Home Health Care Network Management Under Fuzzy Environment Using meta-heuristic algorithms

Fariba Goodarzian[1], Aida Goodarzian[1], Ajith Abraham[1], Sohaib Dastgoshade [2]

[1]Machine Intelligence Research Labs (MIR Labs), Scientific Network for Innovation and Research Excellence, 11, 3rd Street NW, P.O. Box 2259. Auburn, Washington 98071, USA
[2]Department of Industrial Engineering, Yazd University, Yazd, Iran
fariba.goodarzian@mirlabs.org; ajith.abraham@ieee.org; eyedagoodarzian@gmail.com; Sohaib.dastgoshade@stu.yazd.ac.ir

Abstract
Home Health Care (HHC) Services is an alternative to hospitalization, which plays an important role in reducing hospital costs for patient care costs. Also, resource planning and routing problems are among the most important problems that need to be addressed when planning home health care resources. Home health care scheduling problem is a combination of the generalization of vehicle routing problem with the time window and the employee planning problem, which ultimately aims to identify and allocation tasks to therapists, taking into account time windows for patients and employee preferences while the best routes are identified. In this paper, we presented a bi-objective model in the planning horizon of more than one day in order to reduce system costs and increase employee satisfaction simultaneously. In addition, the routing-allocation-scheduling-planning of home health care problem is of NP-hard problem. Meanwhile, we use a fuzzy approach to cope with this uncertainty due to the uncertain nature of transportation and travel cost parameters in the routing-allocation-planning of HHC problem. To solve this model in different sizes, we used meta-heuristic algorithms.

Keywords: Home health care, Meta-heuristic algorithms, Fuzzy environment

1 Introduction

With the advancement of medical and healthcare in recent years, we often face with an increase in the number of elderly people, and since these elderly people need different care, the need to improve the performance of these care centres are increasing day by day. In these situations, more elderly people prefer to live in their homes instead of living in care centres for the elderly, and receive the care and treatment they need. Therefore, the older the population grows, the demand for HHC services will also increase. On the one hand, HHC is a unique part of health care that has been little attention in the past, and the industry faces challenges that another industry is not facing and, on the other hand, organizations that provide home care services should be able to optimize their activities in order to meet increasing demand. Recently, we are witnessing the importance of planning and determining the route for therapists in HHC centers for therapists and ignoring them will lead to higher costs, which is of great importance to those involved, such as researchers, doctors and policymakers [1, 23].

In the HHC operations, therapists are planning in a way and determine the route, which provides a variety of services at the customer home. Because this requires a combination of vehicle routing, synchronization, work-time balance, and time planning approaches, as a result, there will be complex optimization problems. The HHC system can be considered as a health service network that includes patients, people involved in logistics (coordinator for the evaluation of material and human needs, pharmacy), HHC sponsor companies (health insurance) and the HHC group (nurses, doctors, therapists, and others) [25].

This paper is intended to provide a routing-allocation-scheduling-planning model with time windows, synchronization, and work-time balance, in which the travel cost and therapists' travel, which is one of the most important costs of the system, is minimized and the satisfaction of therapists is maximized by allocation and planning. Finally, with optimization aiming to reduce costs and increase the satisfaction of therapists, the model will determine the best routes and the best time schedule for each therapist to provide therapists with satisfaction with planning according to their personal and desirable lifestyle programs, as well as the cost of transportation, which is one of the most important costs of HHC centers. In addition, we use a fuzzy approach to cope with this uncertainty due to the uncertain nature of transportation and travel cost parameters. Therefore, due to the NP-hard and complexity of the model, we used multi-objective meta-heuristic algorithm and the results of this algorithm are compared with other meta-heuristic algorithms for different sizes of the problem.

The structure of the paper is as follows: In the next section of this paper, we first review the review of the literature on HHC and uncertainty approach. In Sections 3, the problem is described and its definitive model is described and devoted to the approach to uncertainty and the mathematical model in uncertainty. In Section 4 the solution methods are described. In Section 5, addresses the computational and validation results of the proposed model. Finally, the conclusions and future research fields are presented in Section 6.

2 literature review

The review of the literature on HHC is very new, the number of papers in this area is estimated to be less than 40, and this number has been moving much forward in recent decades, indicating the need for further review. Table 1 presents an overview of the characteristics of the models used and their solving methods.

