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A green home health care supply chain: New modified simulated annealing algorithms

Amir Mohammad Fathollahi-Fard [a,*], Kannan Govindan [b], Mostafa Hajiaghaei-Keshteli [c], Abbas Ahmadi [a]

[a] Department of Industrial Engineering and Management Systems, Amirkabir University of Technology, Tehran, Iran
[b] Centre for Sustainable Engineering Operations Management, Department of Technology and Innovation, University of Southern Denmark, Odense, Denmark
[c] Department of Industrial Engineering, University of Science and Technology of Mazandaran, Behshahr, Iran

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ABSTRACT

Generally, in Home Health Care (HHC) logistics, caregivers which are started from a pharmacy are scheduled and routed to do different care services at patients' home. At the end, they go to their laboratory to update the patients' health records. In addition to scheduling and routing of the caregivers, there are some other optimization decisions which can increase the competitive advantages of HHC organizations as a supply chain network. The location decisions of the pharmacies and laboratories and the assignment of patients to the nearest pharmacies are two of the several important logistics factors for an HHC organization. The literature shows that the green emissions and sustainability achievements for HHC logistics are still scarce. To cover more logistics and sustainability factors and make the HHC more practical, this study contributes a Green Home Health Care Supply Chain (GHHCSC) for the first time by a bi-objective location-allocation-routing model. Already applied successfully to this research area, the Simulated Annealing (SA) is also employed in this study. Another main innovation of this paper is to propose a set of new modified SA algorithms to better solve the proposed NP-hard problem. As a bi-objective optimization model, the epsilon constraint method is also utilized to check the algorithms' results in small sizes. By using some multi-objective assessment metrics, the algorithms are compared with each other and their performance is evaluated. As such, some sensitivity analyses are performed to reveal the efficiency of the developed model. Finally, some managerial insights are deployed to achieve the sustainability for the HHC organizations.

1. Introduction

Official reports from the World Health Organization (WHO) state that there is much attention in the rate of independent care for old persons in the western and European countries (European Commission, 2007). These reports also revealed that the elderly people prefer to get the informal cares at patients' home instead of formal cares at hospital (Grenouilleau et al., 2019). These reasons motivate the Home Health Care (HHC) to support a full range of care services at clients' homes by using a group of caregivers (Shi et al., 2017; Fathollahi-Fard et al., 2018; Decerle et al., 2019). They start their activities from a pharmacy and after visiting of the patients, they go to pharmacies to analyze the biological samples taken from patients and to update the patients' health records (Harris, 2015; Bahadori-Chinibelagh et al., 2019).

The HHC is cited as many names such as social care, in-home care and domiciliary care (Mankowska et al., 2014). It can help the hospitals, retirement homes, and medical staff to free capacity of their facilities and also decrease the demand of formal care (Cappanera et al., 2018). As reported by Fathollahi-Fard et al. (2019), the HHC services are one of significant drivers of economic growth in the western countries such the USA. In 2016, these activities provide 1,600,000 job opportunities in the USA to employ the caregivers including expert nurses, doctors, physiotherapist and nutritionists in general. The planning of the caregivers is performed manually by an experienced nurse who has the role of coordinator

* Corresponding author.
E-mail addresses: amirfard@aut.ac.ir (A.M. Fathollahi-Fard), kgov@iti.sdu.dk (K. Govindan), mostafahaji@mazust.ac.ir (M. Hajiaghaei-Keshteli), abbas.ahmadi@aut.ac.ir (A. Ahmadi).

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(Shi et al., 2018). The estimated medications and biological samples of the patients and their availability are some important parameters to find a valid planning of the caregivers (Lin et al., 2018). To provide the home care services, some logistics activities are needed. By another point of view, the HHC can be considered as a supply chain network between the supporting companies with a set of caregivers to present a full range of care and also patients as the clients of these services (Fard et al., 2018). This motivates the Home Health Care Supply Chain (HHCSC) as one of hot topics in today's logistics systems.

The HHCSC includes several optimization decisions from the locations of pharmacies and laboratories, the assignment of patients to the closest pharmacy and scheduling and routing decisions of caregivers (Bahadori-Chinibelagh et al., 2019). The transportation costs can effect on these decisions and the goal is to find a valid planning to reach the best optimal cost (Harris, 2015; Shi et al., 2017, 2018). In addition to the economic factors of the transportation, nowadays, the sustainable transportation is an active research topic and refers to any means of transportation which is green and has low impact on the environment (Estêvão et al., 2019; Moktadir et al., 2018 and 2018a). Generally, the transportation sectors are responsible for a large portion of the pollution for Green House Gas (GHG) emissions worldwide (Moktadir et al., 2018b; Seles et al., 2019). Accordingly, the Environmental Protection Agency (EPA) in the USA has published a number of reports yearly regarding the main sources and concerns of GHG emissions (Roy et al., 2019; Ali et al., 2018). These impacts are five significant factors as revealed in Fig. 1. Form a report in 2015 by the EPA, the transportation sector is accounted by 27% GHG emissions in the USA (Rahman et al., 2019). As mentioned earlier, the main decision for an HHCSC company is to optimize the transportation cost based on the locations of pharmacies and their right allocation. By another point of view, the transportation sector of the HHCSC is to transform the caregivers to support the patients' required medications s by cars, buses, vans and trains etc. With regards to these logistics activities, one of the main majorities of GHG emissions is CO_2 emission (Moktadir et al., 2018a). Based on this motivation, this study develops a Green Home Health Care Supply Chain (GHHCSC) for the first time in this research area.

To formulate the proposed GHHCSC, a bi-objective location-allocation-routing model is proposed. As a type of NP-hard models, this study applies a successful metaheuristic from the literature, namely, Simulated Annealing (SA) (Kirkpatrick et al., 1983). Another innovation of this study is to propose a set of new modified SA algorithms to better solve the proposed GHHCSC.

Generally, the main contributions of this paper can be outlined as below:

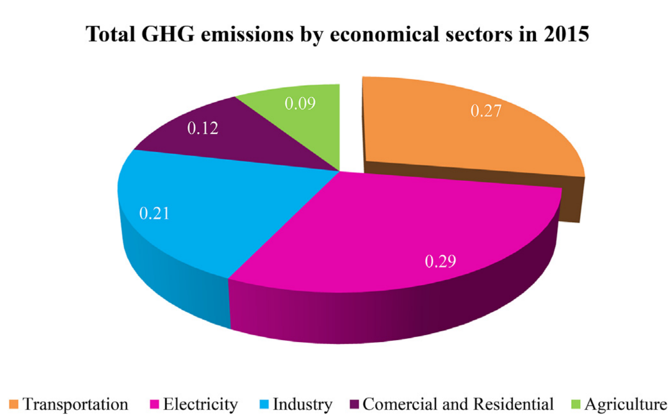

Fig. 1. Sources of GHG emissions in the USA.

✓ This paper develops a bi-objective location-allocation-routing model for GHHCSC;
✓ Five new modified versions of SA are introduced to solve the problem;
✓ The results of metaheuristics are checked by the epsilon constraint method in small sizes.
✓ The metaheuristics are compared with each other by the multi-objective assessment metrics and the model is analyzed by some sensitivity analyses.
✓ Some managerial insights are deployed to achieve sustainability for HHC organizations.

The other sections of this work can be detailed as follows. The next section reviews and explores the main papers in this research area. The employed mathematical model along with its comprehensive description are presented in Section 3. Furthermore, the encoding and decoding representation and the proposed modifications of SA are deployed in Section 4. A comparative study based on evaluation of proposed algorithms and some sensitivity analyses are employed in Section 5. The managerial insights of this paper is provided in Section 6. Finally, the main research directions and future studies have been discussed and recommended in Section 7.

2. Literature review

Academically, most of developed models in the area of HHC due to importance of logistics activities are a variation of Vehicle Routing Problem (VRP) (Bahadori-Chinibelagh et al., 2019). The VRP can be defined as a company aims at addressing and supplying the clients' demands by using some vehicles (Shi et al., 2018). The common goal in the VRP is to minimize the traveling cost of vehicles (Fikar and Hirsch, 2017). The complexity of this problem relays on the number of clients and vehicles, directly (Fathollahi-Fard et al., 2018, 2019). This problem is also known as NP-*hard* one. The literature of VRP shows that most of the exact methods are not recommended to reach an optimal solution in a logical time (Hiermann et al., 2015; Liu et al., 2013). Therefore, there is a great deal of interest in developing metaheuristics as the best alternative answers to solve these NP-*hard* problems (Liu et al., 2014; Shi et al., 2017; Decerle et al., 2019).

Based on the recent review literature reviews (Fikar and Hirsch, 2017; Shi et al., 2018; Fathollahi-Fard et al., 2019), there is a penalty of studies during the two last decades. To analyze the main similarities and differences of studies and find the literature gaps, Table 1 provides the literature review based on six classifications. We classify the papers based on the number of objective functions, number of depots, number of periods, the outputs of model including location decisions of pharmacies, assignment of patients to pharmacies, routing and scheduling of the caregivers. Since most of models are a variation of Mixed Integer Linear Programming (MILP), the model type has not been considered in the table. Another group of papers is classified by some recent suppositions in the models such as the time windows, delivery time, synchronization, travel balancing, working time balancing and uncertainty of some parameters as well as green emissions of logistic activities. The last item is based on the solution algorithms.

Here, some important papers are summarized to consider the literature gaps of this research area. To the best of our knowledge, Begur et al. (1997) can be considered as one of the earliest studies. They offered a Spatial Decision Support System (SDSS) in their case study in the USA. In addition, an MILP model was developed by Cheng and Rich (1998). To solve their model, a simplified heuristic was used. In another similar paper, Bertels and Fahle (2006) proposed a hyper heuristic algorithm by hybridizing constraint programming and linear programming and also some heuristic

Table 1
Literature review of HHC.

Reference	Number of objectives		Number of depots		Number of periods		Outputs of the model				Suppositions of the model							Solution algorithm
	Single objective	Multi-objective	Single depot	Multi-depot	Single period	Multi-period	Locations of pharmacies	Assignment of patients	Routing of caregivers	Scheduling of caregivers	Time windows	Delivery time	Synchronization	Travel balancing	Working time balancing	Uncertainty	Green emissions	
Begur et al. (1997)	*	–	*	–	*	–	–	–	*	–	–	–	–	–	–	–	–	SDSS
Cheng and Rich (1998)	*	–	*	–	*	–	–	–	*	–	–	–	–	–	–	–	–	Heuristic
Bertels and Fahle (2006)	*	–	*	–	*	–	–	–	*	–	–	–	–	–	–	–	–	Hyper heuristic
Eveborn et al. (2006)	*	–	*	–	*	–	–	–	*	–	–	–	–	–	–	–	–	DSS
Akjiratikarl et al. (2007)	*	–	*	–	*	–	–	–	–	*	–	–	–	–	–	–	–	PSO
Kergosien et al. (2009)	*	–	*	–	*	–	–	–	*	*	*	–	–	–	–	–	–	Heuristic
Eveborn et al. (2009)	*	–	*	–	*	–	–	*	*	*	*	–	–	–	–	–	–	Exact
Trautsamwieser et al. (2011)	*	–	*	–	*	–	–	–	*	*	–	*	–	–	–	*	–	VNS
Rasmussen et al. (2012)	*	–	*	–	*	–	–	–	*	*	*	*	–	–	–	–	–	Exact
Nickel et al. (2012)	*	–	*	–	–	*	–	–	–	*	–	*	–	–	–	–	–	Heuristic
Liu et al. (2013)	*	–	*	–	*	–	–	–	*	*	*	*	–	–	–	–	–	GA and TS
Liu et al. (2014)	*	–	*	–	*	–	–	–	*	*	*	*	–	–	–	–	–	Feasible rules for TS
Mankowska et al. (2014)	*	–	*	–	*	–	–	–	*	*	*	*	–	–	*	–	–	Exact
Hiermann et al. (2015)	*	–	–	*	*	–	–	–	*	*	*	*	–	–	–	–	–	VNS, MA, SS and SA
Fikar and Hirsch (2015)	*	–	*	–	–	*	–	–	*	*	*	*	–	–	*	–	–	TS
Braekers et al. (2016)	–	*	*	–	–	*	–	–	*	*	*	*	–	–	–	–	–	Dynamic metaheuristic
Shi et al. (2017)	*	–	*	–	*	–	–	–	*	*	*	*	–	*	–	*	–	Hybrid of GA and SA
Shi et al. (2018)	*	–	*	–	*	–	–	–	*	*	*	*	–	*	–	*	–	GA, SA, BA and FA
Fard et al. (2018)	*	–	–	*	*	–	*	*	*	*	*	*	–	*	–	–	–	ICA
Cappanera et al.,. (2018)	*	–	*	–	–	*	–	–	*	*	*	*	–	–	–	*	–	Exact
Lin et al. (2018)	*	–	–	*	–	*	–	*	*	*	*	*	–	–	–	–	–	Hybrid of HAS and GA
Fathollahi-Fard et al. (2018)	–	*	*	–	*	–	–	–	*	*	*	*	–	*	–	–	*	Heuristics, SA and SSA
Fathollahi-Fard et al. (2018a)	*	–	*	–	*	–	–	–	*	*	*	*	–	*	–	–	–	Lagrangian relaxation
Bahadori-Chinibelagh et al. (2019)	*	–	–	*	*	–	–	*	*	*	*	*	–	*	–	–	–	Heuristics
Demirbilek et al. (2019)	*	–	*	–	–	*	–	–	–	*	–	*	–	–	*	*	–	Exact
Grenouilleau et al. (2019)	*	–	–	*	–	*	–	*	–	*	–	*	–	–	–	–	–	Heuristics
	–	*	*	–	*	–	–	–	*	*	*	*	*	–	*	–	–	MA

