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Introducing a novel multi-objective optimization model for volunteer assignment in the post-disaster phase: Combining fuzzy inference systems with NSGA-II and NRGA

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ABSTRACT

Each year, disasters (natural or man-made) cause a lot of damage and take many people's lives. In this situation, many volunteers come to help. While the proper management of volunteers is very effective in controlling the crisis, the lack of proper management of volunteers can create another crisis. Therefore, we introduce a model to deal with the volunteer assignment problem by considering two qualitative objective functions: The first one is minimizing the mean importance of Emergency Department (ED) centers' unmet needs by volunteers, and the second one is minimizing the mean degree of unsatisfied preferences of selected volunteers. To evaluate the introduced qualitative indexes, two Fuzzy Inference Systems (FISs) are used to encapsulate decision makers' knowledge as well as the human reasoning process. FISs are embedded in two evolutionary algorithms for solving the proposed model: Non-Dominated Sorting Genetic Algorithm II (NSGA-II) and Non-Dominated Ranked Genetic Algorithm (NRGA). Also, 30 small-size problems, as well as 30 large-size problems, are randomly generated and solved by both metaheuristic algorithms. Using the obtained data, the performance of NSGA-II and NRGA is measured and compared based on four criteria: CPU Time, Number of Non-dominated Solutions (NNS), Mean Ideal Distance (MID), and Spacing Metric (SM). Statistical tests show that both algorithms have the same performance in small-size problems. However, in large-size problems, NSGA-II is faster, and NRGA produces more optimal solutions. The proposed model is flexible enough to adapt to different scenarios just by updating linguistic rules in FISs. Also, since employed algorithms produce a set of optimal solutions, decision-makers can easily choose the most appropriate solution among the Pareto front based on the circumstances.

1. Introduction

Unfortunately, disasters (natural or man-made) are an inevitable part of our life on planet Earth. Just in 2020, 389 disasters are recorded worldwide. About 98.4 million people were affected, and 15,080 lost their life. Additionally, a minimum of US$ 171.3 billion of economic loss has been imposed (CRED & UNDRR, 2020).

According to Altay and Green (2006), we can break out the field of Disaster Operations Management (DOM) into 4 phases: Mitigation, Preparedness, Response, and Recovery. Immediately after a disaster occurs, the response stage, the most urgent phase in the humanitarian operation, starts. During this stage, which could last for a significant amount of time depending on the scope of the disaster, the primary concern is saving the lives of those who have been affected (Aranda, Fernandez, & Stantchev, 2019). At this stage, various individuals and organizations voluntarily come to help the affected people.

In this investigation, our focus is on spontaneous individuals. We use the spontaneous volunteer definition by the U.S. Federal Emergency Management Agency (FEMA): "Unaffiliated volunteers, also known as spontaneous volunteers, are individuals who offer help or self-deploy to assist in emergencies without fully coordinating their activities. They are considered 'unaffiliated' in that they are not part of a disaster relief organization" (FEMA, 2013). For example, over two million people (nearly 10% of the population) volunteered to help after the 1985 Mexico City earthquake (Fernandez, Barbera, & van Dorp, 2006). Also, Red Cross processed about 15,000 volunteers just in two and one-half weeks after the September 11 terrorist attack in 2001 (Lowe & Fothergill, 2003).

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Table 1
Differences between characteristics of Classical Manpower Planning and Volunteer Management in DOM.

Attribute	Classical Manpower Planning	Volunteer Management in DOM	Researcher(s)
Objective Function	Maximizing revenues	Saving lives	(Falasca, Mauro, Christopher W. Zobel, and Gary M. Fetter., 2009)
Labor Pool Size	Considered to be sufficient	Uncertain	(Falasca, Mauro, Christopher W. Zobel, and Gary M. Fetter., 2009) (Mayorga et al., 2017)
Availability	Not an issue	Uncertain	(Mayorga et al., 2017)
Commitment	Not an issue	Uncertain	(Mayorga et al., 2017)
Skill Level to Fulfill the Tasks	Meets the required level	Uncertain	(Falasca, Mauro, Christopher W. Zobel, and Gary M. Fetter., 2009)
Task Labor Shortages	Not an issue	Should be considered and balanced	(Sampson, 2006)

Spontaneous volunteers are essential for effective relief efforts, providing emergency management infrastructure capacity (Lodree & Davis, 2016), freeing responders to focus on their specialized duties (Wachtendorf & Kendra, 2001), and providing a variety of skills quickly and efficiently (Paret, Mayorga, & Lodree, 2020).

On the other hand, Unorganized volunteers can reduce the effectiveness of response activities (Wachtendorf & Kendra, 2001), and divert responders from their primary duties (Fernandez et al., 2006); Besides, there may be concerns to guarantee their health and safety in unpredictable and uncertain situations (Barsky, Trainor, Torres, & Aguirre, 2007). As stated, “It is a paradox — people’s willingness to volunteer versus the system’s capacity to use them effectively” (Points of Light Foundation, 2002).

So, while spontaneous volunteers are potentially a valuable resource in the DOM context, unorganized volunteers will lead to a significant obstacle to emergency operations (Paret et al., 2020). Even volunteer convergence is referred to as “the disaster within the disaster” in the literature (Points of Light Foundation, 2002). This highlights the importance of an efficient and effective volunteer management system (Fernandez et al., 2006).

Rather than maximizing revenues in classical workforce planning, the objective function of volunteer management in DOM is saving lives. This field is highly blended with uncertainty. Regarding other attributes indicated in Table 1, it can be stated that volunteer management in humanitarian context differs from classical workforce planning by nature. Therefore, volunteer management in DOM requires applying different decision-making models.

Humanitarian organizations rapidly assemble a workforce capable of meeting the immediate needs of a community in the aftermath of a disaster. However, these requirements shift over time, as do the volunteer pool (and their skill sets). As a result, it may be necessary to quickly update volunteer assignments (Lassiter, Khademi, & Taaffe, 2015). In addition, the current assignment of duties has a direct relationship with the level of future commitment of volunteers.

Therefore, on the one hand, humanitarian organizations must manage volunteers effectively so that they become a renewable resource. On the other hand, in order to maximize the effectiveness of their efforts, these organizations must keep shortages to a minimum. Such Decision-making situations in DOM (unlike classical workforce planning) are characterized by large quantities of ambiguous information and are typically too complicated to be represented by precise quantitative data (Falasca & Zobel, 2012).

Therefore, in this context, we need decision-making models that can adapt to constantly changing conditions of DOM away from mathematical complexities. However, this field has not received adequate attention.

This investigation focuses on assigning volunteers to tasks effectively and efficiently. It provides a proper solution for volunteer convergence (Skar, Sydnes, & Sydnes, 2016), increases volunteer retention, and undoubtedly is one of the critical aspects of volunteer management (Lassiter et al., 2015) which is, in its turn, a key driver for successful disaster operations.

The rest of this paper is organized as follows: In section 2, the literature on volunteer assignment and optimization algorithms is reviewed. Section 3 presents a model formulation for volunteer assignment. Section 4 deals with introducing concepts used in the work such as Fuzzy Inference Systems (FISs) as well as employed evolutionary algorithms. Performance analysis of evolutionary algorithms is conducted in section 5. Finally, concluding remarks and suggestions for future research are discussed in section 6.

2. Literature review

In DOM literature, there are three main areas of focus: Facility location, Network design and relief distribution, and Mass evacuation (Habib et al., 2016). Volunteer management is another important field of research in the DOM context that has received little attention. Volunteer management includes all volunteer processes such as recruitment, training, scheduling, supervision, and evaluation (Paret et al., 2020).

Since in the current study we address the problem of spontaneous volunteer assignment in the response phase of a disaster, we review the literature from two aspects: workforce scheduling vs. spontaneous volunteer assignment and optimization algorithms:

2.1. Workforce scheduling vs. spontaneous volunteer assignment

Traditional workforce scheduling has received extensive attention in the literature. It is applied to a wide range of subjects: Çakırgil, Yücel, and Kuyzu (2020) proposed a model to form teams in the electricity sector and assign them some tasks based on their skills. Li, Zhang, Jia, Li, and Zhu (2019) dealt with the problem of assigning restoration tasks to teams of technicians when a vital infrastructure is disrupted. Shi and Landa-Silva (2017) and Ang, Lam, Pasupathy, and Ong (2018) addressed the nurse scheduling problem. Baysan, Durmusoglu, and Cinar (2017) proposed a methodology to assign team-based labors to new product projects. Chen et al. (2016) established a model to assign multi-skilled workforces to services requested by customers in different locations.

