure 11: The result of the second objective function.

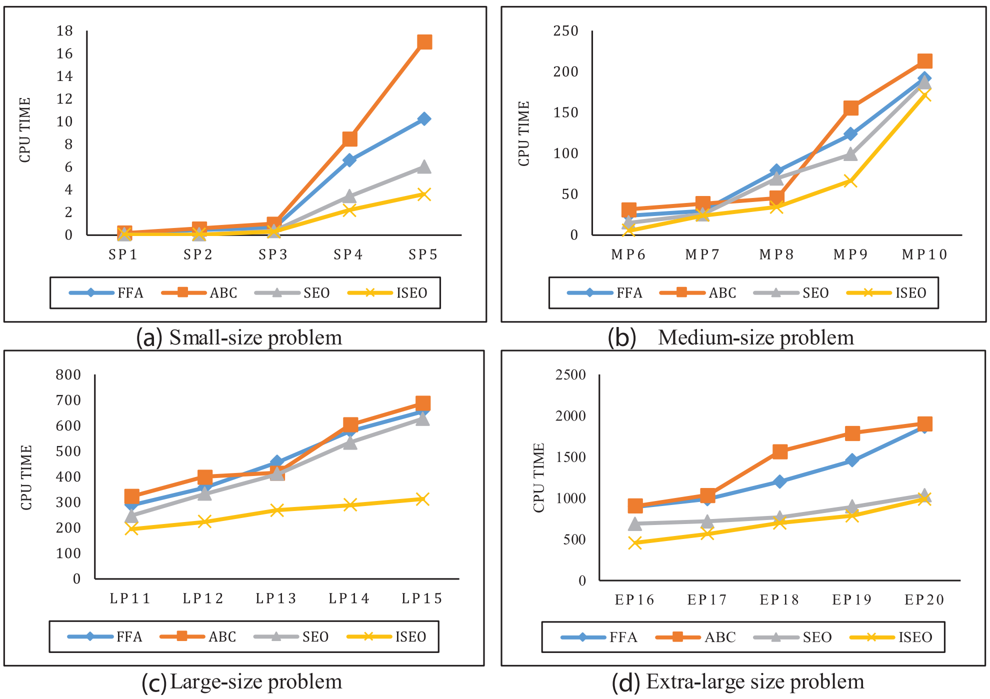


Figure 12: The result of CPU time.

quality of algorithms. As a result, the means plot for the introduced modified algorithms; the outputs run by the Minitab software are indicated in Fig. 16.

Referring to Fig. 16a, according to the NPS, first, it proves that ISEO metaheuristics are more successful than other metaheuristics, having obtained the best CPU time. The introduced ISEO algorithm is the most efficient among all the algorithms. Briefly, the ISEO designates the best efficiency in the NPS metric. Figure 16b shows that the ISEO algorithm is forcibly better than other algorithms. The ABC proves weak efficiency, while

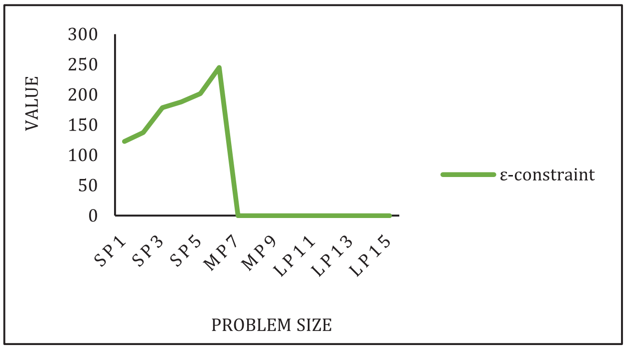


Figure 13: The result of the ε-constraint approach.