(continued on next page)

Table 1 (*continued*)

Reference	Number of objectives		Number of depots		Number of periods		Outputs of the model				Suppositions of the model							Solution algorithm
	Single objective	Multi-objective	Single depot	Multi-depot	Single period	Multi-period	Locations of pharmacies	Assignment of patients	Routing of caregivers	Scheduling of caregivers	Time windows	Delivery time	Synchronization	Travel balancing	Working time balancing	Uncertainty	Green emissions	
Decerle et al. (2019)																		
Fathollahi-Fard et al. (2019)	*	–	*	–	*	–	–	–	*	*	*	*	–	*	–	–	–	Heuristics and hybrid of VNS and SA
This study	–	*	–	*	–	*	*	*	*	*	*	*	–	*	–	–	*	Modifications of SA

techniques based on Cheng and Rich (1998). By assuming a real-world case study in Sweden, a Decision Support System (DSS) was suggested by Eveborn et al. (2006) based on Begur et al. (1997). They added L_{APS} and C_{ARE} into their decision policy to control the transportation cost.

One of the first studies contributed to the metaheuristics was referred to Akjiratikarl et al. (2007) who proposed a Particle Swarm Optimization (PSO) by using a case study in Ukraine. They also considered a heuristic technique called ESTPDA to solve scheduling of caregivers. Furthermore, Eveborn et al. (2009) proposed two optimization models by employing a case study in Sweden. In another research, a Variable Neighborhood Search (VNS) based on heuristic procedures was developed by Trautsamwieser et al. (2011). Their model was considered under uncertainty through disruption. Accordingly, a flood disaster in 2002 from Austria was taken into consideration.

To the best of our knowledge, Kergosien et al. (2009) was among the first studies to consider the limitations of time windows through a simplified HHC problem. To solve the model, they proposed a fast heuristic algorithm. Similarly, Rasmussen et al. (2012) ordered an HHC crew scheduling model. Their problem was an extent version of VRP with Time Window (VRPTW). They also suggested an exact approach based on the branch-and-price to address their proposed VRPTW. Moreover, Nickel et al. (2012) firstly offered an integrated multi-period model for both MSP and OPP of the HHC scheduling planning by using case study in Germany. They proposed a heuristic algorithm combined with the constraint programming approach. Later in 2013, Liu et al. (2013) introduced a set of heuristics to use as the initial solutions of two metaheuristics including Genetic Algorithm (GA) and Tabu Search (TS) to address the HHC with the delivery time and time window suppositions. The same authors in 2014 (Liu et al., 2014) innovated some new feasible procedures based on TS to better solve the HHC logistics.

From recent studies, more new suppositions are taken into consideration of the models. In 2015, Mankowska et al. (2014) assumed the balancing time of the services for the first time in the literature. In this regard, an MILP formulation was ordered to model HHC routing problem. In 2015, Hiermann et al. (2015) introduced a multi-depot HHC in Austria for the first time. Their work mainly focused on the solution approach by introducing a two-stage solution methodology. In the first stage, they reduced the number of constraints to make bigger the feasible space by the constraint programming approach. The second stage was to employ different types of the metaheuristics including VNS, Memetic Algorithm (MA), Scatter Search (SS) and a SA hyper-heuristic. Following Fikar and Hirsch (2015) considered two versions of hybrid TS to solve a number of specific instances from both small- and large-scale problems for a multi-period HHC routing problem with the supposition of working time balancing.

One of the first multi-objective models in this research area can be referred to Braekers et al. (2016). They developed a dynamic metaheuristic based on local searches to find a balance between the total cost as the first objective function and patient inconvenience as the second objective function. In 2017, Shi et al. (2017) proposed a VRPTW based on fuzzy numbers. A hybrid GA and SA was to apply for solving the benchmarked instances. The same authors in 2018 (Shi et al., 2018) applied different metaheuristics including GA, SA, Bat Algorithm (BA) and Firefly Algorithm (FA) to solve an HHC routing and scheduling problem by considering stochastic travel and service times. By adding more logistics factors to consider the locations of pharmacies and the assignment of patients, Fard et al. (2018) proposed a location-allocation-routing model to contribute a HHCSC for the first time. They utilized an Imperialist Competitive Algorithm (ICA) to solve the model.

The first study to contribute a robust optimization model in this research area was Cappanera et al. (2018). They maintained on the demand uncertainty in a multiple-day horizon time. To address their model, a non-standard cardinality-constraint robust approach was proposed. In 2018, Lin et al. (2018) claimed that a coordinated model is needed to explore the HHC routing and scheduling problem. A Harmony Search Algorithm (HSA) was combined by GA to address the problem. In another multi-objective model, Fathollahi-Fard et al. (2018) considered the green emissions for an HHC routing problem for the first time. They proposed a set of heuristics as well as SA and Salp Swarm Algorithm (SSA) to find a trade-off between the green emissions and total cost of system. In another work, the same authors (Fathollahi-Fard et al., 2018a) proposed a Lagrangian relaxation algorithm to solve an HHC routing and scheduling problem.

More recently in 2019, Bahadori-Chinibelagh et al. (2019) proposed multi-depot HHC routing problem and solved it by two fast heuristics. A set of efficient heuristics and a hybrid of VNS and SA to solve a single depot HHC routing model were developed by Fathollahi-Fard et al. (2019). In another different study, Demirbilek et al. (2019) introduced a multi-period HHC scheduling considering working time balancing in a dynamic environment. Grenouilleau et al. (2019) developed a set of heuristics to solve a multi-depot and multi-period HHC routing and scheduling problem. At last but not least, Decerle et al. (2019) proposed a multi-objective HHC routing and scheduling problem considering working time balancing and synchronization of caregivers. They applied the MA to solve their NP-hard problem.

Based on the aforementioned literature and main findings of Table 1, following research gaps can be explored:

- There are only three multi-objective optimization models among the works (Braekers et al., 2016; Fathollahi-Fard et al., 2018; Decerle et al., 2019).
- Most of the developed models are a single depot and single period HHC.
- An HHCSC to consider the locations of pharmacies and the right assignment of patients in addition to routing and scheduling of the caregivers, was only proposed by Fard et al. (2018). However, their model was not a multi-objective and multi-period. They also did not consider the green emissions.
- The green emissions were only contributed by Fathollahi-Fard et al. (2018). However, their model was a single depot and single period HHC routing problem.
- The time window and delivery time were contributed to most of HHC models.
- Most of recent papers considered the travel balancing or working time balancing in their models.
- The SA was successfully applied to many earlier studies in this research area and can be employed for future studies as well.

To fill the aforementioned gaps, this study formulates a new bi-objective MILP by considering a Location-Allocation-Routing (LAR) strategy named as Green Home Health Care Supply Chain (GHHCSC). The model is multi-depot and multi-period as well. The main new suppositions of proposed problem are the time window, delivery time, travel balancing and green emissions. To the best of our knowledge, Fathollahi-Fard et al. (2018) only assumed the green emissions and environmental pollution for a single-depot and single period home health care routing model. They did not consider the LAR strategy to result the suitable positions of pharmacies and laboratories, assignment of patients to pharmacies, routing and scheduling of caregivers. An HHCSC was only contributed by Fard et al. (2018). However, they did not assume the green emissions. Another innovation of this study was to propose some new modified metaheuristics. Already applied successfully to several earlier studies, this paper is also utilized SA and developed some new modifications of this algorithm to better solve the problem.

3. Proposed GHHCSC problem

In this paper, a LAR strategy by formulating a bi-objective MILP model is presented. In addition to the total cost of system, the environmental impacts and green emissions are the second objective function. The proposed GHHCSC problem is a multi-objective, multi-depot and multi-period HHC considering the green emissions, travel balancing, time window and delivery time suppositions. Based on the LAR model, first of all, the location of pharmacies and laboratories are determined. Then, the patients should be assigned to only one pharmacy. For each pharmacy, only one laboratory should be considered as well. Regarding this allocation, the company caries out different supply chain and transportation activities. The main one is to deliver the required medications s from a pharmacy to the patients. Another main activity is the transportation of collected biological instances from the homes of patients to a laboratory. To do this end, the decisions related to routing and scheduling of caregivers should be made in each time period. According to the stated steps, Fig. 2 shows a simple instance with three pharmacies and laboratories and twenty-four patients with two caregivers for each pharmacy to perform the home care services.

3.1. Description

The description of the developed GHHCSC in this paper is mainly inspired by Shi et al. (2017); Fathollahi-Fard et al. (2018) and Fathollahi-Fard et al. (2019). Based on the following description, one naive user with no backgrounds of operation research can employ this model for a real-world application. In this regard, consider a city or town with M patients in which an HHC organization wants to provide the home care services for the patients. In this city, there are P pharmacies with the opening cost of FCP_p and the capacity of $CAPP_p$ and also L laboratories with the opening cost of FCL_l and the capacity of $CAPL_l$. Each pharmacy is the counterpart of each laboratory. Only a maximum desired number of these facilities should be opened (MAX). Every day, each patient requires a set of certain medications (A_{it}) and after visiting; some biological samples should be transformed to the laboratories (B_{it}). As such, this company employs N_p caregivers for each pharmacy. These caregivers should be assigned to one route which starts from a pharmacy to a laboratory. The distances between each level of this supply chain network are based on two dimensions, geographically. In this regard, D^M_{ij}, D^P_{ip} and D^L_{pl} show the distance between two patients, a patient and its pharmacy and also the pharmacy and its laboratory, respectively. Each patient should be assigned to only one pharmacy with the dependent cost of the distance ($CS \times D^P_{ip}$). This cost can be considered as the fixed cost of home care services. As such, each pharmacy should be assigned to its laboratory with the cost of $CS \times D^L_{pl}$. This cost has a high impact on the logistics cost of HHCSC as well. As mentioned earlier, the start point of the caregivers is from their pharmacy. Accordingly, all patients should be visited. The end point of the caregivers' routes is to go back to their laboratory. With regards to this transportation activity, one nurse can assign to only one vehicle. Therefore, there are different versions of transportation systems including cars, publics, and trains. The capacity of CAP_k and transportation cost of TC_k and also for green emission of CC_k which is considered for the released amount of CO_2 for each distance unit, have been considered for each transportation system. The green emissions of vehicle k are based on a linear relationship between the rate of CO_2 emissions generated by vehicle and fuel consumption per unit of distance which are vary for different vehicles (Fathollahi-Fard et al., 2018). Similar to green