However, the literature on the assignment of spontaneous volunteers in humanitarian context is very limited (Einolf, 2018; Lodree & Davis, 2016; Paret et al., 2020; Skar et al., 2016). First attempts to volunteer management date back to 1975, when Fritz and Mathewson (1957) studied volunteer convergence as well as the movement of reliefs to the affected areas. Most recently, in a radioactively contaminated area, Janiak and Kovalyov (2006) developed a scheduling problem in which a single worker should execute tasks. We just found five investigations in the literature that specifically addressed volunteer assignment in the DOM context: Falasca, Zobel, and Gary (2009) introduced a multi-criteria optimization model to assign volunteers to tasks in a humanitarian context based on two objective functions: minimizing total shortage costs and maximizing individual preferences. To meet the second objective function, they tried to minimize the number of undesired assignments that volunteers do not prefer, regarding task or time block of assignment. Also, to solve the introduced bi-criteria problem, they applied the efficient frontier method to have a set of optimal solutions. Test results showed the model’s reliability. Later in 2012, they addressed the same problem with a fuzzy approach (Falasca & Zobel, 2012). By utilizing fuzzy membership functions, they incorporated the decision makers’ expertise into the model. It can represent their preferences toward each objective function. However, this will lead to obtain just a single solution. Lassiter et al. (2015) developed an optimization framework in the aftermath of a humanitarian disaster to assign volunteers to tasks regarding two objective functions: minimizing the unmet demand as well as maximizing the preference of volunteers. To consider volunteers' preference, they introduced a constraint into the model that specifies the minimum percent of volunteers matched to their task-skill. Mayorga, Lodree, and Wolczynski (2017) developed a multi-server queueing system to assign tasks to volunteers with stochastic server arrival abandonment in a disaster's recovery phase (e.g., debris cleaning). The only objective function of their model is to maximize the benefit obtained from completing work units. Paret et al. (2020) applied a multi-server queueing model by employing Markov Decision Process (MDP) for assigning volunteers to tasks in a post-disaster setting and compared the optimal policy to some heuristic ones. This study expanded the work of Mayorga et al. (2017) by allowing for stochastic demand, but still used one objective function of maximizing benefits.

Studies that have been done in the past have some shortcomings. In order to maximize the effectiveness of the system, Mayorga et al.; Paret et al. (2017; 2020) tried to assign volunteers to tasks based on just one objective function: maximizing the gained benefit. However, preferences of volunteers are ignored in their model, which can reduce the future commitment of volunteers. In the study of Falasca and Zobel (2012), Falasca et al. (2009), their model incorporates both minimizing total shortage costs and maximizing individual preferences. However, considering individual preferences, they attempted to minimize the number of undesirable assignments for volunteers. Just regarding the number of undesired assignments is not an appropriate index, because each of them has a different level of importance and should not be considered the same. Also, their model does not optimize both objective functions simultaneously. It focuses first on minimizing shortage costs to obtain maximum coverage, and then on minimizing the number of undesirable assignments. Finally, in the efficient frontier method, the decision makers' preferences regarding the relative significance of each objective are only considered post hoc when they trade objective values along the efficient frontier. In the study of Falasca and Zobel (2012), fuzzy membership functions are employed to take the preferences of decision makers into account. However, their model can be improved by employing fuzzy inference systems to focus on objective functions. Also, Lassiter et al. (2015) rather than optimizing the objective function of volunteer preferences, considered it as a constraint which should be above a determined threshold.

2.2. Optimization algorithms

In optimization problems, exact algorithms are widely applied in the literature. Such algorithms can find optimum solutions. However, in dealing with large-scale data, either they cannot find the solution or a lot of space and time is required to do the calculations (Boonmee, Arimura, & Asada, 2017). Dijkstra algorithm and Dynamic programming method are categorized among exact algorithms.

Another category of algorithms is known as metaheuristics. While these algorithms cannot guarantee to find the optimal solution, they are able to find a feasible solution rapidly (Ropke, 2005). Some well-known metaheuristic algorithms are Genetic Algorithm (GA), Tabu Search (TS), Imperialist Competitive Algorithm (ICA), and Ant Colony Optimization (ACO). In optimization problems literature, both deterministic and metaheuristic approaches are applied by researchers.

In the DOM context, to the best of our knowledge, no research has applied metaheuristic algorithms in the volunteer assignment literature. However, in traditional workforce scheduling, metaheuristics are vastly used for workforce scheduling: Pereira et al. (2020) addressed the problem of assigning teams of varying skills to services involving dependent tasks requested by customers. Results show that the ACO metaheuristic algorithm performs better than the Mixed Integer Programming model. Algethami, Martínez-Gavara, and Landa-Silva (2019) applied a GA with a novel crossover operator to assign personnel to visits in different geographical sites. In sub-assembly lines of a car manufacturer, Yurtkuran, Yagmahan, and Emel (2018) addressed a workforce scheduling problem considering two objectives: minimizing the workforce as well as unbalanced workloads. In this way, they used an Artificial Bee Colony (ABC) algorithm to solve the model. To tackle the problem of staff scheduling in a glass manufacturing unit by considering the satisfaction of employees as well as workload balance, Rocha, Oliveira, and Carravilla (2014) proposed a new constructive heuristic. They assigned working shifts and days off to employees' teams in two ways: using a constructive heuristic and mixed integer programming. For a large number of teams, the heuristic performance was desirable, while mixed integer programming failed to find any solutions.

As is indicated, efficient and effective spontaneous volunteer assignment is one of the most critical humanitarian logistic challenges in the post-disaster phase of humanitarian operations. It involves large-scale data and is tied up with uncertainty in evaluating and assigning volunteers to tasks. However, it has not received adequate attention in the literature. Also, metaheuristic algorithms are not used in this context.

To deal with the gap in the literature, and capture the uncertainty mixed with the mentioned problem in a more realistic way, we are going to develop a multi-criteria optimization model to assign spontaneous volunteers to tasks in the humanitarian context. Our contribution to the literature is threefold:

1. Instead of considering classic indexes, we introduce two qualitative indexes: the importance of unmet needs by volunteers and the degree of unsatisfied preferences of volunteers. These qualitative indexes are more realistic and can better represent the complexity of the volunteer assignment in DOM context.

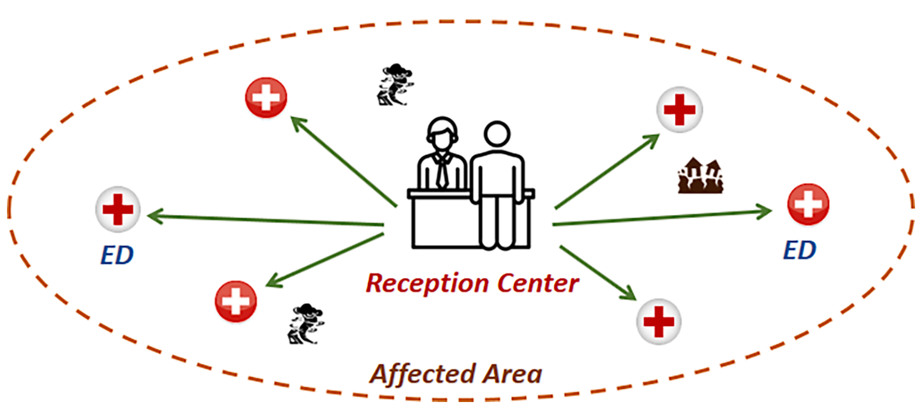

Fig. 1. Established ED services in the affected area.

2. To evaluate qualitative indexes efficiently, we employ two FISs to capsulate the knowledge of experts and simulate the process of human reasoning;
3. We implement two evolutionary algorithms to solve the model: Non-dominated Sorting Genetic Algorithm II (NSGA-II) and Non-dominated Ranked Genetic Algorithm (NRGA). In this way, both objective functions are optimized simultaneously. To the best of our knowledge, it is the first time in the literature that FISs are embedded in evolutionary algorithms to solve the volunteer assignment problem.

This model will be consistent with the constantly changing environment just by making changes in linguistic rules away from mathematical complexities.

3. Model formulation for volunteer assignment

3.1. Problem definition

After a disaster onset, many people have been seriously injured. However, infrastructures such as hospitals may also be severely damaged and unable to provide services to the affected people. In order to deliver superior medical treatment and monitor patients more effectively remotely, innovative healthcare services are currently being developed (Opazo Basaez et al., n.d). In the disaster context, even such services might be collapsed and unavailable. In this situation, the rapid establishment of an Emergency Department (ED) service plays a vital role in saving human lives. Considering defined criteria, some volunteers registered in reception centers are selected and assigned to EDs. A schematic diagram of established ED services is depicted in Fig. 1.

At this stage, in an emotional environment blended with uncertainty in Emergency Rooms (ER), we face lots of patients waiting to receive immediate medical services. Two expertise are vital in this step:

1. ***Triage Nurse:*** A registered nurse in the emergency room who is the first person that assesses the patients and determines whether a patient needs immediate medical attention;
2. ***Primary ER nurse:*** the second person who visits the patients. Such nurses do more in detail assessments of patients and begin the proper treatment.