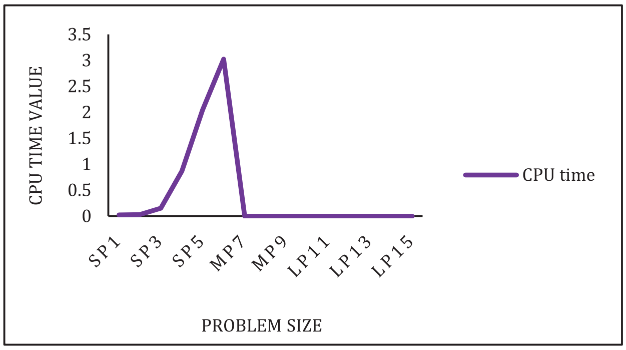


Figure 14: The result of CPU time.

ISEO is greatly better than the other algorithms in the MID metric.

This point of view for an MS metric is true. Although ABC displays the worst behavior in this item (Fig. 16c), contrary to the three described metrics, the outputs of the SNS metric are different. In this instance, ISEO is strongly more reliable than the other metaheuristic algorithms. The proposed ISEO is more efficient than the other metaheuristics, as well as it indicates the most competent efficiency between all metaheuristics for SNS metric (Fig. 16d).

5.4 Sensitivity analyses and managerial insights

To show the applicability of our HHCP and practical insights, some sensitivities on the key parameters are performed as follows:

Hereabouts, we perform sensitivity analyses on the model to appraise the effectiveness of the model. In the comparison section, the ISEO algorithm was the most powerful and effectual. Hence, this algorithm is selected for sensitivity analysis. The objective functions including the total cost of the logistics activities of HHC services abbreviated as TTC and the total time of the HHC services, abbreviated as TTO, are shown. A small-size experimental problem, e.g. *SP2*, is shown. To investigate the model, only two main parameters, i.e. transportation cost TC and the number of sorts of caregivers p (doctors DO, nurses NU, and therapists TH), are examined in this section. The reason of this selection among the parameters is the high impact of these parameters in the objective functions. It clearly indicates that the transportation cost plays a key role in the total cost and the various availability of caregivers are very useful to reduce the time of HHC services. To this end, five experiments for each parameter are designed and changes related to the objective functions are investigated.

A sensitivity analysis is performed on this parameter and the relevant outcomes are exhibited in Table 9. Furthermore, the trade-off amid objective functions including the total time of service and transportation cost is displayed as given Fig. 17. The outcomes expose an astonishing similarity within the objective functions. Overall, with the increase in transportation costs, not only does the total time of operations increase, but it also enhances the transportation cost objective function.

In general, the most meaningful contribution of the presented multiobjective model is to consider various skills of the caregivers to support a full range of HHC services. In this regard, a sensitivity analysis has been carried out with an increasing variety of caregivers to appraise its impression on objective functions. Table 10 shows the outcomes of the sensitivity analysis related to the sorts of caregivers and Fig. 18 exhibits the behavior of the objective functions.

The results show the similarity between the objective functions. Accordingly, the total time of operations and also the transportation costs have increased with a variety of caregivers. Overall, choosing the best strategy for deploying the most suitable caregiver can be very powerful in responding to concerns about time of operation and transportation costs.

According to the HHCP, the service center could decide the operation time (service and transportation) policy that best suits them. Results show that the HHCP is robust across the network size (i.e. the number of caregivers, patients, and vehicles in the network of HHCP) and also, that the model can be utilized for developing policies for service centers and hospitals. So if service centers and hospitals are experiencing high patient variation, it is strongly recommended to employ the ISEO algorithm. Further, when the transportation cost is significantly higher or lower than that in the case of the setting considered in this study, it is proper to utilize the ISEO algorithm.

Most notably, the demand for visits by each patient, with constraints based on the kind of caregiver (doctors, nurses, or therapists) utilized to design ideal routes from the service center to various patients' homes, is notable as they control other decisions made in the caregiving centers (hospitals and service centers). Most importantly, the main novelty of our model is the simultaneous consideration of route balancing, service time, and working time balancing.