Table 1. Summary of literature review

Reference	Multi-objective	Single-objective	Fuzzy	Time windows	Scheduling	Planning	Allocation	Routing	method
[2]	-	√	-	√	√	-	-	√	Exact
[3]	-	√	-	√	√	-	-	√	VNS
[4]	-	√	-	√	√	-	-	√	Exact
[5]	-	√	-	√	√	-	-	√	GA and TS
[6]	-	√	-	√	√	-	-	√	Heuristic
[7]	-	√	-	√	√	-	-	√	Heuristic

[8]	-	√	-	√	√	-	-	√	VNS
[9]	√	-	-	√	√	-	-	√	Heuristic
[10]	-	√	-	√	√	-	-	√	GA
[11]	-	√	-	√	√	-	-	√	GA and HSA
[12]	√	-	-	-	√	√	-	√	Heuristic
[13]	√	-	-	-	√	-	-	√	Ga and HGA
[14]	-	√	-	-	√	-	-	-	Heuristic
[15]	-	√	-	-	√	-	-	√	VNS
This paper	√	√	√	√	√	√	√	√	MOSEO, MOICA. NSGA-II

In general, according to the literature review, the summary of the results of Table 1 reveals a number of similarities and research gaps:

- Most developed models in this area can be considered as a type of vehicle routing with time windows.
- According to the strategic decision making in the field of health, which is directly related to the lives of patients, there are models which, in addition to the routing, location, scheduling, allocation and scheduling with time windows, synchronization and balance during work time, have not been considered.
- Developed methods have generally been based on heuristic and meta-heuristic algorithms.
- Assumptions such as considering different occupations of nurses, the variety of available vehicles and time window constraints have been used in many papers in recent years.

To solve the problems mentioned above and to bring these types of models closer to the real world, this paper aims to develop a new model for home health care problem. Hence, the scheduling-allocation-routing-scheduling problem with time windows, synchronization, and work-time balance were adopted to develop a comprehensive model for this problem. In addition, we use a fuzzy approach to cope with this uncertainty due to the uncertain nature of transportation and travel cost parameters. Another attraction of this paper is the use of different meta-heuristic algorithms.

3 Problem description and mathematical formulation

In this problem, a set of therapists should be given according to the program allocated to them in patient homes on specific days of the week and at the appointed time according to the time windows and with a specific route and service, they will refer and serve. Each customer needs to meet certain schedules in the planning horizon, and they must meet in certain hours (time windows). Each therapist also has definite working hours per day, as well as the number of specific days in each horizon for planning his working days, and, finally, specific days are the closing days where the number of these days is the same for all therapists. In order to increase the satisfaction of the therapist, he/she is given the right to set points prior to the start of the planning horizon, according to his own judgment, for each day, as the day it is more likely to be working on that day, the more points and fewer points to days that, according to their own preferences, tend to be less likely to work. In this regard, the planning horizon is flexible and can last for more than a day.

In this way, the planner considers these preferences before the start scheduling for the planning and allocation of therapists. Also, try to make as many as possible allocations are made in such a way that these privileges and thus the fulfillment of employee preferences, and thus increase their satisfaction to the highest possible level.

In summary, we allocated a set of therapists to a set of patients in the planning horizon of more than one day to maximize the satisfaction of these therapists. In addition, since these therapists need to serve the patients' homes, their best paths should be tailored to the time windows, synchronization and balance at work, and the cost of the system should be minimized.

3. 1 Assumption

Modeling assumptions are as follows:

- The number of therapists is fixed and does not change.
- There is no rest (interruption) in working hours.
- The number of working days for therapists is fixed and specific.
- There is a time window for patients' appointment.
- Each patient is only visited by one of the therapists.

3.2 Sets

N: Sets of patients

N_O: Sets of patients and points including point o and $n+1$. A virtual peak or healthcare center that therapists must start every day from a point o and refer to the homes of patients who were allocated to that day. After the completion, all the houses are back to the point $n+1$ and to the same health center will refer.