Triage nurses and primary ER nurses have a significant role in establishing an effective and efficient emergency department service. Therefore, in this investigation, we are going to select among volunteers registered in the reception center for two types of vacancies: triage nurse and primary ER nurse, under some assumptions:

1. There is a single reception center where volunteers are registered;
2. The location of the reception center, as well as EDs, is known. Also, the distance from the reception center to each ED is known;
3. Each ED has several vacancies, all categorized in just two types: triage nurse and primary ER nurse;
4. The number of volunteers is more than the number of vacancies;
5. All the vacancies of all the EDs should be filled with volunteers;
6. Each vacancy should be filled with just one volunteer;
7. If a volunteer is selected, he/she will be assigned to just one vacancy;
8. The emergency level of each ED is determined by experts on the [0 100] interval;
9. The number of patients in each ED is known;
10. Triage ability and nursing ability of each volunteer are known and measured on a scale of 0 to 100;
11. The workload of all the vacancies in the EDs is known and determined by experts on the [0 100] interval;
12. Each volunteer has stated the importance of difficult situations for him/her on a scale of 0 to 100.

Table 2
Notations and variables.

Notation (or Variable)	Description
C_0	Reception Center
C	Set of n ED Centers $C = \{1, 2, \cdots, n\}$
i	Index to refer Centers $i \in C$
s_i	Number of vacancies in the center i that should be filled by volunteers
k	Index to refer vacancies in centers
V	Set of m volunteers $V = \{1, 2, \cdots, m\}$
j	Index to refer volunteers $j \in V$
r_k	A binary value, $r_{ik} = 1$ indicates that vacancy k in the center i is a triage vacancy; otherwise, $r_{ik} = 0$
u_{ik}	A binary value, $u_{ik} = 1$ indicates that vacancy k in the center i is a nursing vacancy; otherwise, $u_{ik} = 0$
q_{jik}	A binary value, $q_{jik} = 1$ indicates that volunteer j is assigned to vacancy k in center i, otherwise $q_{jik} = 0$
E_i	Emergency level of center C_i, $E_i \in [0\ 100]$
P_i	The number of patients in Center C_i
N_j	Nursing ability of Volunteer j, $j \in V$, $N_j \in [0\ 100]$
T_j	Triage ability of Volunteer j, $j \in V$, $T_j \in [0\ 100]$
x'_{ji}	Importance of unmet triage needs by volunteer j in center C_i, $x'_{ji} \in [0\ 100]$
x''_{ji}	Importance of primary ER nurse unmet needs by volunteer j in center C_i, $x''_{ji} \in [0\ 100]$
x_{ik}	Importance of unmet needs by volunteers for vacancy k in center C_i, $x_{ik} \in [0\ 100]$
Z_1	Mean importance of unmet needs by volunteers for all vacancies in all centers
D_i	Distance between C_0, C_i (distance from the Reception Center to C_i)
W_{ik}	The workload at vacancy k in center i, $W_{ik} \in [0\ 100]$
F_j	The importance of difficult situations for volunteer j, $F_j \in [0\ 100]$
y'_{jik}	Degree of unsatisfied preferences of volunteer j at vacancy k in center i, $y'_{jik} \in [0\ 100]$
y_j	Degree of unsatisfied preferences of volunteer j at the position he/she is assigned to $y_j \in [0\ 100]$
Z_2	Mean degree of unsatisfied preferences of all selected volunteers

Suppose we have two EDs with the same number of covered patients with a vacancy for the triage nurse. This is not necessarily an optimum decision if we assign two triage nurses with the same ability level to the mentioned vacancies. The reason is that other influential factors, such as the emergency level of EDs, also matter. A vacancy in an ED with a higher level of emergency should be filled with a more skillful volunteer compared to another vacancy with the same number of covered patients but a lower level of emergency. Therefore, in this investigation, we are going to introduce the importance of unmet needs by volunteers, which is a more realistic index than the unmet needs by volunteers index. We calculate the introduced index based on three indexes by establishing FISs and encapsulating the knowledge of experts: the number of covered patients in ED, the emergency level of the ED, and the level of triage ability (or nursing ability) of the volunteer who is assigned to the vacancy.

The same is true for volunteers' preferences objective. We introduce a qualitative index to deal with the volunteers' preferences: the degree of unsatisfied preferences of volunteers index. It will be measured by implementing a FIS considering the distance from the reception center to the ED, the workload of the ED, and the importance of difficult situations for the volunteer.

For the problem of selecting volunteers and assigning them to the vacancies in the EDs, we introduce a two-phase model:

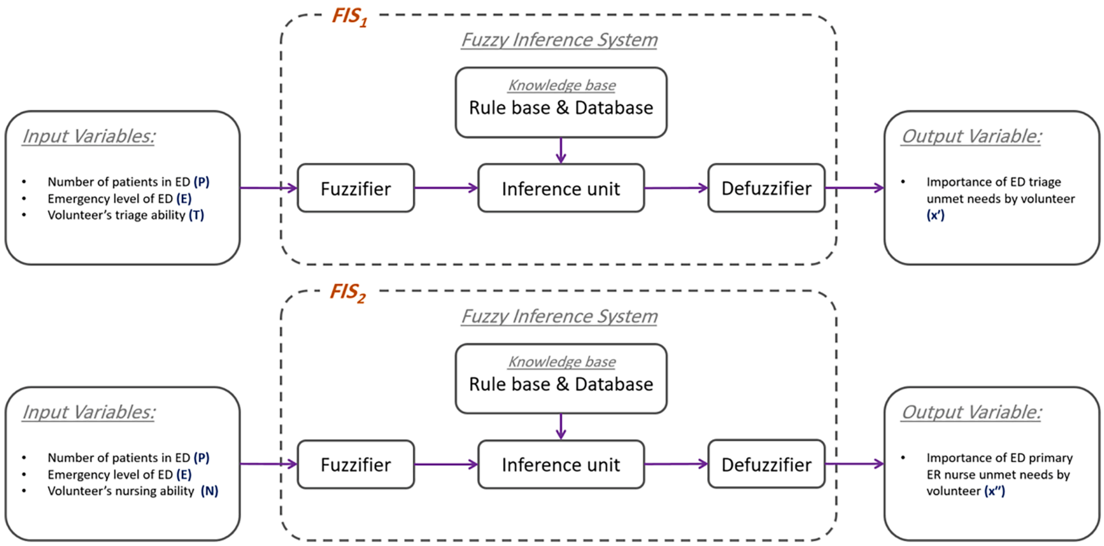

Fig. 2. Structure of proposed FISs for evaluating the importance of unmet needs in ED.

1. Considering the objective functions, three FISs are developed to measure the importance of unmet needs by volunteers (including two FISs for triage nurses as well as primary ER nurses) and the degree of unsatisfied preferences of volunteers;
2. By establishing two metaheuristic algorithms, we select among volunteers and assign them to the vacancies. The objectives are: minimizing the importance of unmet needs by volunteers and minimizing the degree of unsatisfied preferences of volunteers.

3.2. Variables and notations

Variables and notations employed in the proposed model are given in Table 2.

3.3. Objective functions

In this investigation, we introduce two objective functions:

3.3.1. The importance of unmet needs by volunteers

Considering the vacancy we address in centers, the importance of unmet needs means the importance of unmet triage needs or the importance of unmet nurse needs. This index is evaluated based on the number of covered patients in the center, the emergency level of the center, and the level of triage ability (or nursing ability) of the volunteer assigned to the vacancy.

However, it is a kind of qualitative reasoning blended with uncertainty. Therefore, in order to capture this ambiguity and uncertainty, we employ two FISs to evaluate the importance of unmet triage needs and the importance of unmet nurse needs by encapsulating experts' qualitative knowledge and reasoning:

$$fis_1 : (P_i, E_i, T_j) \rightarrow x'_{ji} \tag{1}$$

$$fis_2 : (P_i, E_i, N_j) \rightarrow x''_{ji} \tag{2}$$

$$x_{ik} = \sum_{j=1}^{m} \left[r_{ik} \times q_{jik} \times x'_{ji} + u_{ik} \times q_{jik} \times x''_{ji} \right] \forall i, k \tag{3}$$

$$Z_1 = \frac{\sum_{i=1}^{n} \sum_{k=1}^{s_i} x_{ik}}{\sum_{i=1}^{n} s_i} \tag{4}$$

Eqs. (1) and (2) show that the importance of unmet triage needs and the importance of unmet nurse needs are evaluated by fis_1 and fis_2, respectively. The importance of the unmet needs of each vacancy is calculated in Eq. (3). Finally, Eq. (4) evaluates the mean importance of unmet needs for all the vacancies.