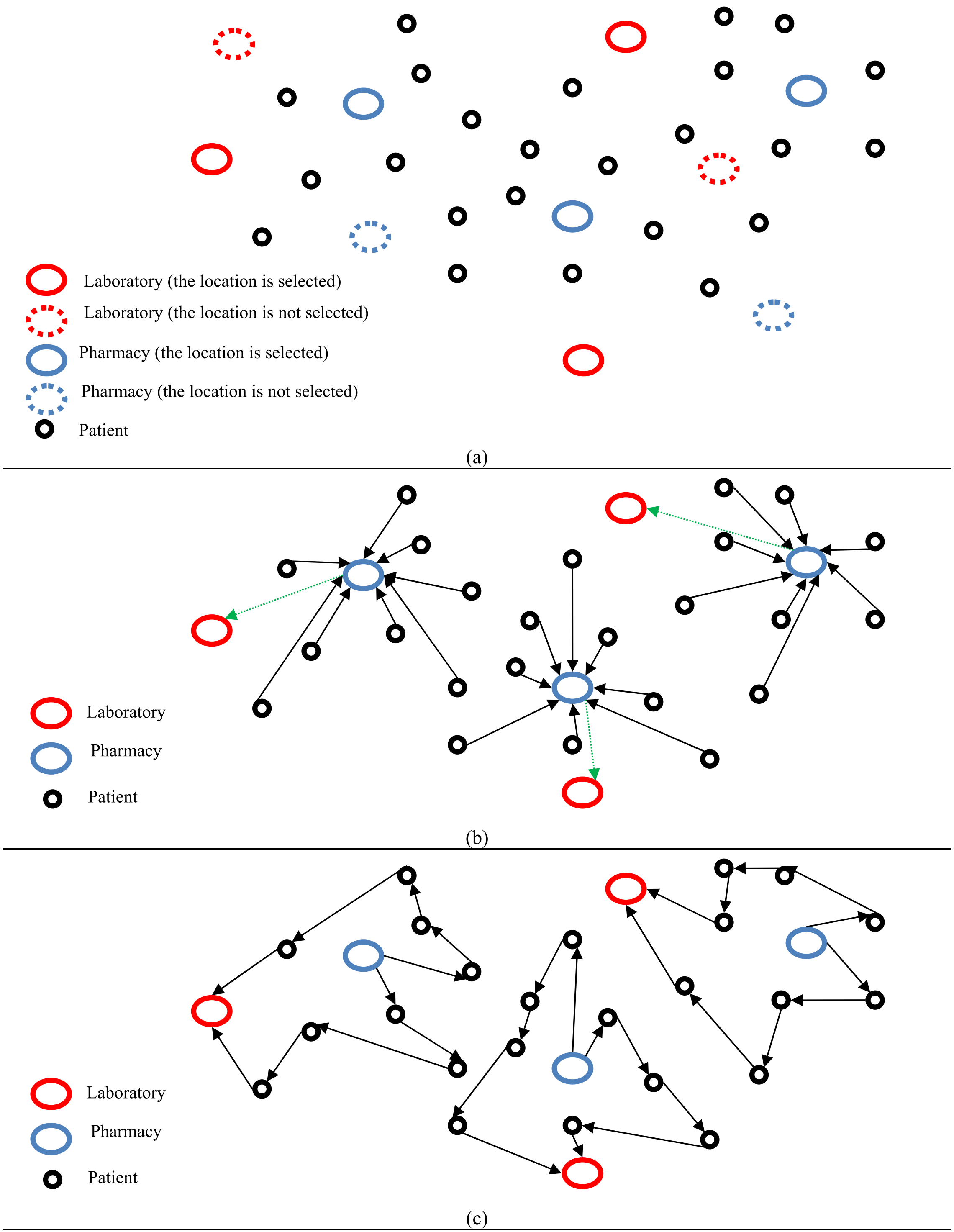

Fig. 2. The LAR strategy of proposed GHHCSC *i.e.* (a) for location decisions, (b) for allocation decisions and (c) for the routing decisions.

supply chain network design (Govindan et al., 2015; Samadi et al., 2018; Abdi et al., 2019), another green dimension is the environmental impact of opening a pharmacy and a laboratory in its potential locations (EOP_p for the pharmacy p and EOL_l for the laboratory l). This means the amount of CO_2 during the establishment of these facilities. In addition, according to the time window, there are an earliest time (E_{it}) and the latest time (L_{it}) for each patient to visit by the caregivers. Based on the home care services in each period time, each patient has an estimated time for working of caregivers (W_{it}). Regarding the traveling time of caregivers for visiting of patients i to j, there is a specified time (T_{ij}) in each period time. Similar to the most of recent studies (Shi et al., 2017; Fathollahi-Fard et al., 2018a, 2019), travel balancing of caregivers is one of main sectors to reduce the total cost and to limit the transported distance by the vehicles. Accordingly, the distance traveling summation for all caregivers and their utilized vehicles must not be greater than a supposed value ($MDIS_{nkt}$). Otherwise, for the rest of traveled distance, a penalty value should be considered (PEN).

3.2. Assumptions

The main assumptions of proposed problem are stated as follows:

- The proposed problem is a multi-objective, multi-depot and multi-period GHHCSC.
- Each day is considered as a period time during the activities of proposed GHHCSC.
- The proposed model is a single product as well. It means that there is no distinction between types of medications.
- There are many distributed patients and an equal number of pharmacies and laboratories.
- Each pharmacy and laboratory has a number of caregivers regarding their skills as a nurse, doctor, physiotherapist and nutritionist to provide a full range of the care.
- The caregivers utilize different types of transportation systems to distribute the required medications s and to collect the biological samples.
- The demand of each patient must to be met.
- The potential locations for the pharmacies and laboratories are predefined.
- The environmental impact of opening activities for a pharmacy and a laboratory is considered.
- The capacity of each pharmacy and laboratory in each location is limited.
- Between the same pharmacies and laboratories no flows exists.
- The start point of each caregiver is his/her pharmacy. Similarly, the end point of caregivers' route is his/her laboratory.
- The caregivers transform the required medications of patients from the pharmacy; after visiting the patients; their biological samples should be collected to analyze in the laboratories. Accordingly, they update the patients' health records in each period time.
- The working time for each patient is predefined and estimated by the caregivers based on their health records.
- Another real-world assumption of proposed model is the time window. Accordingly, there are two limitations i.e., the availability of patients at their earliest time and the latest time.
- Regarding the transportation activities of considered HHCSC, there are a number of vehicles with different capacities, transportation costs and the CO_2 emission rate for each unit of distance traveled by the caregiver between patients *i* to *j*.
- The travel balancing is also considered by this study. Accordingly, there is a penalty value for each type of vehicle for overall distance.

3.3. Notations

Here, a set of nations of developed GHHCSC formulation has been provided as follows:

Indices:	
k	Index of transport systems (vehicles), $k \in \{1,2,\ldots,K\}$
i,j	Index of patients, $i,j \in \{1,2,\ldots,M\}$
p	Index of Pharmacies, $p \in \{1,2,\ldots,P\}$
l	Index of Laboratories, $l \in \{1,2,\ldots,L\}$
n	Index of nurses for each pharmacy, $n \in \{1,2,\ldots,N_p\}$
t	Index of time periods, $t \in \{1,2,\ldots,T\}$
Parameters:	
D^M_{ij}	Distance between patients i and j
D^P_{ip}	Distance between patient i and pharmacy p
D^L_{pl}	Distance between pharmacy p and laboratory l
FCP_p	Fixed cost of opening pharmacy p
FCL_l	Fixed cost of opening laboratory l
EOP_p	Environmental impact during the establishment of pharmacy p
EOL_l	Environmental impact during the establishment of laboratory l
$CAPP_p$	The capacity of pharmacy p
$CAPL_l$	The capacity of laboratory l
CS	The allocation cost of whole partners of system per unit distance
TC_k	The transportation cost for each traveled distance regarding the vehicle k
CAP_k	The capacity of vehicle k
CC_k	The CO_2 emission for rate of distance unit regarding the vehicle k
W_{it}	The working time of servicing to the patient i in time period t
E_{it}	The earliest time of servicing to the patient i in time period t
L_{it}	The latest time of servicing to the patient i in time period t
T_{ijt}	The traveling time of patients i to j in time period t
PEN	Amount of penalty for overall distanced traveling between patients ($1 < PEN < 5$)
BIG	A positive large number for constructing of the time window constraints
$MDIS_{nkt}$	Maximum desired traveling distances regarding each caregiver n by employing transportation system k in time period t
A_{it}	Demand of patient i in time period t
B_{it}	Amount of biological sample received from patient i after visiting by the caregiver in time period t
MAX	Maximum desired number of established sites for pharmacies and laboratories
Decision variables:	
X^{kt}_{ijnpl}	It gets 1 if the caregiver n started from pharmacy p to laboratory l by applying transportation system k visits the patients i before j in time period t, otherwise 0.
Y_p	It gets 1 if pharmacy p is to be established, otherwise 0.
Q_l	It gets 1 if laboratory l is to be established, otherwise 0.
Z^P_{ip}	It gets 1 if patient i assigned to pharmacy p, otherwise 0.
Z^L_{pl}	It gets 1 if pharmacy p assigned to laboratory l, otherwise 0.
S^t_{inpl}	Denotes the time at which nurse n started from pharmacy p to laboratory l begins to service the patient i in time period t. It should be noted that if this event has not been occurred, S^t_{inpl} does not mean anything.
O^t_{nkpl}	The overall traveled distances for nurse n from pharmacy p to laboratory l using transport system k in time period t.

3.4. Formulation

Here, the developed mathematical formulation as a type of bi-objective MILP model is presented as follows:

$$Z_1 : min\left(\sum_{p=1}^{P} FCP_p \times Y_p + \sum_{l=1}^{L} FCL_l \times Q_l + \sum_{i=1}^{M}\sum_{p=1}^{P} CS \times D_{ip}^{P} \times Z_{ip}^{P} + \sum_{p=1}^{P}\sum_{l=1}^{L} CS \times D_{pl}^{L} \times Z_{pl}^{L} + \sum_{k=1}^{K}\sum_{n=1}^{N_p}\sum_{i=1}^{M}\sum_{j=1}^{M}\sum_{p=1}^{P} \times \sum_{l=1}^{L}\sum_{t=1}^{T} D_{ij}^{M} \times TC_k \times X_{ijnpl}^{kt} + \sum_{n=1}^{N_p}\sum_{k=1}^{K}\sum_{p=1}^{P}\sum_{l=1}^{L} \times \sum_{t=1}^{T} O_{nkpl}^{t} \times TC_k \times PEN\right) \quad (1)$$

$$Z_2 : min\left(\sum_{p=1}^{P} EOP_p \times Y_p + \sum_{l=1}^{L} EOL_l \times Q_l + \sum_{p=1}^{P}\sum_{l=1}^{L}\sum_{k=1}^{K}\sum_{n=1}^{N_p}\sum_{i=1}^{M} \times \sum_{t=1}^{T}\sum_{j=1}^{M} D_{ij} \times CC_k \times X_{ijnpl}^{kt}\right) \quad (2)$$