Other managerial insights can be inferred from the dynamic sensitivity of the algorithms, presented in Figs 15 and 16, to confirm the efficiency and performance of the developed ISEO when compared to the other applied algorithms. Furthermore, the applicability of our HHCP is demonstrated by the results obtained, such as the sensitivities of the model (see Figs 17 and 18). Therefore, the outcomes of this study are useful for HHC companies to find a trade-off between the time of the services and their cost, with the consideration of time windows, route balancing, and working time balancing constraints.

6. Conclusion and Future Works

The present paper studied a new biobjective optimization model for a practical HHCP with simultaneous consideration of time windows, route balancing, and working time balancing constraints. The objectives are the total service time and the cost of HHC services – both of which are to be minimized simultaneously. Since the proposed HHCP is much more complex than the classical version of VRPTW, four metaheuristic algorithms were

Table 8: The computational outputs of NPSs, MIDs, MSs, and SNSs for the offered algorithms.

Experiment problem	NPS				MID			
	FFA	ABC	SEO	ISEO	FFA	ABC	SEO	ISEO
SP1	6	8	5	4	1.322	5.225	1.278	1.761
SP2	8	9	7	5	1.566	5. 441	2.183	1.233
SP3	10	11	8	6	2.321	6.876	2.298	1.678
SP4	12	13	10	8	3.403	8.245	4.256	2.427
SP5	14	14	12	9	4.577	9.276	5.534	2.321
MP6	13	14	12	9	6. 232	8.344	6.921	3.214
MP7	13	10	10	10	8.782	9.312	4.130	3.877
MP8	14	11	13	8	2.455	7.342	4.123	3.432
MP9	13	12	10	8	3.024	9.034	3.858	1.271
MP10	14	12	9	9	8.254	6.438	5.739	1.237
LP11	14	10	10	9	8.665	8.788	5.345	2.237
LP12	14	9	10	9	9.823	4.126	6.345	3.344
LP13	13	12	10	8	8.589	9.705	7.254	4.442
LP14	12	14	12	7	4.367	6.252	3.372	2.761
LP15	11	15	11	10	7.313	7.341	6.512	1.532
EP16	13	17	13	11	9.453	9.456	5.771	2.344
EP17	15	19	15	12	11.234	10.567	4.566	2.788
EP18	16	22	14	14	13.567	8.678	8.987	3.788
EP19	16	25	14	15	16.677	7.345	9.123	4.789
EP20	18	21	17	16	17.654	11.567	11.233	6.789
	MS				SNS			
	FFA	**ABC**	**SEO**	**ISEO**	**FFA**	**ABC**	**SEO**	**ISEO**
SP1	55 445	74 511	38 727	33 662	86 336	95 812.7	78 163.5	64 267
SP2	63 712	85 328	54 191	48 927	90 143	104 512	837 621	68 421
SP3	62 337	94 518	64 632	49 181	92 324.6	138 215	85 225.6	72 235
SP4	77 323	103 322	67 352	51 378	982 456	162 454	86 729.5	75 123
SP5	85 617	116 201	78 929	53 437	102 749	179 455	88 153.4	81 701
MP6	96 439	128 329	85 654	56 821	1927 563	194 948	93 447	84 544
MP7	105 451	138 023	94 538	68 348	214 252	237 881	101 967.2	86 572
MP8	128 454	148 421	102 156	71 469	243 132	287 157	122 025.3	87 534
MP9	137 342	164 556	114 871	83 941	268 429	314 637	142 505.8	94 631
MP10	147 134	172 326	128 092	94 567	271 332	352 781	177 071	99 129
LP11	156 211	193 443	134 254	96 607	316 251	398 512	185 136	102 338
LP12	167 231	233 655	148 982	102 343	344 527	415 792	223 961	134 291
LP13	173 471	263 018	150 512	115 252	362 781	434 287	241 882	163 471
LP14	183 323	283 328	162 783	123 554	391 241	453 692	251 141	214 276
LP15	193 238	2943 831	174 902	135 871	412 301	519 337	283 266	267 340
EP16	234 566	3046 770	189 657	140 857	436 781	526 790	295 751	279 810
EP17	278 986	3240 571	197 760	156 863	467 811	548 769	307 684	287 691
EP18	312 506	3487 013	201 451	167 892	490 430	569 801	318 792	298 714
EP19	389 087	3678 011	223 098	178 946	527 591	580 921	326 789	307 601
EP20	412 839	3891 122	267 791	180 462	548 791	620 165	347 651	318 262