3.3.2. The degree of unsatisfied preferences of volunteers

Also, we consider the unsatisfied preferences of volunteers as our second objective function. This index is evaluated based on the distance from the center to ED, the workload in ED, and the importance of difficult situations for the volunteer. A FIS is used to appraise the degree of unsatisfied preferences of volunteers. The employed equations are as follows:

$$fis_3 (D_i, W_{ik}, F_j) \rightarrow y'_{jik} \tag{5}$$

$$y_j = \sum_{i=1}^{n} \sum_{k=1}^{s_i} q_{jik} \times y'_{jik} \forall j \tag{6}$$

$$Z_2 = \frac{\sum_{j=1}^{m} y_j}{\sum_{i=1}^{n} s_i} \tag{7}$$

Eq. (5) indicates that fis_3 assesses the unsatisfied preferences of volunteers. Also, in Eq. (6), the volunteer's degree of unsatisfied preferences regarding the vacancy he/she is assigned to is evaluated. Eq. (7) calculates the mean degree of unsatisfied preferences for all selected volunteers.

3.4. The model settings

This model aims to minimize two objective functions: the mean importance of unmet needs by volunteers and the mean degree of unsatisfied preferences of selected volunteers. Regarding the defined objective functions, the model is formulated as follows:

$$\boldsymbol{Min} Z_1 = \frac{\sum_{i=1}^{n} \sum_{k=1}^{s_i} x_{ik}}{\sum_{i=1}^{n} s_i} \tag{8}$$

$$\boldsymbol{Min} Z_2 = \frac{\sum_{j=1}^{m} y_j}{\sum_{i=1}^{n} s_i} \tag{9}$$

Subject *to:*

$$r_{ik} + u_{ik} = 1 \forall i \in C, \forall k \leq s_i \tag{10}$$

$$\sum_{i=1}^{n} s_i < m \tag{11}$$

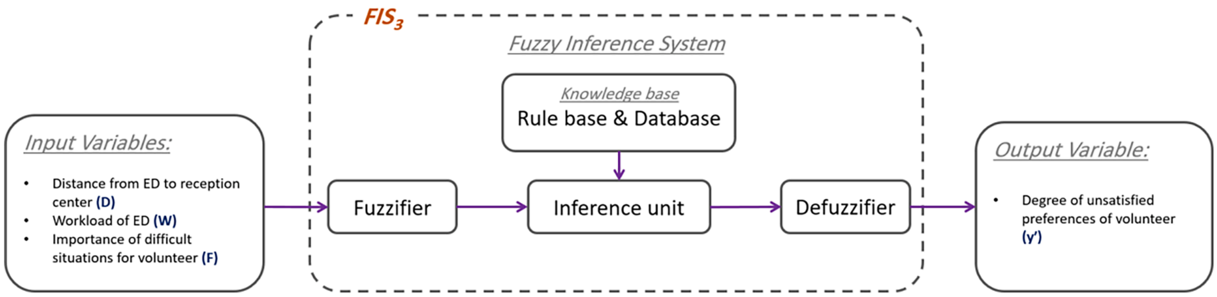

Fig. 3. Structure of proposed FIS for evaluating the degree of unsatisfied preferences of the volunteer.

Table 3
Inputs and outputs linguistic variables.

Fuzzy Inference System	Variable Type	Variable Name	Notation
FIS_1	input	Number of patients in ED	P
		Emergency level of ED	E
		Volunteer's triage ability	T
	output	Importance of ED triage unmet needs by volunteer	x′
FIS_2	input	Number of patients in ED	P
		Emergency level of ED	E
		Volunteer's nursing ability	N
	output	Importance of ED primary ER nurse unmet needs by volunteer	x′′
FIS_3	input	Distance from ED to the reception center	D
		The workload of ED	W
		Importance of difficult situations for volunteer	F
	output	Degree of satisfied preferences of volunteer	y′

$$\sum_{j=1}^{m} q_{jik} = 1 \forall i \in C, \forall k \le s_i \tag{12}$$

$$\sum_{i=1}^{n} \sum_{k=1}^{s_i} q_{jik} \le 1, \forall j \in V \tag{13}$$

$$\sum_{i=1}^{n} s_i = \sum_{i=1}^{n} \sum_{k=1}^{s_i} \sum_{j=1}^{m} q_{jik} \tag{14}$$

$$s_i > 0, m > 0, \forall i \in C \tag{15}$$

Objective functions are formulated in Eqs. (8) and (9): minimizing the mean importance of unmet needs by volunteers and minimizing the mean degree of unsatisfied preferences of selected volunteers, respectively. Constraint (10) indicates that all the vacancies in each ED are triage nurse positions or primary ER nurse positions. Constraint (11) specifies that the number of vacancies is less than the number of volunteers. Constraint (12) guarantees that just one volunteer is selected for each vacancy. Constraint (13) indicates that if a volunteer is selected, he/she will be assigned to just one vacancy. Constraint (14) states that all the vacancies will be filled with volunteers, and constraint (15) limits the value of parameters to positive values.

4. Algorithm design

In this section, we overview the FISs used in this study as well as two evolutionary algorithms to solve the model: NSGA-II and NRGA.

Table 4
Linguistic values and fuzzy numbers for unmet needs FISs (FIS_1, FIS_2).

Linguistic variable	Linguistic value	Fuzzy number
Number of patients in ED	Low	[0 0 25 50]
	Medium	[25 50 75]
	High	[50 75 100 100]
Emergency level of ED	Low	[0 0 25 50]
	Medium	[25 50 75]
	High	[50 75 100 100]
Volunteer's triage ability	Low	[0 0 25 50]
	Medium	[25 50 75]
	High	[50 75 100 100]
Volunteer's nursing ability	Low	[0 0 25 50]
	Medium	[25 50 75]
	High	[50 75 100 100]
Importance of ED triage unmet needs by volunteer	Very low	[0 0 10 30]
	Low	[10 30 50]
	Medium	[30 50 70]
	High	[50 70 90]
	Very high	[70 90 100 100]
Importance of ED primary ER nurse unmet needs by volunteer	Very low	[0 0 10 30]
	Low	[10 30 50]
	Medium	[30 50 70]
	High	[50 70 90]
	Very high	[70 90 100 100]

4.1. The structure of used FISs

The structure of employed FISs to evaluate the importance of unmet needs in EDs and the degree of unsatisfied preferences of selected volunteers are depicted in Figs. 2 and 3, respectively.

Introduced FISs in this investigation are of Mamdani type (Mamdani & Assilian, 1975). Input and output variables in such types of FISs are linguistic variables to capture the inherent uncertainty and ambiguity of the problem (Zimmermann, 2011). The values of linguistic variables are linguistic terms such as "Very High", "Medium", "Low", etc. Used input and output linguistic variables are given in Table 3. Fuzzy numbers and membership functions represent linguistic variables. We employed triangular and trapezoidal fuzzy numbers (Tables 4 and 5).

As depicted in Figs. 2 and 3, Knowledge base consists of two parts: a database containing membership functions and a rule base enclosing fuzzy if-then rules. In fact, rules are formed based on the experts'

Table 5
Linguistic values and fuzzy numbers for unsatisfied preferences FIS (FIS_3).

Linguistic variable	Linguistic value	Fuzzy number
Distance from ED to the reception center	Low	[0 0 40 70]
	Medium	[40 70 100]
	High	[70 100 150 150]
The workload of ED	Low	[0 0 25 50]
	Medium	[25 50 75]
	High	[50 75 100 100]
Importance of difficult situations for volunteer	Low	[0 0 25 50]
	Medium	[25 50 75]
	High	[50 75 100 100]
Degree of unsatisfied preferences of volunteer	Very low	[0 0 10 30]
	Low	[10 30 50]
	Medium	[30 50 70]
	High	[50 70 90]
	Very high	[70 90 100 100]

Table 6
Feature of FISs.

FIS type	mamdani
And method	Min
Or method	MAX
Implication method	Min
Aggregation method	MAX
Defuzzification	Centroid

knowledge and can be modified easily to be consistent with different situations. As it is apparent in Table 3, for each FIS, three input variables are defined. Each of them also has three membership functions. So, we will have $3\times3\times3 = 27$ rules. Defined rule bases of FIS_{trg}, FIS_{nrs}, and FIS_{prf} are available in appendices I to III, respectively.

The process performed in a FIS is as follows:

1. **Fuzzifying:** translating the crisp values of input variables to membership degrees of associated linguistic values;
2. **Inferencing:** Producing fuzzy result, regarding the knowledge base and the output of the Fuzzifier unit;
3. **Defuzzifying:** transforming the obtained fuzzy result to a crisp output value.

Feature of employed FISs is available in Table 6.

4.2. Evolutionary algorithms: NSGA-II and NRGA

In a multi-objective optimization context, the goal is to optimize two or more objective functions. However, it is impossible to optimize all the objective functions simultaneously. Instead, a tradeoff among goals is achievable. In this study, we employ two efficient and well-known Multi-Objective Evolutionary Algorithms (MOEAs) to solve the volunteer selection problem:

1. Non-dominated Sorting Genetic Algorithm II (NSGA-II) (Deb et al., 2002) produces a set of non-dominated solutions known as the Pareto front. None of the solutions is superior to the other ones. In fact, solutions represent the tradeoff among objective functions;
2. (Jadaan & Lakishmi Rajamani, 2008) also produces Pareto front. The structure of NRGA is similar to NSGA-II except in the parent selection strategy.

