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RESEARCH ARTICLE

Designing a green home healthcare network using grey flexible linear programming: heuristic approaches

Fariba Goodarzian[1,*], Ajith Abraham[2,3], Peiman Ghasemi[4], Maria Di Mascolo[5] and Hadi Nasseri[1]

[1]Research Center of Optimization and Logistic, University of Mazandaran, Babolsar, Iran; [2]Machine Intelligence Research Labs (MIR Labs), Scientific Network for Innovation and Research Excellence, 11, 3rd Street NW, PO Box 2259, Auburn, WA 98071, USA; [3]Center for Artificial Intelligence, Innopolis University, Innopolis, Russia; [4]Department of Industrial Engineering, South Tehran Branch, Islamic Azad University, Tehran, Iran and [5]University Grenoble Alpes, CNRS, Grenoble INP∗∗, G-SCOP, 38000 Grenoble, France

*Corresponding author. E-mail: fariba.goodarzian@mirlabs.org

Abstract

In developing countries, the demand for old aged people requiring private health care at home is dramatically growing with the improvement of living standards. Since vehicles are used for transferring the medical staff (or doctors) to patient homes, it may be interesting to select a vehicle type based on the cost, capacity, and environmental sustainability (fuel consumption and CO2 gas emission per unit of distance) to maximize profits and social responsibility. In this paper, the first contribution, a new green home health care network for location, allocation, scheduling, and routing problems is developed with uncertain conditions. Another novelty, the time window to serve patients is also considered. In this regard, a novel grey flexible linear programming model is developed to cope with the uncertain nature of costs and capacity parameters that is as one important novelty. Due to this model's high complexity and difficulty in large-scale instances, this research develops two novel hybrid algorithms. The first hybrid strategy called the HSEOSA algorithm combines the Social Engineering Optimizer algorithm with the Simulated Annealing method. In terms of contribution to the related solution methodology, additionally, the Keshtel Algorithm is incorporated with the Genetic Algorithm called the HGAKA algorithm as the second new hybrid metaheuristic. An extensive comparison among the proposed algorithms is performed to find the most efficient one for the application of home healthcare in real practice. To validate the proposed model, a novel real case study is illustrated in the home healthcare services in Tehran/Iran.

Keywords: green home healthcare network, location–allocation–routing problem; grey flexible linear programming, hybrid algorithms

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1. Introduction

We are facing an increasingly aging population, resulting in an increasing demand for healthcare. Home healthcare is a particularly growing industry, where the elderly is nursed at home instead of at retirement homes, which is preferred by most patients (Ahmadi-Javid *et al.*, 2017; Ding *et al.*, 2018; Willis *et al.*, 2018). Therefore, home healthcare services, including housekeeping, cleaning, and medicine delivery as well as physiotherapy tests, are highlighted in recent studies (Denoyel *et al.*, 2017; Bidhandi *et al.*, 2019).

First of all, the company supporting the home healthcare services must define which one of the pharmacies and laboratories employing the nurses can be established (Gomes & Ramos, 2019). This is a healthcare facility location problem (Lin & Chou, 2020). Each pharmacy includes a set of nurses who provide home healthcare services. Then, all the patients must be allocated to one of the pharmacies and laboratories to define the patients' clustering (Begur *et al.*, 1997; Fikar & Hirsch, 2017; Burdett & Kozan, 2018). This creates an allocation optimization problem for the patients (Cheng & Rich, 1998; Bertels & Fahle, 2006). One of the challengeable issues in the home healthcare is that nurses or other caregivers must visit the patients according to a timetable (Eveborn *et al.*, 2006). This confirms the needed optimization for the scheduling of the nurses (Akjiratikarl *et al.*, 2007; Nasir & Dang, 2017; Yalçındağ & Matta, 2017; Szander *et al.*, 2019). The last main action of the home healthcare services is the routing optimization of the caregivers to visit the patients (Trautsamwieser *et al.*, 2011; Hiermann *et al.*, 2015; Braekers *et al.*, 2016; Shi *et al.*, 2017). The transportation cost and the capacity of the vehicles are two main factors in the routing optimization for home healthcare (Sinthamrongruk *et al.*, 2017; Decerle *et al.*, 2018; Nasir & Dang, 2018). Therefore, the majority of the studies have focused on the routing optimization of the caregivers rather than the scheduling or the allocation decisions (Issabakhsh *et al.*, 2018; Khodaparasti *et al.*, 2018; Liu *et al.*, 2018; Nasir & Dang, 2018; Veenstra *et al.*, 2018; Moussavi *et al.*, 2019).

Uncertainty makes these decisions much difficult and a valid plan to find the right allocation of the patients, routing, and scheduling of the nurses may not be available. Accordingly, a plan to control the uncertainty is needed (Veenstra *et al.*, 2018; Decerle *et al.*, 2019; Fathollahi-Fard *et al.*, 2020; Grenouilleau *et al.*, 2019; Moussavi *et al.*, 2019). Although the robust, stochastic, and fuzzy programming methods were studied in the literature to evaluate the uncertainty of the home healthcare model (Veenstra *et al.*, 2018; Decerle *et al.*, 2019; Fathollahi-Fard *et al.*, 2020; Grenouilleau *et al.*, 2019; Moussavi *et al.*, 2019), a grey flexible linear programming (GFLP; Shi *et al.*, 2005; Xie & Liu, 2011; Nasseri & Darvishi, 2018) has not been studied yet for home health care problem (Karmakar & Mujumdar, 2006; Nasseri & Darvishi, 2016; Nasseri & Bavandi, 2018). To the best of our knowledge, all of the location, allocation, scheduling, and routing decisions are usually not considered simultaneously in a home healthcare system. Our research provides an extension to the location–allocation–routing problem presented in Fathollahi-Fard *et al.* (2019) to the green home healthcare under uncertainty. To tackle the uncertainty parameters in this paper, a GFLP approach for the first time is used.

Our research can also be seen as another green home healthcare problem, which, until now, is considered only by two other studies (Fathollahi-Fard *et al.*, 2018a, 2019). In this regard, it is worth seeing the report of environmental protection agencies that ranked USA very high for contributing to the environmental pollution in the world (Fathollahi-Fard *et al.*, 2019). They classified the main resources into transportation, electricity, commercial and residential, industry, and agriculture (Fathollahi-Fard *et al.*, 2018a). Among them, transportation is a big challenge, and therefore, our study proposes a new green home healthcare location–allocation–routing problem. The main difference with the studies of Fathollahi-Fard *et al.* (2018a, 2019) is that we now apply a GFLP and two new hybrid metaheuristic algorithms. As a result, our extension to the problem definition is the use of uncertainty with the grey theory. Since this model is more complex than the basic models, new efficient solution algorithms are contributed.

Another contribution of our paper is related to the efficient solution methods. This study uses the merits of two recent metaheuristic algorithms including the Social Engineering Optimizer (SEO; Fathollahi-Fard *et al.*, 2018b) and the Keshtel Algorithm (KA; Hajiaghaei-Keshteli & Aminnayeri, 2014). In this regard, we develop the hybrid of SEO with a local search metaheuristic called Simulated Annealing (SA). This hybridization is abbreviated as HSEOSA. Another hybrid metaheuristic is the combination of the KA with a well-known evolutionary algorithm called the Genetic Algorithm (GA). This hybridization is abbreviated as HGAKA in this paper. These new ideas are compared with their individuals in a comparative study during different tests. Also, another considered novelty in this paper is the Adaptive Improved Epsilon-Constraint Algorithm (AIECA) to solve the proposed model. Due to the use of slack and surplus variables, this algorithm has a higher ability and flexibility to find effective Pareto points than the original Epsilon-constraint approach.

All in all, this paper highlights some new issues in the home health care network for the first time that can be effective for HHC practitioners and academics. The important contributions of the proposed paper are explained as follows:

1. Considering location, allocation, scheduling, and routing problems simultaneously in a green home healthcare network under uncertainty for the first time.
2. Considering simultaneously economic and environmental aspects in the home health care network.
3. Providing a GFLP approach to cope with uncertain parameters for the first time.
4. Developing two new heuristic methods based on metaheuristic algorithms called HSEOSA and HGAKA to solve the proposed model.
5. Suggesting AIECA approach to solving the presented problem for the first time.
6. Providing a real case study in Tehran/Iran to validate the proposed model.

The structure of the paper is as follows: Section 2 is the summary of the literature review based on the important and recent works in the research area of home healthcare problems. Section 3 establishes the deterministic and the uncertain version of the proposed model. Section 4 describes our proposed metaheuristics with their steps. Section 5 addresses the computational, validation analyses on the performance of the model, the efficiency of the algorithms, and the case study results. Finally, the conclusions and future research fields are given in Section 6.

2. Literature Review

As far as we know, the first paper in the area of home health care scheduling and routing problem is by Begur *et al.* (1997). They reviewed decision-making techniques for the home healthcare decision-making problems. Besides, Cheng and Rich (1998) developed a Mixed-Integer Linear Programming (MILP) formulation for routing and scheduling problems in the home health care network. Then, they proposed a heuristic algorithm for solving their model. Later, Bertels and Fahle (2006) combined a linear programming algorithm, planning limitation, and several heuristic techniques from other past studies. Their model can be called a simple model of vehicle routing optimization. The decision support system technique was used using a control policy for the home health care problem in Sweden by Eveborn *et al.* (2006). Torres-Ramos *et al.* (2014) developed a mathematical model for the home health care routing and scheduling problem with multiple treatments and time windows. Also, they presented an MILP model for planning, scheduling, and vehicle routing problems. Nasir and Dang (2017) presented a mathematical model for home health care network with the recruitment of health care staff, selection of home healthcare offices, and identification of patients' clusters centers. Therefore, they used the CPLEX solver to solve their model. Yalçındağ and Matta (2017) proposed a decomposition approach for the home health care problem with time windows. Also, they presented an MIP model for vehicle routing, assignment, and scheduling problems. In addition, they solved the model by the CPLEX solver. Szander *et al.* (2019) presented a routing and workforce scheduling algorithm in the home health care problem. They considered the optimal allocation of care resources, sustainability, the reduction of transport costs, and environmental aspects.

The metaheuristic algorithms in the recent decade have been used repeatedly in the literature review of this field. The Particle Swarm Optimization (PSO) algorithm was used as a collective intelligence-based algorithm to solve a routing and scheduling home health care problem in a case study in Ukraine by Akjiratikarl *et al.* (2007). Their other novelty was a heuristic for scheduling nurses and patients in the name of the closest priority time of starting with the shortest allocation interval. Additionally, a Variable Neighborhood Search (VNS) algorithm was designed by Trautsamwieser *et al.* (2011). Hiermann *et al.* (2015) presented a multimodal home health care scheduling problem. In addition, they used four metaheuristic algorithms including VNS, a Memetic Algorithm (MA), Scatter Search, and an SA hyperheuristic to solve their model. Braekers *et al.* (2016) stated a new multi-objective model for the home health care routing and scheduling problem. Also, there are two objectives including minimizing operating cost and maximizing the service level. In addition, to solve their model, they utilized a metaheuristic algorithm, embedding a Large Neighborhood Search heuristic in a multidirectional local search framework. Shi *et al.* (2017) proposed a fuzzy chance constraint programming for vehicle routing and scheduling problems. Also, they considered the uncertain quantity of medicines for patients in the home health care services. Accordingly, a hybrid GA integrated with the stochastic simulation method was developed. Sinthamrongruk *et al.* (2017) extended an adaptive local search based on GA in the home health care network for the staff routing problem. Decerle *et al.* (2018) formulated an MIP model. They presented an MA for a home health care routing and scheduling problem. Nasir and Dang (2018) designed a new scheduling and routing problem for a home healthcare service system. Their main aim was to develop a home healthcare service system from the perspective of long-term economic sustainability as well as operational efficiency. Also, an MILP model was formulated. In addition, two heuristic methods were developed to solve their model by the VNS algorithm.

More recently, Liu *et al.* (2018) developed a bi-objective approach for home health care medical team planning and scheduling problem. Then, the problem as an MIP was formulated. Hence, an ε-constraint method for the small-scale problem and three heuristic approaches for the large-scale problem were developed to solve their model. Khodaparasti *et al.* (2018) formulated a multiperiod location–allocation model for nursing home network planning under uncertainty. A covering model in which the capacity of facilities, and also the demand elasticity was formulated. Issabakhsh *et al.* (2018) suggested a vehicle routing problem for home health care problem with logistic service under travel time uncertainty and a conservative approach called robust optimization. Veenstra *et al.* (2018) extended a simultaneous facility location and vehicle routing problem for health care network. A branch-and-bound method with a fast hybrid heuristic to solve their model was developed. Moussavi *et al.* (2019) suggested an extension of the home health care planning problem. They developed a metaheuristic algorithm based on the decomposition method.

Decerle *et al.* (2019) offered a hybrid memetic-ant colony optimization algorithm for the routing and scheduling in a home health care problem with time window, synchronization, and working time balancing. Fathollahi-Fard *et al.* (2020) presented three efficient heuristics for a home health care problem. Also, they developed a new mathematical model based on the Lagrangian relaxation theory. As such, to solve their model, they utilized three new heuristics and a hybrid constructive metaheuristic. Grenouilleau et al. (2019) suggested a set of partitioning heuristics for the home health care routing and scheduling problem. Additionally, they proposed five new large neighborhood search operators fitted for their problem. Fathollahi-Fard *et al.* (2020) proposed a home healthcare routing and scheduling problem considering the patients' satisfaction. They handled the uncertainty of their model with the Jimenez method based on the triangular fuzzy numbers. They proposed an adaptive SEO to solve their model. Goodarzian *et al.* (2021a) designed a bi-objective home health care logistics according to the route balancing and working time. Their main aims were to minimize total service time and total costs. To solve their model, the metaheuristic algorithms including artificial bee colony, firefly, and SEO algorithms were used. They developed a new metaheuristic algorithm based on SEO algorithm called improved social engineering optimization algorithm to find the best solutions.

Liu *et al.* (2021) developed four hybrid metaheuristics for solving a home health care routing and scheduling problem considering time windows, synchronized visits, and lunch breaks. In their paper, an MIP mathematical model was provided. Finally, they proposed the statistical information that computed by the Friedman test. Shahnejat-Bushehri *et al.* (2021) proposed a robust home health care routing–scheduling problem with temporal dependences under uncertainty. They provided integrating Monte Carlo simulation and metaheuristic algorithms such as SA, GA, and MA to solve their developed models. In addition, they considered the dependence between synchronized services and continuity of care as well as multiple deployments of one caregiver in a one-day planning horizon. Tanoumand and Ünlüyurt (2021) suggested exact algorithm for the resource-constrained home health care vehicle routing problem. Thus, they used a branch-and-price algorithm to solve their model. Finally, a comprehensive computational study was performed

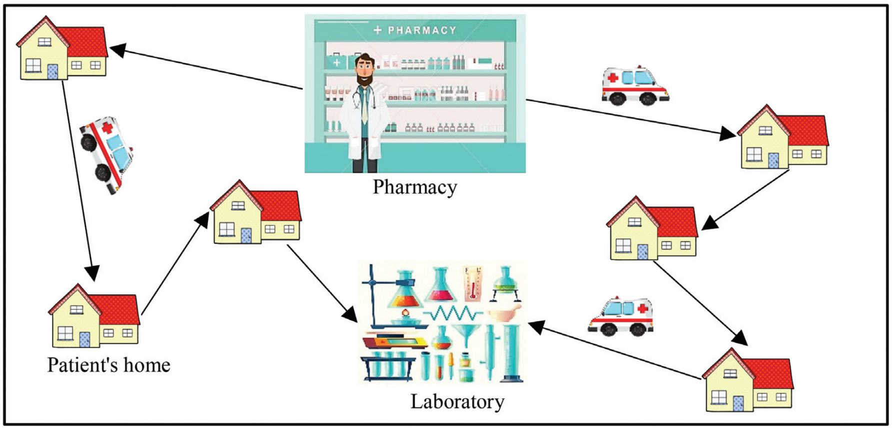

Figure 1: Graphical explanation of the presented home healthcare network.

on Solomon-based samples. Mousavi *et al.* (2021) formulated a stochastic MILP mathematical model for a health care facility location problem. In their proposed model, the main aims were to minimize the total cost, the transferring time, and the waiting time inside the trauma center. Then, they used an artificial neural network by a simulation model to estimate their third objective function. A hybrid multi-objective algorithm was developed according to a nondominated sorting water flow algorithm for searching the solution space.

Wang *et al.* (2020a) developed a green logistics location–routing problem with eco-packages in a state–space–time (SST) network. Additionally, they proposed a two-phase optimization model for green eco-packages' pickup and delivery. A Lagrangian relaxation-based heuristic algorithm to solve their model was designed. To allocate customers to their respective service providers in the pickup and delivery process, the Gaussian mixture clustering algorithm was used. In this regard, to optimize pickup and delivery routes, and improve their cost effectiveness and degree of synchronization, a Clarke–Wright saving method-based nondominated sorting GA-II was developed. Wang *et al.* (2020b) designed a collaborative two-echelon multicenter vehicle routing problem according to the SST network. They formulated a bi-objective optimization model for their problems. They developed an integrated method based on SST-based dynamic programming, K-means, and improved nondominated sorting GA-II. Finally, a case study to test their proposed approach in real world was conducted. Wang *et al.* (2021) devised a hybrid algorithm with k-means clustering and Clarke and Wright _NSGA-II to solve their model. They proposed an emergency logistics network design problem with resource sharing under collaborative alliances. Then, an SST network-based bi-objective MIP model to optimize the vehicle routes was formulated. Finally, a real case study to indicate the applicability of their model and algorithms was suggested. Wang *et al.* (2017) suggested an integer-programming model to minimize the total costs. A multiphase hybrid approach with clustering, dynamic programming, and heuristic algorithm was proposed to solve their model. Hence, improved Shapley value model with optimal sequential selection was suggested. Eventually, the empirical results showed that their presented approach outperforms other methods. Di Mascolo *et al.* (2021) and Cissé *et al.* (2017) provided a review of relevant routing and scheduling problems in the home health care network.