$s.t.$

$$\sum_{p=1}^{P} Y_p = MAX \quad (3)$$

$$\sum_{l=1}^{L} Q_l = MAX \quad (4)$$

$$\sum_{p=1}^{P} Z_{ip}^{P} = 1, \forall i \in M \quad (5)$$

$$\sum_{i=1}^{M} A_{it} \times Z_{ip}^{P} \leq CAPP_p, \forall p \in P, t \in T \quad (6)$$

$$\sum_{p=1}^{P} Z_{pl}^{L} = 1, \forall l \in L \quad (7)$$

$$\sum_{l=1}^{L} Z_{pl}^{L} = 1, \forall p \in P \quad (8)$$

$$\sum_{i=1}^{M}\sum_{j=1}^{M}\sum_{n=1}^{N_p}\sum_{k=1}^{K}\sum_{p=1}^{P} B_i \times X_{ijnpl}^{kt} \leq \sum_{p=1}^{P} CAPL_l \times Z_{pl}^{L}, \forall l \in L, t \in T \quad (9)$$

$$\sum_{n=1}^{N}\sum_{k=1}^{K}\sum_{j=1}^{M}\sum_{p=1}^{P}\sum_{l=1}^{L} X_{ijnpl}^{kt} = 1, \forall i \in M, t \in T \quad (10)$$

$$\sum_{i=1}^{M} A_{it} \times \sum_{j=1}^{M} X_{ijnpl}^{kt} \leq CAP_k, \forall k \in K, n \in N_p, p \in P, l \in L, t \in T \quad (11)$$

$$\sum_{i=1}^{M} X_{ihnpl}^{kt} - \sum_{j=1}^{M} X_{hjnpl}^{kt} = 0, \forall h \in M, k \in K, n \in N_p, p \in P, l \in L, t \in T \quad (12)$$

$$S_{inpl}^{t} + T_{ijt} + W_{it} - BIG \times \left(1 - X_{ijnpl}^{kt}\right) \leq S_{jnpl}^{t}, \forall i,j \in M, k \in K, n \in N_p, p \in P, l \in L, t \in T \quad (13)$$

$$E_{it} \leq S_{inpl}^{t} \leq L_{it}, \forall i \in M, n \in N_p, p \in P, l \in L, t \in T \quad (14)$$

$$O_{nkpl}^{t} \geq \left(\sum_{i=1}^{M}\sum_{j=1}^{M} D_{ij}^{M} \times X_{ijnpl}^{kt}\right) - MDIS_{nkt}, \forall p \in P, l \in L, n \in N_p, k \in K, t \in T \quad (15)$$

$$O_{nkpl}^{t} \geq 0 \quad (16)$$

$$Z_{ip}^{P} \leq Y_p, \forall p \in P, i \in M \quad (17)$$

$$Z_{pl}^{L} \leq Y_p, \forall p \in P, l \in L \quad (18)$$

$$Z_{pl}^{L} \leq Q_l, \forall l \in L, p \in P \quad (19)$$

$$X_{ijnpl}^{kt} \leq Z_{pl}^{L}, \forall l \in L, p, n \in N_p, i,j \in M, t \in T, k \in K \quad (20)$$

$$S_{inpl}^{t} \in R^{+} \quad (21)$$

$$X_{ijnpl}^{kt}, Y_p, Q_l, Z_{ip}^{P}, Z_{pl}^{L} \in \{0,1\} \quad (22)$$

Equation (1) formulates the first objective function remaining the total cost of the GHHCSC problem. In this regard, the first and second terms aim to show the opening cost of pharmacies and laboratories, respectively. The third and fourth terms represent the allocation cost between the levels of GHHCSC. The patients allocate to their pharmacies at the third terms. The fourth term represents the assigning of pharmacies to laboratories. From the last two terms, the routing and scheduling of the caregivers are determined for each time period. With regards to the traveled distance of the caregivers, the transportation cost is calculated. In the last term based on the travel balancing of the caregivers, regarding the type of vehicles, the overall distances of caregivers traveling should be optimized.

Equation (2) shows the second objective function which aims at addressing both environmental impact and green emissions of developed GHHCSC problem to be minimized. The first and second terms represent the environmental impact during the establishment of the pharmacies and laboratories, respectively. In the last term, according to the amount of released CO_2 emission rate of vehicles for transportation, the goal of third term is to reduce the environmental pollution.

Equations (3)–(22) represents the constraints of the developed GHHCSC model. Equations (3) and (4) aim to guarantee the number of opened pharmacies and laboratories which are equaled by a maximum desired number, respectively. Equation (5) defines that each patient should be assigned to only one pharmacy. Equation (6) ensures that the required medications of each assigned patient to its pharmacy should be met. Equations (7) and (8) show that each pharmacy should be assigned to only one laboratory. Equation (9) specifies that the capacity of a laboratory should be met the whole biological samples during the visiting of patients. Equation (10) represents that the patients should be visited once only. Equation (11) guarantees that the capacity of selected vehicles should be greater than the summations of transported medications for the patients. Equation (12) states that after visiting a patient, the caregiver should leave this patient. Regarding the mathematical view of the model as a kind of VRPTW, the aim of this constraint is to decrease the overall number of unfeasible sub-tours of the caregivers. Regarding the time window, Equation (13) explores that the caregivers cannot arrive at patient *j* before $S^t_{inpl} + T_{ijt} + W_{it}$. It specifies that each patient has a working time of W_i. Similarly, the patients traveling from *i* to *j* is considered by T_{ijt}. In this regard, *BIG* is a large scalar to construct this constraint. Equation (14) shows that each patient has a time window. Equations (15) and (16) aim to compute the extra traveling distance of the caregivers limited by a maximum desired distance. Equation (17) ensures that the patients can be assigned to a pharmacy if it is open. Equations (18) and (19) similarly shows that a pharmacy and a laboratory can be allocated to each other if they are open. Equation (20) is another statement of Equation (17) for the laboratories. Equations (21) and (22) ensures the decision variables of the developed GHHCSC model.

This is the first attempt to employ a LAR strategy to design a GHHCSC. There is no similar study to propose a multi-objective, multi-period and multi-depot HHCSC considering the time window and delivery time as well as the travel balancing and green emissions.

4. Solution methodology

As a LAR model, the GHHCSC is NP-hard. In this regard, the metaheuristics are the best alternatives to reach a global optima instead of local ones. The literature is rich in using metaheuristics. SA, VNS, GA and MA have been successfully applied in many earlier studies (Hiermann et al., 2015; Shi et al., 2017; Shi et al., 2018; Fathollahi-Fard et al., 2018; Decerle et al., 2019; Fathollahi-Fard et al., 2019). Among them, in our previous experiments, we found that SA is more suitable to solve the proposed GHHCSC problem. Because, it is easy to manipulate the search space of the problem and has less controlling parameters compared to most of existing algorithms in the literature (Velik and Nicolay, 2014; Shi et al., 2018; Fathollahi-Fard et al., 2018b). These reasons motivate our attempts to focus on the development of SA. In this study, we propose five modifications of SA to find that which one will be the best choice to solve the proposed LAR model. Since the GHHCSC is a bi-objective optimization model, we firstly illustrate the multi-objective optimization structure. Next, the solution representation of proposed LAR model is addressed by heuristic procedures. Finally, the proposed modifications of SA are explained to show the contributions in the development of the SA algorithm.

4.1. Multi-objective optimization

As mentioned before, the developed GHHCSC model is a kind of multi-objective optimization problem by two conflicting objective functions. Accordingly, the optimal solution is a Pareto optimal frontier (Safaeian et al., 2019; Fu et al., 2019). The best Pareto frontier as the first front is the non-dominated solutions compared to other solutions generated by the algorithm (Fathollahi-Fard et al., 2018; Samadi et al., 2018). As such, the second front is made by all other solutions that are only dominated by the solutions in the first one (Maghsoudlou et al., 2016). Fig. 3 indicates the relation between the decision variables and the solution space for a bi-objective problem. Each point in the feasible space of the problem has a unique point in the space of objective functions. Since there are many papers focusing on multi-objective optimization models, interested readers are referred to study the recent comprehensive works in this regard (Hajiaghaei-Keshteli and Fathollahi-Fard, 2018). Note that the evaluation of the multi-objective algorithms is based on the multi-objective assessment metrics which relays on the quality of the first front of Pareto-based solutions (Fu et al., 2019).

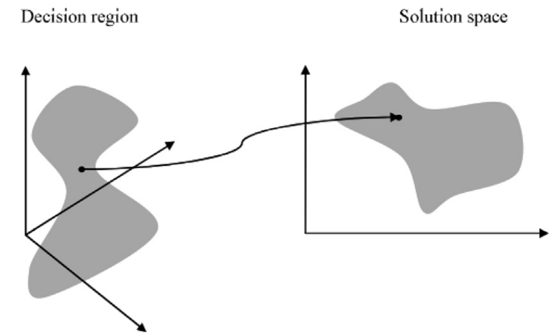

Fig. 3. Representation of multi-objective optimization (Fu et al., 2019).

4.2. Solution representation

To implement the metaheuristics for solving the optimization models, a plan is usually needed to encode and decode the solution representation to show the search space and computation of objective functions (Hajiaghaei-Keshteli, and Aminnayeri, 2013; Fard and Hajiaghaei-Keshteli, 2016; Fathollahi-Fard et al., 2018b). This study utilizes a two-stage heuristic procedure called *Random-Key* (*RK*) (Snyder and Daskin, 2006). The aim of this technique is to convert the continuous search space of the metaheuristic to a feasible discreet one by using some heuristic techniques (Hajiaghaei-Keshteli et al., 2011; Govindan et al., 2015; Golmohamadi et al., 2017).

According to the LAR strategy, location, allocation and routing decisions are the main decision variables of the problem. To select the established sites of the pharmacies (Y_p) and laboratories (Q_l), firstly, a random matrix distributed by $U(0,1)$ is generated. The second step is to sort this matrix and the lowest values are chosen to be equaled 1 to represent the established sites. Fig. 4 depicts an example with five potential sites in which three of them would be opened ($MAX = 3$). The P_1, P_2 and P_3 pharmacies are opened in this example.

In addition, the allocation's variables including the assignment of the patients to pharmacies (Z^P_{ip}) as well as the allocation of pharmacies to laboratories (Z^L_{pl}) are determined by Figs. 5 and 6, respectively. From Fig. 5, the ten patients are allocated to three pharmacies by the random numbers. For example, as can be envisaged, the patients including m_2, m_4, m_5 and m_6 are assigned to pharmacy P_1.

Furthermore, Fig. 6 represents the assignment of the pharmacies to the laboratories. Regarding the figure, a priority-based representation is applied to do the allocation one by one (Hajiaghaei-Keshteli and Fathollahi-Fard, 2018). The established sites of pharmacies and laboratories are allocated by one to one. As can be seen at this figure, pharmacies P_1, P_2 and P_3 are assigned to laboratories L_2, L_3 and L_1, respectively.

To make the routing and scheduling of the caregivers in each

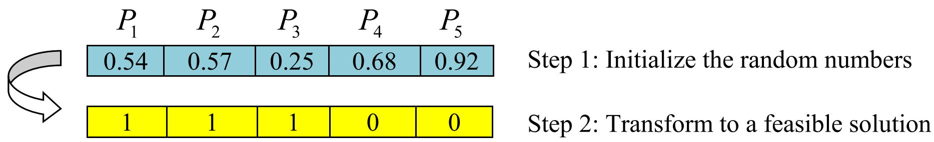

Fig. 4. Technique to choose the established sites of the pharmacies and laboratories.

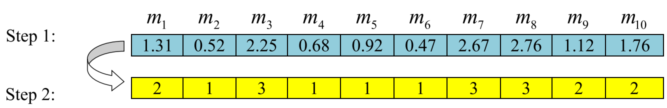

Fig. 5. Technique for the assignment of the patients to the pharmacies.

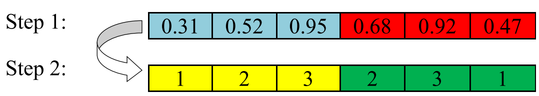

Fig. 6. Technique for the allocation of the pharmacies and the laboratories.

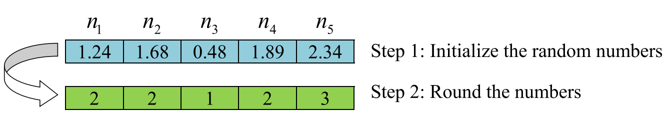

Fig. 7. Technique for the assignment of the type of vehicle for the caregivers.

time period, first of all, the used vehicles for each caregiver in each pharmacy should be selected. The considered procedure is an array by a length of N. The uniform distribution of $U(0, K)$ is conducted to generate the first step of RK. where K is the number of vehicle types. In the second step by rounding the generated numbers, the type of vehicles for each caregiver is determined. These procedures are depicted by Fig. 7. As can be envisaged from this figure, for the caregivers n_1, n_2 and n_4, the selected transportation system is the second type of vehicles. As such, regarding the caregivers n_3 and n_5, the first and third types of transportation systems are chosen, respectively.

