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A BI-OBJECTIVE MEDICAL RELIEF SHELTER LOCATION PROBLEM CONSIDERING COVERAGE RATIOS

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Under disaster circumstances, people in the impacted areas need different levels of medical services provided by the temporary or existing medical relief shelters whose medical service capability should be equal to or greater than their needs. It is an important but challenging problem to provide effective and efficient medical or relief services to the affected people. This study proposed a bi-objective mathematical programming model to overcome this challenging situation considering the patients' severities, medical service level, and geographical locations under disaster circumstances. The proposed bi-objective mathematical model intends to determine the appropriate locations for temporary medical relief shelters (MRS), specifying the service level of MRS and plan the logistics network for medical supplies. The objective is to achieve the maximum coverage of medical relief service and the minimum logistics costs, including the construction and operating costs of temporary MRSs and the procurement and transportation costs of medical supplies from medical deployment centers simultaneously. This paper solves a bi-objective medical shelter location problem with differential coverage ratios, using the non-dominated sorting genetic algorithm II (NSGA-II) and the modified NSGA-II (mNSGA-II) to find the Pareto front. Due to the sensitivity of those algorithms to parameter values, the Taguchi method is used to tune the parameters of the algorithms. We have chosen five measures into two groups. Qualitative metrics include the number of Pareto solutions (NPS), diversity metric, and spacing metric, and quantitative metrics include mean ideal distance (MID) and calculation times to evaluate the performance of our proposed algorithms. Various test problems of different sizes are tested to compare the performance of the NSGA-II and mNSGA-II. The computational results compared the pros and cons of two algorithms in solving the bi-objective medical relief shelter location problem.

Keywords: NSGA-II and mNSGA-II; bi-objective optimization; Medical relief shelter location problem; Taguchi method; Pareto solutions

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1. INTRODUCTION

Extreme events such as natural or human-made disasters have become regular occurrences in recent years. Such extreme events may cause significant losses of property damages, economic disruptions, and environmental degradation. In addition, many people are affected, frequently leading to deaths or injuries, and tremendous demands for medical supplies occur in the impacted areas in a short period. Affected people in disaster-impacted regions may have various severity and require different levels of medical services.

In response to reducing the consequences of the extreme events, it is essential to recognize the severity and the required level of medical service for the affected people. Establishing the MRSs with different service levels and transporting the affected people to appropriate medical treatments can help to reduce the consequences of extreme events, considering the location of medical deployment centers, which provide the medical supplies (medical staffs, equipment, medicines, etc.).

In any circumstance of disasters, it becomes challenging for the relief worker to distribute the relief supplies among the affected people to meet their requirements. Jia *et al.* (2007) proposed a maximal covering facility location model which efficiently found locations for tremendous demands of medical services in emergencies. A Chinese national emergency warehouse location problem was presented by Ye *et al.* (2015) with considering transportation, economic condition,

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population distribution, and multi-coverage for some critical areas. Many facility systems are hierarchical in terms of the types of services they provided in nature. By applying the maximal covering location problem, Moore and ReVelle, (1982) introduced the hierarchical covering location problem to the health care service area, assuming that different kinds of services can be provided for customers. Lee and Lee (2010) proposed a tabu-based heuristic for the generalized hierarchical covering location problem to determine the locations and levels of the facilities and the set of customers which facilities needed to be served. Farahani *et al.* (2014) reviewed around 100 references on hierarchical location problems and classified all papers in terms of models, solutions, performance measures, and applications. Recently, Gao *et al*. (2017) presented a hybrid genetic algorithm for multi-emergency medical service center location-allocation problems in disaster response.