According to the investigated studies, there are some gaps that are explained as follows:

1. Ignoring location, the decisions of the allocation, scheduling, and routing simultaneously in a green home healthcare network under uncertainty.
2. Lack of attention to simultaneously economic and environmental aspects in the home health care network.
3. Lack of attention to a GFLP approach to cope with uncertain parameters for the proposed problem.
4. Ignoring two new heuristic approaches based on metaheuristic algorithms called HSEOSA and HGAKA to solve the presented model.
5. Lack of attention to the AIECA approach to solving the presented problem.
6. Ignoring a real case study in this research area.

In conclusion, as noticed in the literature review, two studies only contributed to the green home healthcare topic. However, their models were deterministic and did not consider the uncertainties. Although the robust, stochastic, and fuzzy programming techniques have been studied in the literature, no study has treated a GFLP. Therefore, a green home healthcare location–allocation–routing problem using a GFLP method is developed and two new hybrid algorithms including HSEOSA and HKAGA for the first time in this research area are proposed. In addition, a real case study is explained to validate the proposed mathematical model.

3. Problem Description

In this problem, we provide a green home healthcare network considering economic and environmental effects. Therefore, we suggest a new location–allocation–routing–scheduling problem based on the proposed network. In the following, a city or a village with a number of patients who are distributed in the area is considered. A company to establish several pharmacies and laboratories aims to satisfy the demand of patients for home healthcare services. There are a certain number of pharmacies and laboratories that should be decided on the construction of potential locations. The main decisions are the allocation of patients to each pharmacy, routing, and scheduling of the nurses. Each nurse starts from his/her pharmacy and after visiting the patients, the caregivers collect the patients' samples and results of the tests to his/her laboratory. Figure 1 shows the description of the routing of the caregivers with one pharmacy, one laboratory, and two caregivers.

In the allocation decisions, the idealist is to assign each patient to the nearest pharmacy. The distances are defined in a 2D geographic space. Therefore, the allocation and the routing decisions are made to minimize the total distance. The proposed model also considers the maximum route balancing to reduce the extra distance for each patient. The developed model controls the extra distance for the routing decisions through the use of a penalty function. If the vehicle goes more than the maximum travel distance policed by the company, the extra distance would be calculated. It goes without saying that the routing decisions are combined with the scheduling decisions. One of the main difficulties of the proposed problem is the time windows of the patients. It supports the scheduling decisions of the proposed problem. Therefore, the first objective function minimizes the total cost regarding these decisions.

In addition, the model also contributes to green home healthcare with the use of an additional objective function to compute the environmental pollution during the establishment of pharmacies and laboratories in addition to the carbon emissions for the routing decisions. The amount of carbon dioxide CO_2 produced by vehicles is considered. Hence, the second objective function aims to minimize environmental pollution that the environmental impact related to the pharmacies and the laboratories is considered.

The last contribution of the proposed problem is to find a grey flexible plan against the uncertainty of the proposed problem. This uncertainty includes the demand of the patients, the capacity of transportation systems regarding an accident, the number of bio-samples taken from the patients as well as the patients' availability, and the time windows. If we cannot meet the patients in their available time window, we need to re-optimize the sequence of the patients.

3.1. Assumption

The assumptions of the developed model are stated as follows:

1. All patients' demands must be met.
2. There are various types of vehicles, such as personal cars, vans, small buses, etc., each with a different cost and capacity.
3. The location or the potential locations related to pharmacies and laboratories are predefined.
4. The model considers time windows to describe the patient availability.
5. Each patient may have a different working time for the staff.
6. In the case of controlling transportation costs, a penalty function is considered to minimize an undesirable excessive amount of predefined cost.

3.2. Mathematical formulation

In this section, sets, parameters, and decision variables are presented for a bi-objective MILP model. Then, the proposed mathematical formulation of the green home healthcare problem is developed.

Indices

i, j	Index of the patients $i, j \in \{1, 2, \ldots, K\}$
r	Index of the pharmacies $r \in \{1, 2, \ldots, R\}$
l	Index of the laboratories $l \in \{1, 2, \ldots, L\}$
n	Index of the staff $n \in \{1, 2, \ldots, N\}$
t	Index of the transportation systems or the vehicles, $t \in \{1, 2, \ldots, T\}$
G	It shows that parameter is under uncertainty ($G =$ grey)

Parameters

D^K_{ij} :	Distance between patient i and j
D^R_{ir} :	Distance between patient i and pharmacy r
D^L_{rl} :	Distance between pharmacy r and laboratory l
ϕ^G_r :	Fixed cost for the establishment of a pharmacy r
ϖ^G_l :	Fixed cost for the establishment of a laboratory l
ψ_r :	Environmental effect for the establishment of the pharmacy r
δ_l :	Environmental effect for the establishment of the laboratory l
C^G_r :	Capacity of pharmacy r
C^G_l :	Capacity of laboratory l
β^G :	Allocation cost of patients, depending on the amount of displacement distance
η^G :	Allocation cost of patients to hospitals (without related to the distance)
μ^G_t :	Transportation cost between vehicles t
C^G_t :	Capacity of vehicles t
ρ_t :	Amount of produced carbon dioxide (CO_2) by vehicle t per unit of distance
α_i :	Amount of work time for staff to serve patient i
Ω^G_i :	Earliest available time to serve patient i
Ψ^G_i :	Latest available time to serve patient i
Δ_{ij} :	Approximate time interval between patient i and patient j
θ :	Amount of penalty considered by the company for an additional amount of distance traveled between patients: $1 < \theta < 5$
ε:	Large scalar number considered for the time dependence variables according to the time window constraint
ε':	Large scalar number considered to depend on the allocation and establishment decision variables
Γ_{nt} :	Maximum distance traveled by staff n, using the transportation system t, determined by the company's policy
ς_i :	Amount of medicine demand by each patient i
λ^G_i:	Amount of biological samples collected from each patient i
ϕ :	Maximum number of established facilities for pharmacies and laboratories

Decision variables

X^t_{ijrln} :	Equal to 1 if staff n from pharmacy r moves to laboratory l using vehicle t and goes from patient i to patient j, 0 otherwise
Y_r :	If pharmacy r is established equal to 1, otherwise 0
Z_l :	If laboratory l is established equal to 1, otherwise 0
U_{ir} :	If patient i is allocated to the pharmacy r equal to 1, otherwise 0
K_{rl} :	If pharmacy r is allocated to the laboratory l equal to 1, otherwise 0
H_{nirl} :	Time at which staff n starts working for patient i from pharmacy r to laboratory l.
R^t_{nrl} :	Amount of extra distance traveled by staff n that has traveled from pharmacy r to laboratory l by using vehicle t

Mathematical formulation:

$$\mathrm{MinObj1} = \sum_{r=1}^{R}(\phi_r^G \times Y_r) + \sum_{l=1}^{L}(\varpi_l^G \times Z_l) + \sum_{i=1}^{K}\sum_{r=1}^{R}(\beta^G \times D_{ir}^R \times U_{ir}) + \sum_{r=1}^{R}\sum_{l=1}^{L}(\eta^G \times D_{il}^L \times K_{rl}) + \sum_{t=1}^{T}\sum_{n=1}^{N}\sum_{i=1}^{K}\sum_{j=1}^{K}\sum_{r=1}^{R}\sum_{l=1}^{L}\left(D_{ij}^K \times \mu_{ts}^G \times X_{ijr\ln}^t\right) + \sum_{n=1}^{N}\sum_{t=1}^{T}\sum_{r=1}^{R}\sum_{l=1}^{L}(R_{nrl}^t \times \mu_t^G \times \theta) \tag{1}$$

$$\mathrm{MinObj2} = \sum_{r=1}^{R}(\psi_r \times Y_r) + \sum_{l=1}^{L}(\delta_l \times Z_l) + \sum_{t=1}^{T}\sum_{n=1}^{N}\sum_{i=1}^{K}\sum_{j=1}^{K}\sum_{r=1}^{R}\sum_{l=1}^{L}\left(D_{ij}^K \times \mu_t^G \times \rho_t \times X_{ijr\ln}^t\right) \tag{2}$$

The objective function (1) represents the economic objective function of the model, which aims to minimize all the costs. In this equation, the first and second terms represent the fixed cost of reopening the pharmacies and the laboratories. The third and fourth terms are related to the allocation cost. First, patients are allocated to their pharmacies. In addition, the pharmacies are allocated to their laboratories. The last two terms represent the cost related to routing and patient scheduling. In this way, the transportation cost for patients visited by staff is calculated. Additionally, the penalty cost for the additional distance on the model is calculated.

The objective function (2) shows the minimizing of the environmental impact of the whole home health care system. In this equation, the first and second terms represent the environmental impact associated with the construction of pharmacies and laboratories. The third term is related to the green effect of the vehicle used, which calculates the amount of carbon dioxide produced by vehicles.

Constraints

:

$$\sum_{r=1}^{R} Y_r \le \phi \tag{3}$$

$$\sum_{l=1}^{L} Z_l \le \phi \tag{4}$$

$$\sum_{r=1}^{R} U_{ir} = 1 \ \ \forall i \in K \tag{5}$$

$$\sum_{r=1}^{R}(\varsigma_i \times U_{ir}) \le C_r^G \ \ \forall i \in K \tag{6}$$

$$\sum_{i=1}^{K}\varsigma_i \times \sum_{j=1}^{K}\sum_{i=1}^{K} X_{ijr\ln}^t \le C_t^G \ \ \forall r \in R,\ l \in L,\ n \in N,\ t \in T \tag{7}$$

$$\sum_{i=1}^{K}\lambda_i^G \times \sum_{j=1}^{K}\sum_{i=1}^{K} X_{ijr\ln}^t \le C_t^G \ \ \forall r \in R,\ l \in L,\ n \in N,\ t \in T \tag{8}$$

$$\sum_{r=1}^{R} K_{rl} = 1 \ \ \forall l \in L \tag{9}$$

$$\sum_{l=1}^{L} K_{rl} = 1 \ \ \forall r \in R \tag{10}$$

$$\sum_{i=1}^{K}\sum_{j=1}^{K}\sum_{n=1}^{N}\sum_{t=1}^{T}\sum_{r=1}^{R}\lambda_i^G \times X_{ijr\ln}^t \le \sum_{r=1}^{R} C_l^G \times K_{rl} \ \ \forall l \in L \tag{11}$$

$$\sum_{l=1}^{L}\sum_{j=1}^{K}\sum_{n=1}^{N}\sum_{t=1}^{T}\sum_{r=1}^{R} X_{ijr\ln}^t = 1 \ \ \forall i \in K \tag{12}$$

$$\sum_{i=1}^{K}\varsigma_i \times \sum_{j=1}^{K} X_{ijr\ln}^t = 0 \ \forall t \in T,\ n \in N,\ r \in R,\ l \in L \tag{13}$$

$$\sum_{i=1}^{K} X_{ijr\ln}^t - \sum_{j=1}^{K} X_{jir\ln}^t = 0 \ \forall t \in T,\ n \in N,\ r \in R,\ l \in L \tag{14}$$

$$H_{nril} + \Delta_{ij} + \alpha_i - \varepsilon \times \left(1 - X_{ijr\ln}^t\right) \le H_{jnrl} \ \forall i, j \in K,\ t \in T,\ n \in N,\ r \in R,\ l \in L \tag{15}$$

$$\Omega_i^G \le H_{inrl} \le \Psi_i^G \ \forall i \in M,\ n \in N,\ r \in R,\ l \in L \tag{16}$$

$$R_{nrl}^t \ge \left(\sum_{i=1}^{K}\sum_{j=1}^{K} D_{ij}^K \times X_{ijr\ln}^t\right) - \Gamma_{nt} \ \forall r \in R,\ l \in L,\ n \in N,\ t \in T \tag{17}$$

$$R_{nrl}^t \ge 0 \ \forall r \in R,\ l \in L,\ n \in N,\ t \in T \tag{18}$$

$$\sum_{i=1}^{K} U_{ir} \le Y_r \times \varepsilon' \ \forall r \in R \tag{19}$$

$$\sum_{l=1}^{L} K_{rl} \le Y_r \times \varepsilon' \ \forall r \in R \tag{20}$$

$$\sum_{r=1}^{R} K_{rl} \le Z_l \times \varepsilon' \ \forall l \in L \tag{21}$$

$$\sum_{i=1}^{K}\sum_{j=1}^{K}\sum_{t=1}^{T} X_{ijr\ln}^t \le K_{rl} \times \varepsilon' \ \forall l \in L,\ r \in R,\ n \in N \tag{22}$$

$$H_{nirl},\ R_{nrl}^t \in R^+ \tag{23}$$

$$X_{ijr\ln}^t,\ Y_r,\ Z_l,\ U_{ir},\ K_{rl} \in \{0, 1\} \tag{24}$$

Constraints (3) and (4) show the maximum number of established facilities for pharmacies and laboratories. Constraint (5) states that each patient should be allocated only to a pharmacy. Constraint (6) indicates that the amount of medicine demand by each patient allocated to a pharmacy should not exceed its maximum capacity. Constraints (7) and (8) state that the transportation capacities. In other words, amount of medicine demand and biological samples collected by each patient i should be less than vehicle capacity, respectively. Constraints (9) and (10) ensure that each pharmacy should only be allocated to a laboratory. These constraints mean that if a pharmacy is allocated to the laboratory is equal to 1. Constraint (11) states that the allocated laboratory should be responsive to the demand of patients according to the samples and tests. Constraint (12) means that each patient is only visited once by the staff. In other words, staff from pharmacy goes to patient's home by using vehicle that can be visited patients just once time. Then, the staff goes to laboratory with biological samples collected. Constraint (13) guarantees that the vehicle allocated to the patient's tour should be responsive to the demand for the relevant request. Constraint (14) indicates that the staff must leave after visiting each patient. This constraint means that staff begins works in patient's home. Then, when works are finished, staff should leave patient's home and goes to laboratory. Constraints (15) and (16) ensure that there is the time window in the model. These constraints show earliest and latest available time to serve patients. Constraints (17) and (18) state that the distance traveled by the staff with the vehicle used should not be greater than the desired value. Otherwise, a penalty coefficient is calculated in

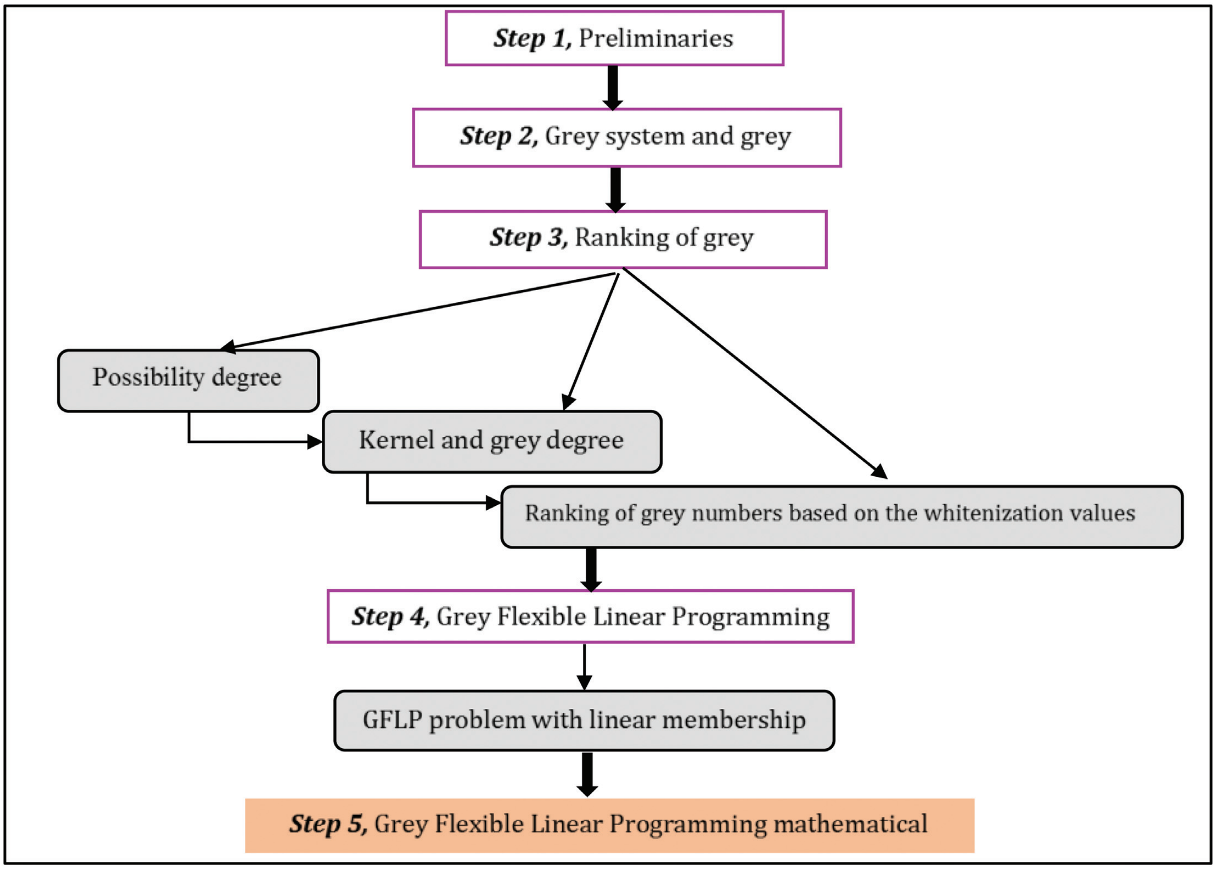

Figure 2: The structure of GST process for the proposed model.

the objective function. Constraint (19) states that patients can only be allocated to a pharmacy if and only if the pharmacy is reopened. Constraints (20) and (21) ensure that pharmacies and laboratories can be allocated to each other if and only if both of them are reopened. Similarly, constraint (22) displays the allocation of laboratories. This constraint means that laboratories should be located in the suitable location. Constraints (23) and (24) state the type of decision variables in this model.