K: Sets of therapists

T: Sets of the number of planning horizon

3.3 Parameters

$\tilde{M}_{ikt}$: The service time at the patient's house i by the therapist K at the day t

D_{ij}: The distance between node i and node j

t_{ij}: Average time required (per hour) for arcing (travel time from patient's home i to patient's home j)

$\tilde{\lambda}_{kt}$: The privilege by the therapist K to their work day

$\tilde{\alpha}_j$: The earliest start of service at the patient's house j

$\tilde{\beta}_j$: The latest start of service at the patient's house j

$S:$ The number of working days of therapists in the planning horizon T

$L_{jt}:$ If the patient j appointments on request at day t 1, otherwise, then 0 (patient demand in the planning horizon)

$V:$ Maximum permissible hours for each therapist in the per day

3.4 Decision variable

$X_{ijkt}:$ If the therapist k at the day t goes from home i to home j to 1, otherwise 0

$U_{kt}:$ If the therapist k to the day t is allocated 1, otherwise 0

$R_{jkt}:$ The onset time of service at the patient's house j by staff k at the day t

The following model is an integer linear programming (ILP) model:

$$Min \sum_{(i,j)\in N_O} \sum_{k\in K} \sum_{t\in T} D_{ij}.X_{ijkt} \tag{1}$$

$$Max \sum_{k\in K} \sum_{t\in T} \tilde{\lambda}_{kt}.U_{kt} \tag{2}$$

$$\sum_{i\in N_O} \sum_{k\in K} X_{ijkt} = L_{jt} \quad \forall j \in N, \forall t \in T \tag{3}$$

$$\sum_{j\in N} X_{ijkt} = U_{kt} \quad \forall k \in K, \forall t \in T \tag{4}$$

$$\sum_{i\in N_o} X_{ijkt} - \sum_{i\in N_o} X_{ijkt} = 0 \quad \forall j \in N, \forall k \in K, \forall t \in T \tag{5}$$

$$X_{ijkt} \le U_{kt} \quad \forall (i, j) \in N_o, \forall k \in K, \forall t \in T \tag{6}$$

$$\sum_{t\in T} U_{kt} \quad \forall k \in K \tag{7}$$

$$\left(R_{ikt} + \tilde{M}_{ikt} + t_{ij} - R_{jkt}\right) \le \left(1 - X_{ijkt}\right) BigM \quad \forall (i, j) \in N_o, \forall k \in K, \forall t \in T \tag{8}$$

$$\left(R_{n+1,kt} - R_{okt}\right) \le V \quad \forall k \in K, \forall t \in T \tag{9}$$

$$\tilde{\alpha}_j \sum_{i\in N_o} X_{ijkt} \le R_{jkt} \le \tilde{\beta}_j \sum_{i\in N_o} X_{ijkt} \quad \forall j \in N,\ \forall k \in K, \forall t \in T \tag{10}$$

$$X_{ijkt} \in \{0,1\}\ \forall (i, j) \in N_o,\ \forall k \in K,\ \forall t \in T \tag{11}$$

$$U_{kt} \in \{0,1\}\ \ \forall k \in K,\ \forall t \in T \tag{12}$$

$$R_{jkt} \ge 0\ \ \forall I \in N_o,\ \forall k \in K,\ \forall t \in T \tag{13}$$

The objective function (1) shows the minimization of distance travelled by the therapists. The objective function (2) expresses the maximization of employee satisfaction. Constraint (3) ensures that all patients are served according to a pre-determined demand. Constraint (4) shows each therapist leaves the HHC center only once when allocated to the workday. Constraint (5) indicates if a therapist enters a patient's home, will be out of there. Constraint (6) states that if a therapist assigns to a specific day, the therapist will be able to perform the services on that day. Constraint (7) defines the number of working days for each therapist. Constraint (8) indicates the initiation of the therapist's service at the patient's home. The maximum hourly per day for each therapist is determined in Constraint (9). Constraint (10) implies that the patient should be served at the time window set for that patient. Constraints (11) - (13) show the structure of decision variables.

3.5 Fuzzy model

In this section, the mathematical model presented in this paper is an integer programming model. Since in the real world of uncertainty an inevitable factor is inevitable, most of the parameters used are considered triangular fuzzy numbers because of their uncertain nature. In general, the fuzzy programming problem must first be transformed into a definite equivalent problem and then solved with standard methods and the optimal solution is obtained. As a result, the final solution of the problem is obtained with respect to the fuzzy structure of the problem.

In the following, to solve the model, a two-step approach has been used: In the first step, the proposed model with fuzzy parameters is transformed into a certain auxiliary model by Khimens et al. [16] method. In the second stage, using the Torabi-Hosseini method [17, 24], we solve the multi-objective certain model, which was obtained in the first stage.