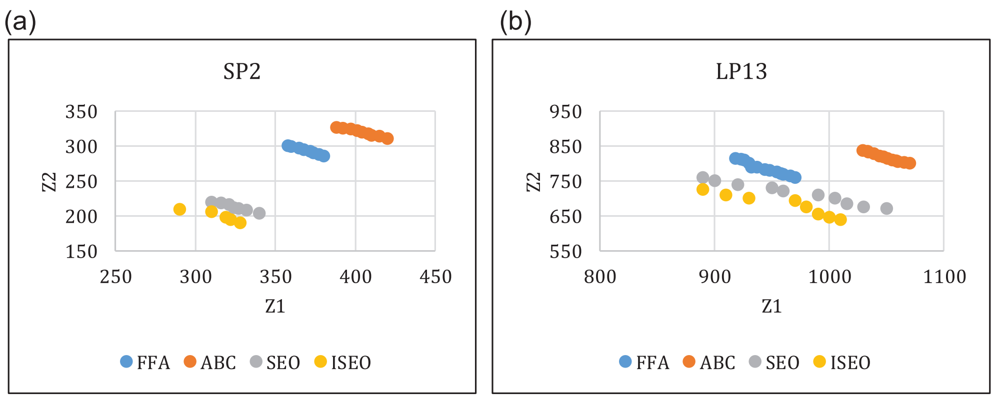


Figure 15: Pareto frontier of the metaheuristics.