3.3. GFLP model

Grey system theory (GST) is one of the convenient tools and fuzzy set theory, which is utilized to interpret the uncertainty of parameters, for solving the GFLP problem, and being premier in the mathematical analysis of systems with uncertain parameters (Nasseri & Darvishi, 2018). All the definitions are given in Supplementary Materials F1.

The suggested model has some uncertain parameters, including $\phi_r^G, \varpi_l^G, C_r^G, C_l^G, \beta^G, \eta^G, \mu_t^G, C_t^G, \Omega_i^G, \Psi_i^G$, and λ_i^G. In this paper, the GFLP is utilized to help decision makers to evaluate the uncertain parameters, including the demand of the patients, the capacity of transportation systems, or the vehicles due to an accident, the number of bio-samples taken from the patients as well as the patients' availability, and the time windows. We have explained the GFLP to convert the optimization model in Supplementary Materials F1 into a definite equivalent model. Additionally, in order to solve it, the standard optimization approaches to find the optimal solution are used. In this study, the presented problem is based on Grey parameters, the model is converted into a multi-objective deterministic model according to the GFLP technique. Hence, the flowchart of the process of GST is explained in Fig. 2 (Shi *et al.*, 2005; Karmakar & Mujumdar, 2006; Xie & Liu, 2011; Nasseri & Darvishi, 2016; Fathollahi-Fard *et al.*, 2018b; Nasseri & Bavandi, 2018).

Therefore, a grey linear optimization model in the form of GFLP is designed as follows:

$$\begin{aligned}\mathrm{MinObj1} = & \sum_{r=1}^{R} (\phi_r^G \times Y_r) + \sum_{l=1}^{L} (\varpi_l^G \times Z_l) \\ & + \sum_{i=1}^{K}\sum_{r=1}^{R} (\beta^G \times D_{ir}^R \times U_{ir}) \\ & + \sum_{r=1}^{R}\sum_{l=1}^{L} (\eta^G \times D_{il}^L \times K_{rl}) \\ & + \sum_{t=1}^{T}\sum_{n=1}^{N}\sum_{i=1}^{K}\sum_{j=1}^{K}\sum_{r=1}^{R}\sum_{l=1}^{L} (D_{ij}^K \times \mu_t^G \times X_{ijrnl}^t) \\ & + \sum_{n=1}^{N}\sum_{k=1}^{T}\sum_{r=1}^{R}\sum_{l=1}^{L} (R_{nrl}^t \times \mu_t^G \times \theta) \end{aligned} \quad (25)$$

$$\begin{aligned}\mathrm{MinObj2} = & \sum_{r=1}^{R} (\psi_r \times Y_r) + \sum_{l=1}^{L} (\delta_l \times Z_l) \\ & + \sum_{t=1}^{T}\sum_{n=1}^{N}\sum_{i=1}^{K}\sum_{j=1}^{K}\sum_{r=1}^{R}\sum_{l=1}^{L} \\ & \times (D_{ij}^K \times \rho_t \times \mu_t^G \times X_{ijrnl}^t) \end{aligned} \quad (26)$$

s.t.

$$\text{Constraints (3)–(5)} \tag{27}$$

$$\sum_{r=1}^{R} (\varsigma_i \times U_{ir}) \leq C_r^G + p_i (1 - \alpha_i), \ \forall i \in K \tag{28}$$

$$\sum_{i=1}^{K} \varsigma_i \times \sum_{j=1}^{K} \sum_{i=1}^{K} X_{ijr\,ln}^{t} \leq C_t^G + p_i (1 - \alpha_i),$$
$$\forall r \in R, \ l \in L, \ n \in N, \ t \in T \tag{29}$$

$$\sum_{i=1}^{K} (\lambda_i^G + p_i (1 - \alpha_i)) \times \sum_{j=1}^{K} \sum_{i=1}^{K} X_{ijr\,ln}^{t} \leq C_t^G + p_i (1 - \alpha_i),$$
$$\forall r \in R, \ l \in L, \ n \in N \, t \in T \tag{30}$$

$$\text{Constraints (9) and (10)} \tag{31}$$

$$\sum_{i=1}^{K} \sum_{j=1}^{K} \sum_{n=1}^{N} \sum_{t=1}^{T} \sum_{r=1}^{R} (\lambda_i^G + p_i (1 - \alpha_i)) \times X_{ijr\,ln}^{t}$$
$$\leq \left(\sum_{r=1}^{R} C_l^G \times K_{rl} \right) + p_i (1 - \alpha_i), \ \forall l \in L \tag{32}$$

$$\text{Constraints (12)–(15)} \tag{33}$$

$$\Omega_i^G + p_i (1 - \alpha_i) \leq H_{inrl} \leq \Psi_i^G + p_i (1 - \alpha_i)$$
$$\forall i \in M, \ n \in N, \ r \in R, \ l \in L \tag{34}$$

Constraints (17)–(24)

$$0 \leq \alpha_i \leq 1 \tag{35}$$

4. Solution Methods

In this section, in order to solve the proposed model in the small-sized problems, the Adaptive Improved Epsilon-Constraint Approach (AIECA) is developed. In this regard, four original metaheuristic algorithms including SA, GA, SEO, and KA algorithms are proposed and two new hybrid algorithms called HSEOSA and HGAKA algorithms are developed to solve the proposed model in medium- and large-sized problems. Therefore, the best algorithm will be used to solve the case study. Due to page limitation, the details of original algorithms including SEO (Hajiaghaei-Keshteli & Aminnayeri, 2014), GA (Fathollahi-Fard & Hajiaghaei-Keshteli, 2019; Morini & Pellegrino, 2018), KA (Hajiaghaei-Keshteli & Aminnayeri, 2014; Hajiaghaei-Keshteli & Fard, 2019), and SA (Booker *et al.*, 1989; Shi *et al.*, 2019) are given in Supplementary Materials F2, F3, F4, and F5. The suggested algorithms and AIECA method were implemented in MATLAB® 2020b software on a PC with 6 GHz RAM and GAMS 24.1, respectively. In the following, the AIECA method and a multi-objective optimization technique are defined. Then, the encoding plan of metaheuristics is illustrated. Finally, the proposed hybrid metaheuristics are explained in detail.

Hybrid proposed algorithms play a prominent role in improving the search capability of algorithms. In addition, the hybrid proposed algorithms are used to ensure a faster convergence rate. Overall, the outcome of hybridization can usually make some improvements in terms of either computational speed or accuracy. The proposed algorithms have the ability to handle random types of objectives and constraints and are easy to implement. Additionally, the suggested algorithms can be utilized independently to solve a given problem and employ simple operators as well as can be utilized to solve problems that have high computational complexity. The provided metaheuristics have a very fast rate of convergence and reduced computational time than the proposed algorithms in the literature review. The proposed original algorithms are very robust, these converge fast, require few parameters, are flexible, and can be combined with other algorithms.

4.1. Adaptive improved ε-constraint algorithm (AIECA)

In this subsection, the original general case of the Epsilon-constraint method is in equations (36)–(41). In this method, y is a feasible solution for the proposed model (Elsayed *et al.*, 2014).

$$\min f_1(y) \tag{36}$$

$$\min f_2(y) \tag{37}$$

$$\min f_3(y) \tag{38}$$

$$\text{subject to } y \in Y$$

$$f_2(y) \leq \varepsilon_2 \tag{39}$$

$$.... \tag{40}$$

$$f_n(y) \leq \varepsilon_n \tag{41}$$

The original Epsilon-constraint approach usually does not provide effective solutions, so the slack variable is used to calculate the difference between objective and bounds functions. The general form of this method is formulated in equations (42)–(45):

$$\min f_1 - \text{£}.s \tag{42}$$

$$f_2(y) + s \leq \varepsilon_2 \tag{43}$$

....

$$f_n(y) + s \leq \varepsilon_n \tag{44}$$

$$y \in Y \text{ and } s \in R^+. \tag{45}$$

Also, the value of is considered between $[10^{-6}, \ 10^{-3}]$. The pseudo-code AIECA is shown in Fig. 3.

In this approach, lexicographic method is used to calculate $f_1(y_{1,2})$, $f_2(y_{2,1})$, and Nadir points $f_1(y_{2,1})$, $f_2(y_{1,2})$. In each iteration, the new Pareto point is stored in the vectors P and F, and in the next round, the value of ε is replaced by the value of the objective function of the previous round. The algorithm continues until the lower limit reached $f_2(y_{2,1})$. The main advantages of the AIECA over the original Epsilon-constraint approach are explained as follows:

1. Using slack and surplus variables to calculate effective Pareto points.
2. Employing the optimal range to calculate the amount of epsilon as $\varepsilon_i \in [\text{Min}(f_i), \ \text{Max}(f_i)]$.
3. The proposed AIECA has high ability and flexibility in calculating $\varepsilon - k$ solutions.

4.2. Multi-objective optimization

The presented model has two objective functions. Therefore, the tradeoff among the solution method is provided by the Pareto optimal set. This set contains the nondominated solutions (Fathollahi-Fard *et al.*, 2020). In terms of nondominated solutions, two solutions are considered, including solutions OBJ1

Start
iteration $j = 0$
solve ideal point $\left(f_1\left(y_{1,2}\right), f_2\left(y_{2,1}\right)\right)$ *and nadir point* $\left(f_1\left(y_{2,1}\right), f_2\left(y_{1,2}\right)\right)$
$y_{1,2} = \arg_{y\in Y} \min f_1\left(y\right); y_{2,1} = \arg_{y\in Y} \min f_2\left(y\right)$
$\bar{\varepsilon} = f_2\left(y_{2,1}\right), \underline{\varepsilon} = f_2\left(y_{1,2}\right)$
$P = \left\{y_{1,2}, y_{2,1}\right\}, F = \left\{\left(f_1\left(y_{2,1}\right), f_2\left(y_{2,1}\right)\right)\right\}; y_0^* = y_{1,2}$
$while f_2\left(y_i^*\right) > \bar{\varepsilon}$
iteration $j = j + 1$
$\varepsilon_j = f_2\left(y_{j-1}^*\right)$
$y_j^* = opt\left(f, \varepsilon_j\right)$
$if y_j^* = Null; goto 15$
$F := F \cup \{(f_1\left(y_j^*\right), f_2\left(y_j^*\right)\}$
$P := P \cup \left\{\left(y_j^*\right)\right\}$
End While
return P, F
End

Figure 3: The pseudo-code of the AIECA.

and OBJ2. Solution OBJ1 dominates OBJ2 when all objectives of OBJ1 are not worse than OBJ2 and there exists at least one objective of OBJ1 that is more robust than those of OBJ2 (Fathollahi-Fard *et al.*, 2020). Therefore, this paper uses several metrics to evaluate the quality of Pareto fronts such as in a recent paper (Fathollahi-Fard *et al.*, 2020), according to the Pareto optimal set. In the next subsection, the encoding representation of employed multi-objective metaheuristics is explained.

4.3. Encoding representation

Metaheuristic algorithms utilize the space of the continuous search, an encoding representation, in order to create feasible solutions to cover the constraints of the presented model (Fathollahi-Fard *et al.*, 2020; Goodarzian *et al.*, 2021a). Hence, the optimization algorithms to the presented optimization problem are connected by encoding representation (Fathollahi-Fard *et al.*, 2020; Goodarzian *et al.*, 2021a). In this regard, the random key (Fathollahi-Fard *et al.*, 2020; Goodarzian *et al.*, 2021a) is one of the reported techniques for the solution scheme. This technique saves time to search and utilizes two phases. It requires no repair to create a feasible solution as well (Goodarzian *et al.*, 2021a). In this paper, this technique is provided to assess the presented home healthcare location, allocation, and routing problem.

Thus, a numerical instance to encode the solution representation is indicated as follows. Then, for example, six caregivers (S) and four kinds of transportation systems (T) are considered. First, the sort of employed transportation system for each staff member should be determined. Hence, an array by a length of S is created by a uniform distribution: U(0, T). Next, the kind of transportation system devoted to each staff member should be specified. In this regard, a set of procedures is indicated in Fig. 4. It is clear that the first kind of transportation system is used for staff member s_2. Then, the second kind of transportation system is employed for staff members s_1 and s_6. The third and fourth transportation systems are utilized for staff members s_3, s_4, and s_5, respectively.

Additionally, the allocation of each patient to the pharmacy (U_{ir}) and each pharmacy to the laboratory (K_{rl}) is shown in Figs 5 and 6. As shown in Fig. 5, eight patients (K), five pharmacies (R), and five laboratories (L) are devoted randomly. For instance, the patients k_2 and k_8 are provided for pharmacy R_1. In next examples, the patient k_7 is considered for pharmacy R_5.

Additionally, the allocations of pharmacies and laboratories are indicated in Fig. 6. The allocation is considered one by one. For instance, the second and third pharmacies are devoted to the second laboratory.

4.4. Hybrid SEO and SA algorithm

In order to solve the suggested problem, a new hybrid algorithm called HSEOSA, combining the SEO in Supplementary Materials F2 and SA algorithm in Supplementary Materials F5, is also presented. The proposed algorithm initially acts as an SEO algorithm; however, if the SEO algorithm was repeated 10 times (half of the stop condition of the SEO algorithm), the SA algorithm becomes activated. For this purpose, the best solution obtained from the SEO algorithm is selected as the first solution to the SA algorithm, and with the same characteristics of the SA algorithm as in the previous section, other computations are performed. Therefore, the steps of the proposed algorithm are explained as follows:

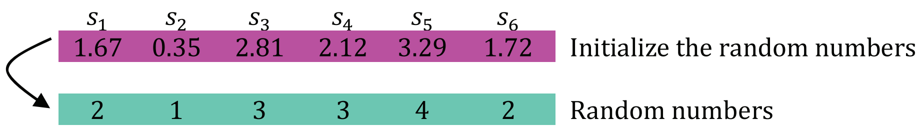

Figure 4: The utilized technique to assign a kind of transportation system for staff members.

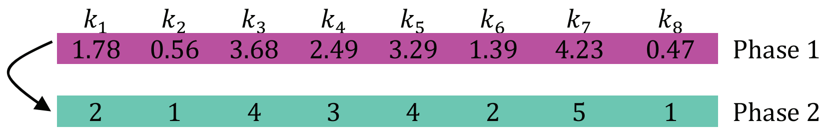

Figure 5: The allocation of the patients to pharmacies.

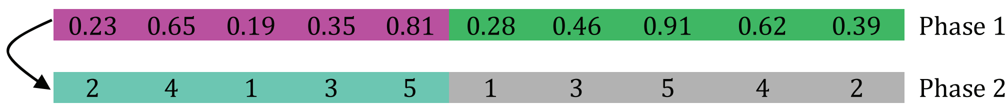

Figure 6: The allocation of the pharmacies to the laboratory.

Step 1: Initialize the attacker and the defender: The goal of optimization is to find the optimal answer among all the possible answers. In this way, an array must be considered for optimization. In the GA, the "chromosome" represents this array. Here, the "person" in this algorithm represents this array. In addition, in genetics, "genes" are used to denote variables to represent them. Here, the "trait" for the determined person the variables of an array for optimization. In an N-dimension space for the optimization problem, each person can be defined with the following formulation:

$$\text{Person} = [X_1, X_2, X_3, \ldots, X_{N_{\text{var}}}]. \tag{46}$$

Hence, the value of the objective function is calculated that is shown in equation (47):

$$\text{Value } f(\text{Person}) = f[X_1, X_2, X_3, \ldots, X_{N_{\text{var}}}]. \tag{47}$$

The algorithm starts with two random answers, which we call the better answer attacker and the other answer defender.

Also, initialize the parameters of SA algorithm including initial temperature (T_0), initial value ($x^{(0)}$), final temperature (T_f), the number of iterations (N), and temperature reduction rate (α).

Step 2: Train and retrain: In this step, we intend to show the train and retrain of the defender and the attacker. In this way, the attacker seeks the most influential trait to choose from. For this purpose, α % of the traits are randomly selected and repeated directly in the same trait in the defender. Then, the number of traits for train is determined based on equation (48).

$$N_{\text{Train}} = \text{round}\{\alpha.\, nVar\}, \tag{48}$$

where α shows the percentage of selected traits and $nVar$ indicates the total number of traits per person. Therefore, N_{Train} will be the number of traits that are randomly tested in the defender.

Step 3: Spot an attack; the algorithm is developed in a way that the user can employ one operator among the four ones:

1. Obtaining
2. Phishing
3. Diversion theft
4. Pretext

Step 4: Respond to attack: The new position of the defender is evaluated and compared with the previous position. If it was better, it was replaced. Also, if the final position of the defender is better than the attacker, the two will be replaced with each other.

Step 5: Create a new person as defender: In this step, the attacker finally destroys the defender and the new defender is randomly replaced.

Step 7: Generating an answer in the neighborhood of the current answer and evaluating the neighborhood answer.

Step 8: Updating algorithm parameters.

Step 9: If the number of iterations becomes more than 100 iterations (half of the stop condition of the SEO algorithm). Consider the best solution obtained from the SEO algorithm as the entrance solution of the SA algorithm and go to step 10. Otherwise, go to the Step 2.

Step 10: End to implement the proposed algorithm.