3.5.1 Khimens method

The Khimens presented a method for ranking fuzzy numbers. In this method, defining the fuzzy parameters of the objective functions is calculated based on the concepts of expected distance and expected value for triangular fuzzy numbers $\tilde{c} = \left(c^p, c^m, c^o\right)$ according to Eqs. (14) and (15).

$$EI(\tilde{c}) = \left[E_1^c, E_1^c\right] = \left[\int_0^1 f_c^{-1}(x) d_x \, , \int_0^1 g_c^{-1}(x) d_x \, , \right] = \left[\int_0^1 \left(x\left(c^m - c^p\right) + c^p\right) d_x \right] = \left[\int_0^1 \left(x\left(c^o - c^m\right) + c^o\right) d_x \right] = \left[\frac{1}{2}\left(c^p + c^m\right), \frac{1}{2}\left(c^m + c^o\right)\right] \quad (14)$$

$$EV(\tilde{c}) = \frac{E_1^c + E_1^c}{2} = \frac{c^p + 2c^m + c^o}{4} \quad (15)$$

Based on Khaminz's method, Eq. (16) is considered for constraint $\left(\tilde{a}_i X \geq \tilde{b}_i, \; i = 1, 2, ..., I\right)$.

$$\left(\alpha \frac{a_i^o + a_i^m}{2} + (1-\alpha) . \frac{a_i^p + a_i^m}{2}\right) X \geq \left(\alpha \frac{b_i^o + b_i^m}{2} + (1-\alpha) . \frac{b_i^p + b_i^m}{2}\right) \quad (16)$$

For equal constraints $\tilde{a}_i X = \tilde{b}_i, i = 1, 2, ..., I$ converted into the certain equivalent constraints, are represented as Eqs. (17) and (18):

$$\left(\frac{\alpha}{2}\frac{a_i^o + a_i^m}{2} + \left(1 - \frac{\alpha}{2}\right).\frac{a_i^p + a_i^m}{2}\right)X \geq \left(\frac{\alpha}{2}\frac{b_i^o + b_i^m}{2} + \left(1 - \frac{\alpha}{2}\right).\frac{b_i^p + b_i^m}{2}\right) \quad (17)$$

$$\left(\left(1 - \frac{\alpha}{2}\right).\frac{a_i^o + a_i^m}{2} + \frac{\alpha}{2}.\frac{a_i^p + a_i^m}{2}\right)X \geq \left(\left(1 - \frac{\alpha}{2}\right).\frac{b_i^o + b_i^m}{2} + \frac{\alpha}{2}.\frac{b_i^p + b_i^m}{2}\right) \quad (18)$$

After Dfuzzy by the help of Eq. (15), the membership function for the minimization objective function is obtained using the Torabi-Hessian method of Eq. (19).

$$\mu_F = \begin{cases} 1 & if\ Z < Z^{\alpha-PIS} \\ \dfrac{Z^{\alpha-NIS} - Z}{Z^{\alpha-NIS} - Z^{\alpha-PIS}} & if\ Z^{\alpha-PIS} < Z < Z^{\alpha-NIS} \\ 0 & if\ Z > Z^{\alpha-NIS} \end{cases} \quad (19)$$

And the membership function for the maximization objective function is obtained using equation (20).

$$\mu_F = \begin{cases} 1 & if\ Z > Z^{\alpha-PIS} \\ \dfrac{Z^{\alpha-NIS} - Z}{Z^{\alpha-PIS} - Z^{\alpha-NIS}} & if\ Z^{\alpha-NIS} \leq Z \leq Z^{\alpha-PIS} \\ 0 & if\ Z > Z^{\alpha-NIS} \end{cases} \quad (20)$$

In which the positive ideal solution $(\alpha - PIS)$ and the negative ideal solution $(\alpha - NIS)$ for each objective function and at the level of feasibility (α). According to the above equations, the formulation of a certain auxiliary model is equivalent to the main problem model in Equations (21) - (27).

$$Min \sum_{(i,j)\in N_O} \sum_{k\in K} \sum_{t\in T} D_{ij}.X_{ijkt} \quad (21)$$

$$Max \sum_{k\in K} \sum_{t\in T} \left(\frac{\tilde{\lambda}_{kt}^p + 2\tilde{\lambda}_{kt}^m + \tilde{\lambda}_{kt}^o}{4}\right).U_{kt} \quad (22)$$