Each solution indicates which volunteers have been selected and in which vacancies in EDs are going to work.

The process of NSGA-II and NRGA is briefly described as follows:

NSGA-II and NRGA Pseudo code – adapted from Omar Al Jadaan, Lakishmi Rajamani, C. R. Rao (2008)

Generate initial population (P_0) randomly – Size N
Sort the population based on non-dominated sorting and crowding distance
For t = 0 to *break-condition* **do**
Select parents from population P_t{*NSGA-II selection technique*: Binary tournament selection*NRGA selection technique*: Ranked-based roulette wheel selection}
Generate child population (Q_t) using crossover operators
Generate child population (R_t) using mutation operators
Merge all populations to form a new population ($P_{new} = P_t \cup Q_t \cup R_t$)
Sort the new population (P_{new}) based on non-dominated sorting and crowding distance
(Elitist) select the best individuals (size N) from P_{new} to form the population of the new generation (P_{t+1})
Sort P_{t+1} based on non-dominated sorting and crowding distance
End for
Return the first Pareto front (F_1) of the population (P_t) as the set of optimum non-nominated solutions.

Step 1: Algorithms start by generating a set of initial solutions randomly. Solutions are also known as chromosomes or individuals. In this investigation, we define a one-dimensional structure for our chromosome (Fig. 4).

Each gene corresponds to a vacancy in an ED. Also, the value of a gene (allele) is an integer number indicating the volunteer ID of whom is assigned to the corresponding vacancy. So, each chromosome is a permutation of the volunteers' ID. This method of encoding solutions in a chromosome guarantees the feasibility of generated solutions.

Each solution is evaluated based on two objective functions: the importance of unmet needs by volunteers and the degree of unsatisfied preferences of volunteers. The evaluation is carried out by applying defined FISs.

Step 2: By applying non-dominated sorting, solutions will be divided into non-dominated fronts. Also, another measure known as crowding distance sorts the solutions in each front.

Step 3: Generate offsprings using crossover and mutation operators and evaluate their fitness. While the crossover operator guarantees genetic inheritance, mutation preserves genetic diversity.

The difference between NSGA-II and NRGA is in their parent selection process:

- NSGA-II uses binary tournament selection technique: for selecting each parent, two random solutions are picked up. The individual with a lower front rank will be chosen. In the case that both solutions

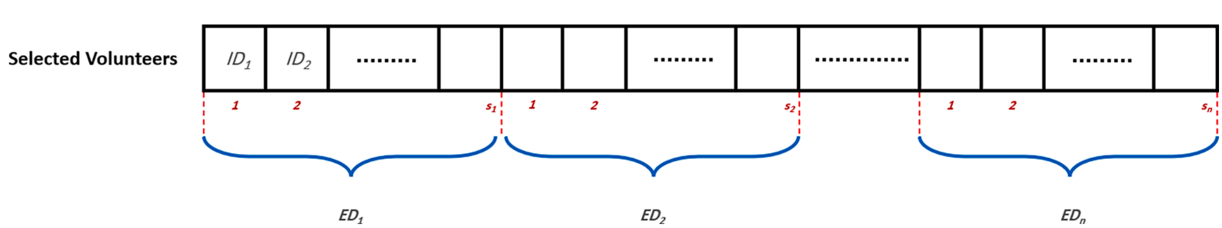

Fig. 4. Structure of the Chromosome.

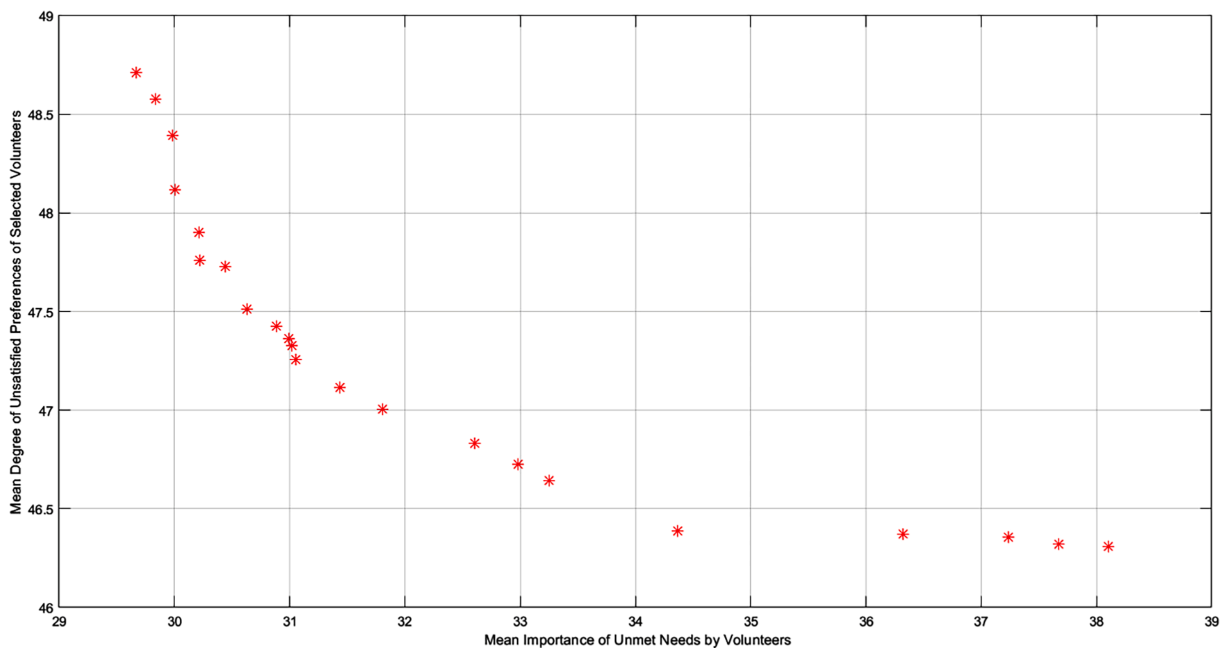

Fig. 5. NSGA-II Pareto front of solving the first large-size problem.

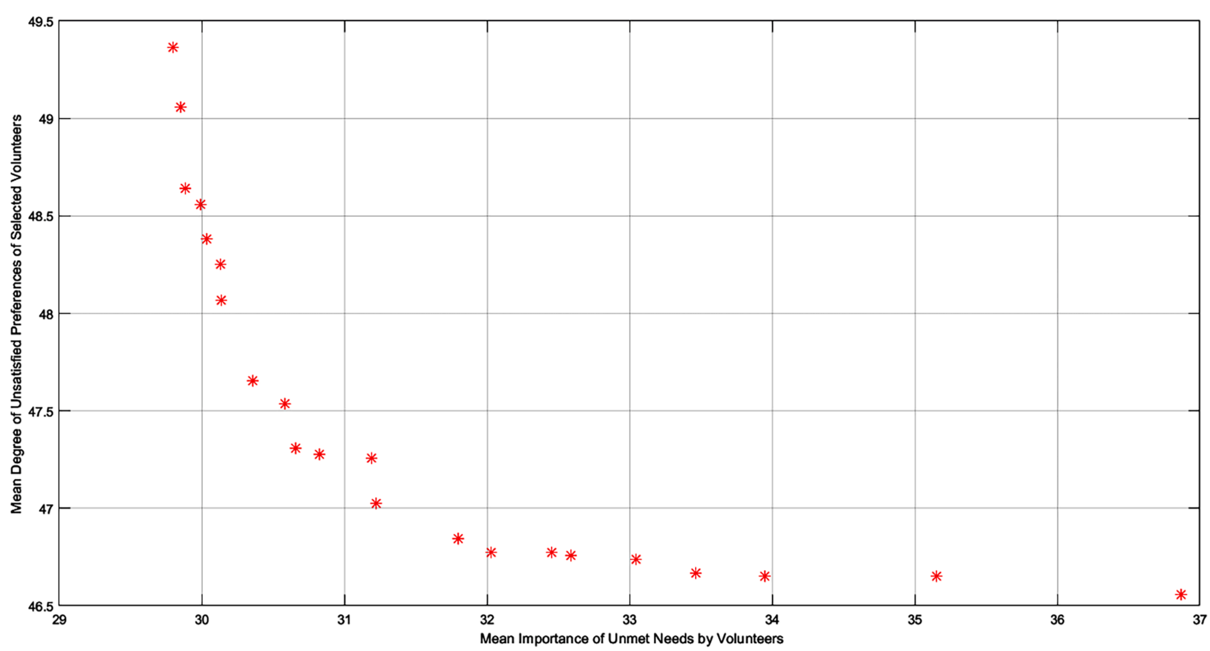

Fig. 6. NRGA Pareto front of solving the first large-size problem.

come from the same front, the one with a higher crowding distance is the winner;

- NRGA employs ranked-based roulette wheel selection strategy: first, a front is selected randomly. Fronts with better ranks have a higher probability of being selected. Afterward, an individual will be selected from the chosen front. In the same way, solutions with higher crowding distances have more chances to be selected.