The structure of the train and retrain, spot an attack, respond to attack, and the values of the parameters are similar to those of the previous two algorithms, with the difference that the condition is going from the SEO algorithm to the SA algorithm is half the stop condition of the SEO algorithm. In Fig. 7, a pseudocode of the HSEOSA algorithm is presented. Additionally, the flowchart of this algorithm is shown in Fig. 8.

4.5. Hybrid GA and KA algorithm

In this section, according to the KA algorithm, we propose a hybrid approach inspired by the body of the KA algorithm that it is done by enhancing the search phases. As stated earlier, search phases play a key role in determining the quality of algorithmic solutions, and in metaheuristic methods, we seek an appropriate interaction between the concentration and diversity phases. In the KA algorithm, the concentration phase is accomplished using the rotation process and local search is performed by moving the Keshtel between the lucky Keshtels. The diversity phase in this algorithm generates random solutions that are the sight of new Keshtels and the flight of other Keshtels. Based on the evidence and results of previous research (Hajiaghaei-Keshteli

```
Initialize attacker and defender
It=100;
Define the objective function and set parameters of the algorithm
   Define the initial temperature T_0 and the initial value of x^(0).
   Define the final temperature T_f and the number of iterations N.
   Define the temperature decrease rate α.

while solving_time < Max_time
    Do training and retraining;
    Num_attack=1;
    while Num_attack < Max_attack
        Spot an attack;
        Check the boundary;
        Respond to attack;
        if the OF of defender is lower than 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;
    T2=clock;
    Solving_time=T2- T1;
End while
Return attacker.
Until (n < N, T > T_f)
   Neighborhood generation and creation of new solutions x_{n+1} = x_n + rand
   Calculation Δf = f_{n+1}(x_{n+1}) − f_n(x_n) (Δf=the value of the objective functions)
  If the new solution is better, it is accepted; otherwise, a random number r is generated, If p = exp(−Δf/T) > r
  the new solution is accepted. (p= The probability of acceptance is based on the Boltzmann distribution)
  End if
Updating x*, f*, n = n + 1
End
End
```

Figure 7: The pseudo-code of HSEOSA.

& Fard, 2019), this algorithm appears to have a robust mechanism for locally searching and focusing the answers using the rotation operator. However, to generate random solutions for the third generation of the algorithm solutions, it causes a random mechanism in the algorithm solutions due to the random nature. However, it seems that it can be augmented by an evolutionary mechanism using GAs. To this end, in the proposed new HGAKA algorithm, we use this procedure to compare this idea with the original KA in Supplementary Materials F3 and GA in Supplementary Materials F4. Therefore, the steps of the proposed algorithm are explained as follows:

Step 1: Initializing of Keshtel population and GA algorithm.
Step 2: Introducing the answers to the problem as chromosomes.
Step 3: Introduction of the fitness function.
Step 4: Use of roulette wheel selection operator.
Step 5: Perform operations on populations consisting of problem solving using genetic operators including reproduction, crossover, and mutation operators.
Step 6: Land the Keshtel in the lake: Since each Keshtel can be just in a moment in a specific place of the lake, an array is designed to display the location of each Keshtel in the problem space according to the dimension of the problem. In fact, Keshtel is the answer of the proposed problem. Each Keshtel (answer) is displayed according to equation (49).

$$\text{Keshtel} = [X_1, X_2, X_3, \ldots, X_{\text{Dimension}}] \tag{49}$$

Also, the objective function (minimization) is calculated according to equation (50).

$$f\,(\text{Keshtel}) = f\,[X_1, X_2, X_3, \ldots, X_{\text{Dimension}}] \tag{50}$$

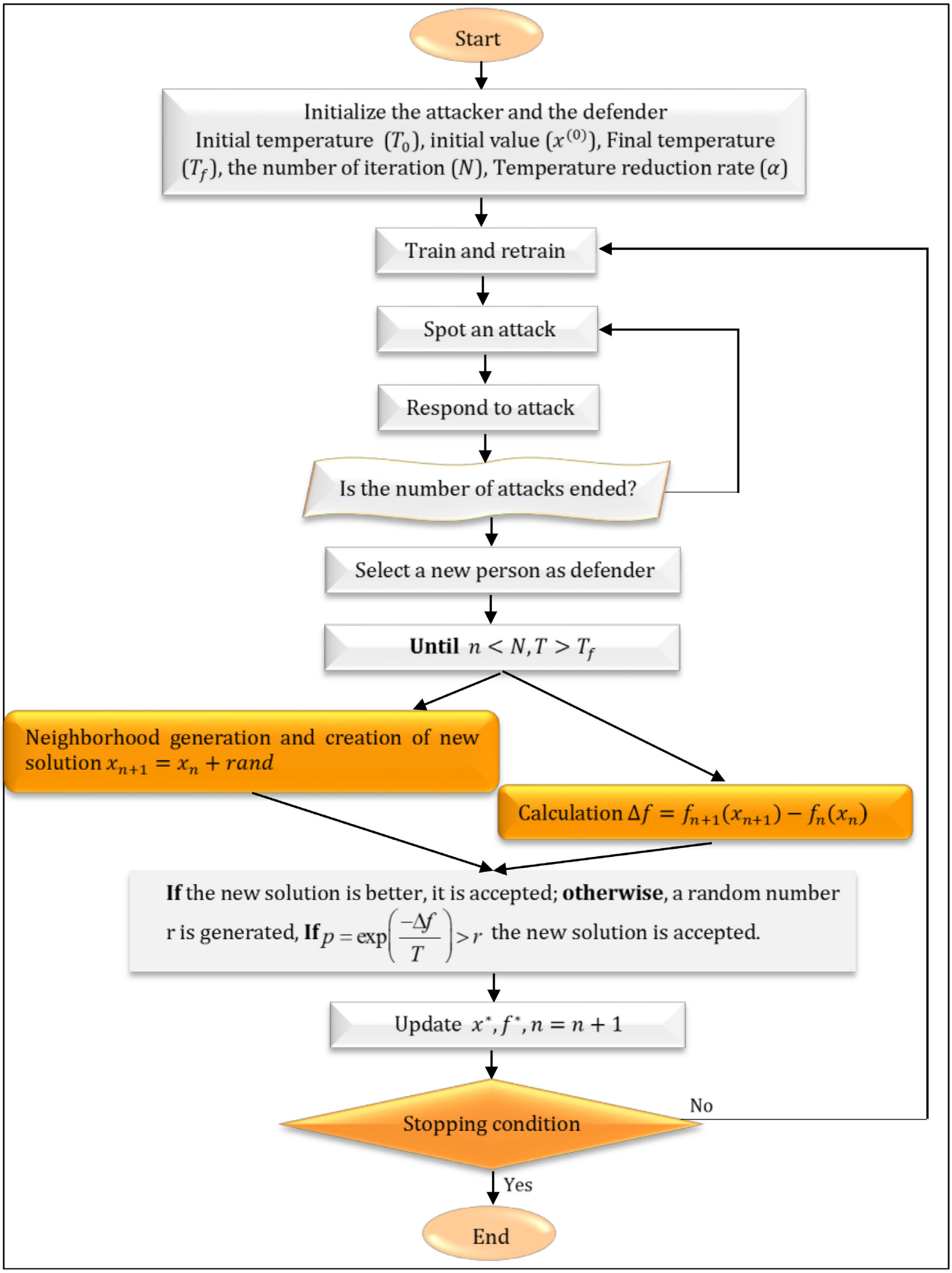

Figure 8: The flowchart of HSEOSA.

To start the algorithm, we need to generate a population of N Keshtels or answers ($N = N_1 + N_2 + N_3$).

Step 7: Find the Lucky Keshtel: In this step, Keshtels that land on a good food source must be identified. Probably the best food source on the lake (global optimal), that is close to one of the good answers. We find $N1$ answers with the best objective function and call them lucky Keshtels. Therefore, there are three processes for each lucky Keshtel, including

```
Initialize Keshtels population.
Calculate the fitness and sort them in three types: N1, N2 and N3.
X*=the best solution.
T1=clock;
while (t< maximum time of simulation)
    for each N1
        Calculate the distance between this lucky Keshtel and all Keshtels.
        Select the closest neighbor.
        S=0;
        while (S< maximum number of swirling)
            Do the swirling.
            if the fitness of this new position is better than prior
                Update this lucky Keshtel.
                    break
            End if
            S=S+1
        End while
    End for
    for each N2
        Move this Keshtel between the two lucky Keshtels.
        if the keshtel is better than the prior one
            Replace this keshtel.
        Else
            Compute δ, δ = |f_old − f_new|.
            if rand< exp(−δ/T)
                Replace the new solution
            End if
        End if
    End for
    for each N3
        Select a pair of Keshtels as parents by roulette wheel selection.
        Perform crossover to generate new Keshtels.
        Replace the offspring instead of parents.
    End for
    Merge the N1, N2 and N3.
    Sort Keshtels and form N1, N2 and N3 for next iteration.
    Update the X* if there is better solution.
    Update T.
    T2=clock;
    t=time (T2, T1);
End while
return X*
```

Figure 9: The pseudo-code of proposed HGAKA.

1. **Process 1:** Swirl the Nearest Keshtel around the Lucky Keshtel.
2. **Process 2:** If Nearest Keshtel finds better food than Lucky Keshtel, replace Nearest Keshtel with Lucky Keshtel, find new Nearest Keshtel, and go to process 1.
3. **Process 2:** If the food still exists, attract the Nearest Keshtel, and go to process 1. If not, go to step 8.

Step 8: Remain the Lucky Keshtels in the lake: After swirl, the Lucky Keshtels $N1$ move to a better food source. We remain this N1 answer for the next iterations. These have the best value of the target function among Keshtels. The first Keshtel among the N1 Keshtels is the global optimal that has ever been found.

Step 9: Startle the Keshtels that have found less food and new Keshtels land in the lake: Keshtels that have not found food or have found less startle to other lakes and are replaced by new Keshtels. We select N_2 Keshtel from N Keshtels that have the worst value of the objective function and replace it with the newly produced *htel* N_2. This is done randomly.

Step 10: Hustle the remaining Keshtels in the lake: The remaining Keshtel $N3$ moves into the lake in a specific period of time. They go to untouched places where there is no Keshtel. When one of these Keshtels $N3$ wants to move, it considers the

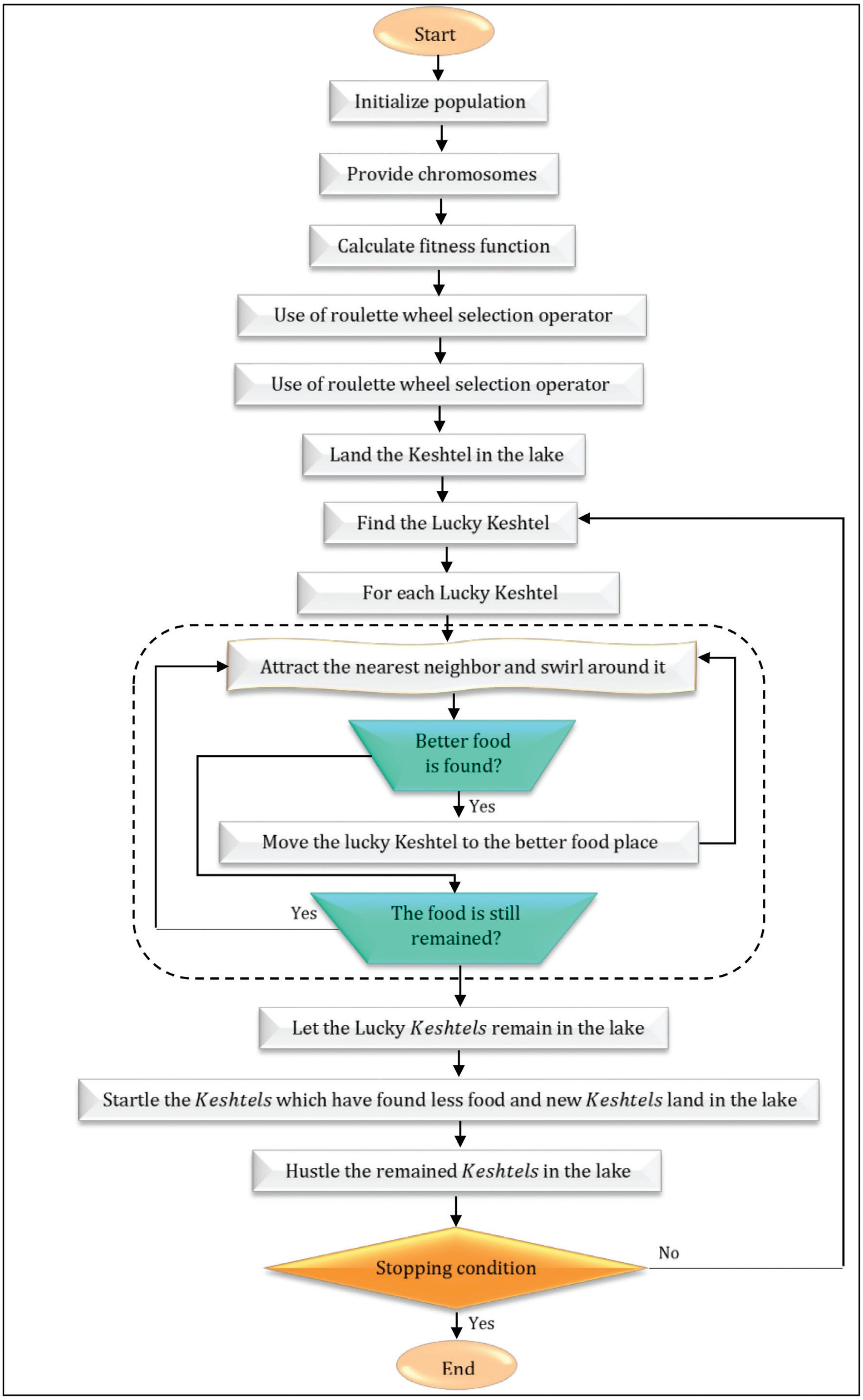

Figure 10: The flowchart of HGAKA.

Table 1: The size of the test problem generated.

Levels	Size problem	Number of laboratories	Number of pharmacies	Number of staff members	Number of vehicles	Number of patients
Small	SP1	2	2	2	3	11
	SP2	4	3	4	2	25
	SP3	5	6	5	4	50
	SP4	6	7	8	2	65
	SP5	8	7	8	3	85
Medium	MP6	9	8	9	4	100
	MP7	9	9	9	5	110
	MP8	10	9	9	6	125
	MP9	11	10	10	6	150
	MP10	12	11	10	6	165
Large	LP11	13	12	13	7	200
	LP12	15	14	14	7	220
	LP13	18	15	16	8	240
	LP14	20	18	20	9	260
	LP15	22	22	24	10	280

Table 2: Details related to the vehicles and dependent parameters.

Number	Type of vehicle	μ_t^G (Transportation cost, $)	ρ_t (Amount of carbon dioxide, CO_2, produced by vehicle)	C_t^G (Vehicle capacity, CM^3)
1	Small car 1 passenger	2	0.1635	300
2	Small car 2 passengers	3	0.089	350
3	Large car 1 passenger	4	0.312	450
4	Large car 2 passengers	6	0.1831	650
5	Large car 4 passengers	12	0.188	1500
6	Train	60	0.087	10 000
7	Coach	300	0.057	50 000
8	Plane	500	0.2351	140 000

location of the other two Keshtels and moves between them. Moving to empty places is done at a random distance.

Step 11: Stop conditions can be a certain number of iterations, the quality of the best answer found, or the time interval.

In the following, the pseudo-code of the proposed algorithm is indicated in Fig. 9. Then, the flowchart of the HGAKA algorithm is indicated in Fig. 10.

5. Computational Experiments

In this section, experimental problems are expressed in a variety of computing volumes and sizes. Then, algorithms are set for the model and compared on different criteria. After performing a comprehensive comparison of algorithms, the most important factors associated with each model are the sensitivity analysis to determine how to change the objective function according to the change of parameters. Then, 15 test problems based on randomly data were designed and developed at the five small levels (SP1 to SP5), the medium (MP6 to MP10), and the large (LP11 to LP15). Table 1 describes the size of the problems. Another of the most important tips is considered for vehicles related to the CO_2 produced by them. Then, details of vehicles including transportation costs (TC_{ts}), the amount of carbon dioxide CO_2 produced (CD_{ts}), and the capacity of vehicle (C_{ts}) are given in Table 2. In addition, the distribution of parameters is given in Table 3. Also, it should be noted that the maximum number of facilities established for pharmacies and laboratories is half the amount of their potential. Therefore, this problem is solved based on the grey model using the proposed solution methods.

5.1. Tune the algorithm's parameters

In this section, the efficiency of metaheuristic algorithms is directly related to the setting of its parameters and operators so that the incorrect selection of the parameters of the effective metaheuristic algorithm will cause it to be ineffective. In this paper, the Taguchi method is used to set up the algorithm's parameters (Fathollahi-Fard *et al.*, 2019).

In Taguchi method, the characteristics are divided into two main groups containing noise and control factors. Also, using the initial range of parameters sensitivity analysis is determined and then the signal-to-noise (S/N) rate values for the various levels of parameters of the proposed algorithms are calculated. The approach considers mainly computing the value of response variation according to the S/N ratio to attain the aim of tuning the algorithms. Hence, the mechanism of the Taguchi approach depends on the type of response. That means the achieved response is relevant to each class of Taguchi classification groups: smaller the better type, the nominal is the better type, and the larger the better type. Since the presented response of the proposed paper is a minimization type, "the smaller is better" is utilized to calibrate each algorithm's parameters. Therefore, equation (51) provides the selected value of the S/N ratio in the

Table 3: Randomly generated parameters in the model.