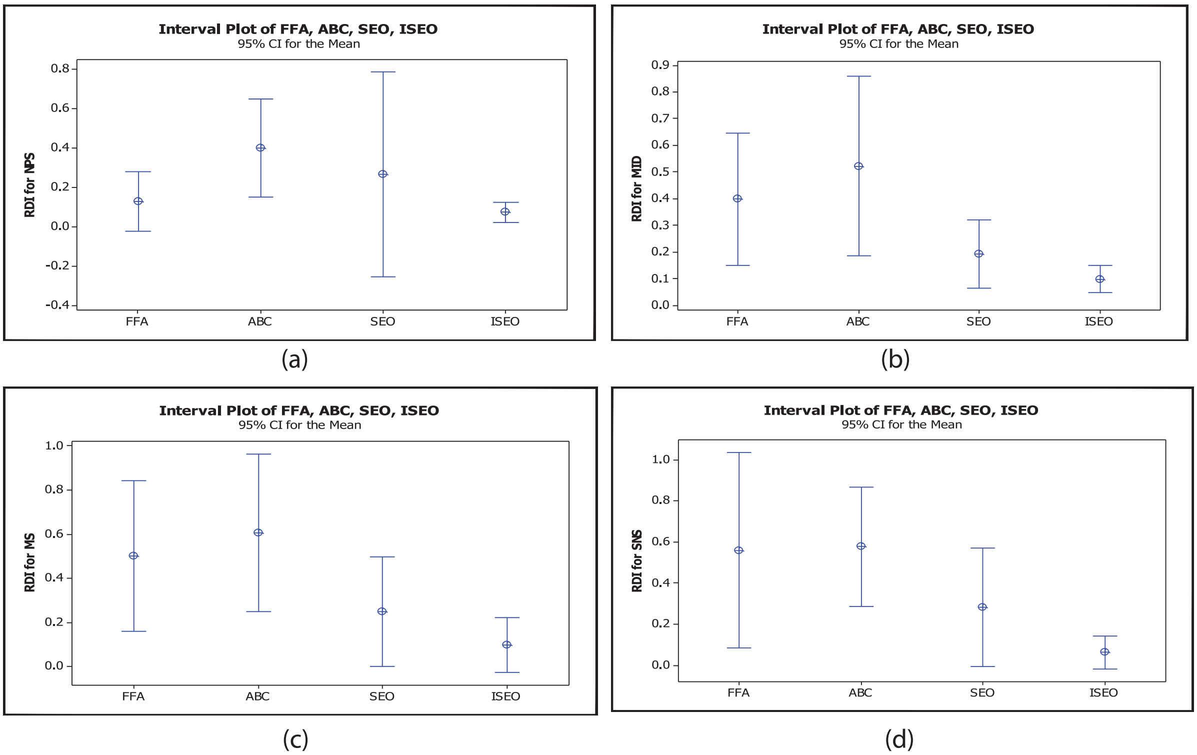


Figure 16: Interval plots for the evaluation metrics in RDI.

Table 9: The outcomes of the sensitivity analysis related to the transportation cost.

The number of cases	TC	TTC	TTO
C1	4	188.3	287.2
C2	10	256.7	385.1
C3	16	593.21	672.5
C4	18	628.76	788.1
C5	20	756.28	822.18

Table 10: The results of the sensitivity analysis related to the sorts of caregivers.

The number of cases	$p\ (\#DO\#NU\#TH)$	TTC	TTO
C1	#3#4#3	188.3	287.2
C2	#4#5#4	256.12	413.32
C3	#5#6#6	362.27	651.56
C4	#6#7#8	567.54	721.41
C5	#7#9#9	640.76	865.32

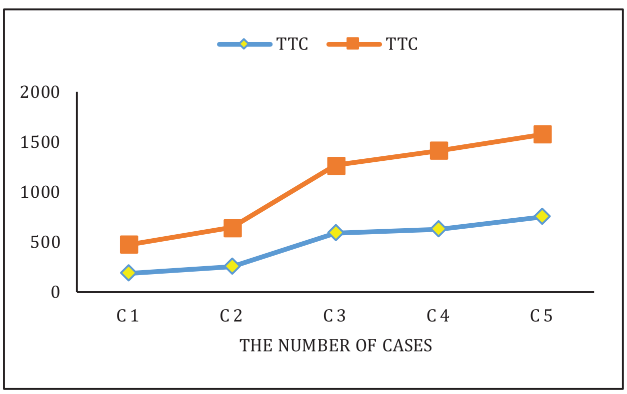


Figure 17: The behavior of the objective functions on the sensitivity analysis of the transportation cost.

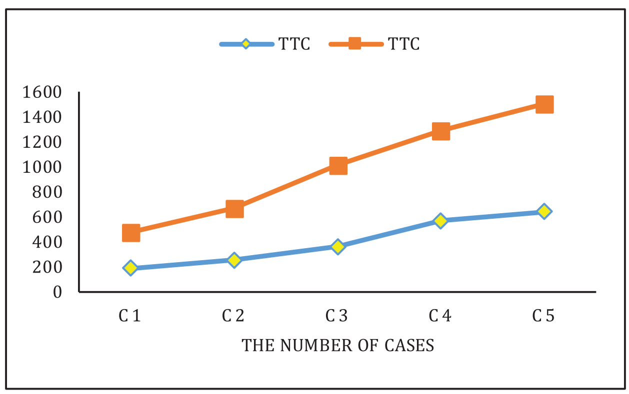


Figure 18: The behavior of the objective functions on the sensitivity analysis of the sorts of caregivers.

applied and among them, the proposed ISEO algorithm proved to have the highest performance in efficiency.