Afshar and Haghani (2012) proposed a mathematical model that controlled the complete flow of several relief commodities from sources to their recipients via a supply chain network. A humanitarian and disaster relief supply chain within the broad area of supply chain management was studied by Day *et al.* (2012). Mohamadi and Yaghoubi (2017) introduced a bi-objective stochastic optimization model to determine the location of transfer points and medical supplies distribution centers considering the priority of injured treatments. Gu *et al.* (2016) proposed a mathematical programming model to determine the locations of temporary MRSs and provide the required medical supplies from medical deployment centers effectively and efficiently under the limited relief budget, considering patients' severities and geographical locations. In recent years, the Epsilon constraint method was adopted to solve multiple-objective humanitarian relief logistic problems by many studies (Baharmand *et al.*, 2019). However, the Epsilon constraint method has difficulty finding an excellent value for the epsilon vector, especially for solving complex problems.

This study assumes that the severity and distribution of the patients in the impacted areas are already known, and the respective medical service levels can be determined easily. Patients can be served by temporary MRSs whose medical service level is equal to or higher than the required. In this study, For seriously injured people, a high level of medical service must be taken care of with high priority. Patients with higher severity need immediate medical assistance and quickly transfer to the nearest medical shelters to have the necessary medical services. In this study, each patient has a severity level compared to the medical service level offered by the MRS. The patients can be assigned to MRSs when MRSs' medical service levels are equal to or higher than their severity levels.

Candidate locations of MRSs are determined in advance before the disaster impact. It is assumed that each candidate location can construct exactly one MRS that provides one level of medical service. The total number of MRSs at each level of medical services to be constructed is known. Patients are only assumed to be covered within a circular region with a specific radius from the MRSs. Sometimes the coverage ratio function may vary depending on the problem. There are many different coverage ratio functions and types; linear or nonlinear, continuous or discrete, and others (Karasakal and Karasakal, 2004). Figure 1 depicts three possible coverage functions: sigmoid partial coverage function, linear partial coverage function, and classical coverage function. In Figure 1, there are two parameters α and β representing the full and maximum partial coverage distances, respectively. If the distance is lower than α, the coverage function is equal to 1 for all the coverage functions. If the distance is higher than β, the coverage function is equal to 0 for all the coverage functions. If the distance is between α and β, the classical coverage function equals 0, while the sigmoid partial coverage function value and the linear partial coverage function values are between 0 and 1.

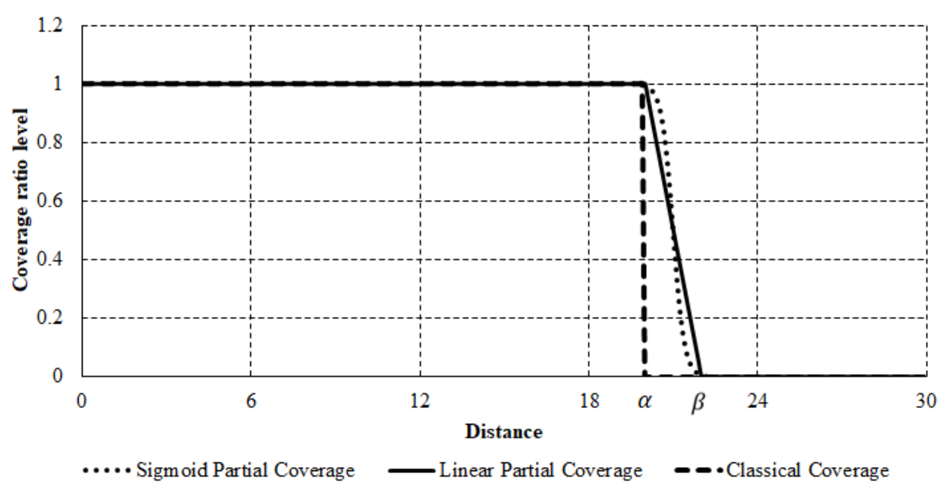

Figure 1. Sample of possible coverage functions.