Parameters	The range of the parameters
(x_i, y_i)	$1000 \times (U(0, 1), U(0, 1))$
(x_j, y_j)	$1000 \times (U(0, 1), U(0, 1))$
(x_r, y_r)	$1000 \times (U(0, 1), U(0, 1))$
(x_l, y_l)	$1000 \times (U(0, 1), U(0, 1))$
D_{ij}^{K}	$\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$
D_{ir}^{R}	$\sqrt{(x_i - x_{ph})^2}+(y_i - y_{ph})^2$
D_{rl}^{L}	$\sqrt{(x_{ph} - x_l)^2}+(y_{ph} - y_l)^2$
ς_i	$rand\{15, 20, ..., 200\}$
C_r^G	$rand\{700, 800, ..., 2000\}$
λ_i^G	$rand\{10, 15, ..., 30\}$
C_l^G	$rand\{30, 40, ..., 120\}$
ϕ_r^G	$rand\{600, 1000, ..., 5000\}$
ϖ_l^G	$rand\{500, 1000, ..., 8000\}$
ψ_r, δ_l	$rand\{5, 4, ..., 20\}$
θ	For small sizes: 0.5, medium sizes: 1.5, large sizes: 3.5
α_i	$rand\{10, 15, ..., 90\}$
Ω_i^G	$rand\{0, 1, ..., 10\}$
Ψ_i^G	$rand\{100, 200, ..., 9000\}$
Δ_{ij}	$\frac{D_{ij}^K}{\sum_{i=1}^{K}\sum_{j=1}^{K} D_{ij}^K} \times 100 \times S^{a}$
Γ_{nt}	$rand\{10\,000, 20\,000, ..., 60\,000\}$
β^G	6
η^G	800
ϕ	200
ε	$rand\{10, 15, ..., 40\}$
ε'	$rand\{10, 15, ..., 40\}$

[a]Parameter related to the speed of vehicles for moving between two patients.

proposed paper.

$$\frac{S}{N} = -10 \times \log\left(\frac{\sum_{i=1}^{n} Y_i^2}{n}\right), \quad (51)$$

where Y_i shows the value of response for ith orthogonal array and n indicates the number of orthogonal arrays.

Since the scale of objective functions in each example is various, they could not be utilized directly. Accordingly, the Relative Percent Deviation (RPD) is employed for each example to solve this problem. The RPD value for the data is obtained using equation (52).

$$\mathrm{RPD} = \frac{Alg_{\mathrm{sol}} - Min_{\mathrm{sol}}}{Min_{\mathrm{sol}}} \times 100, \quad (52)$$

where Min_{sol} and Alg_{sol} show the achieved best solution and the values of the achieved objective for each iteration of the experiment in a provided example, respectively. Therefore, the mean RPD is computed for each experiment after transforming the values of the objective to RPDs.

In this paper, six metaheuristic algorithms including SA, GA, KA, SEO, HSEOSA, and HGAKA are presented. The algorithms' parameters are the terminology of factors for each metaheuristic algorithm. Then, the proposed factors and levels are shown in Table 4. Hence, a maximum of five levels are provided to algorithms' factors.

It should be noted that the Taguchi approach diminishes the total number of tests by providing a set of orthogonal arrays to tune the algorithm's parameters within a reasonable time. Taguchi's approach suggests L25 for SA, KA, SEO, and GA and L16 for both HSEOSA and HGAKA. The details related to orthogonal arrays of the proposed algorithms are reported in Tables A1, A2, A3, and A4 in Appendix A. To find the best levels of each algorithm, the output of the S/N ratio should be analysed as shown in Fig. 11. Overall, according to Fig. 11, the tuned parameters for all algorithms are based on smaller is better.

Also, the RPD is utilized for confirming the selected best factors based on S/N ratios. Figure 12 demonstrates the outcomes of RPD for each parameter level. It is clear that in Fig. 12, the RPD shows the best factors, which confirm the same outcomes as S/N ratios.

5.2. Comparison of metaheuristic algorithms

According to the assessment metrics and computational time, the metaheuristic algorithms are evaluated for three different test problems. First, the results of multi-objective metaheuristics should be checked by a single objective exact method. It should be noted that the proposed algorithms are a type of stochastic optimization in nature. Therefore, to validate the results and to make them reliable, a method should be provided. Here, the AIECA approach is used to attain this aim. The method structure is formulated by one objective to be optimized and the second objective as the constraint of the model restricted by allowable bounds. Hence, by modifying the allowable bounds of objective functions, the Pareto optimal set will be generated.

The results and details of the proposed algorithms are presented in Table 5. The developed problem is a bi-objective model. In Table 5, then, the values of the first and second objective functions show with (Z1) and (Z2), respectively. Also, the computational time of the algorithms illustrates with (T), which shows based on seconds. As can be seen, the computational (CPU) time of the AIECA approach has increased exponentially with increasing problem size. This proves that the proposed model is NP-hard. Also, due to the high CPU time, the AIECA approach is not capable of solving large-scale problems.

In computer science, big O notation is used to classify algorithms according to how their run time or space requirements grow as the input size grows. In analytical number theory, big O notation is often used to express a bound on the difference between an arithmetical function and a better understood approximation (White, 2010). First of all, we compare the proposed metaheuristic algorithms based on CPU time so that we can identify the most efficient algorithm. Figure 13 shows the CPU time of the proposed methods for solving experimental problems in different sizes. In this figure, the proposed algorithms have a close CPU time. It is clear that in Fig. 13a, all proposed methods are close to each other in SP1, SP2, and SP3 test problems. In addition, all suggested approaches increase sharply between SP3 and SP5 test problems. According to this figure, HSEOSA has less CPU time than the other proposed algorithms, but GA has a higher CPU time than other presented algorithms in small-sized problems. In terms of the CPU time in medium- and large-sized problems, with the increase in the size of the test problem, the CPU time of the proposed algorithms is increased. In terms of the CPU time in medium- and large-sized problems, with the increase in the size of the test problem, the CPU time of the proposed algorithms is increased. Then, the developed algorithm called HSESA has less CPU time than the other suggested algorithms according to Fig. 13b and c. As a result, first, HSEOSA has high quality than other the proposed algorithms, and second, HGAKA has high performance than the SA, SEO, KA, and

Table 4: The factors and levels of the proposed algorithms.

Algorithms	Factors	Levels				
		1	2	3	4	5
SA	A: *Maxit*	A1 = 500	A2 = 1000	A3 = 1500	A4 = A2000	A5 = 2500
	B: *Subit*	B1 = 10	B2 = 20	B3 = 30	B4 = 40	B5 = 50
	C: T_m (operator used for local search)	C1 = Swap	C2 = Reversion	C3 = Insertion	-	-
	D: T_0 (Initial temperature)	D1 = 1000	D2 = 1500	D3 = 2000	D4 = 2500	D5 = 3000
	E: R (Temperature decrease rate)	E1 = 0.55	E2 = 0.6	E3 = 0.65	E4 = 0.7	E5 = 0.75
SEO	A: *Maxit*	A1 = 500	A2 = 1000	A3 = 1500	A4 = 2000	A5 = 2500
	B: Number of Attacks (*Natt*)	B1 = 20	B2 = 30	B3 = 40	B4 = 50	B5 = 60
	C: Training rate (α)	C1 = 0.3	C2 = 0.4	C3 = 0.5	C4 = 0.6	C5 = 0.7
	D: The solution rate to the attack (β)	D1 = 0.25	D2 = 0.35	D3 = 0.45	D4 = 0.55	D5 = 0.65
GA	A: *Maxit*	A1 = 500	A2 = 1000	A3 = 1500	A4 = 2000	A5 = 2500
	B: *nPop*	B1 = 100	B2 = 200	B3 = 300	B4 = 400	B5 = 500
	C: Crossover (*pc*)	C1 = 0.5	C2 = 0.5	C3 = 0.55	C4 = 0.6	C5 = 0.65
	D: Mutation (*pm*)	D1 = 0.1	D2 = 0.2	D3 = 0.3	D4 = 0.4	D5 = 0.5
KA	A: *Maxit*	A1 = 500	A2 = 1000	A3 = 1500	A4 = 2000	A5 = 2500
	B: *nPop*	B1 = 100	B2 = 200	B3 = 300	B4 = 400	B5 = 500
	C: n_1	C1 = 0.5	C2 = 0.5	C3 = 0.55	C4 = C0.6	C5 = 0.65
	D: n_2	D1 = 0.1	D2 = 0.2	D3 = 0.3	D4 = 0.4	D5 = 0.5
	E: *Swirl*	E1 = 2	E2 = 3	E3 = 4	E4 = 5	E5 = 6
HSEOSA	A: *Maxit*	A1 = 500	A2 = 1000	A3 = 1500	A4 = 2000	A5 = 2500
	B: *Subit*	B1 = 10	B2 = 20	B3 = 30	B4 = 40	B5 = 50
	C: T_m (operator used for local search)	C1 = Swap	C2 = Reversion	C3 = Insertion	-	-
	D: T_0 (Initial temperature)	D1 = 1000	D2 = 1500	D3 = 2000	D4 = 2500	D5 = 3000
	E: R (Temperature decrease rate)	E1 = 0.55	E2 = 0.6	E3 = 0.65	E4 = 0.7	E5 = 0.75
	F: Number of attacks (*Natt*)	F1 = 20	F2 = 30	F3 = F40	F4 = 50	F5 = 60
	G: Training rate (α)	G1 = 0.3	G2 = 0.4	G3 = 0.5	G4 = 0.6	G5 = 0.7
	H: The solution rate to the attack (β)	H1 = 0.25	H2 = 0.35	H3 = 0.45	H4 = 0.55	H5 = 0.65
HGAKA	A: *Maxit*	A1 = 500	A2 = 1000	A3 = 1500	A4 = 2000	A5 = 2500
	B: *nPop*	B1 = 100	B2 = 200	B3 = 300	B4 = 400	B5 = 500
	C: Crossover (*pc*)	C1 = 0.5	C2 = 0.5	C3 = 0.55	C4 = 0.6	C5 = 0.65
	D: Mutation (*pm*)	D1 = 0.1	D2 = 0.2	D3 = 0.3	D4 = 0.4	D5 = 0.5
	E: n_1	E1 = 0.5	E2 = 0.5	E3 = 0.55	E4 = 0.6	E5 = 0.65
	F: n_2	F1 = 0.1	F2 = 0.2	F3 = 0.3	F4 = G0.4	F5 = 0.5
	G: *Swirl*	G1 = 2	G2 = 3	G3 = 4	G4 = 5	G5 = 6

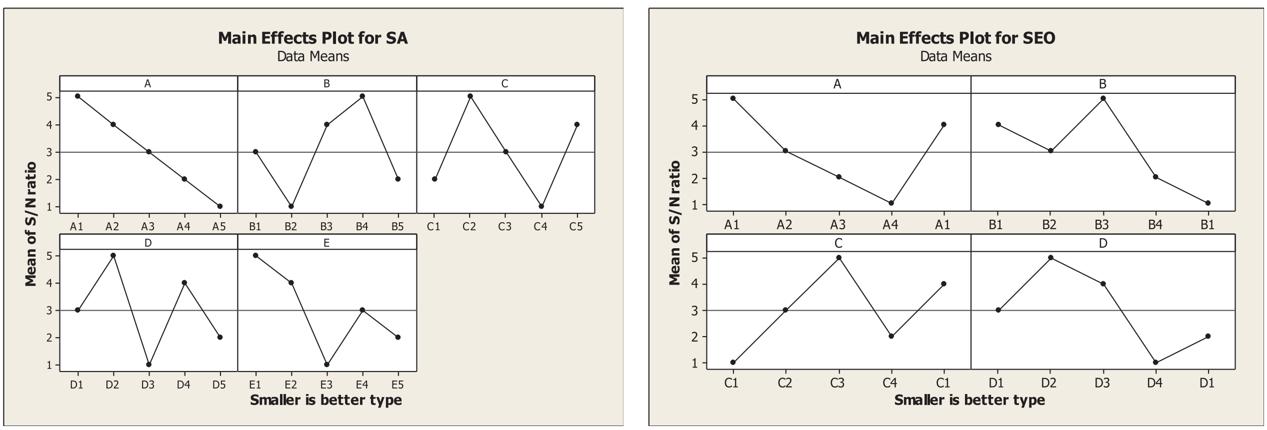

Figure 11: Minitab Software output for the S/N ratio of the proposed algorithms.

GA algorithms, but GA has the worst efficiency than other the proposed algorithms in terms of CPU time.

According to Fig. 13, the performance (Runtime) of an algorithm depends on n; that is the size of the input or the number of operations is required for each input item. The algorithms can be classified as follows from the best-to-worst performance (Running Time Complexity): 1- HSEOSA, 2- HGAKA, 3-KA, 4-SEO, 5-SA, and 6-GA.

Hence, the comparison of the metaheuristic algorithms in the term of multi-objective programming is difficult. In this regard, scholars were provided a number of assessment metrics to evaluate the quality of Pareto fronts for the algorithms. In

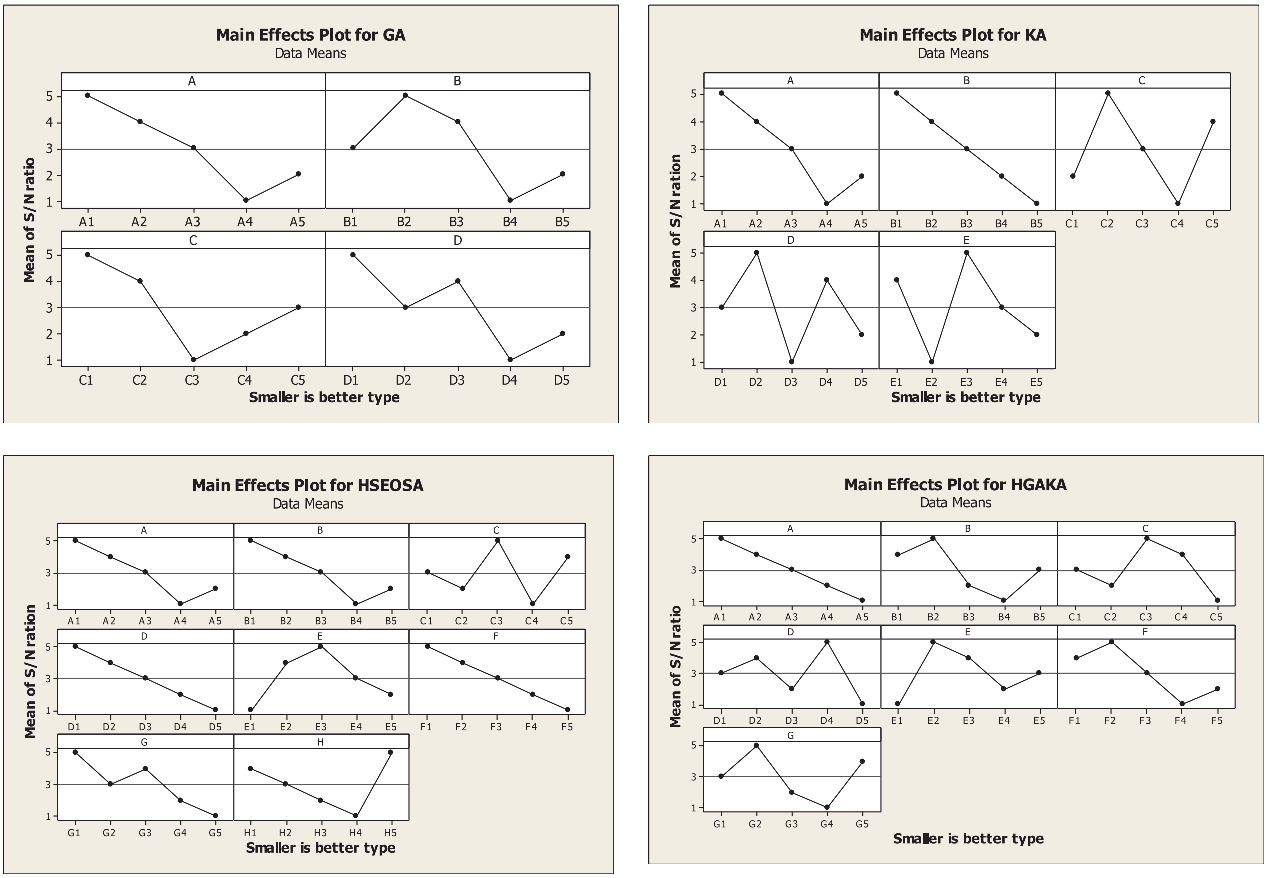

Figure 11: Continued.

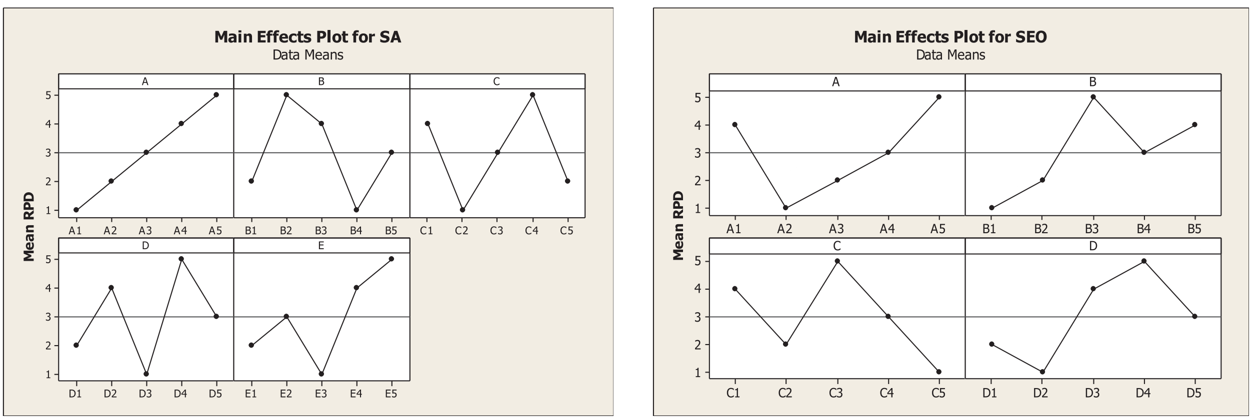

Figure 12: Mean RPD plot for each level of the factors.

the following, four popular assessment metrics are used in this paper. These metrics were employed in the recent studies (e.g. Goodarzian *et al.*, 2020, 2021a, c, d).