Four classifications of simulated test studies were considered to show that the exact solvers are not able to solve this model optimality in real-scaled instances. Henceforth, by integrating large-scaled and extra-large-scaled data into the HHCP, the model solution can receive the fluctuations. Accordingly, it is also exhibited that the association of large-scaled and extra-large-scaled data into the HHCP enlarges the computational time (CPU) and the model cannot be solved optimally in the present paper.

An exact solver by using the framework of the ε-constraint approach was provided for small-sized samples. Another contribution of this paper was an ISEO algorithm for large-sized and extra-large-sized samples that provided a solution very near to optimum. Four metaheuristic algorithms, namely FFA, ABC, SEO, and ISEO algorithms, were offered to have a comparative study. With regard to the multiobjective analysis of these algorithms, four assessment metrics, namely NPS, SNS, MID, and MS, were suggested to analyse the metaheuristic algorithms. The results prove that ISEO improves the convergence rate of SEO. In addition, this convergence outperforms other algorithms. Then, the convergence of ISEO is significantly faster than that of the other algorithms in this paper. This algorithm tends to outweigh other algorithms of optimization in our HHCP context. The results were discussed and analysed in terms of Pareto optimal solutions, convergence speed, and computational time. In addition, some sensitivity analyses were performed to show the behaviors of the total cost and operational times in different cases. As per the results, findings, discussions, and analysis of this paper, we conclude that the performance of SEO is significantly improved. This novel idea is effective not only for Pareto optimal solutions and our HHCP, but also for other variants of VRPTWs.

Future research may consider the following aspects: The synchronized visits can be added to our model. In addition, the environmental regulations for the HHC companies can be considered by adding the green emissions into our HHCP to achieve sustainability for HHC companies. Furthermore, considering machine-learning techniques can improve the search operators of our metaheuristics, without a doubt, the developed ISEO algorithm also needs further analyses based on benchmark tests and warrants additional attempts to combine it with other recent metaheuristics.

Conflict of interest statement

None declared.

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Appendix

A1. ε-Constraint Method

The ε-constraint method is one of the known methods dealing with multi-objective optimization problems. Since the proposed HHCP is a bi-objective MILP model, the ε-constraint method is employed. The algorithm transfers all objective functions, except for one of them ($f_1(\mathbf{x})$) at each stage as the constraints ($f_i(\mathbf{x}) \geq e_i$), in addition to the main constraints ($g(\mathbf{x}) \geq 0$), and solves them. By updating the bounds of each objective (e_i) and the main objective, the Pareto solutions are generated. Haimes et al. (1971) introduced this algorithm as summarized in Equation (A.1):

$$\begin{aligned} &\min f_1(\mathbf{x}) \\ &\text{s.t.} \\ &g(\mathbf{x}) \geq 0 \\ &f_i(\mathbf{x}) \geq e_i;\ i = 2, \ldots, m \\ &\mathbf{x} \in S. \end{aligned} \tag{A.1}$$

Generally, the steps of the ε-constraint method are:

- One of the objective functions is selected as the main objective function;
- After solving the single objective form of the model, the values of other objectives are reported. After that, with regards to other objective functions, the optimal values of them are reached and are reported;
- Based on the optimal value of each objective and other values when this objective was not the main one, the bounds to limit the objectives when running Equation (A.1) are ε, e_2, ..., e_m;
- Based on allowable bounds of each objective, we run Equation (A.1) multiple times to generate a group of Pareto solutions.
- We select the non-dominated solutions among all Pareto solutions generated by the above steps.

The concepts of Pareto solutions and how to identify the non-dominated solutions are defined in the following subsection.

A2. Multi-Objective Optimization Evaluation

As discussed earlier, the offered HHCP has two objectives based on two different items, i.e. the time and the cost. The goal is to find a trade-off between the two objectives. This interaction among the solutions is observed by the Pareto optimal solutions. These solutions can be divided into different fronts. The best front which has the high-quality solutions, is the non-dominated solutions (Goodarzian and Hosseini-nasab, 2019).