Medical deployment centers provide the medical staff and supplies to MRSs and have their maximum capacity for each supply. Transportation cost includes the vehicle cost and variable cost. Nicholl *et al.* (2007) surveyed the relationship between the distance to the hospital and the patient death in an emergency. It is natural to see that fast evacuation is crucial to saving human lives. Figure 2 shows an example of the MRS location problem considered in this study. Square, triangle, and pentagon denote the MRSs with different medical service levels. The cylinders represent the medical deployment centers. The circles indicate patients, and the numbers in the circle represent the levels of medical service required for particular patients. The black dash line represents patients assigned to MRSs, and medical relief centers provide medical supplies to the MRS.

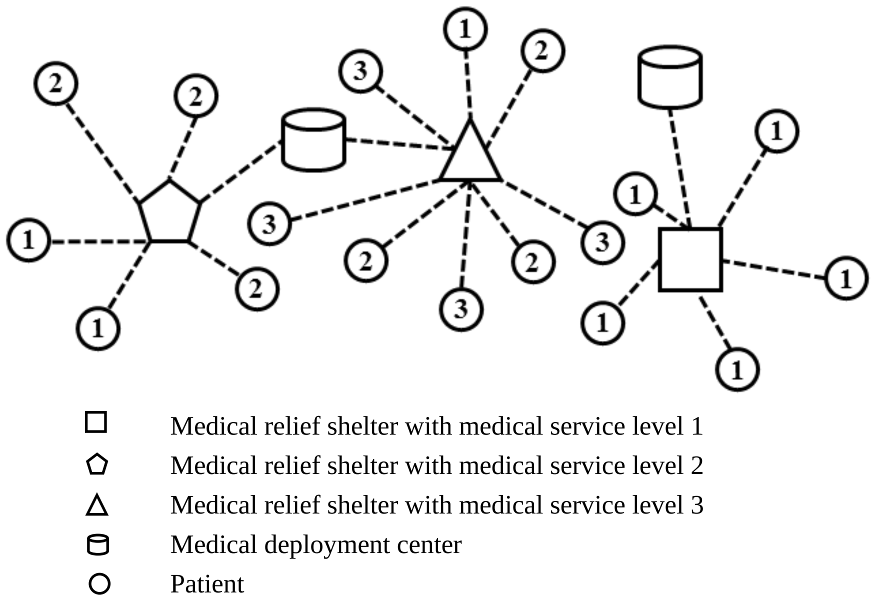

Figure 2. An example of the proposed medical relief shelter location problem in this study.

This study aims to maximize the number of patients who get medical services at MRSs and simultaneously minimize the total cost. The total cost includes the fixed construction cost to establish temporary MRSs, the procurement cost of medical supplies, and the transportation cost of the medical supplies, including medical staff. The total cost also includes the variable construction cost of MRSs, which is proportional to the capacity of shelters, in addition to the fixed construction cost.

NSGA (Srinivas and Deb, 1994) is a popular non-domination-based sorting genetic algorithm for multi-objective optimization problems. It received criticism for adding up high computational complexity, lack of elitism, and need for sharing parameters. Then, NSGA-II (Deb *et al.*, 2002) was developed with a better sorting algorithm, elitism, and no sharing parameter. NSGA-II still has the drawbacks such as lack of uniform diversity in obtained non-dominated solutions and absence of a lateral diversity-preserving operator among the currently-best non-dominated solutions. These two drawbacks have been overcome by introducing dynamic crowding distance and controlled elitism into the modified NSGA-II (nNSGA-II).

This study proposes a bi-objective mathematical programming model to address the concerns above. The bi-objective optimization method has been studied in different areas (Karimi *et al.*, 2010; Das and Bera, 2015; Akkan and Gülcü, 2018). To solve the proposed bi-objective mathematical programming model, NSGA-II and mNSGA-II have been implemented (Wang *et al.*, 2017). Various test problems were tested to compare the performance of the NSGA-II and mNSGA-II for the proposed model in this study.

The performance of solution methods for multi-objective optimization problems cannot be compared to single-objective optimization problems. We have chosen five performance metrics into two groups. Qualitative metrics are the number of Pareto solutions (NPS), diversity metric and spacing metric and quantitative metrics are
mean ideal distance (MID) and calculation times to evaluate the performance of our proposed algorithms.