1. Number of Pareto Solutions (NPS; Govindan *et al.*, 2015).
2. Mean Ideal Distance (MID; Govindan *et al.*, 2015; Goodarzian *et al.*, 2021c).
3. Spread of Non-Dominance Solution (SNS; Goodarzian *et al.*, 2021c).
4. Maximum Spread (MS; Karimi *et al.*, 2010).

Therefore, the performance of the SA, KA, GA, SEO, HGAKA, and HSEOSA algorithms is assessed using the proposed assessment metrics as the comparison metrics for achieved Pareto sets under each experimental problem. The results of the proposed assessment metrics are presented in Table 6. In terms of the NPS, this metric computes the total nondominated solutions acquired by an algorithm, which the more value of this metric is better. According to Table 6, the results of the HESOSA are further than other proposed algorithms in terms of the NPS metric. MID shows the distance between the ideal point and nondominated solutions. In this metric, whatever the value of this

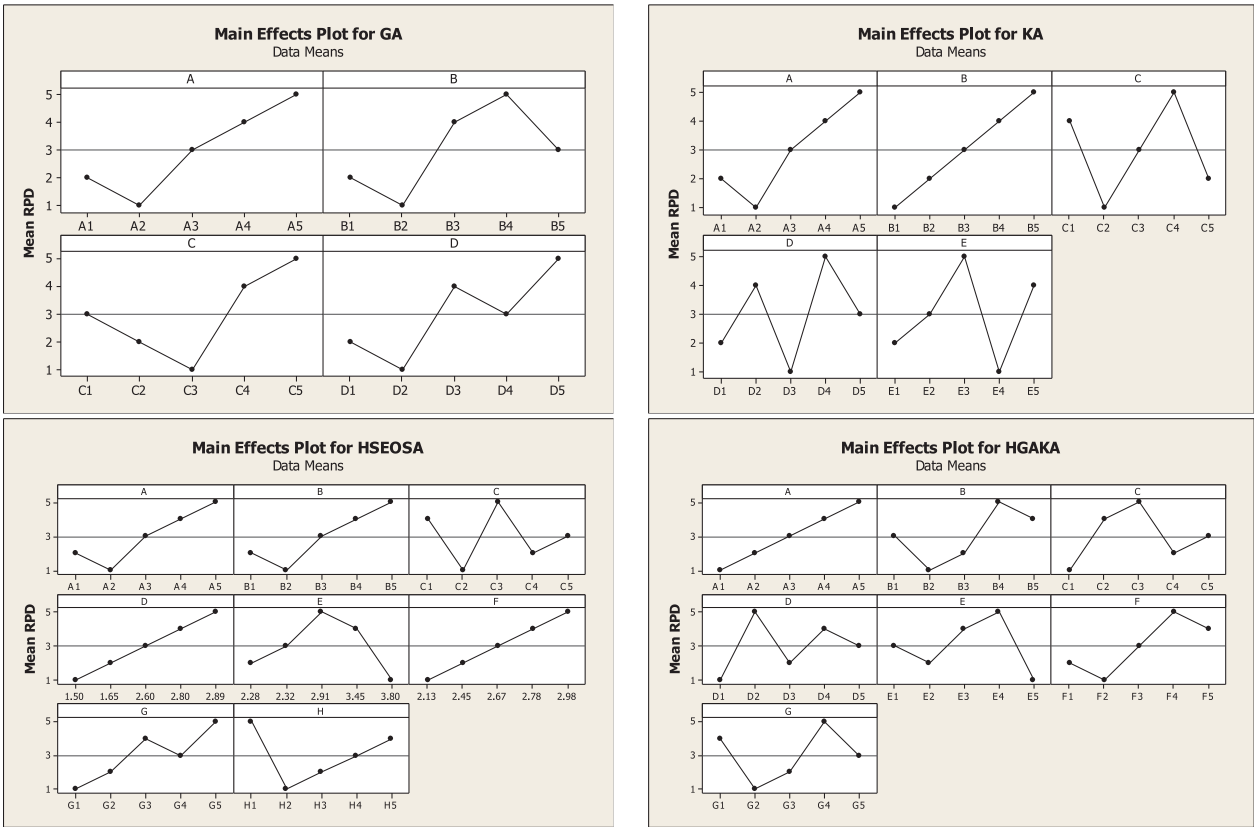

Figure 12: Continued.

Table 5: The results and details of the proposed algorithms.

Algorithms		SP1	SP2	SP3	SP4	SP5	MP1	MP2	MP3	MP4	MP5	LP1	LP2	LP3	LP4	LP5
SA	Z_1	4404	5341	5637	8912	9894	10 297	14 060	16 518	18 213	21 516	25 782	28 238	34 553	38 802	42 001
	Z_2	598	679	728	1236	1436	1881	1956	10 141	11 337	13 069	14 628	15 804	16 788	17 033	18 085
	T	0.041	0.061	0.664	4.30	7.61	19.12	34.40	106.5	115.6	209.7	256.7	471.5	512.6	644.6	710.3
SEO	Z_1	3612	5058	5371	8431	8901	9181	9326	9892	11 747	13 770	15 481	17 890	19 034	20 124	26 034
	Z_2	434	658	699	1076	1148	1341	1562	1673	1366	1593	10 791	11 033	13 045	14 708	15 067
	T	0.0371	0.042	0.354	3.414	6.01	15.31	25.23	69.1	98.7	117.4	245.6	332.6	410.4	533.1	667.3
KA	Z_1	3876	4341	4562	7602	7932	8560	9211	9670	9876	11 234	13 541	15 651	17 871	19 760	22 321
	Z_2	456	331	467	589	623	690	723	792	823	876	910	945	1021	1134	1343
	T	0.039	0.078	0.321	2.17	4.23	6.01	25.51	35.21	67.14	193.1	201.3	235.1	288.1	301.5	324.5
GA	Z_1	5441	6322	6907	9122	7823	9126	15 771	17 823	19 872	26 716	29 831	32 225	37 821	41 835	45 671
	Z_2	680	775	822	1455	1667	1933	2234	13 321	16 787	18 262	19 878	21 838	25 732	27 076	29 032
	T	0.088	0.122	0.771	5.58	8.23	22.18	38.21	124.7	145.8	235.5	451.7	532.1	632.1	734.5	817.2
HGAKA	Z_1	3132	4542	4877	6798	7821	8330	9211	9312	9812	11 232	13 241	15 326	18 273	19 311	22 343
	Z_2	267	372	410	632	682	693	685	721	782	854	882	972	993	1135	1326
	T	0.031	0.045	0.275	2.89	4.82	6.31	23.31	33.98	66.3	181.4	199.1	229.5	272.4	294.1	319.4
HSEOSA	Z_1	3018	4341	4562	6808	7660	8330	8900	9233	9703	10 344	12 445	14 556	16 679	18 901	21 293
	Z_2	245	331	355	561	571	591	665	710	773	821	865	933	989	1021	1223
	T	0.028	0.031	0.275	2.17	3.57	5.51	23.81	33.98	66.3	181.4	195.1	223.5	267.4	289.1	312.4
	Z_1	3014	4330	4558	6794	7649	-	-	-	-	-	-	-	-	-	-
AIECA	Z_2	245	330	352	553	566	-	-	-	-	-	-	-	-	-	-
	T	0.031	0.036	4.621	15.15	20.45	-	-	-	-	-	-	-	-	-	-

metric is lower, it is better. HSEOSA brings better performance and efficiency, but GA has the worst quality in the MID metric (see Table 6). According to the MS assessment metric, it provides the extension of Pareto optimal solutions, which the higher value of this metric brings a better quality. The HSEOSA shows high quality and performance based on the MS metric in Table 6. In terms of the SNS, this assessment metric assesses the diversity of solutions. Based on the SNS metric, the value of this metric is further; it is favorable. The HSEOSA obtains better efficiency, but GA brings the worst performance in terms of the SNS. HGAKA gains better performance and high quality after the HSEOSA algorithm in all assessment metrics.

An instance of nondominated solutions of suggested algorithms in an experiment problem e.g. LP2 is shown in Fig. 14. It is evident that the HSEOSA and the HGAKA indicate that they have the best efficiency. On the other hand, SA and GA algorithms show the worst performance and are close to each other.

Further, this paper conducts a set of statistical comparisons between algorithms according to the Pareto optimal analyses

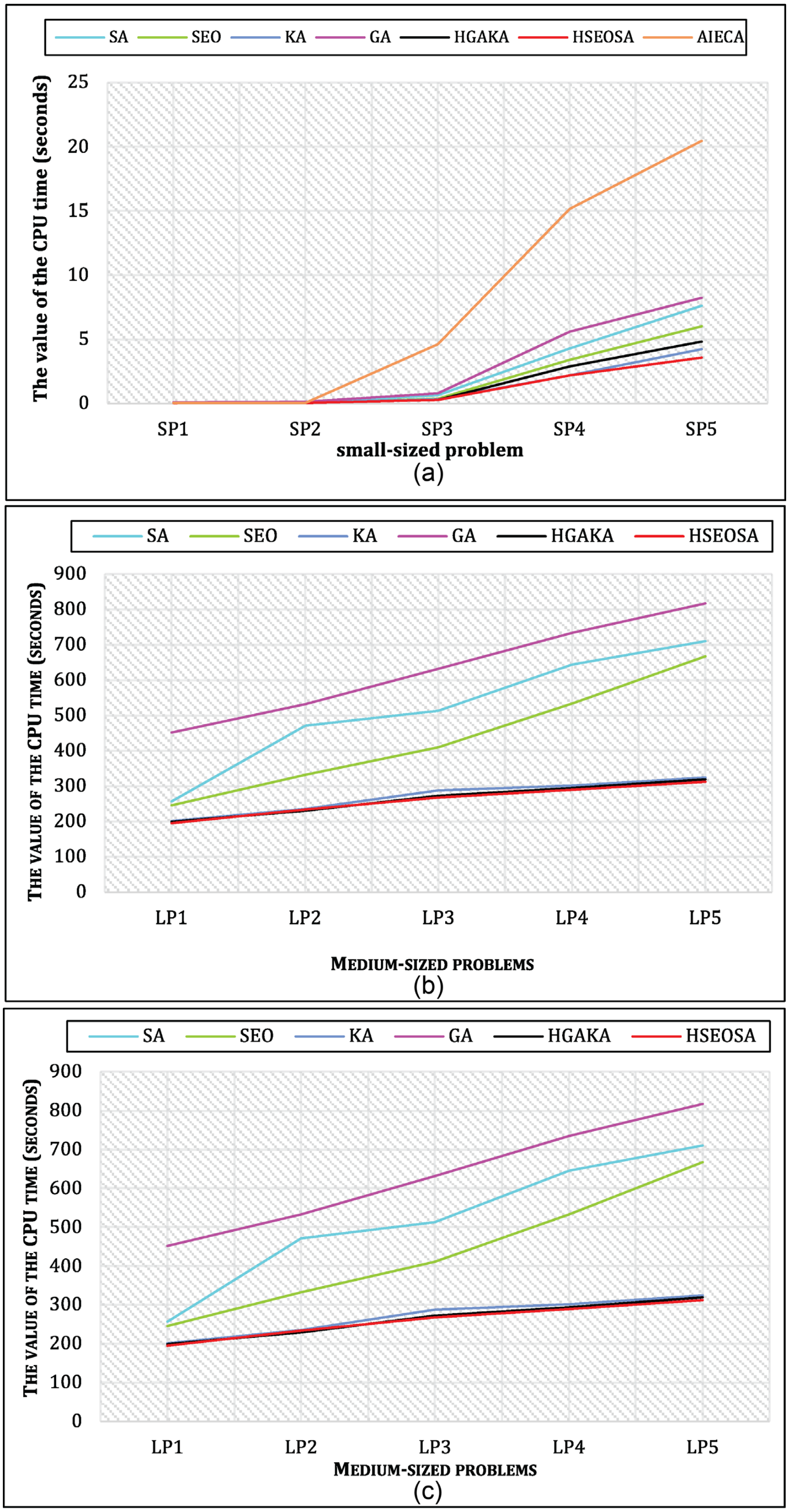

Figure 13: The CPU time for the proposed methods in different sizes.

taken by assessment metrics to find out the best algorithm decisively. Hence, the outcomes were provided in Table 6. Accordingly, a well-known metric called Relative Deviation Index (RDI) is formulated as detailed below (Goodarzian *et al.*, 2020, 2021a, b, e):

$$\mathrm{RDI} = \frac{|Alg_{\mathrm{sol}} - Best_{\mathrm{sol}}|}{Max_{\mathrm{sol}} - Min_{\mathrm{sol}}} \times 100, \tag{52}$$

Table 6: The result of assessment metrics for the proposed algorithms in different sizes.

Problem size	NPS			MID			MS			SNS		
	SA	SEO	HSEOSA	SA	SEO	HSEOSA	SA	SEO	HSEOSA	SA	SEO	HSEOSA
SP1	3	5	7	4.918	2.490	1.230	121 173.1	126 785.1	261 272.5	156 571.1	287 722.1	342 655.7
SP2	4	7	13	4.426	2.784	1.788	261 451.3	278 452.2	477 299.6	565 232.2	756 312.4	745 847.4
SP3	6	8	16	5.137	3.120	2.012	431 681.5	457 681.5	605 645.9	889 221.3	1096 551.3	1043 759.1
SP4	7	11	17	6.497	3.325	2.344	524 418.3	534 458.8	683 716.4	912 223.5	1562 788.3	1718 174.1
SP5	8	13	17	7.314	3.688	2.801	651 251.8	667 251.8	877 052.6	956 128.2	2671 172.1	2365 464.7
MP1	9	14	15	8.132	4.328	3.233	731 511.6	741 543.2	1024 970.3	967 434.6	2787 344.2	2778 609.5
MP2	6	12	13	8.819	5.246	3.781	875 514.2	895 714.1	1316 216.7	1098 771.2	3123 348.7	3271 811.5
MP3	7	16	17	9.975	5.844	4.122	916 511.4	923 545.2	1911 095.3	1235 621.7	3459 781.4	3933 614.2
MP4	8	13	14	10.23	6.720	4.344	1013 131.2	1114 532.5	2462 375.14	2342 126.7	556 247.2	5815 821.5
MP5	6	10	11	12.84	7.287	4.896	1241 047.4	1341 247.2	2589 766.76	3562 212.1	6672 292.1	6653 122.2
LP1	6	15	12	13.22	7.918	5.012	1462 172.3	1572 872.1	2625 328.3	3894 256.3	6987 218.5	7101 821.2
LP2	6	12	16	15.02	8.385	5.344	2042 232.9	2145 662.3	2744 006.4	5144 521.2	7567 327.5	7913 643.4
LP3	11	12	16	15.78	8.965	5.766	2211 121.8	2348 341.1	2944 013.2	6982 210.3	7982 132.2	8112 343.5
LP4	9	12	17	16.04	9.112	6.122	2592 012.3	2695 412.2	3141 016.3	7237 566.2	8137 451.1	8414 612.8
LP5	7	10	15	16.77	11.344	6.455	2721 458.3	2721 458.3	3641 126.4	7987 433.2	8567 237.9	8913 611.7
Problem size	**NPS**			**MID**			**MS**			**SNS**		
	KA	**GA**	**HGAKA**	**KA**	**GA**	**HGAKA**	**KA**	**GA**	**HGAKA**	**KA**	**GA**	**HGAKA**
SP1	5	2	6	2.433	5.567	1.031	213 432.1	199 573.8	224 563.1	321 534.1	147 502.7	345 521.4
SP2	8	3	12	2.788	6.233	1.231	357 679.5	371 253.1	397 653.3	680 351.1	550 251.4	690 411.9
SP3	9	5	14	3.121	7.344	2.234	465 678.3	536 673.6	578 621.7	970 332.5	871 254.7	986 122.2
SP4	12	6	15	4.423	8.455	2.454	567 713.9	611 408.1	634 401.3	1106 721.3	902 291.5	1236 981.4
SP5	13	7	16	5.398	9.566	2.801	697 872.3	859 254.5	878 214.2	2032 021.4	936 178.3	2232 820.2
MP1	14	8	14	6.677	10.412	3.677	764 970.2	988 505.7	1028 405.3	2304 564.8	957 914.4	2454 784.2
MP2	13	5	12	7/223	12.355	3.981	906 436.6	1078 534.4	1128 474.7	2623 728.1	993 711.3	2891 248.8
MP3	15	6	15	8.432	13.341	4.566	945 095.2	1216 732.6	1322 712.3	3166 551.6	1064 121.7	3246 890.2
MP4	13	7	12	9.211	14.788	5.677	1262 325.13	1418 251.7	1538 271.4	5043 178.4	2262 436.5	5273 123.2
MP5	11	4	10	10.278	15.232	5.991	159 886.23	1429 147.7	1599 047.3	6032 492.2	3302 412.3	6452 432.6
LP1	15	4	10	11.167	17.581	6.012	2225 678.1	1982 579.5	2183 478.2	6591 878.1	3794 219.8	6761 823.9
LP2	6	13	14	12.233	18.233	6.321	2456 016.2	2202 201.3	2342 561.7	7047 127.2	4947 127.1	7246 771.8
LP3	12	10	13	13.178	20.213	6.721	25 612 138	2518 121.6	2678 221.5	7505 621.2	6852 230.2	7895 321.2
LP4	13	8	15	14.704	22.123	7.131	2778 116.5	2782 211.7	2892 321.9	7787 231.6	7007 326.7	7947 245.4
LP5	11	6	14	16.77	25.344	8.455	3641 126.4	2912 421.8	2912 421.8	7947 237.5	7657 151.9	8043 227.4

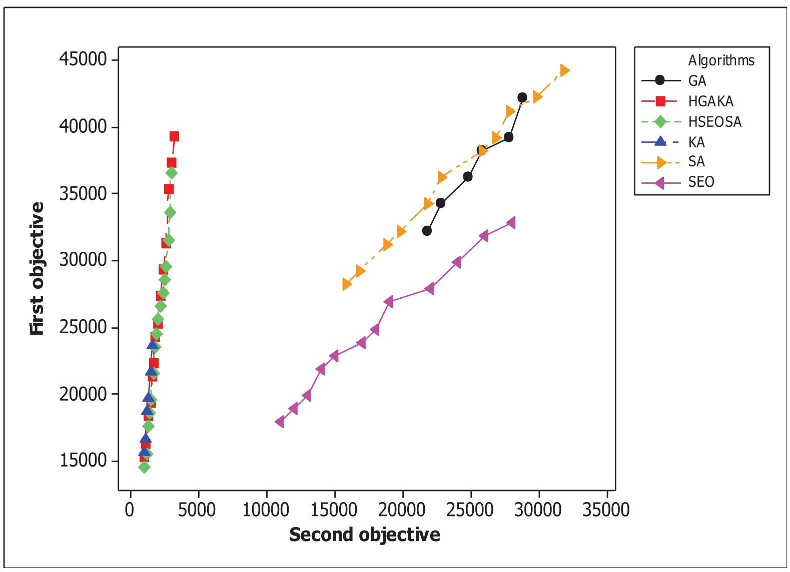

Figure 14: Pareto frontier of suggested algorithms in LP2.