To describe the non-dominated solutions, consider two solutions for our model: Solutions A and B. Let Z_1^A, Z_2^A, and Z_1^B, Z_2^B be the corresponding optimal objective values for the first and second objective functions of Solutions A and B, respectively.

```
Initialize attacker and defender;
Set the input parameters of the algorithm;
It=1;
Create a list with the size of max_iter;
while It < max_iter
    Do training and retraining;
    num_attack = 1;
    while num_attack < max_attack
        Spot an attack;
        Check the boundary;
        Respond to attack;
        if the defender is able to dominate the attacker
          Exchange the defender and attacker position;
        End if
        num_attack = num_attack + 1;
    End while
    Create a new solution as defender;
    It = It + 1;
    Save the attacker in the list;
End while
Evaluate the best non-dominated solutions from the list;
```

Figure A.1: The pseudo-code of the proposed MOSEO algorithm.

Begin
Define objective functions $f_i(x)$;
Define operating parameters for **FFA**;
Generate initial population of fireflies;
Calculate the Pareto fronts from the initial population of fireflies;
Calculate light intensity li at xi by using $f_i(x)$;
$t = 0$;
While $(t < \max iteration)$
For $i = 1{:}\, n$
For $j = 1{:}\, i$
If $(li < lj)$
Move firefly i towards firefly j;
End if
Update attractiveness;
Evaluate new solutions and update intensity;
End for j
End for i
Rank the fireflies and find the current best one;
Update the Pareto solutions and the best non-dominated solutions;
End while
Return results;
end

Figure A.2: The pseudo-code of the MOFFA.

Therefore, Solution A dominates Solution B when $\binom{Z_1^A}{Z_2^A} \le \binom{Z_1^B}{Z_2^B}$ and $\binom{Z_1^A}{Z_2^A} \ne \binom{Z_1^B}{Z_2^B}$ (Nguyen et al., 2019; Devika et al., 2014).

The evaluation of a multi-objective optimization model is difficult as there is no global solution. There is a group of non-dominated solutions as the outputs of each algorithm. Therefore, some assessment metrics have been defined to analyze the quality of the algorithms. The Number of Pareto Solutions (NPS), Mean Ideal Distance (MID), Spread of Non-Dominance Solution (SNS), and Maximum Spread (MS) are four well-known metrics in this field, with a substantial number of studies in the literature that have used them (Fathollahi-Fard et al., 2018c; 2019a; Sahebjamnia et al., 2020).

A3. SEO

The Social Engineering Optimizer (SEO) algorithm was introduced by Fathollahi-Fard et al. (2018a), which was inspired by the rules of social engineering as an emerging phenomenon in today's real-world context of data security. With regards to the randomization of the SEO, this algorithm begins with two random solutions, called attacker and defender. As a single-point metaheuristic, the search phases of the SEO are formulated by the social engineering techniques.

In this metaheuristic, each answer expresses a person and its characteristics, including the abilities in mathematics, sports, business, music and so on; it expresses the variables of the problem. This algorithm focuses on the simulation of the learner's training and retraining from the attacker to the defender (Fathollahi-Fard et al., 2019b). In this regard, some random tests are defined for each attribute in which the attacker tests as an attribute in the defender and the amount of learning is calculated and the new defender which has the highest retraining rate is a replacement for the current defender if exists. Further, attacks from the defender are carried out according to the techniques that are available to the attacker (Zhang et al., 2019). With regards to these actions, the defender moves toward the attacker to find a response to the attack of the attacker. After a new evaluation of the fitness of the defender, an exchange may be acted if this defender is better than this attacker (Goodarzian et al., 2020a). Finally, a new defender is used to reboot the algorithm. In this algorithm, like other metaheuristic algorithms, the phases of the search are considered. Also, the training and retraining of the defender and the attacker improves the exploitive behavior of the algorithm. In addition, the attacker's attacks on the defender and the responses focus on the exploration phase. Last but not least, the choice of the new defender will represent the phase of diversity to improve the explorative behavior (Baliarsingh et al., 2019).