Constraints (3)-(7) (23)

$$\left(R_{ikt} + \left(\left(\frac{\alpha}{2}\frac{\tilde{M}_{ikt}^p + \tilde{M}_{ikt}^m}{2}\right) + \left(1 - \frac{\alpha}{2}\right)\frac{\tilde{M}_{ikt}^o + \tilde{M}_{ikt}^m}{2}\right) + t_{ij} - R_{jkt}\right) \leq \left(1 - X_{ijkt}\right)BigM \quad \forall(i,j) \in N_o, \forall k \in K, \forall t \in T \quad (24)$$

$$\left(R_{n+1,kt} - R_{okt}\right) \leq V \quad \forall k \in K, \forall t \in T \quad (25)$$

$$\left(\left(\frac{\alpha}{2}\frac{\tilde{\alpha}_j^p+\tilde{\alpha}_j^m}{2}\right)+\left(\left(1-\frac{\alpha}{2}\right)\frac{\tilde{\alpha}_j^o+\tilde{\alpha}_j^m}{2}\right)\right)\sum_{i\in N_o}X_{ijkt}\le R_{jkt}\le\left(\left(\frac{\alpha}{2}\frac{\tilde{\beta}_j^p+\tilde{\beta}_j^m}{2}\right)+\left(\left(1-\frac{\alpha}{2}\right)\frac{\tilde{\beta}_j^o+\tilde{\beta}_j^m}{2}\right)\right)\sum_{i\in N_o}X_{ijkt} \quad (26)$$
$$\forall j\in N,\ \forall k\in K, \forall t\in T$$

$$\text{Constraints (11)-(13)} \quad (27)$$

4 Solution methods

Multi-objective optimization is one of the most active and highly applied research areas among optimization topics. So far, several methods have been proposed for solving multi-objective optimization problems, among which intelligent optimization methods have a special place. In this paper, the proposed model has been used of meta-heuristic algorithms are including multi-objective imperialist competitive algorithm (MOICA), non-dominated sorting genetic algorithm II algorithm (NSGA-II) and multi-objective social engineering optimization (MOSEO) algorithm.

4.1 Multi-objective imperialist competitive algorithm

Imperialist Competitive Algorithm (ICA) proposed by Atashpaz-Gargari and Lucas [18] is utilized, to solve the proposed problem. MOICA is a type of evolutionary algorithm which maintains a population of solutions to search by an interaction between exploration and exploitation phases, intelligently. This algorithm is greatly welcomed due to its appropriate efficiency, convergence speed, and high ability to optimize in the field of optimization. For more details, scholars can refer to [19, 22]:

4.2 Non-dominated sorting genetic algorithm II algorithm

One of the most efficient and most popular multi-objective optimization algorithms is the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) proposed by Deb [20]. NSGA-II algorithm is one of the fastest and most powerful optimization algorithms that has less complexity than other methods. And by using the non-overcoming and calculating the distance of the nodes, Pareto's optimum points are obtained which have a desirable scope for the purpose of changing functions. In this algorithm, elitism and dispersion are considered, simultaneously. For more details, a reader may refer to [20, 26-28].

4.3 Multi-objective social engineering optimization algorithm

The social engineering optimization (SEO) algorithm was introduced by Fathollahi-Fard et al., [21]. In this algorithm, each solution is a counterpart to a person and traits of each person such as his/her ability in contents of mathematical, sport, business are the counterparts of all variables of each solution in search space. To start the algorithm, the two random solutions are initialized and better solution is selected as attacker and the other is named as the defender. To simulate training and retraining of the attacker from the defender, some random experiments for each trait of the defender are designed. The attacker tries to evaluate the defender by his/her traits. The counterpart of training and retraining in search space is copying a trait from the attacker to the same trait in defender and computing the rate of retraining of the attacker from the defender, simultaneously. In the next step, spotting a SE attack from the attacker to the defender is the counterpart of changing the position of defender by an intelligent way in feasible space. In responding a SE attack, the fitness of new position of the defender is calculated and the old and current positions of the defender is compared and the best position is selected. If the ability of the defender is better than the attacker, positions of the attacker and the defender are changed. At the end, to strike to the defender, it is annihilated and replaced by a new random solution in search space.

5 Computational experiments

In this section, the results of the implementation of proposed solution methods on experimental problems are generated and analyzed. In this paper, 30 random tests were designed with the number of patients and the number of different therapists. In order to eliminate the uncertainty in the outputs, the algorithms were implemented for each problem three times, and the average of the three implementations of each problem as the final response variable has been.