In this study, we have used permutation crossover as well as three mutation operators: swap, insertion, and reversion.

Step 4: The current population and the generated offsprings together form the new population. Again, this new population will be sorted using non-dominated sorting and crowding distance.

Step 5: To build the next generation population, we select the best individuals from the new population (elitism strategy) with the size of the original population and sort them using non-dominated sorting and crowding distance.

Step 6: If the break condition (reaching a specified number of iterations in the algorithm) is not met, go to step 3; otherwise, break the loop.

Step 7: Return the first Pareto front of the population (Pareto-optimal) as the algorithm's output. All the returned solutions are optimal and represent the tradeoff between objective functions.

Table 7
NSGA-II and NRGA performance comparison for small-size problems (NNS, SM, and HV).

Independent Samples Test										
		Levene's Test for Equality of Variances		*t*-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
NNS	Equal variances assumed	0.165	0.686	−1.088	58	0.281	−1.833	1.685	−5.207	1.540
	Equal variances not assumed			−1.088	57.991	0.281	−1.833	1.685	−5.207	1.540
SM	Equal variances assumed	0.951	0.334	0.882	58	0.382	0.04088	0.04637	-0.05193	0.13369
	Equal variances not assumed			0.882	57.306	0.382	0.04088	0.04637	-0.05195	0.13372
HV	Equal variances assumed	0.002	0.963	-0.102	58	0.919	-0.00213	0.02094	-0.04404	0.03978
	Equal variances not assumed			-0.102	57.973	0.919	-0.00213	0.02094	-0.04404	0.03978

5. Performance analysis of evolutionary algorithms

In order to assess the performance of NSGA-II and NRGA in solving volunteer selection problem, we define two problem sizes:

- Small size problem: 5 EDs, each ED has 5 vacancies, 75 volunteers are registered for vacancies.
- Large size problem: 10 EDs, each ED has 5 vacancies, 150 volunteers are registered for vacancies.

Regarding each problem size, 30 problems are generated randomly and solved by proposed evolutionary algorithms. Pareto front of the first large-size problem solved by NSGA-II and NRGA are depicted in Figs. 5 and 6, respectively.

To compare the performance of algorithms, five criteria are considered based on works by Zitzler, Deb, and Thiele (2000), Zitzler and Thiele (1998), and Schott (1995):

CPU time: A critical performance measure of algorithms, especially in solving large problems, is the algorithm's execution time. This measure is calculated in seconds, and the lower CPU time means better algorithm performance;

1. **Number of Non-dominated Solutions (NNS):** The number of solutions in the optimal Pareto front. The higher number of non-dominated solutions corresponds to more diversity and better exploration;
2. **Mean Ideal Distance (MID)**: The mean distance of optimal Pareto front solutions from the ideal solution (16):

$$MID = \sum_{i=1}^{n} \frac{C_i}{n} \tag{16}$$

C_i is the distance from solution i to the ideal point (0, 0), and n is the number of solutions in the optimal Pareto front. Lower MID values indicate better solutions.

3. **Spacing Metric (SM):** The distribution of solutions in the optimal Pareto front (17):

$$SM = \frac{\sum_{i=1}^{n-1} |\overline{d} - d_i|}{(n-1)\overline{d}} \tag{17}$$

Where d_i is the distance between two sequential solutions in the optimal Pareto front, $\overline{d}$ is the mean of d_i values, and n is the number of solutions.

4. **Hypervolume (HV):** the volume (or area) covered by the discovered optimal solutions relative to a given reference point (18):

Table 8
NSGA-II and NRGA performance comparison for small-size problems (CPU Time and MID).

Test Statistics[a]	CPU Time	MID
Mann-Whitney U	374.000	436.000
Wilcoxon W	839.000	901.000
Z	−1.124	-0.207
Asymp. Sig. (2-tailed)	0.261	0.836

a. Grouping Variable: Algorithm (NSGA-II and NRGA).

$$HV = volume\left(\bigcup_{i=1}^{n} v_i\right) \tag{18}$$

Where v_i is the volume (or area) derived from the i answer and the determined reference point in the objective space.

In this study, the reference point is formed based on the biggest value of mean importance of unmet needs by volunteers and mean degree of unsatisfied preferences of all selected volunteers generated in Pareto fronts of solved problems in the current study by both NSGA-II and NRGA.

Hypervolume indicates both the diversity and convergence criteria. The greater the value of Hypervolume, the greater the algorithm's efficacy.

NSGA-II and NRGA are implemented using MATLAB R2021b on a computer with Intel(R) Core ™ i5-3230 M CPU @ 2.60 GHz and 6 GB DDR3 Memory. Also, statistical tests are performed in IBM SPSS Statistics 26.

5.1. *Performance analysis of algorithms in small-size problems*

To examine if measurement metrics are normally distributed, we conduct the Shapiro-Wilk test on obtained data from solving small-size problems by NSGA-II and NRGA. Results show that while NNS, SM, and HV are distributed normally, CPU Time and MID distribution are not normal.

To compare the performance of heuristic algorithms, we employ Independent-samples T-Test on variables with normal distribution: NNS, SM, and HV. The results are available in Table 7. Regarding the output of Independent-Samples T-Test, we can conclude that:

1. There is no significant difference between the mean of NNS metric obtained from NSGA-II and NRGA (P-value = 0.281);
2. There is no significant difference between the mean of SM metric obtained from NSGA-II and NRGA (P-value = 0. 382);

Table 9
NSGA-II and NRGA group statistics for large-size problems (CPU Time and NNS).

Group Statistics					
	Algorithm	N	Mean	Std. Deviation	Std. Error Mean
CPU Time	NSGA-II	30	474.8405	2.11858	0.38680
	NRGA	30	476.9825	1.78698	0.32626
NNS	NSGA-II	30	19.33	4.589	0.838
	NRGA	30	22.97	7.726	1.411

3. There is no significant difference between the mean of HV metric obtained from NSGA-II and NRGA (P-value = 0. 919).

Also, Mann-Whitney *U* test is used to compare the mean of variables that are not distributed normally: CPU Time and MID. The results are given in Table 8. It can be concluded that:

1. There is no significant difference between the mean of CPU Time metric obtained from NSGA-II and NRGA (P-value = 0.261);
2. There is no significant difference between the mean of MID metric obtained from NSGA-II and NRGA (P-value = 0.836).

Regarding the results, there is no statistically significant difference between NSGA-II and NRGA performance in all five performance metrics in small-size problems: CPU Time, NNS, MID, SM, and HV.

5.2. *Performance analysis of algorithms in large-size problems*

Similarly, we conducted Shapiro-Wilk test on NSGA-II and NRGA measurement metrics obtained from solving large-size problems. Based on results, CPU Time, NNS, and HV are distributed normally. However, the distribution of MID and SM is not normal.

We use Independent-samples T-Test on variables with normal distribution: CPU Time, NNS, and HV. The results are shown in Tables 9 and 10. Considering the output of Independent-Samples T-Test, it can be concluded that:

1. There is a significant difference between the mean of CPU Time metric obtained from NSGA-II and NRGA (P-value = 0.000). The mean CPU Time in NSGA-II is lower than in NRGA;
2. There is a significant difference between the mean of NNS metric obtained from NSGA-II and NRGA (P-value = 0.032). The mean of NNS in NRGA is higher than NSGA-II;
3. There is no significant difference between the mean of HV metric obtained from NSGA-II and NRGA (P-value = 0. 989).

Also, Mann-Whitney *U* test is used to compare the mean of MID and SM, which are not distributed normally. Based on the results in Table 11, we can conclude that:

1. There is no significant difference between the mean of MID metric obtained from NSGA-II and NRGA (P-value = 1.000);
2. There is no significant difference between the mean of SM metric obtained from NSGA-II and NRGA (P-value = 0.209);

Comparisons of algorithms in all five metrics are also depicted in Figs. 7-11.

Therefore, NSGA-II performs better than NRGA in terms of CPU Time. However, NRGA outperforms NSGA-II in NNS. Also, there is no statistically significant difference between NSGA-II and NRGA performance in MID, SM, and HV metrics.

To sum up, regarding the statistical tests, we can conclude that the performance of NSGA-II and NRGA in small-size problems is the same in all five metrics. Regarding large-size problems, NSGA-II performs better in the CPU Time metric. However, NRGA produces more NNS in its Pareto front. There is no significant difference between employed algorithms in the remaining three metrics (MID, SM, and HV).