Since the proposed model has more than one objective, we consider a multi-objective extension to the SEO (Fathollahi-Fard et al., 2020b). In this regard, in each iteration, only one solution is selected with regards to the attacker, which is one of the best non-dominated solutions and has the lowest MID. After the last iteration, all attackers are evaluated once again to form the non-dominated solutions. In conclusion, Figure A.1 shows the pseudo-code of the MOSEO algorithm.

A4. FFA

The FireFly Algorithm (FFA) is a metaheuristic firstly presented by Yang (2010) as a multi-agent algorithm. The basis of this algorithm lies in the flashing behavior of the fireflies in emitting light from themselves. Most fireflies can use the emitted light for communication, to attract partners for mating, warn other fireflies of potential predators, and trap smaller insects that they hunt. The intensity of light available to other fireflies depends on the distance from the source, the intensity of the light source, and the absorption power of the light, so the firefly is generally visible from a limited distance. For more and complete information about the FFA, the interested reader is referred to Dekhici et al. (2019). Generally, these characteristics can be summarized as follows:

- All fireflies are unisexual. In other words, each firefly is able to attract other fireflies without a consideration of its sexuality.
- A less bright firefly moves toward a brighter firefly. Otherwise, it moves randomly.
- The brightness or intensity of light of the fireflies is computed by the landscape of the objective function that is being optimized.

Begin
Initialize food sources;
Generate the Pareto solutions;
Create the best non-dominated solutions;
Find one of the best non-dominated solutions which has the lowest MID as the global best food sources;
For cycle←1 to Maximum number of iteration **do**
For each employed bee i **do**
Choose a food source x_k in the neighborhood of x_i;
Select a jth dimension above all dimensions;
Generate a food source v_i in the neighborhood of x_i and x_k;
Apply greedy selection between $x_i$and v_i;
End
For each onlooker bee i **do**
Select a food source $x_i$depending on probability p_i;
Choose a food source $x_k$in the neighborhood of x_i;
Generate a food source $v_i$in the neighborhood of x_i and x_k;
Apply greedy selection between x_i and v_i;
End
If there exists an abandoned food source**, then**
Scout bee determines a new food source;
End
Update the Pareto solutions;
Update the global best food source;
End
End

Figure A.3: The pseudo-code of the MOABC algorithm.

According to these three idealized rules, the original version of FFA is defined. Since our HHCP is a multi-objective optimization problem, we need to apply the multi-objective version of FFA abbreviated as MOFFA. The main difference between this algorithm and the FFA is the non-dominated sorting concept, as illustrated in F2 before starting the next iteration. Therefore, the MOFFA can be summarized as a pseudo-code, as shown in Figure A.2.

A5. ABC

The Artificial Bee Colony algorithm (ABC) is an optimization theory introduced by Karaboga (2005) and developed in view of the intelligent foraging behavior of honey bee swarms. This algorithm is a technique that simulates the search behavior of honey bees for food. The algorithm performs a local search that combines with random searches and can be used for an optimized composition or functional optimization.

In the ABC algorithm, a food source is defined as a state of the search space (a solution to the optimization problem), and the number of food sources initially is equal to the number of available bees in the hive (Gergin et al., 2019). The quality of food sources is determined by the value of the objective function in that position (proportionality value). Based on this concept, the ABC is built. Note that as our model has two objectives, the Multi-Objective ABC (MOABC) is considered to solve our problem based on the presented encoding scheme. The main difference is represented by the concept of multi-objective assessment of solutions. After each iteration, the Pareto solutions should be updated. Based on the evaluation of the non-dominated solutions, Figure A.3 indicates the pseudo-code of the MOABC algorithm.