Additionally, to choose the patients' route, an array with the length of all assigned patients to this pharmacy (in this example is equal to 12) is distributed by $U(0, 1)$. Fig. 8 reveals a simple instance with the used arrays for the generated matrix is adopted for this methodology. In this case, there are 12 patients. The second step is to sort these numbers to specify the routes of the patients. Notably, these routes should meet the maximum desired total distance of traveling for each period ($MDIS_{nkt}$), the capacity of the used vehicle (CAP_k) and also the time window. As a result, the routes adopted from this example are numerically as follows:

$$n_1 = \{m_2 \to m_1 \to m_8\},\ n_2 = \{m_5 \to m_{11} \to m_3\},\ n_3 = \{m_{10} \to m_9 \to m_7 \to m_{12}\},\ n_4 = \{m_4 \to m_6\}$$

4.3. Simulated Annealing (SA)

Already applied successfully to numerous optimization problems, the SA is also employed in this study. The SA firstly introduced by Kirkpatrick et al. (1983) was inspired by chemical process of metal annealing. As a type of local search strategies, the SA is a well-known single-solution heuristic. Here, we propose a multi-objective version of SA to solve the proposed GHHCSC problem. Regarding the steps of SA, it starts with a random answer, initially. Next, a neighbor solution should be generated. To generate a neighborhood of this solution, three neighboring procedures including Swap, Reversion and Insertion are existed (Fathollahi-Fard et al., 2018; Hajiaghaei-Keshteli and Sajadifar, 2010). Regarding the multi-objective version of SA, for a bi-objective minimization problem, this new solution should be assessed by using following formula:

$$\Delta f_j = f_j(x_{new}) - f_j(x_{old}), j = 1, 2, ..., n_{obj} \tag{23}$$

where x_{old} is the initial solution and x_{new} is the new solution. Also, n_{obj} specifies the number of objective function. Fig. 9 gives the pseudo-code of proposed algorithm. Note that regarding two minimizing objective functions, three cases are existed for the development of multi-objective SA algorithm.

4.3.1. Modifications of SA (MSA)

As discussed earlier, the main innovation is to develop different modifications of SA to tackle the problem. The literature of SA shows that there are several modifications of SA to solve different NP-hard optimization problems *e.g.*, (Ishibuchi et al., 1995; Misevičius, 2003; Mousavi and Tavakkoli-Moghaddam, 2013; Velik and Nicolay, 2014; Matai, 2015; Grobelny and Michalski, 2017; Fathollahi-Fard et al., 2018). One goal in most of modifications is to introduce a better balance and interaction between the search phases *i.e.* exploration and exploitation (Govindan et al., 2015; Fathollahi-Fard et al., 2018c). Following Fathollahi-Fard et al. (2018), two new accepting rules to update the probability of accepting new solutions as two different versions of SA are introduced as below formulas:

$$P_j = \exp\left(-\frac{\left|\frac{f_j(x_{new}) - f_j(x_{old})}{f_j(x_{old})}\right|}{T}\right); j = 1, 2, ..., n_{obj} \tag{24}$$

$$P_j = \exp\left(-\left|\frac{f_j(x_{new}) - f_j(x_{old})}{f_j(x_{old})}\right|\right); j = 1, 2, ..., n_{obj} \tag{25}$$

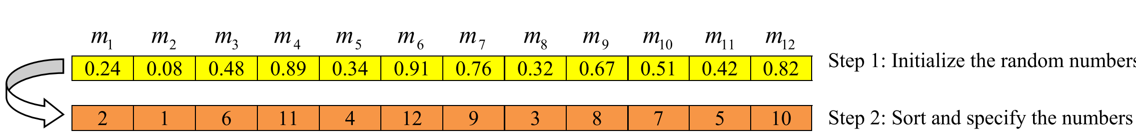

Fig. 8. Technique to assign the patients to each route of the caregiver.

```
Parameter setting
Initialize and evaluation fitness functions ( x_old , f_j( x_old ))
Best solution = ( x_old , f_j( x_old ))
it=1;
while it ≤ Maxit
    sub=0;
    while sub ≤ Subit
     Do one of mutation procedures and generate x_new
     Calculate the fitness function and (Δf_j)
    if Δf_1 ≤ 0 && Δf_2 ≤ 0
          Update the Best solution =(x′, f_j(x′))
          Update the solution  x_old = x_new
    else if Δf_1 ≥ 0 && Δf_2 ≤ 0 || Δf_1 ≤ 0 && Δf_2 ≥ 0
          Put this solution in Pareto set.
    else Δf_1 ≥ 0 && Δf_2 ≥ 0
          P_1 = exp((−Δf_1)/T) , P_2 = exp((−Δf_2)/T) , h=rand
          if h<P_1 && h<P_2
          Update the solution  x_new = x_new
          endif
    endif
    sub=sub+1;
    endwhile
    Update temperature (T=α*T).
    Do non-dominate sorting in this Pareto set.
    it=it+1;
endwhile
```

Fig. 9. Pseudo-code for the multi-objective version of SA.

The main contributions of the developed modifications are to consider three new accepting rules to find a better balance between the intensification and diversification to have a better convergence rate. Based on the Equations (24) and (25), two modified SA algorithms are applied from the literature and we call them as MSA_{V1} and MSA_{V2}, respectively. Furthermore, this work proposes three new formulas based on the number of iterations to update the probability of new solutions acceptance. Developing an adaptive strategy to update the accepting probability is the main contributions of the proposed modifications. Based on our previous experiments which are not reported here, using these adaptive versions of accepting rules are generally useful to generate a better balance between two main search phases. By another point of view, the proposed modifications mainly increase the exploration properties based on the last iterations, successfully. In this regard, the probability of accepting a new solution is developed as following formulas:

$$P_j = \exp\left(-\left|\frac{f_j(x_{new}) - f_j(x_{old})}{f_j(x_{old})}\right| \times \frac{6 \times it}{Maxit}\right); j = 1, 2, \ldots, n_{obj} \quad (26)$$

$$P_j = \exp\left(-\left|\frac{f_j(x_{new}) - f_j(x_{old})}{f_j(x_{old})}\right| \times \frac{4 \times it}{Maxit}\right); j = 1, 2, \ldots, n_{obj} \quad (27)$$

$$P_j = \exp\left(-\left|\frac{f_j(x_{new}) - f_j(x_{old})}{f_j(x_{old})}\right| \times \left|\frac{1}{Maxit - it - 1}\right|\right); j = 1, 2, \ldots, n_{obj} \quad (28)$$

where *it* is the current iteration and *Maxit* is the maximum number of iteration. In these modifications of SA, two parameters of the original algorithm are removed by an adaptive strategy for updating the accepting rule based on the number of iterations. They are the initial temperature and its rate of reduction. Here, these three new versions *i.e.* Equation (26)–(28) are called as MSA_{V3}, MSA_{V4} and MSA_{V5}, respectively. The other steps of these algorithms are the same as original idea of algorithm as explained by Fig. 9.

5. Experimental results

In this section, first of all, some benchmarks are generated to have different problem complexities for GHHCSC model. Next, assessment metrics of Pareto-based algorithms are proposed. To tune the algorithms' parameters, Taguchi method is utilized. To check the quality of the algorithms' non-dominated solutions in small sizes, an epsilon constraint method is utilized. A comparative study is performed to identify the best algorithm among modifications proposed. Finally, some sensitivity analyses are done to show the efficiency of the developed GHHCSC.

5.1. Instances

Based on the literature, we have utilized the benchmarks proposed by Fathollahi-Fard et al. (2018) to have different test problems. In this regard, the test problems can be generated by a new approach. There are twelve test problems in three classifications. In this regard, SP1:SP4, MP5:MP8 and LP9:LP12 are presented for small, medium and large instances, respectively. Table 2 provides these instances. The planning horizon is changed from one day to two months. Due to limitation of run time, we have not considered more than 60 period times in our experiments. The details of generation of parameters as given in Table 3 are provided from the literature and readers can refer to read Shi et al. (2017), 2018; Fathollahi-Fard et al. (2018), 2019 and Bahadori-Chinibelagh et al. (2019). It should be noted that based on supply chain models (e.g., Govindan et al. (2015); Abdi et al. (2019)), the maximum desired number of the pharmacies and laboratories to be located (*MAX*) are estimated by half of its potential units.

Table 2
Size of instances.

Classification	Instance	Number of time periods (T)	Number of pharmacies (P) and laboratories (L)	Number of nurses (N_p)	Types of vehicles (K)	Number of patients (M)
Small	SP1	2	2	2	2	10
	SP2	4	2	3	2	25
	SP3	4	4	4	3	40
	SP4	6	6	6	3	65
Medium	MP5	12	8	8	3	80
	MP6	16	9	8	4	85
	MP7	18	9	9	5	95
	MP8	22	10	10	5	100
Large	LP9	30	12	12	6	120
	LP10	40	14	15	6	150
	LP11	50	16	16	7	160
	LP12	60	18	20	8	200

Table 3
Details on computation of GHHCSC's parameters.

Parameters	Distribution
(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_p, y_p)	$1000\times(U(0,1),U(0,1))$
(x_l, y_l)	$1000\times(U(0,1),U(0,1))$
D^M_{ij}	$\sqrt{(x_i-x_j)^2+(y_i-y_j)^2}$
D^P_{ip}	$\sqrt{(x_i-x_p)^2+(y_i-y_p)^2}$
D^L_{pl}	$\sqrt{(x_p-x_l)^2+(y_p-y_l)^2}$
A_{it}	$rand\{5,10,\ldots,100\}$
$CAPP_p$	$rand\{800,900,\ldots,2000\}$
B_{it}	$rand\{1,2,\ldots,30\}$
$CAPL_l$	$rand\{50,60,\ldots,100\}$
FCP_p	$rand\{1000,1500,\ldots,3000\}$
FCL_l	$rand\{2000,2500,\ldots,5000\}$
EOP_p, EOL_l	$rand\{1,2,\ldots,10\}$
PEN	For small sizes: 1.5, medium sizes: 3, large sizes: 4.5
W_{it}	$rand\{5,10,\ldots,60\}$
E_{it}	$rand\{0,1,\ldots,10\}$
L_{it}	$rand\{500,1000,\ldots,5000\}$
T_{ijt}	$\frac{D^M_{ij}}{\sum_{i=1}^{M}\sum_{j=1}^{M}D^M_{ij}}\times 90\times S$[a]
$MDIS_{nkt}$	$rand\{25000,30000,\ldots,50000\}$
CS	2

[a] Speed transfer coefficient according to the used vehicle for transferring between patient i and j.

5.2. Assessment metrics of Pareto-based algorithms

As discussed earlier, having a multi-objective optimization model, the evaluation of metaheuristics will be changed (Li et al., 2017). To evaluate Pareto-based solutions, scholars offered some metrics to assess the quality of Pareto fronts (Samadi et al., 2018; Abdi et al., 2019). In this study, Number of Pareto Solution (NPS) (Govindan et al., 2015), Mean Ideal Distance (MID) (Maghsoudlou et al., 2016), Spread of Non-dominance Solution (SNS) (Hajiaghaei-Keshteli and Fathollahi-Fard, 2018) and Maximum Spread (Fathollahi-Fard et al., 2018) have been utilized. Due to page limitation, their mathematics are not presented here.

5.3. Parameter tuning: Taguchi method

Tuning of algorithms' parameters is always one of important sectors of a paper utilizing the metaheuristics to identify a high-performance level of to better do the search phases more efficiently (Liu et al., 2014). If a metaheuristic is not tuned well, its performance is not reliable (Abdi et al., 2019). Here, Taguchi method is employed to tune the parameters of the presented algorithm. In 1986, Taguchi (1986) developed this algorithm to reduce the time of calibration for the fields of quality control management. There are some other calibration methods such as response surface or F-race methods. Since most of the papers in the literature utilized the Taguchi method, this work is also applied this calibration algorithm.