To solve numerical examples, at first 30 problems were designed in small, medium and large sizes. The range of sample parameters is shown in Table 2. Also, problems 1 through 30 are illustrated in Table 3.

Table 2. The range of parameters

T	7 days
S	5 days
$\tilde{M}_{ikt}$	45 minutes
$\tilde{\lambda}_{kt}$	Rand [1 15]
$\tilde{\alpha}_j$	Rand i([20 250])
$\tilde{\beta}_j$	α+10

Table 3. Numerical example

Problem size	Problem number	Patient number	Therapists number	Problem size	Problem number	Patient number	Therapists number
Small	1	9	2	Medium	11	22	5
	2	10	2		12	23	5
	3	12	2		13	24	5
	4	14	3		14	25	6
	5	15	3		15	27	6
	6	16	3		16	28	6
	7	17	3		17	30	6
	8	18	4		18	31	7
	9	19	4		19	32	7
	10	20	4		20	33	7
Large	21	34	8				
	22	36	8				

	23	37	8
	24	38	9
	25	39	9
	26	40	9
	27	41	9
	28	42	10
	29	44	10
	30	46	10

Also, the total days of the planning horizon of 7 days and the number of working days per therapist is 5 days. The service time for each patient is also 45 minutes. After these problems are designed, these problems are solved by the algorithms MOICA, NSGA-II, and MOSEO, and the result is shown in Table 4.

Table 4 The result of MOICA, NSGA-II, and MOSEO algorithms

Problem size	Problem number	MOICA	CPU time of MOICA	NSGA-II	CPU time of NSGA-II	MOSEO	CPU time of MOSEO
Small	1	3025	21/45	3345	22/35	2334	20/45
	2	3550	23/67	3809	24/07	2455	21/56
	3	3701	29/77	4112	27/68	2677	26
	4	3902	35/45	4453	29/56	2998	32/12
	5	4133	41/12	4667	35/34	3012	34/14
	6	4556	47/33	4890	39/21	3244	37/66
	7	4788	52/55	5012	43/15	3440	40/12
	8	4901	61/03	5334	50/34	3778	46/34
	9	5228	67/44	5899	58/12	3988	56/13
	10	5709	83/44	6233	71/14	4221	70/56
Medium	11	5990	97/33	6553	85/16	4566	82/5
	12	6012	102/45	6990	97/28	4881	92/01
	13	6455	131/45	7233	116/77	5112	112/66
	14	6788	145/78	7880	135/33	5334	127/5
	15	6901	188/76	8112	163/22	5778	140/55
	16	7233	201/55	8556	178/35	6034	151/4
	17	7566	234/11	8991	191/88	6233	166/22
	18	7889	256/78	9344	211/23	6566	190/44
	19	8022	289/45	9880	245/67	6980	223/13
	20	8344	312/45	10455	288/45	7344	245/66
Large	21	8677	356/14	13566	302/33	7811	268/44
	22	9122	387/5	16775	343/13	8122	288/12
	23	9566	422/12	19807	390/12	8344	313/56
	24	9855	467/44	20233	450/78	8766	377/55
	25	10122	500/12	23455	488/23	9012	412/33
	26	13455	518/15	26770	510/25	9233	456/55
	27	16770	589/32	29881	578/09	9567	523/13
	28	19455	657/66	32240	612/34	9788	545/56
	29	20125	711/67	37880	683/33	10134	577/14
	30	24556	768/34	41123	723/22	13455	599/34

In addition, Fig. 1. shows the behaviour of MOICA, NSGA-II, and MOSEO algorithms in terms of solution time. Although, MOICA in all of test problems needed more time, it seems that there is no difference between metaheuristic algorithms in this item. Also, Fig.2. shows the results of MOICA, NSGA-II, and MOSEO algorithms in the different size. As a result, the MOSEO has a better performance in comparison of the NSGA-II and MOICA algorithms.