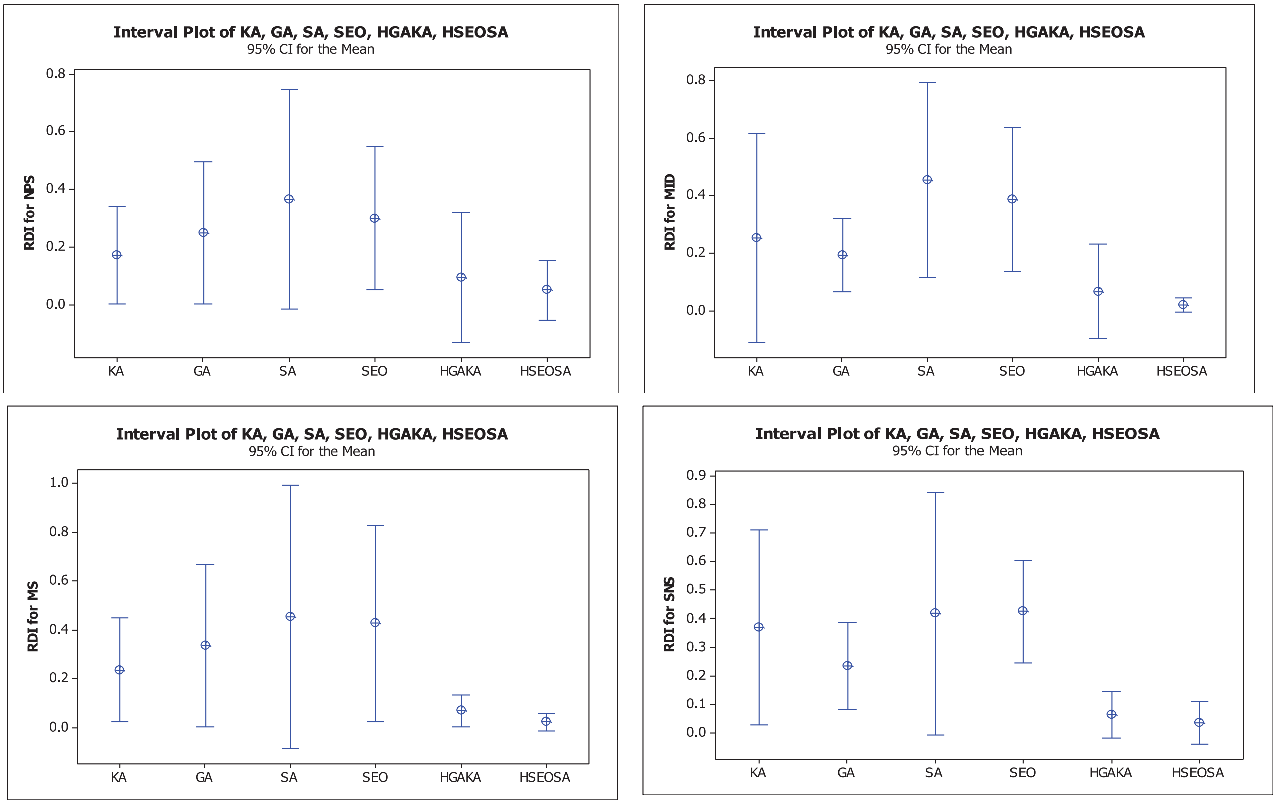

Figure 15: ANOVA plots for the assessment metrics in terms of RDI of the proposed algorithms.

where Alg_{sol} shows the obtained value of the objective function based on an assessment metric, and Max_{sol} and Min_{sol} indicate the values maximum and the minimum between all generated values by metaheuristics, respectively. $Best_{sol}$ displays the best solution between algorithms. It is clear that a lower value of RDI shows a more robust and higher quality of methods. As a result, the means plot and Least Significant Difference for the suggested algorithms have provided to validate the proposed algorithms. The results run by *Minitab 16 Statistical Software* are indicated in Fig. 15. Moreover, the confidence interval of 95% for the assessment metrics in the proposed metaheuristics is conducted to statistically analyse the performance of metaheuristics. It is clear that in Fig. 15, HSEOSA has more quality, performance, and efficiency, but SA has the worst performance based on RDI. Accordingly, HSEOSA statistically outperformed the other proposed algorithms.

The performance of the suggested algorithms related to their convergence is evaluated by the convergence plots. Therefore, the plots of the convergence for the suggested algorithms according to the objective functions are indicated in Fig. 16. It is evident that HSEOSA and HGAKA are fixed after 67 and 70 iterations, respectively, with a steady line. On the other hand, the SA, GA, KA, and SEO algorithms are converging in 100 iterations. Accordingly, the HSEOSA has best quality and performance and high convergence compared to other proposed algorithms.

5.3. Case study

Tehran is one of the most populous cities in Asia and with 8693 706 people is the most populous city in Iran. Tehran is divided into 22 districts and 122 urban districts. This city is located between two mountain and desert valleys and on the southern slopes of Alborz and has an area of 730 square kilometers. In this city, there are private and government organizations for home healthcare services. Figure 17 shows a case study map. As can be seen, there are 27 patient's homes, 7 pharmacies, and 5 laboratories to serve patients.

Table 7 reports the distance between pharmacies and laboratories in kilometers. Google Maps has been used to estimate the distances between two points. Table 8 represents the demand for each patient in kilograms. Additionally, the fixed cost of setting up laboratories in dollars is shown in Table 9. Table 10 indicates the amount of released carbon dioxide by each vehicle. There are 12 vehicles to move available demand. The amount of released carbon dioxide by each vehicle is determined based on the vehicle's technical inspections.

5.4. Case study results

According to the superiority of the HSEOSA algorithm, the case study has been solved using this algorithm. Also, based on the proposed bi-objective model and the priority of the cost objective function than the environmental objective function, the Pareto point that has the lowest cost is reported as the solution to the case study. Therefore, the optimal Pareto point for the first objective function is 76 268.3 and for the second objective function it is 33 763.2. Table 11 shows the established laboratories. The results indicate that all potential laboratories have been established. Table 12 reports the location results of pharmacies. Values 1 indicate establishment and values 0 indicate nonestablishment. The results indicate that the only potential pharmacy in Tajrish has not been established. Table 13 represents the results of patient allocation to pharmacies. Values of 0 indicate no allocation and values of 1 show allocation. For example, as

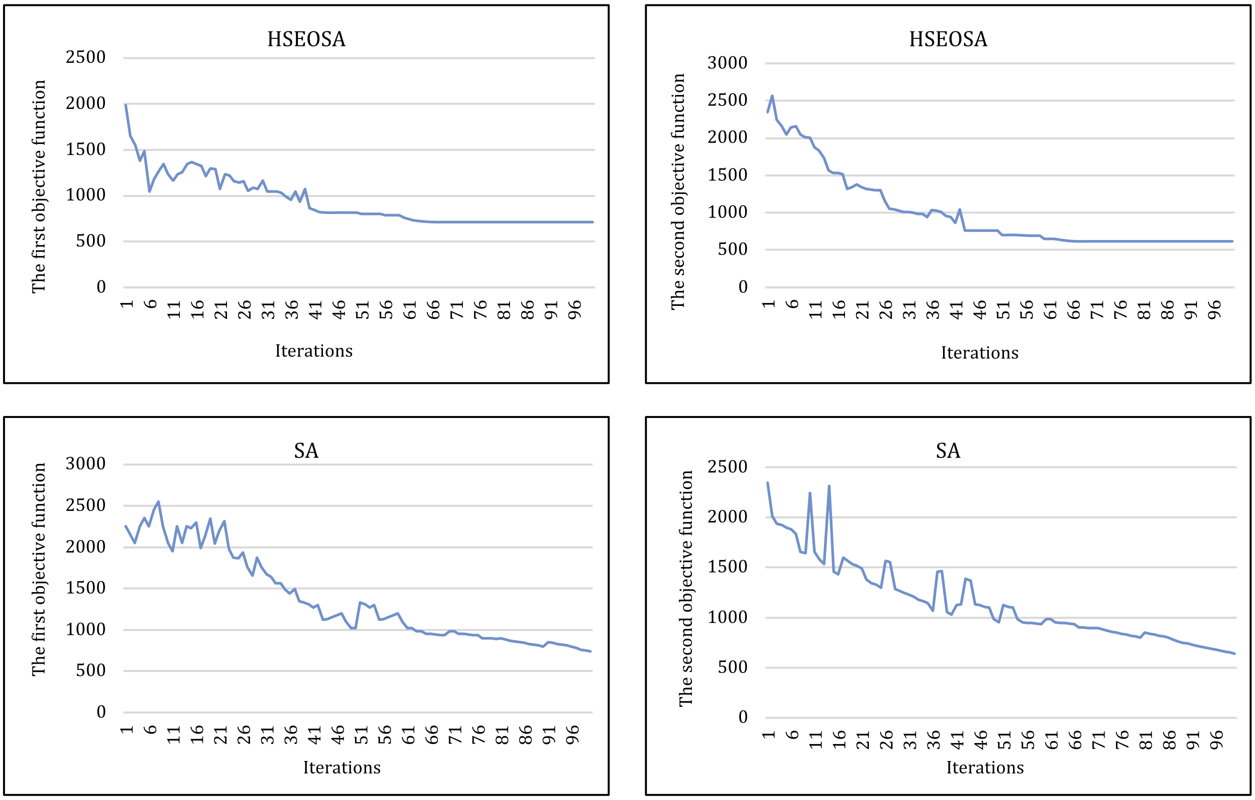

Figure 16: The plots of the convergence for the suggested algorithms according to the objective functions.

it is known, patients 1, 2, and 3 are allocated to Fajr, Nikan, and Kasra pharmacies, respectively. Additionally, the results of the allocation of pharmacies to laboratories are reported in Table 14. Values of 0 indicate no allocation and values of 1 indicate allocation. For instance, it is clear that Moniriye Laboratory is assigned to Nikan, Besat, and Taleghani pharmacies.

5.5. Sensitivity analysis

In order to evaluate the model and analyse the effect of the parameters on the decision variables and the value of the objective function, a series of sensitivity analyses for the model were performed. In the following, sensitivity analysis on the key parameters of the case study and their effect on the case study is explained.

The most important feature of the model is to be the bi-objective and to consider environmental considerations. Then, we do a series of analyses on the model to examine the effectiveness of the model. In the comparison section, the HSEO-SA algorithm is most effective; hence, this algorithm is selected for sensitivity analysis. An economic objective function with Z1 and an environmental objective function with Z2 are shown. In order to examine the model, only two parameters called the number of facility establishments (ϕ) and the capacity of facilities (C_r^G, C_l^G) are examined. Therefore, for each parameter, five experiments are designed and changes related to the objective functions are examined.

As stated earlier, another major parameter in the proposed green home health care model is the number of facility establishments including pharmacies and laboratories. Then, sensitivity analysis on this important parameter has been performed and the relevant results are presented in Table 15. In addition, the interaction between the economic and environmental objective functions as normalized values is indicated in Fig. 18. Therefore, the results suggest a stunning similarity between the objective functions. In general, with the increase in the number of facilities establishments, not only will the economic cost related to their establishment be increased, but also the environmental impact related to the facility establishment increases in the context of environmental pollution. For example, a 30% increase in the number of established facilities increases the first and second objective functions to 81 789 and 38 820.567 units, respectively. Also, a 10% reduction in the number of established facilities will reduce the first and second objective functions to 74 919 and 31 745.146 units, respectively.

Table 16 shows the results of the sensitivity analysis of the mathematical model according to changes in the capacity of established laboratories and pharmacies. As shown in Table 16, increasing the capacity of established facilities increases costs and increases the detrimental effects on the environment. By a 30% increase in the capacity of the established facilities, the first and second objective functions increase to 77 897 and 35 315.87, respectively. Also, by a 30% reduction in the capacity of the established facilities, the first and second objective functions will be reduced to 72 437 and 31 745.54 units, respectively. Figure 19 displays the trend of change in the capacity of the established facility on the objective functions. It is clear that by increasing the capacity of the established centers, the costs and destructive effects of the environment increase, but by raising 30%, the slope of the graph decreases. The reason for this is that as the capacity of the established facilities increases, the number of established facilities decreases. Reducing the number of established facilities reduces the costs of the entire supply chain and reduces the harmful effects on the environment.

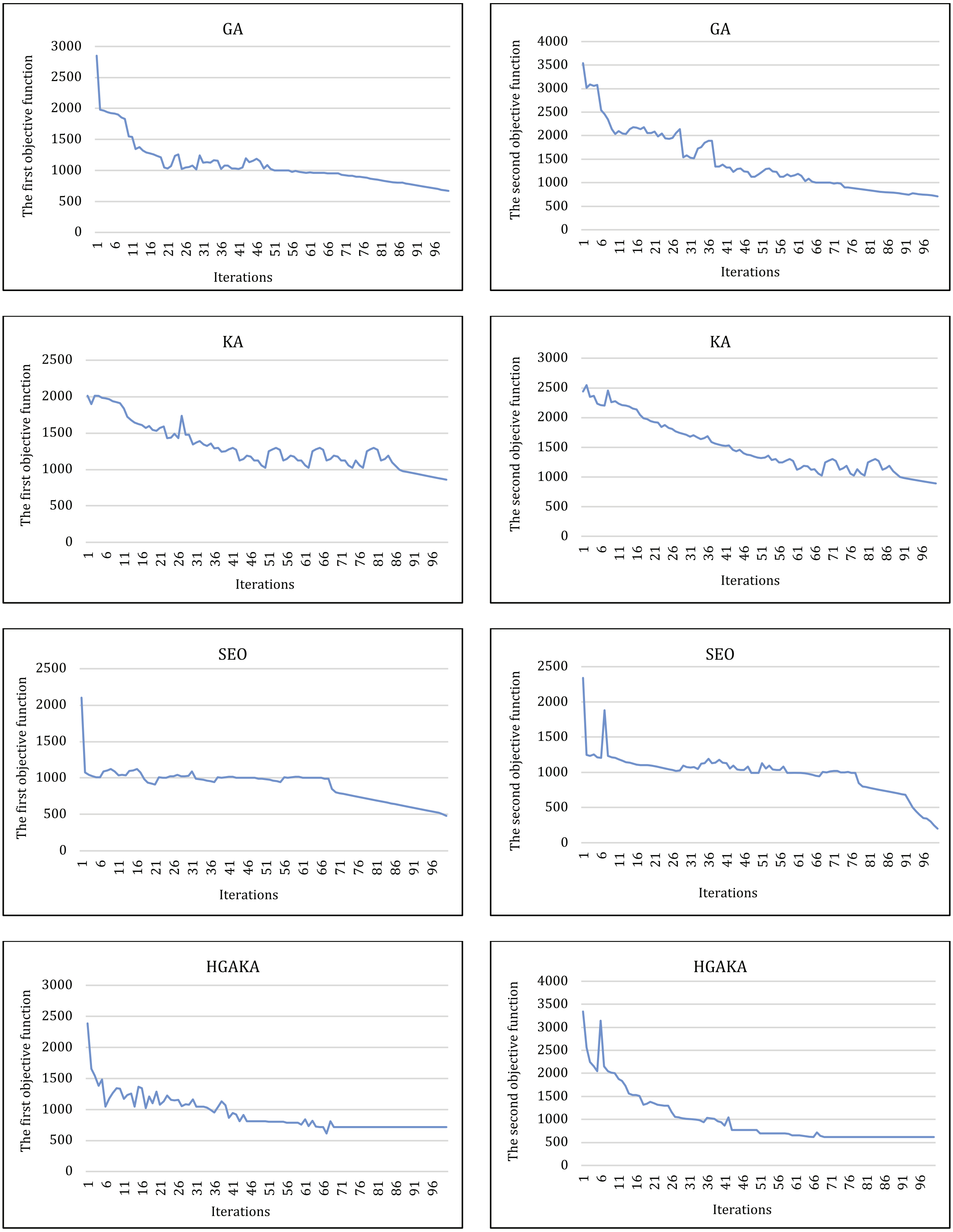

Figure 16: Continued.