6. Results and discussion

In the current study, we introduced a multi-objective model to deal with the problem of volunteer assignment in a disaster occurrence. In this context, meeting the immediate needs of the EDs is as important as meeting the volunteers' preferences. That is because retaining volunteers has a critical effect on providing continuous high-quality medical services for affected people when needs as well as volunteer base change rapidly. Therefore, we considered two objective functions: The first is to minimize the mean importance of unmet needs by volunteers, and the second is to minimize the mean degree of unsatisfied preferences of selected volunteers. It should be noted that introduced objective

Table 11
NSGA-II and NRGA performance comparison for large-size problems (MID and SM).

Test Statistics[a]		
	MID	SM
Mann-Whitney U	450.000	365.000
Wilcoxon W	915.000	830.000
Z	0.000	−1.257
Asymp. Sig. (2-tailed)	1.000	0.209

a. Grouping Variable: Algorithm (NSGA-II and NRGA).

Table 10
NSGA-II and NRGA performance comparison for large-size problems (CPU Time, NNS, and HV).

Independent Samples Test										
		Levene's Test for Equality of Variances		*t*-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
CPU Time	Equal variances assumed	0.394	0.533	−4.233	58	0.000	−2.14203	0.50602	−3.15494	−1.12912
	Equal variances not assumed			−4.233	56.397	0.000	−2.14203	0.50602	−3.15555	−1.12851
NNS	Equal variances assumed	6.154	0.016	−2.215	58	0.031	−3.633	1.641	−6.917	-0.349
	Equal variances not assumed			−2.215	47.197	0.032	−3.633	1.641	−6.933	-0.333
HV	Equal variances assumed	0.069	0.794	-0.013	58	0.989	-0.00018	0.01325	-0.02670	0.02635
	Equal variances not assumed			-0.013	57.979	0.989	-0.00018	0.01325	-0.02670	0.02635

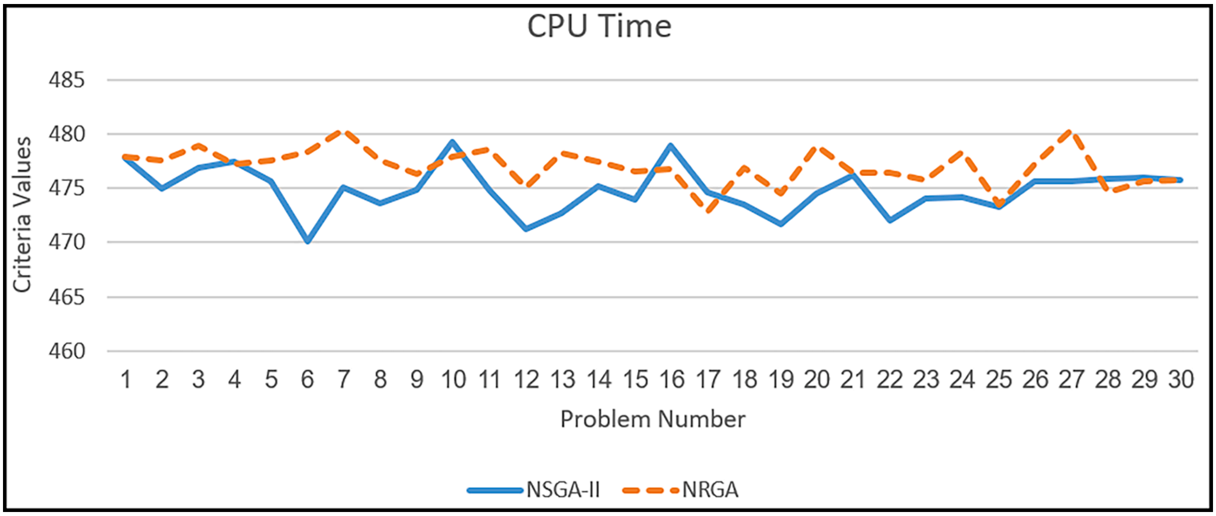

Fig. 7. Comparison of NSGA-II and NRGA in CPU Time metric (large-size problems).

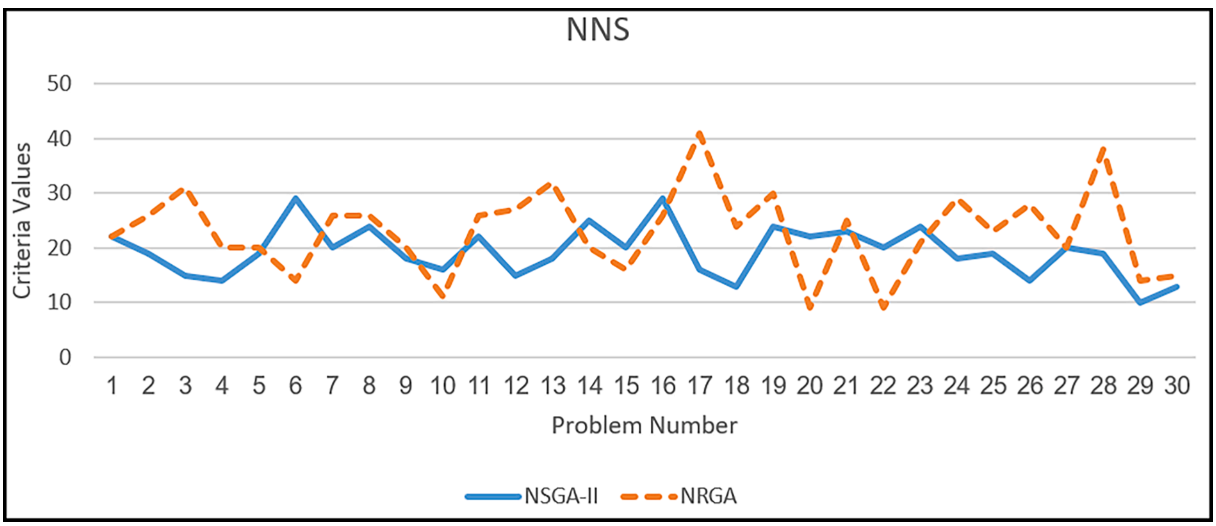

Fig. 8. Comparison of NSGA-II and NRGA in NNS metric (large-size problems).

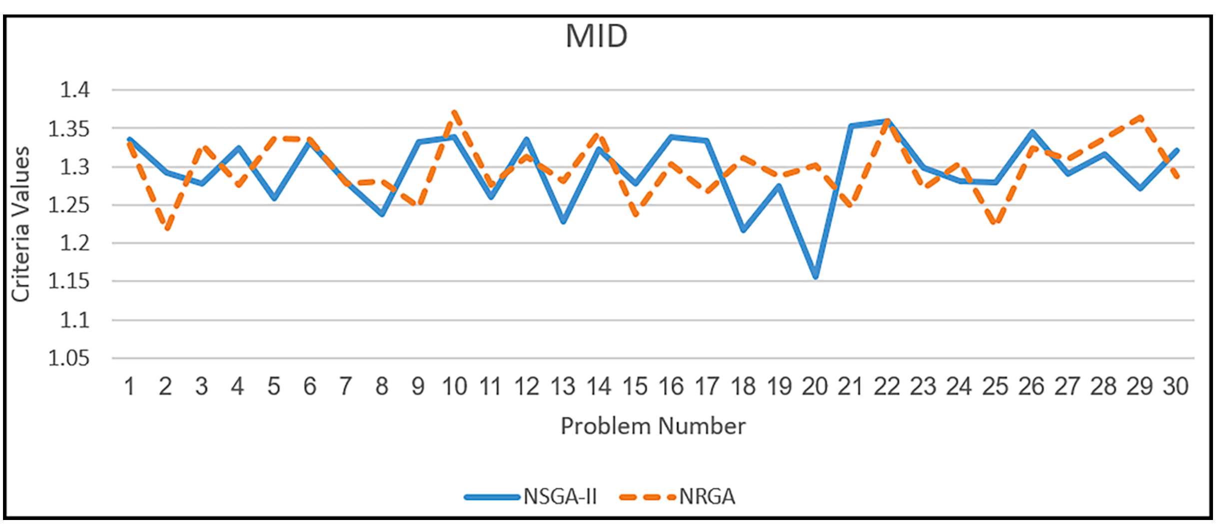

Fig. 9. Comparison of NSGA-II and NRGA in MID metric (large-size problems).