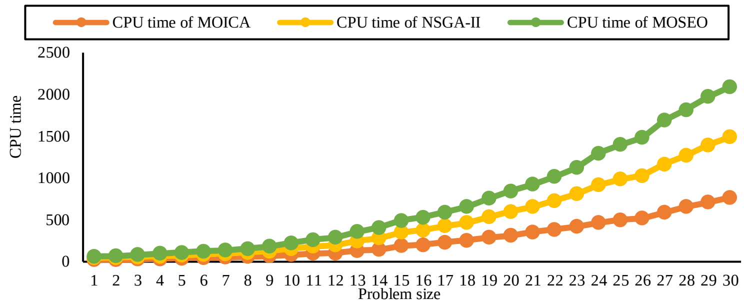

Fig. 1. The CPU time of MOICA, NSGA-II, and MOSEO algorithms

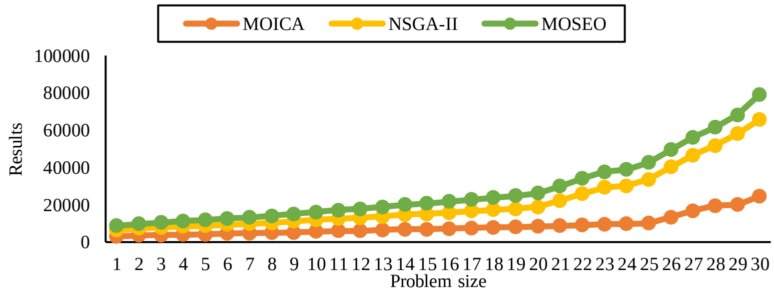

Fig. 2. The results of MOICA, NSGA-II, and MOSEO algorithms

6 Conclusion and future works

In this paper, an integer linear programming model was employed to formulate a bi-objective home health care routing, allocation, planning and scheduling problem. According to the literature, this paper was for the first time used the fuzzy approach. To solve the model, three metaheuristic algorithms were offered to handle the proposed problem. Finally, results showed the performance of the MOSEO the better than the NSGA-II and MOICA algorithms as well as the efficiency of developed model.

For future works, more comprehensive experiments on the developed model are needed to be probed. In addition, developing other metaheuristic algorithms to compare the results of this study may be required. Also, some new assumptions and innovations can be added into the present model for future studies. For example, considering the patient's inconvenience, green emission and environmental pollution as different objectives looks interesting. Besides the total cost of transforming nurses and drugs quantity while adding the location decisions for pharmacies and laboratories and proposing multi-period and also multi-products (considering different required drugs for patients) are good ideas for future works.

References

1. Fathollahi-Fard, A. M., Ahmadi, A., Goodarzian, F., & Cheikhrouhou, N. (2020). A bi-objective home healthcare routing and scheduling problem considering patients' satisfaction in a fuzzy environment. *Applied soft computing*, 106385.
2. Eveborn, P., Rönnqvist, M., Einarsdóttir, H., Eklund, M., Lidén, K., & Almroth, M. (2009). Operations research improves quality and efficiency in home care. *Interfaces*, *39*(1), 18-34.
3. Trautsamwieser, A., Gronalt, M., & Hirsch, P. (2011). Securing home health care in times of natural disasters. *OR spectrum*, *33*(3), 787-813.
4. Rasmussen, M. S., Justesen, T., Dohn, A., & Larsen, J. (2012). The home care crew scheduling problem: Preference-based visit clustering and temporal dependencies. *European Journal of Operational Research*, *219*(3), 598-610.
5. Liu, R., Xie, X., Augusto, V., & Rodriguez, C. (2013). Heuristic algorithms for a vehicle routing problem with simultaneous delivery and pickup and time windows in home health care. *European Journal of Operational Research*, *230*(3), 475-486.
6. Liu, R., Xie, X., & Garaix, T. (2014). Hybridization of tabu search with feasible and infeasible local searches for periodic home health care logistics. *Omega*, *47*, 17-32.
7. Mankowska, D. S., Meisel, F., & Bierwirth, C. (2014). The home health care routing and scheduling problem with interdependent services. *Health care management science*, *17*(1), 15-30.
8. Fikar, C., & Hirsch, P. (2015). A matheuristic for routing real-world home service transport systems facilitating walking. *Journal of Cleaner Production*, *105*, 300-310.
9. Braekers, K., Hartl, R. F., Parragh, S. N., & Tricoire, F. (2016). A bi-objective home care scheduling problem: Analyzing the trade-off between costs and client inconvenience. *European Journal of Operational Research*, *248*(2), 428-443.
10. Shi, Y., Boudouh, T., & Grunder, O. (2017). A hybrid genetic algorithm for a home health care routing problem with time window and fuzzy demand. *Expert Systems with Applications*, *72*, 160-176.
11. Lin, C. C., Hung, L. P., Liu, W. Y., & Tsai, M. C. (2018). Jointly rostering, routing, and re-rostering for home health care services: A harmony search approach with genetic, saturation, inheritance, and immigrant schemes. *Computers & Industrial Engineering*, *115*, 151-166.
12. Liu, M., Yang, D., Su, Q., & Xu, L. (2018). Bi-objective approaches for home healthcare medical team planning and scheduling problem. *Computational and Applied Mathematics*, *37*(4), 4443-4474.
13. Lin, Y. K., & Chou, Y. Y. (2019). A hybrid genetic algorithm for operating room scheduling. *Health Care Management Science*, 1-15.
14. Demirbilek, M., Branke, J., & Strauss, A. (2019). Dynamically accepting and scheduling patients for home healthcare. *Health care management science*, *22*(1), 140-155.