Generally, the Taguchi method utilizes the comparison properties based on two main categories: control and noise factors. To get the objective of calibration, Taguchi mainly adopts the values of response variation based on the signal to noise ration (S/N). Accordingly, the following formula is considered to compute this metric:

$$S/N = -10\times\log\left(\frac{\sum_{i=1}^{n} Y_i^2}{n}\right) \tag{29}$$

where n specifies the number of orthogonal arrays. Y_i can be defined as the response value for ith orthogonal array. Regarding the applied assessment metrics of the Pareto optimal frontier, the convergence and diversity of the metrics are two main concepts to use. From the following equation, we define MCOV by considering, the MID metric measuring the convergence rate as well as MS metric calculating the diversity of algorithms' solutions (Fathollahi-Fard et al., 2018).

$$MCOV = \frac{MID}{MS} \tag{30}$$

In this paper, six versions of SA *i.e.*, a general idea and five modifications are utilized. From the Taguchi methodology, the parameters of algorithms are the counterpart of the factors in each treatment. Table 4 provides the suggested levels for each factor to calibrate the algorithms. In this regard, maximum three levels are assumed. Regarding the tuning with the help of orthogonal arrays, Taguchi method cuts down the number of experiments. In this regard, Taguchi offers L_{18} for both SA and MSA_{V1}. L_9 is also applied for rest of modifications including MSA_{V2}, MSA_{V3}, MSA_{V4} and MSA_{V5}.

Due to the page limitation, the results of *S/N* ratio and MCOV for the algorithms are not reported. Finally, the tuned parameters for all algorithms are illustrated in Table 5.

5.4. Accreditation of presented algorithms by using epsilon constraint method

Commonly, the metaheuristics results must be validated, then

Table 4
The algorithms' collaborations by considered factors and their suggested levels.

Algorithm	Factor	Levels		
		1	2	3
SA and MSA_{V1}	A: Maximum iteration (*Maxit*)	1000	1500	–
	B: Sub-iteration (*Subit*)	10	20	30
	C: Used methodology of local search (T_m)	Swap	Reversion	Insertion
	D: Initial temperature (*T0*)	1000	1500	2000
	E: Rate of reduction (*R*)	0.85	0.9	0.99
MSA_{V2}, MSA_{V3} MSA_{V4} and MSA_{V5}	A: Maximum iteration (*Maxit*)	900	1200	1500
	B: Sub-iteration (*Subit*)	10	20	30
	C: Used methodology of local search (T_m)	Swap	Reversion	Insertion

Table 5
The tuned algorithms' parameters.

Algorithm	Parameters
SA	*Maxit=1200; Subit=20;* T_m*=Swap; T0=2000; R=0.99;*
MSA_{V1}	*Maxit=1200; Subit=30;* T_m*=Reversion; T0=2000; R=0.99;*
MSA_{V2}	*Maxit=1200; Subit=30;* T_m*=Reversion;*
MSA_{V3}	*Maxit=1500; Subit=30;* T_m*=Insertion;*
MSA_{V4}	*Maxit=1500; Subit=20;* T_m*= Reversion;*
MSA_{V5}	*Maxit=1500; Subit=30;* T_m*= Reversion;*

the comparison can be performed (Safaeian et al., 2019). Considerably, the original version of the Epsilon Constraint (EC) is applied to get this target. This approach was firstly offered by Haimes et al. (1971) to evaluate the multi-objective optimization problems. The structure of the EC is modeled by only one objective to be optimized and the other objectives as the constraints by considering allowable bounds (Fathollahi-Fard et al., 2018). Hence, the Pareto optimal solutions will be made by generating the objective bounds. Therefore, the following model is presented to illustrate the framework of this methodology:

$$\begin{aligned} &\min Z_1 \\ &s.t. \\ &Eq.(3)-(22) \\ &Z_2 \le \varepsilon \\ &Z_2^{min} \le \varepsilon \le Z_2^{max} \end{aligned} \tag{31}$$

With regards to the above formula, the optimal value for the first objective function (Z_1) is found. Next, the positive (Z_2^{min}) and negative (Z_2^{max}) idea solutions for the second objective function should be reached. In addition to these two solutions, the allowable bound (ε) is also considered the average point between them $((Z_2^{min}+Z_2^{max})/2)$. Finally, three non-dominated solutions will be existed by checking all these generated solutions.

In addition to the development of EC, the tuned metaheuristics are employed to solve the test problems. Table 6 reveals the Pareto optimal solutions in a small test problem for both exact and metaheuristic algorithms. To make the comparison easier, the algorithms' solutions are sorted in the provided table. Regarding the Pareto frontier of EC, the solutions of metaheuristic approaches are checked. Accordingly, the non-dominated solutions of each metaheuristic by considering the non-dominated solutions of EC are

Table 6
Algorithms' Pareto solutions resulted in the test problem SP1.

Number	EC		SA		MSA_{V1}		MSA_{V2}		MSA_{V3}		MSA_{V4}		MSA_{V5}	
	Z_1	Z_2	Z_1	Z_2	Z_1	Z_2	Z_1	Z_2	Z_1	Z_2	Z_1	Z_2	Z_1	Z_2
1	**10001**	2695	**10253**	2720	**10146**	2864	**10819**	2815	**10067**	2791	**10320**	2698	**10860**	2678
2	11432	2552	10710	2714	10310	2810	11128	2776	11615	2766	10526	2647	10954	2612
3	12970	**2509**	10836	2712	10395	2786	11248	2762	12018	2718	10785	2591	11037	2603
4	-	-	11786	2696	10606	2714	11440	2722	12151	2650	10921	2566	11258	2589
5	-	-	11913	2675	11415	2650	12659	**2712**	12237	2589	11035	2528	11317	2575
6	-	-	12919	**2672**	11931	2586	-	-	12655	2536	11268	**2509**	11592	2546
7	-	-	-	-	12170	**2523**	-	-	12662	**2510**	-	-	11861	**2530**

Table 7
Validation of algorithms' Pareto solutions with modified number of non-dominated solutions and its percentage based on EC method.

Test problem	SA		MSA_{V1}		MSA_{V2}		MSA_{V3}		MSA_{V4}		MSA_{V5}	
	MNPS	MNPS/NPS	MNPS	MNPS/NPS	MNPS	MNPS/NPS	MNPS	MNPS/NPS	MNPS	MNPS/ NPS	MNPS	MNPS/ NPS
SP1	0	0	2	0.33	0	0	2	0.28	5	0.83	6	**0.85**
SP2	1	0.12	2	0.25	3	0.42	3	0.33	3	0.37	4	**0.44**
SP3	2	0.28	1	0.11	2	0.25	3	0.3	4	**0.44**	4	0.4
SP4	2	0.22	3	0.33	3	**0.42**	4	0.36	3	0.33	3	0.27
MP5	3	0.3	2	0.22	2	0.25	3	0.3	5	**0.55**	4	0.4
MP6	2	0.22	2	0.2	3	0.33	4	0.5	4	0.44	5	**0.62**
Average		0.19		0.24		0.27		0.34		**0.49**		**0.49**

Table 8
Computational results based on NPS metric.

Test problem	SA	MSA_{V1}	MSA_{V2}	MSA_{V3}	MSA_{V4}	MSA_{V5}
SP1	7	7	5	8	6	7
SP2	9	9	7	10	8	9
SP3	7	10	8	11	9	10
SP4	9	9	7	10	9	11
MP5	10	9	8	11	9	10
MP6	9	10	9	9	9	8
MP7	10	8	10	10	9	10
MP8	11	9	8	9	9	10
LP9	12	11	9	11	11	10
LP10	10	10	9	12	10	12
LP11	11	9	10	10	10	10
LP12	9	6	8	9	8	10

highlighted. Consequently, for the rest of test problems, the performance of Pareto frontier of the algorithms would be analyzed. Therefore, the modified number of Pareto solution (MNPS) and its successful percentage *i.e.* $\frac{MNPS}{NPS}$ have been calculated. Accordingly, the results are provided in Table 7. Notably, the higher value of $\frac{MNPS}{NPS}$ confirms the better capability of algorithm's solutions.

Based on the results, SA shows a weak performance while MSA_{V4} and MSA_{V5} reveal a high-performance validation of their solutions. Moreover, according to the time computation, although EC needs 2319 s for MP6. The maximum time among the meta-heuristic is reported as 460 s. As a result, the proposed algorithms generally can be recommended for the large instances. At the end, the presented modifications are completely validated as seen in Table 7.

Table 9
Computational results based on MID metric.

Test problem	SA	MSA_{V1}	MSA_{V2}	MSA_{V3}	MSA_{V4}	MSA_{V5}
SP1	3.9089	2.7834	3.9089	2.3656	3.2417	2.80365
SP2	2.3264	2.9856	3.7623	2.1409	2.8038	2.47235
SP3	2.1379	3.5849	7.8549	3.0635	4.1603	3.1491
SP4	5.4977	4.2781	6.2716	4.6701	5.179375	4.728738
MP5	3.2147	3.5903	3.9504	2.9635	3.429725	3.196613
MP6	5.0322	2.5784	7.9413	5.7248	5.319175	3.948788
MP7	4.8199	5.0439	5.6588	7.3716	5.72355	5.271725
MP8	4.9755	3.1685	8.0392	4.5463	5.182375	4.175438
LP9	5.1396	4.2894	5.1675	6.8472	5.360925	4.825163
LP10	5.8434	3.1503	6.9328	3.6925	4.90475	4.027525
LP11	8.2262	5.8627	7.1453	5.7481	6.745575	6.246838
LP12	8.0259	6.0591	5.8625	2.6435	5.64775	4.145625

5.5. Comparison of employed modifications

Here, a comparative study based on the four assessment metrics are reported to consider the effectiveness and efficiency of the proposed modifications. In this comparison, the average during thirty run times are achieved to consider the results more reliable. Based on the time consumption of the algorithms, there is a little difference between the performances of the algorithms. The run time of modifications are in a same range based on the size of test problem. Therefore, their results are not reported here.

As mentioned before, the effectiveness and efficiency of the algorithms are assessed by the evaluation metrics of the Pareto optimal sets *i.e.*, NPS, MID, SNS and MS, for each test problem. Their results are given by Tables 8–11.

Fig. 10 reveals a simplified instance of the non-dominated solutions for an example *e.g.*, MP8. What can be envisaged at the first glance of this figure pinpoints that there are some striking similarities between the algorithms specifically between MSA_{V4} and MSA_{V5}. Regarding the figure, although MSA_{V1} and MSA_{V2} reveal the worst effectiveness and efficiency among the algorithms. As such, MSA_{V3} mostly overcome the other algorithms. Furthermore, SA reaches an area with lowest cost and highest environmental

Table 10
Computational results based on MS metric.

Test problem	SA	MSA_{V1}	MSA_{V2}	MSA_{V3}	MSA_{V4}	MSA_{V5}
SP1	199573.8	279855.99	261272.52	322971.24	265918.4	294444.8
SP2	371253.15	500187.3	477299.61	583346.08	483021.5	533183.8
SP3	536673.68	631031.38	605645.92	674618.163	611992.3	643305.2
SP4	611408.12	610550.85	683716.45	756024.795	665425.1	710724.9
MP5	859254.95	739449.25	877052.63	894850.313	842651.8	868751
MP6	788505.79	1265849.6	1024970.31	1261434.82	1085190	1175520
MP7	978534.4	1014281.7	1016216.79	1053899.18	1015733	1034816
MP8	946732.69	1046694.8	991195.13	1035657.58	1005070	1025882
LP9	1418253.75	1152504.2	1462375.14	1506496.52	1384907	1445702
LP10	1429147.7	1456494.1	1589766.76	1750385.81	1556449	1653417
LP11	982579.05	1485237.5	1325328.39	1668077.74	1365306	1516692
LP12	1702201.3	1561655.2	1644006.48	1585811.66	1623419	1662810

Table 11
Computational results based on SNS metric.