5.6. Implication

The results of this research can be useful and practical for pharmacies and laboratories. Also, according to that in this research, attention has been paid to the environmental effects, transportation, and location of facilities, and environmental organizations, municipalities, and organizations carrying medical equipment can be named as the beneficiaries of this research. In addition, this study has tried to reduce the environmental

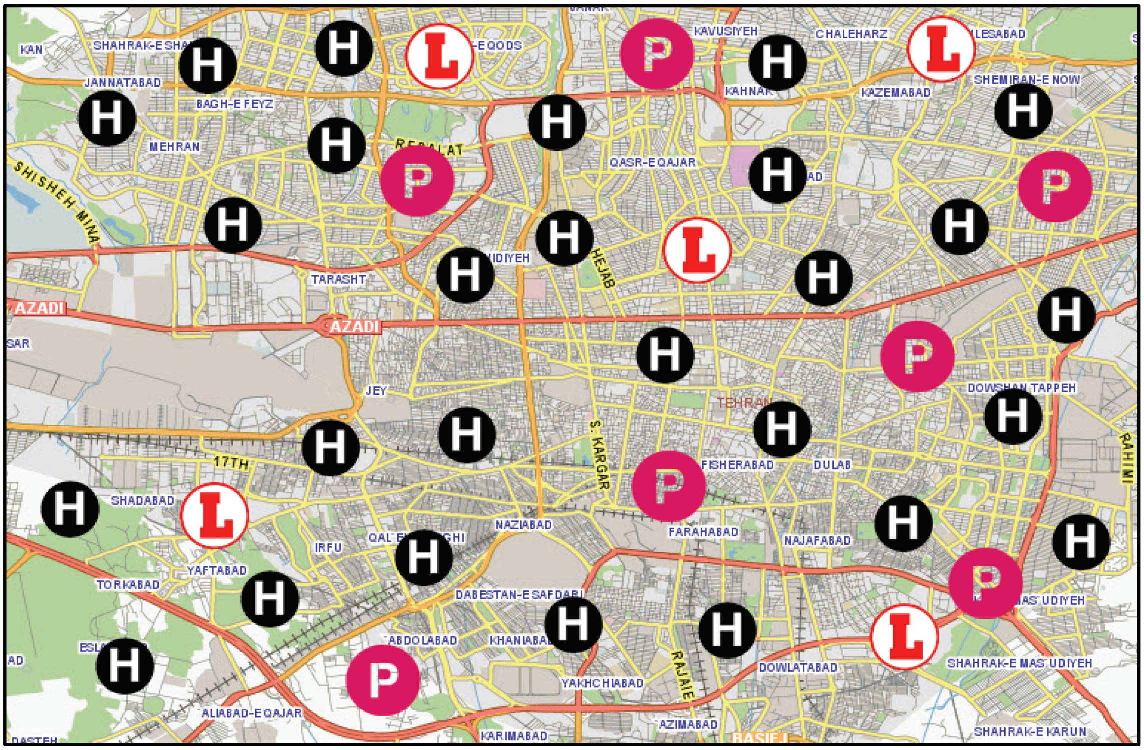

Figure 17: Case study map (H: Patient Home, L: Laboratory, P: Pharmacy).

Table 7: Distance between pharmacies and laboratories (km).

Laboratory	Pharmacy						
	Nikan	Fajr	Besat	Tajrish	Kasra	Jam	Taleqani
Moniriye	143	94	82	109	117	54	135
Ferdowsi	131	60	74	141	11	36	73
Narmak	124	43	124	103	60	112	73
Poonak	104	131	25	36	97	22	77
Dibaji	139	51	94	83	74	113	139

Table 8: Amount of drug demanded by each patient (kg).

Patient no.	Demand	Patient no.	Demand
1	4	**15**	5.5
2	3	**16**	6
3	2.5	**17**	5
4	3.5	**18**	3.5
5	5	**19**	2.5
6	1	**20**	5
7	6	**21**	3
8	6.4	**22**	3
9	4.5	**23**	6.6
10	4	**24**	6
11	2.6	**25**	7.5
12	7	**26**	5
13	4.3	**27**	3.5
14	4.5		

effects of the establishment of pharmacies and laboratories as much as possible. Since air is associated with breathing, the most common injuries to pulmonary patients are in the airways and lungs. Moreover, it can be said that the results of this study can be useful and practical for patients with pulmonary disease. Also, reducing transportation costs, allocating and setting up centers can help governments and the private sector invest the savings in other healthcare sectors, such as purchasing medical equipment and new transportation. Then, the proposed metaheuristic algorithms in this research are user friendly and do not require derivative functions and additional information to solve the proposed model. Additionally, all presented algorithms are flexible and compatible with all objective functions and constraints.

6. Conclusions, Future Works, and Limitations

In this research, a novel mathematical formulation for the bi-objective green home health care network routing–location–

Table 9: Fixed cost for the establishment of a laboratory ($).

Laboratory	Moniriye	Ferdowsi	Narmak	Poonak	Dibaji
Fixed cost	250 000	220 000	310 000	190 000	400 000

Table 10: Amount of carbon dioxide CO_2 produced by vehicles per unit of distance (kg).

Vehicle	Amount of carbon dioxide CO_2	Vehicle	Amount of carbon dioxide CO_2
1	0.1	7	0.3
2	0.1	8	0.3
3	0.2	9	0.2
4	0.1	10	0.1
5	0.3	11	0.2
6	0.2	12	0.2

Table 11: The established laboratories.

Laboratory	Moniriye	Ferdowsi	Narmak	Poonak	Dibaji
Established center	1	1	1	1	1

Table 12: The established pharmacies.

Pharmacy	Nikan	Fajr	Besat	Tajrish	Kasra	Jam	Taleqani
Established center	1	1	1	0	1	1	1

Table 13: The allocation of the patients to pharmacies.

Pharmacy/patient	Nikan	Fajr	Besat	Kasra	Jam	Taleqani
1	0	1	0	0	0	0
2	1	0	0	0	1	0
3	0	0	0	1	0	0
4	0	0	0	0	0	1
5	0	0	0	0	0	1
6	1	0	0	0	0	0
7	0	1	0	0	0	0
8	0	0	1	0	0	0
9	0	0	1	0	0	0
10	0	0	1	0	0	0
11	0	0	0	0	1	0
12	0	0	0	1	0	0
13	1	0	0	0	0	0
14	1	0	0	0	0	0
15	0	0	0	1	0	0
16	0	1	0	0	0	0
17	0	1	0	0	1	0
18	1	0	0	0	0	0
19	0	0	0	0	0	1
20	0	0	0	0	0	1
21	0	0	1	0	0	0
22	0	0	0	1	0	0
23	0	0	1	0	0	0
24	0	1	0	0	0	0
25	0	0	0	0	1	0
26	0	0	0	0	0	1
27	0	0	0	0	1	0

Table 14: The allocation of the pharmacies to laboratories.

Pharmacy/Laboratory	Nikan	Fajr	Besat	Kasra	Jam	Taleqani
Moniriye	1	0	1	0	0	1
Ferdowsi	0	1	1	1	1	0
Narmak	1	1	0	1	0	1
Poonak	1	1	1	1	0	1
Dibaji	0	0	1	0	1	0

Table 15: The result of sensitivity analyses related to the number of facility establishments for the model.

The number of cases	Z1	Z2
−30% change of the number of the facilities	74 427	30 031.149
−10% change of the number of the facilities	74 919	31 745.146
No change	76 268	33 763.237
+10% change of the number of the facilities	79 721	36 917.918
+30% change of the number of the facilities	81 789	38 820.567

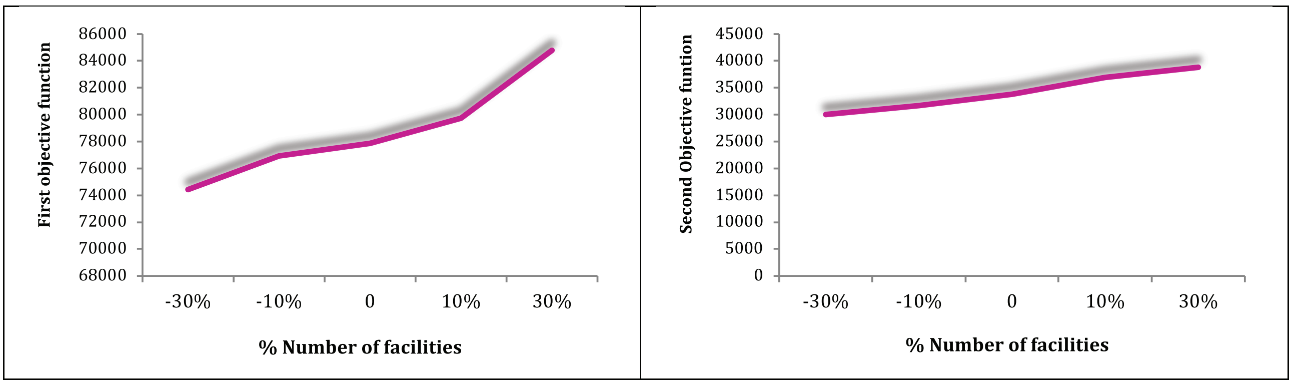

Figure 18: The behavior of objective functions for sensitivity analysis on the number of facilities established.

Table 16: The result of sensitivity analyses related to the capacity of facilities.

Number of cases	Z1	Z2
−30% change in the capacity of the established facilities	72 437	31 745.54
−10% change in the capacity of the established facilities	74 559	32 197.11
No change	76 268	33 763.23
+10% change in the capacity of the established facilities	77 216	34 975.09
+30% change in the capacity of the established facilities	77 897	35 315.87

allocation problem by considering economic efficiency and environmental pollution was extended. We concentrated on flexible linear programming with grey parameters in the objective functions and constraints, so that the newly proposed model can be more adaptive to real complex situations. In this regard, to solve the presented mathematical model, AIECA was used in small- and medium-sized problems. Moreover, the proposed problem is solved employing multi-objective metaheuristic algorithms including SA, SEO, HSEOSA, GA, KA, and HGAKA algorithms. The novel hybrid HSEOSA and HGAKA algorithms illustrated in this paper are one of the main contributions in this paper. Then, to tune and control the algorithm's parameters, the Taguchi method is utilized. Hence, an extensive analysis using 15 sets of instances of different sizes is performed to illustrate the effectiveness and efficiency of the proposed metaheuristic algorithms. Computational results depicted that the proposed HSEOSA algorithm has credible results and demonstrated the efficiency and superiority over the other algorithms. Moreover, the considered case study in Tehran/Iran was solved using the HSEOSA algorithm. Eventually, several sensitivity analyses were performed on the key parameters of the problem for the model. Additionally, to validate the proposed model, a real case study is illustrated.

The results indicate that all potential laboratories have been established as well as all potential pharmacies have been established except Tajrish Pharmacy. Also, Moniriye Laboratory has been assigned to Nikan, Besat, and Taleghani pharmacies, and Ferdowsi Laboratory has been assigned to Fajr, Besat, and Kasra pharmacies. The results of the sensitivity analysis show that by increasing the capacity of established centers, costs and destructive environmental effects increase. Thus, a 30% increase in the number of established facilities will increase the first and second objective functions to 81 789 and 38 820.567 units, respectively. Additionally, a 10% reduction in the number of

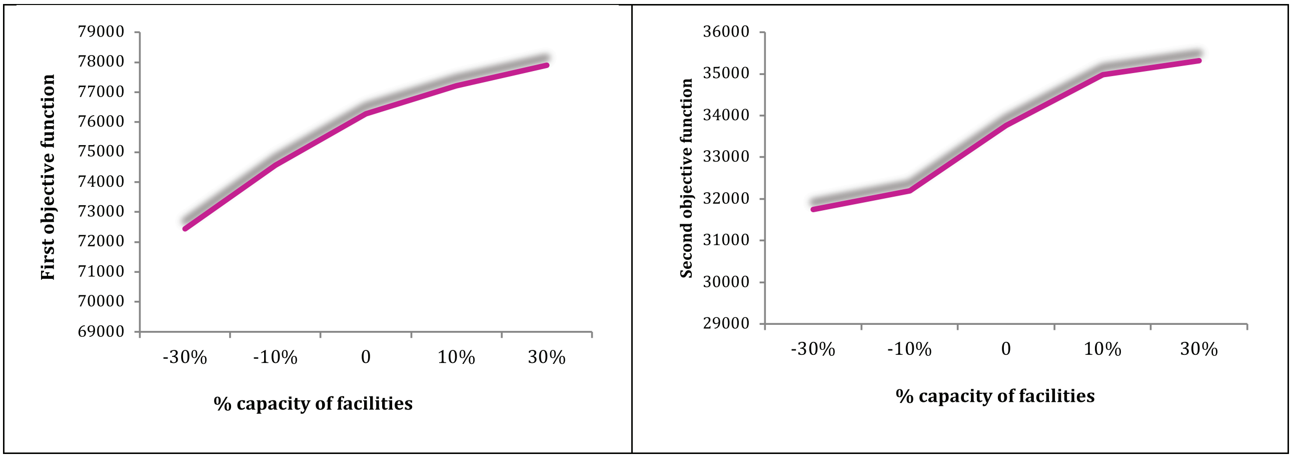

Figure 19: The behavior of objective functions for sensitivity analysis on the capacity of facilities.

established facilities will reduce the first and second objective functions to 74 919 and 31 745.146 units, respectively.

Although this study provided an extension to green home healthcare, there are many other suppositions that can be added to achieve environmental sustainability for home healthcare organizations. First, the carbon emissions under uncertainty with regard to weather and unpredicted events can be ordered. The environmental sustainability guidelines like PM2.5 for environmental pollution can be considered in the optimization model. Most importantly, other novel metaheuristics can be examined to solve the proposed problem and to provide a comparison with the novel approaches of this paper.

This research, like other cases, has its own limitations and assumptions, which are expressed as follows:

1. As there was no official database for some parts of cost elements, the driver's experiences and blood transfusion center officers were used for information related to the costs. The questions about the transportation costs for each route have been categorized and the estimated costs have been entered into the mathematical model.
2. In addition, the recent high inflation rate and the rising transportation costs in Iran make it more difficult to estimate the relevant costs.
3. The final solution obtained using Keshtel, Genetic, and SA algorithms depends on the coder's skill in defining the initial value of its parameters.
4. In order to implement the presented solution approach for the real case study, high-RAM and CPU hardware facilities and software facilities are required, which are the limitations of the proposed paper.

Supplementary Data

Supplementary data are available at *JCDENG* online.

Conflict of interest statement

None declared.

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Appendix 1:

Table A1: The orthogonal array for SA and KA algorithms.

L25	A	B	C	D	E
1	1	1	1	1	1
2	1	2	2	2	2
3	1	3	3	3	3
4	1	4	4	4	4
5	1	5	5	5	5
6	2	1	2	3	4
7	2	2	3	4	5
8	2	3	4	5	1
9	2	4	5	1	2
10	2	5	1	2	3
11	3	1	3	5	2
12	3	2	4	1	3
13	3	3	5	2	4
14	3	4	1	3	5
15	3	5	2	4	1
16	4	1	4	2	5
17	4	2	5	3	1
18	4	3	1	4	2
19	4	4	2	5	3
20	4	5	3	1	4
21	5	1	5	4	3
22	5	2	1	5	4
23	5	3	2	1	5
24	5	4	3	2	1
25	5	5	4	3	2

Table A2: The orthogonal array for SEO and GA algorithms.

L25	A	B	C	D
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	1	4	4	4
5	1	5	5	5
6	2	1	2	3
7	2	2	3	4
8	2	3	4	5
9	2	4	5	1
10	2	5	1	2
11	3	1	3	5
12	3	2	4	1
13	3	3	5	2
14	3	4	1	3
15	3	5	2	4
16	4	1	4	2
17	4	2	5	3
18	4	3	1	4
19	4	4	2	5
20	4	5	3	1
21	5	1	5	4
22	5	2	1	5
23	5	3	2	1
24	5	4	3	2
25	5	5	4	3

Table A3: The orthogonal array for HSEOSA algorithm.

L16	A	B	C	D	E	F	G	H
1	1	1	1	1	1	1	1	1
2	1	2	2	2	2	2	2	2
3	2	1	1	1	1	2	2	2
4	2	2	2	2	2	1	1	1

Table A3: Continued

L16	A	B	C	D	E	F	G	H
5	3	1	1	2	2	1	1	2
6	3	2	2	1	1	2	2	1
7	4	1	1	2	2	2	2	1
8	4	2	2	1	1	1	1	2
9	5	1	2	1	2	1	2	1
10	5	2	1	2	1	2	1	2
11	6	1	2	1	2	2	1	2
12	6	2	1	2	1	1	2	1
13	7	1	2	2	1	1	2	2
14	7	2	1	1	2	2	1	1
15	8	1	2	2	1	2	1	1
16	8	2	1	1	2	1	2	2

Table A4: The orthogonal array for HGAKA algorithms.

L16	A	B	C	D	E	F	G
1	1	1	1	1	1	1	1
2	1	2	2	2	2	2	2
3	2	1	1	1	1	2	2
4	2	2	2	2	2	1	1
5	3	1	1	2	2	1	1
6	3	2	2	1	1	2	2
7	4	1	1	2	2	2	2
8	4	2	2	1	1	1	1
9	5	1	2	1	2	1	2
10	5	2	1	2	1	2	1
11	6	1	2	1	2	2	1
12	6	2	1	2	1	1	2
13	7	1	2	2	1	1	2
14	7	2	1	1	2	2	1
15	8	1	2	2	1	2	1
16	8	2	1	1	2	1	2