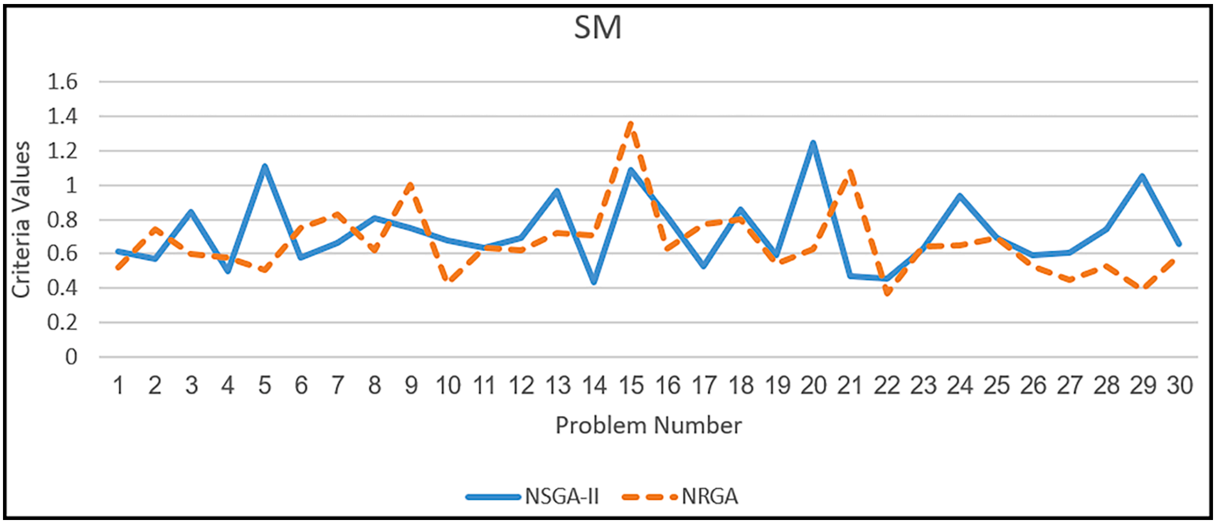

Fig. 10. Comparison of NSGA-II and NRGA in SM metric (large-size problems).

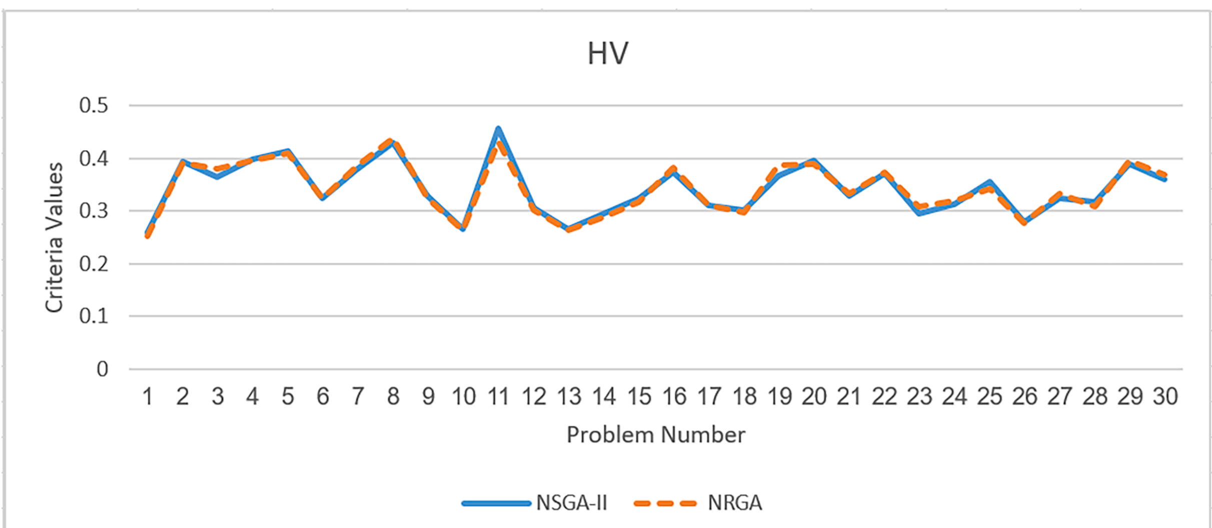

Fig. 11. Comparison of NSGA-II and NRGA in HV metric (large-size problems).

functions are qualitative. A FIS is developed to capture the system's uncertainty and ambiguity to evaluate each objective function. Also, two evolutionary algorithms are employed to solve the model: NSGA-II and NRGA. 30 small-size problems as well as 30 large-size ones are generated randomly and solved. In the next step, statistical tests are conducted on obtained data to evaluate the performance of algorithms. Based on the test results, both algorithms have the same performance on small-size problems. However, in large-size problems, NSGA-II solves the problems faster. Nevertheless, NRGA produces more NNS.

Moreover, we tried to make our model flexible enough to suit various situations. Introduced FISs are critical to this flexibility: In addition to encapsulating experts' knowledge and the method of human reasoning in FISs to deal with uncertainty, decision-makers can easily change the model just by updating linguistic rules regarding different situations. Last but not least, employing evolutionary algorithms instead of a single solution produces a set of optimum solutions, which are a tradeoff between our two objective functions. Decision-makers should choose the final solution among the optimum solutions. Regarding the situation, it is up to them to decide which objective function is more critical and to what extent. Obtained results show that our model is promising in capturing the uncertainty of volunteer selection problem in humanitarian and representing the tradeoff between objective functions. However, it should be validated in real cases. Besides, our proposed model is limited to two qualitative objective functions. Considering other objective functions, such as the importance of volunteers' desire to work in specific groups, will be valuable. As a suggestion for future works, the following topics might be of great interest:

1. Adapting the proposed model to meet other scenarios in humanitarian context as well as other disaster phases.
2. Using other evolutionary algorithms and comparing the results with this study.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Daniel Arias-Aranda reports financial support was provided by European Commission.

Data availability

Data will be made available on request.

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Appendix A. Rule base of FIS1

Rule No.	IF (Input variables)			Then (Output variable)
	P	E	T	x′
1	Low	Low	Low	Very Low
2	Low	Low	Medium	High
3	Low	Low	High	Very High
4	Low	Medium	Low	Medium
5	Low	Medium	Medium	Medium
6	Low	Medium	High	High
7	Low	High	Low	High
8	Low	High	Medium	Low
9	Low	High	High	Medium
10	Medium	Low	Low	Low
11	Medium	Low	Medium	Medium
12	Medium	Low	High	High
13	Medium	Medium	Low	Medium
14	Medium	Medium	Medium	Low
15	Medium	Medium	High	Medium
16	Medium	High	Low	High
17	Medium	High	Medium	Very Low
18	Medium	High	High	Low
19	High	Low	Low	Medium
20	High	Low	Medium	Low
21	High	Low	High	Medium
22	High	Medium	Low	High
23	High	Medium	Medium	Very Low
24	High	Medium	High	Low
25	High	High	Low	Very High
26	High	High	Medium	Low
27	High	High	High	Very Low

Appendix B Rule base of FIS2.

Rule No.	IF (Input variables)			Then (Output variable)
	P	E	N	X″
1	Low	Low	Low	Very Low
2	Low	Low	Medium	High
3	Low	Low	High	Very High
4	Low	Medium	Low	Medium
5	Low	Medium	Medium	Medium
6	Low	Medium	High	High
7	Low	High	Low	High
8	Low	High	Medium	Low
9	Low	High	High	Medium
10	Medium	Low	Low	Low
11	Medium	Low	Medium	Medium
12	Medium	Low	High	High
13	Medium	Medium	Low	Medium
14	Medium	Medium	Medium	Low
15	Medium	Medium	High	Medium
16	Medium	High	Low	High
17	Medium	High	Medium	Very Low
18	Medium	High	High	Low
19	High	Low	Low	Medium
20	High	Low	Medium	Low
21	High	Low	High	Medium
22	High	Medium	Low	High
23	High	Medium	Medium	Very Low
24	High	Medium	High	Low
25	High	High	Low	Very High
26	High	High	Medium	Low
27	High	High	High	Very Low

Appendix C Rule base of FIS_3.

Rule No.	IF (Input variables)			Then (Output variable)
	D	W	F	y′
1	Low	Low	Low	Very Low
2	Low	Low	Medium	Very Low
3	Low	Low	High	Very Low
4	Low	Medium	Low	Very Low
5	Low	Medium	Medium	Low
6	Low	Medium	High	Low
7	Low	High	Low	Low
8	Low	High	Medium	Medium
9	Low	High	High	Medium
10	Medium	Low	Low	Very Low
11	Medium	Low	Medium	Low
12	Medium	Low	High	Low
13	Medium	Medium	Low	Low
14	Medium	Medium	Medium	Medium
15	Medium	Medium	High	Medium
16	Medium	High	Low	Medium
17	Medium	High	Medium	High
18	Medium	High	High	High
19	High	Low	Low	Low
20	High	Low	Medium	Medium
21	High	Low	High	Medium
22	High	Medium	Low	Medium
23	High	Medium	Medium	High
24	High	Medium	High	High
25	High	High	Low	High
26	High	High	Medium	Very High
27	High	High	High	Very High

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