Test problem	SA	MSA_{V1}	MSA_{V2}	MSA_{V3}	MSA_{V4}	MSA_{V5}
SP1	363533.66	324194.39	353683.66	284855.12	331566.7	347550.2
SP2	700352.33	693547.18	699981.33	686742.02	695155.7	697754
SP3	1091855.54	1036584.9	1089612.5	981314.18	1049842	1070849
SP4	1702788.11	1551823.2	1700420.1	1400858.3	1588972	1645880
MP5	2360089.14	2248145	2355835.1	2136201	2275068	2317578
MP6	2707964.92	2647039.1	2701689.9	2586113.3	2660702	2684333
MP7	3225718.13	3096438.6	3219535.1	2967159	3127213	3176465
MP8	3969656.49	3844213.7	3963876.5	3718771	3874129	3921893
LP9	5842456.34	5626115.4	5840232.3	5409774.5	5679645	5761050
LP10	6212492.49	5957651.4	6210873.5	5702810.3	6020957	6116725
LP11	6190238.64	6117121.2	6185450.6	6044003.8	6134204	6162221
LP12	6807157.37	6563369	6801526.4	6319580.6	6622908	6715033

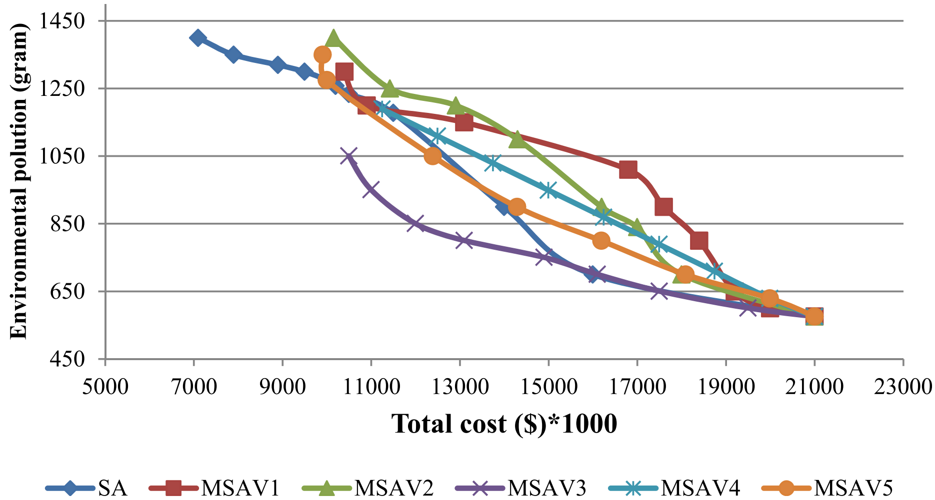

Fig. 10. Pareto frontier of presented algorithms in MP8.

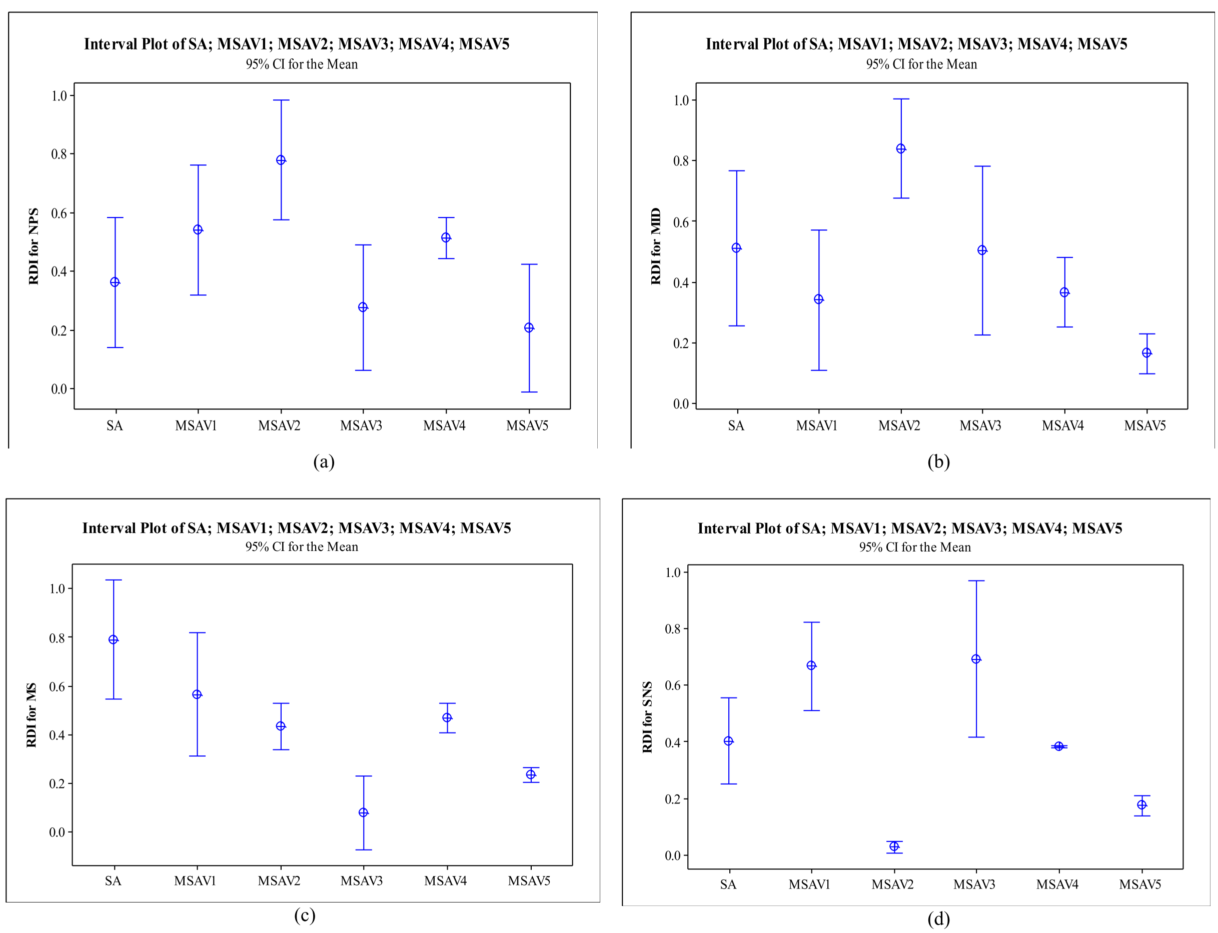

Fig. 11. Interval plots and LSD for comparison of algorithms based on the evaluation metrics (*i.e.* (a) for NPS, (b) for MID, (c) for MS and (d) for SNS).

pollution. Overall, the rest of the algorithms' solutions are close and same to each other.

At the last but not the least, some statistical analyses are done to find the best algorithm. Regarding the natural stochastic of SAs, the results reported in Tables 8–11 are transformed to Relative Deviation Index (RDI) to be reliable as follows:

$$RDI = \frac{|Alg_{sol} - Best_{sol}|}{Max_{sol} - Min_{sol}} \tag{32}$$

where Alg_{sol} is the value outputted by the measurement metrics. As such, Max_{sol} and Min_{sol} are the worst and the best solutions in a minimization case, respectively. $Best_{sol}$ is the best solution ever found. Notably, the lower value of *RDI* is better. To show the analyses, the interval plot by using the means values and the Least Significant Difference (LSD) for all modifications and the general SA are provided in the results run by *Minitab* software as can be seen in Fig. 11.

Generally, what can be seen at first glance of Fig. 11 is that we face a mixed performance for each comparison's item of SA and the modification algorithms. According to the Fig. 11(a), based on *NPS*, first of all, although MSA_{V5} shows the best solution's quality, its range is varied so much. In this regard, among the algorithms, the solutions of MSA_{V4} show a robust behavior and are more reliable than others. Furthermore, the quality of MSA_{V2} indicates a weak performance. It should be noted that only our modifications *i.e.* MSA_{V3} and MSA_{V5} show a better performance in comparison to general SA. Fig. 11(b) also demonstrates all modifications except MSA_{V2} show a better robust behavior compared to SA in the term of MID. Regarding the figure, MSA_{V5} shows the best performance and is the most reliable output in the MID metric. For the MS metric (Fig. 11(c)), this point view is more complete. In this regard, SA has the weakest algorithm in this item. MSA_{V5} pinpoints an idle robust behavior and MSA_{V3} is the best quality in MS metric. Contrary to three mentioned metrics, the outputs of SNS metric (Fig. 11(d)) are so different. As such, MSA_{V2} has the best performance and shows a better quality. Similarly, the quality of MSA_{V5} is close to MSA_{V2}. In addition, MSA_{V4} pinpoints to an idle reliable form of algorithms. Furthermore, MSA_{V3} is the worst algorithm in this item. What can be concluded from the above metrics is that the MSA_{V5} can be the best modification that shows a better quality and a mixed performance compared to general SA and other modifications.

5.6. Sensitivity analyses on the developed GHHCSC model

To analyze the proposed GHHCSC model, some sensitivity analyses are required. Accordingly, SP2 as one of smallest test problems, by assuming four pharmacies and laboratories with their caregivers, three types of transportation systems and forty patients are chosen in a four-day planning horizon. To handle the model, the best modified SA algorithm, that is, MSA_{V5} is utilized. To find a solution among all Pareto candidate frontiers, MID metric is utilized to select a solution which has the lowest distance with ideal solutions compared to the rest of non-dominated solutions. Some sensitive parameters are selected to perform a set of changes. They are: the impact of penalty value for overall traveling distance (*PEN*), the number of caregivers for the pharmacies (N_p), the number of distributed patients (M) and the maximum desired number of pharmacies and laboratories (*MAX*) and also the types of applied transportation system (K) for the developed GHHCSC problem. Four cases are considered and numbered as C1 to C4 for each analysis. Eventually, the provided results are given by Tables 12–16 and also Figs. 12–16.

As illustrated earlier, the penalty value of extra traveling distance (*PEN*) help the model to do the travel balancing. By changing the value of this parameter, some sensitivity analyses are reported and summarized in Table 12. The objectives functions are noted by Total Cost (TC) as the first objective and Environmental Pollution (EP) as the second one. To have a better analyses, the normalized

Table 12
Sensitivity analyses on the penalty value.

Number of cases	*PEN*	*TC*	*EP*
C1	1.5	10959	345.196
C2	2.5	12292.33	345.196
C3	3.5	13625.67	345.196
C4	4.5	14959	345.196

Table 13
Sensitivity analyses on the number of caregivers.

Number of cases	N_p	*TC*	*EP*
C1	3	9875	318.854
C2	4	10959	345.196
C3	5	11576.28	378.54
C4	6	11576.28	378.54

Table 14
Sensitivity analyses on the number of distributed patients.

Number of cases	*M*	*TC*	*EP*
C1	30	10546.837	332.685
C2	40	10959	345.196
C3	50	14876	426.57
C4	60	17076	537.898

Table 15
Sensitivity analyses on the established sites number.

Number of cases	*MAX*	*TC*	*EP*
C1	1	10486.724	330.145
C2	2	10959	345.196
C3	3	12168	366.817
C4	4	15721	387.918

Table 16
Sensitivity analyses on the applied vehicles types.

Number of cases	*K*	*TC*	*EP*
C1	3	10959	345.196
C2	4	11759	321.483
C3	5	17876	287.547
C4	6	19076	239.811

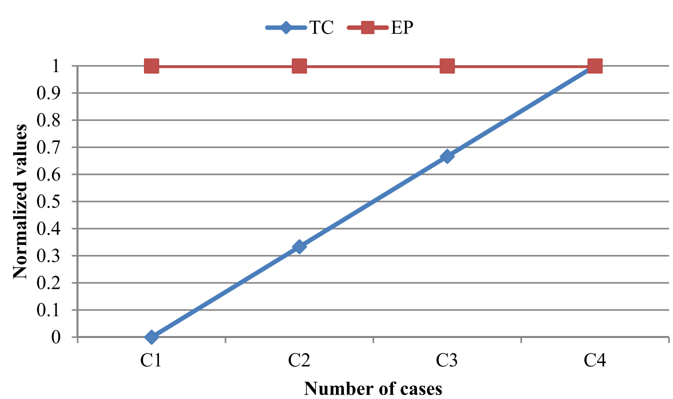

Fig. 12. Sensitivity analyses on the behavior of both objective functions regarding the penalty value.

values are computed and depicted by Fig. 12. Generally speaking, the findings states that the main effect of this parameter is on the total cost. When this parameter increases, the total cost will be increased. However, there is no effect on the green emissions as the second objective function.