15. Nasir, J. A., & Dang, C. (2019). Quantitative thresholds based decision support approach for the home health care scheduling and routing problem. *Health care management science*, 1-24.
16. Jimenez, M., Arenas, M., Bilbao, A. & Guez, M. V. (2007). "Linear programming with fuzzy parameters: an interactive method resolution." European Journal of Operational Research, 177, 1599-1609.
17. Torabi, S.A. and Hassini, E. (2008). "An interactive possibilistic programming approach for multiple objective supply chain master planning". *Fuzzy Sets and Systems. 159, (2*), *193-214*.
18. Atashpaz-Gargari, E. and C. Lucas, Imperialist competitive algorithm: an algorithm for optimization inspired by imperialistic competition, in: Proc. of IEEE Congress on Evolutionary computation, Singapore, 2008, pp. 4661–4667.
19. Sahebjamnia, N., Goodarzian, F., & Hajiaghaei-Keshteli, M. (2019). Optimization of Multi-Period Three-echelon Citrus Supply Chain Problem. *Journal of Optimization in Industrial Engineering*, 41-50.
20. Goodarzian, F., & Hosseini-Nasab, H. (2019). Applying a fuzzy multi-objective model for a production–distribution network design problem by using a novel self-adoptive evolutionary algorithm. *International Journal of Systems Science: Operations & Logistics*, 1-22.
21. Fathollahi-Fard, A. M., Hajiaghaei-Keshteli, M., & Tavakkoli-Moghaddam, R. (2018). The social engineering optimizer (SEO). *Engineering Applications of Artificial Intelligence*, *72*, 267-293.
22. Fakhrzad, M. B., & Goodarzian, F. (2019). A fuzzy multi-objective programming approach to develop a green closed-loop supply chain network design problem under uncertainty: modifications of imperialist competitive algorithm. *RAIRO-Operations Research*, *53*(3), 963-990.
23. Goodarzian, F., Hosseini-Nasab, H., Muñuzuri, J., & Fakhrzad, M. B. (2020). A multi-objective pharmaceutical supply chain network based on a robust fuzzy model: A comparison of meta-heuristics. *Applied Soft Computing*, 106331.
24. Goodarzian, F., Shishebori, D., Nasseri, H., Dadvar, F. A bi-objective production-distribution problem in a supply chain network under grey flexible conditions. DOI: https://doi.org/10.1051/ro/2020111
25. Goodarzian, F., Hosseini-Nasab, H., & Fakhrzad, M. B. (2020). A Multi-objective Sustainable Medicine Supply Chain Network Design Using a Novel Hybrid Multi-objective Metaheuristic Algorithm. *International Journal of Engineering*, *33*(10), 1986-1995.
26. Fakhrzad, M. B., Talebzadeh, P., & Goodarzian, F. (2018). Mathematical formulation and solving of green closed-loop supply chain planning problem with production, distribution and transportation reliability. *International Journal of Engineering*, *31*(12), 2059-2067.
27. Fakhrzad, M. B., Goodarzian, F., & Golmohammadi, A. M. (2019). Addressing a fixed charge transportation problem with multi-route and different capacities by novel hybrid meta-heuristics. *Journal of Industrial and Systems Engineering*, *12*(1), 167-184.
28. Fakhrzad, M. B., & Goodarzian, F. (2020). A new multi-objective mathematical model for a Citrus supply chain network design: Metaheuristic algorithms. *Journal of Optimization in Industrial Engineering*. DOI: 10.22094/JOIE.2020.570636.1571