Additionally, the number of employed caregivers (N_p) is assessed by some sensitivity analyses. The provided outputs are given in Table 13. In addition, both objective functions are analyzed and depicted in Fig. 13. While the number of caregivers increases, both the total cost and environmental pollution show a growth, similarly. Consequently, their behaviors are robust with a little

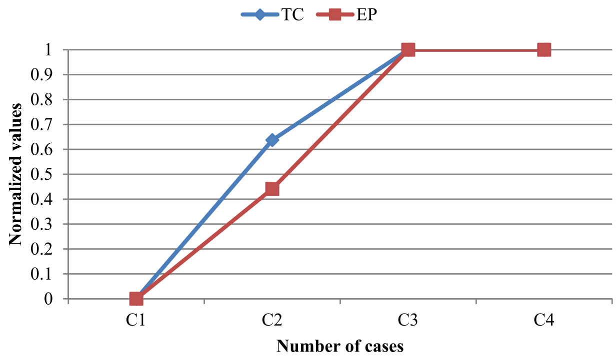

Fig. 13. Sensitivity analyses on the behavior of both objective functions regarding the number of employed caregivers.

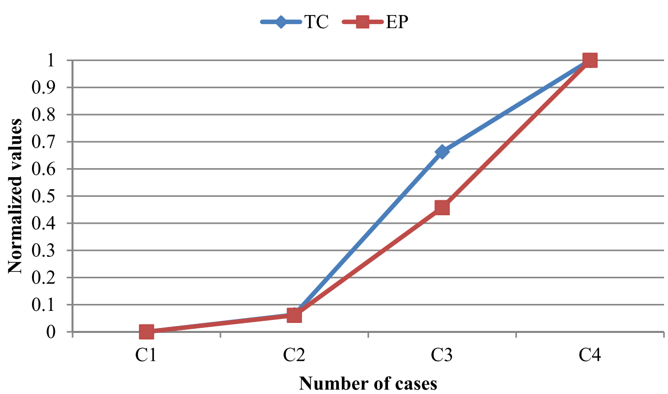

Fig. 14. Sensitivity analyses on the behavior of both objective functions regarding the number of distributed patients.

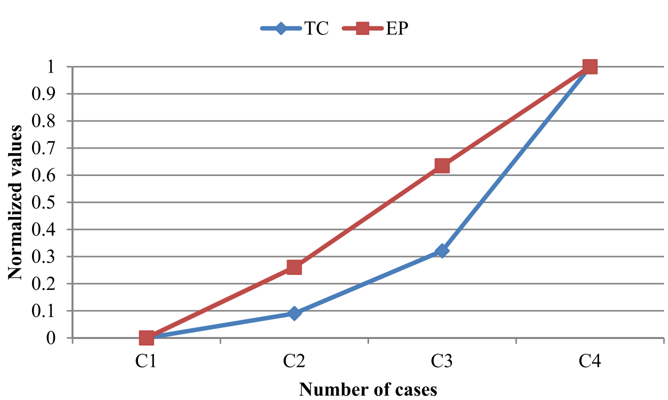

Fig. 15. Sensitivity analyses on the behavior of both objective functions regarding the number of established sites.

change. Accordingly, the number of tours for visiting of patients shows an increase at first. Next, their behaviors are fixed. Based on the behavior of objective functions, an additional caregiver may be not suitable to satisfy all patients.

Furthermore, the number of distributed patients (M) is considered according to the problem complexity in Table 2. The distributed patients' number are analyzed by some sensitivity analyses. In this regard, the results are provided in Table 14. As such, both objective functions' behavior are normalized as can be seen in Fig. 14. Clearly, an increase can be seen for both objective functions. Meanwhile, the number of distributed patients is increased. The main reason refers to the length of tours for the patients' visit

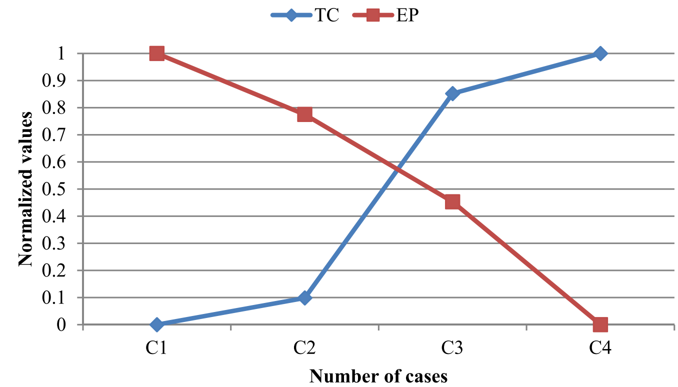

Fig. 16. Sensitivity analyses on the behavior of both objective functions for regarding the number of types of employed transportation systems.

which is not decreased.

Another main parameter is the maximum desired number of established sites for the facilities (MAX). The sensitivity analyses on this parameter are done and results are provided in Table 15. Additionally, the interaction between the objective functions using the normalized values is depicted decisively by Fig. 15. The results provided reveal some surprising similarities between the two objective functions. Generally, an increase in the number of established sites is likely to an increase in the value of the total cost as well as the environmental pollution.

Generally, one of main contributions of this work is to consider the green emissions of the transportation systems. With regards to the number of vehicles types (K), the amount of this parameter is increased. The final results are given in Table 16. Similarly, Fig. 16 reveals the normalized behavior of the objective functions during the sensitivity analyses. Similar to the pervious experiments, the results reveal that there is some conflicting cases. While the environmental pollution is decreased, the total cost shows an increase, simultaneously. As the result, choosing a robust strategy to find an interaction between the total cost and environmental pollution is highly recommended. The transportation in the proposed GHHCSC model is so operational and significant from the economic aspect. However, the environmental pollution is a strategic decision for the present real-world. Generally speaking, the considered findings should be analyzed more for the proposed GHHCSC organizations regarding both academia and HHC contributors. The main managerial implications are concluded in the next section.

6. Managerial insights

Academically, an HHC decision-making model seeks to optimize the scheduling and routing of the caregivers using some vehicles independently, employing a simplified objective function. In many contexts; however, and perhaps most especially in the western countries where the management of ageing population is of particular concern, such a simplified approach to HHC management is failing to deliver satisfactory all sustainable outcomes. To do this end, more logistics factors for an HHC system is needed. The locations of pharmacies and laboratories as the fixed opening costs and the assignment of patients to pharmacies as the fixed cost of home care services are transformed an HHC to a complex HHCSC. The aim of this study is to develop an integrated framework for an HHCSC optimization that is practical and efficient. Practicality requires a multi-objective optimization process that accommodates all locations, allocation and routing decisions across a structured logistics network with intermediate facilities. Efficiency requires an algorithm to better solve this complex problem that is robust and computationally manageable.

The results of this study have demonstrated the viability of an HHCSC optimization with multiple objectives and complex constraints. With regards to the suppositions of time window, travel balancing, delivery time and green emissions, a GHHCSC is contributed for the first time. An MILP is applied to the GHHCSC problem and three new adaptive extensions to SA is also introduced. Among five modifications of SA algorithms, MSA_{V5} performs especially well given the particular problem definition. The problem definition itself is still somewhat simplified relative to the full scope and dynamics of all potential HHCSC problems in practice, but it does represent an order of magnitude more complexity than the vast majority of previous HHC problem definitions. Most notably, this study includes objective functions that accommodate the full scope of sustainable logistics for the optimization of HHCSC. The efficiency of the proposed modifications especially MSA_{V5} in this context also lend a great encouragement to the broader adoption and application of the SA in this research area as already successfully applied to similar HHC problems.

In addition to the technical contribution of this study to the development of an efficient and robust method for multi-objective optimization, the application and testing of different modified SA algorithms to a more representative GHHCSC problem framework reveals new operational management highlights. The principal highlight is to confirm the future tractability of GHHCSC problem optimization in practice when a LAR strategy is adopted. It is now credible to claim that the multiple sustainable objectives combined with dynamic constraints that characterize practical HHC problems can be optimized in an efficient way.

Whilst the primary goal of this study is to develop an integrated framework for an HHCSC optimization that is practical and efficient, a number of insights into the dynamics of GHHCSC for practice have emerged in the process. The problem definition as a multi-period and multi-depot makes the model more realistic. One significant insight is that the conceptual shift from HHC management to GHHCSC entails a practical solution to better design of logistics networks of an HHC organization. This study demonstrates that the introduction of sustainable logistics options through the use of multiple pharmacies and laboratories, right assignment of patients and the scheduling and routing of caregivers during different period times, analyzing the biological samples at laboratories to update the patients' health records creates the strong potential for added value across all HHC organizations to cover the social responsibilities (ISO26000). Considering the amount of CO_2 emissions through different transportation systems as well as these emissions during the establishment of pharmacies and laboratories are of particular significance for HHC organizations due to recent advances of environmental assessment (ISO14000).

Other practical insights include the dynamic sensitivity of the objective functions relative to changes in key parameters illustrated in Figs. 12–16. Most especially, the volatility of the total cost and the environmental pollution to variations in the employed transportation systems shown in Fig. 16, warrants further investigation and consideration. As such, analyzing different modifications of SA by using NPS, MID, SNS and MS assessment metrics of Pareto frontier confirm that MSA_{V5} is generally better than other modified algorithms as seen in Fig. 11.

Finally, the fact that such practical insight is possible when a more reasonable GHHCSC framework is addressed strongly encourages further application and development of high-efficiency algorithms, such as the proposed modified algorithm for practice. The potential utility of an integrated framework of GHHCSC for routing optimization of the caregivers for more effective decision-making is demonstrably high. The key parameters included in this study are clearly significant factors for consideration in practice. No doubt other parameters of equivalent significance could also be identified with further study. Certainly, the nature of the GHHCSC problem demands other parameters and fuzzy or stochastic treatments of parameters become an important direction for further research in this field.

7. Conclusion and future remarks

In this paper, a LAR strategy was applied to design a Green Home Health Care Supply Chain (GHHCSC) for the first time. The proposed novel formulation aimed at addressing the total cost of system and environmental pollution. To solve this new framework for HHC organizations, different versions of SA were employed. Three new formulas for accepting rule to update the probability for accepting a new solution according to the number of iteration were firstly proposed to create a better balance between the exploration and exploitation phases. The calibration of proposed SA algorithms was done by Taguchi method to have a fair comparison. The algorithms were also validated by the epsilon constraint method to check the quality of non-dominated solutions. Additionally, according to the developed bi-objective model, four evaluation metrics including NPS, MID, SNS and MS were employed to examine the algorithms, decisively. Regarding the results, it is evident that the performance of modifications especially the fifth version of SA (MSA_{V5}) is high compared to other proposed modifications. To analyze the key parameters of the model, some sensitivity analyses are done to assess the efficiency of proposed GHHCSC. Finally, a comprehensive discussion about the managerial implications of results are provided.

There are some new directions as the continuations of this work. First of all, more comprehensive analyses by using a real case study in one of developed countries for the offered GHHCSC are required to be investigated. Secondly, the developed modifications of SA can be applied to address other real scale optimization problems. Researchers can also develop some other modifications of SA. For example, modifications of SA to change the strategy of the local searches can be suggested. Moreover, the developed GHHCSC can be extended by some new suppositions. For example, the patients' satisfaction can be considered as another individual objective function. As such, considering the synchronization of the services and working time balancing of the caregivers as well as the electronic vehicles are some good contributions for future works of proposed GHHCSC.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2019.118200.

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