The Taguchi method is a statistical method, sometimes called a robust design method, developed by Genichi Taguchi to improve the quality of manufactured goods. It has been used in various areas, and it is also used to optimize the process control parameters for the best performance. Urval et al. (2008, 2010) applied the Taguchi method to optimize the power injection modeling process. Li et al. (2019) studied a multi-objective optimization of the fiber-reinforced composite injection molding process using the Taguchi method to determine the effect of the process parameters. Pradeepmon et al. (2020) adopted the Taguchi method to determine the optimal combination of parameters and operators for the genetic algorithm.

Decision-makers in the deployment stage of disaster management can choose their most preferred solution from the solution set obtained by the NSGA-II and mNSGA-II.

The remainder of this paper is organized as follows. In Section 2, a bi-objective mathematical programming model is proposed. The solution method is studied in Section 3. The computational results are discussed in Section 4. Finally, in Section 5, the conclusions are presented.

2. MATHEMATICAL MODEL

The proposed bi-objective mathematical programming model has been formulated based on the hierarchical covering location problem (Lee and Lee, 2010) and a maximal covering location problem (Gu *et al.*, 2018). Gu *et al.* (2018) proposed a mathematical programming model for the MRS location problem with the limited operational budget. This study extended their mathematical programming model to a multi-objective programming model by lifting the budget constraints to an objective function. Their study focused only on the MRS locations, but this study minimizes the transportation costs and maximizes the number of patients for the medical treatment. Their study introduced the criteria as a single objective function considering the severity level of patients and the distance to the potential MRS to be established. We also used this approach in our greedy method to construct the final solutions.

Before introducing the proposed bi-objective mathematical programming model, several assumptions are made as follows.

Problem assumptions

- The severities, locations, and required level of medical services for patients are known.
- Patients with different severity levels require different quantities of medical supplies.
- The patients can be served by MRSs whose medical service level is equal to or higher than their severities.
- Each patient is assigned to only one MRS.
- The total number of MRSs that are allowed to be constructed with different levels of medical service is limited.
- The medical deployment centers provide medical supplies to MRSs at the maximum of pre-set quantities.
- Each type of medical supply has a fixed volume.
- A vehicle transporting medical supplies has the maximum capacity in volume.

In this section, sets, parameters, and decision variables are initially summarized.

Sets

I	Set of individual patients, $i \in I$
K	Set of types of medical supplies, $k \in K$
L	Set of medical service levels or severity levels
R	Set of candidate locations for MRSs, $r \in R$
C	Set of medical deployment centers, $c \in C$

Parameters

A_k^l	Quantity of medical supply k, required for a patient with severity level l
$A_k^{S_i}$	Quantity of medical supply k, required for patient i
MK_{kc}	Maximum quantity of medical supply k at medical deployment center c
V_k	Volume of medical supply k
MV	Maximum capacity of a vehicle in volume
S_i	Severity level of patient i
D_{ir}	Distance from the location of patient i to medical relief shelter r
CV	Vehicle cost per vehicle
CT	Transportation cost per vehicle per unit distance
CCF_{lr}	Fixed construction cost for a medical relief shelter at candidate location r for medical service level l
CCV_{lr}	Variable construction cost per additional capacity for a medical relief shelter at candidate location r for medical service level l
CO_{lr}	Operating cost for a medical relief shelter at candidate location r for medical service level l

CP_k	Procurement cost of medical supply k
SL_r	Maximum medical service level provided by the medical relief shelter r
P_l	Maximum number of MRSs allowed to constructed with medical service level l
CR_{irl}	The coverage ratio level determined by the coverage function, for patient i, MRS r, and medical service level l.
MSL_i	The medical service level required by patient i
Q	A large number

Decision variables

y_{lr}	1, if MRS with level l is constructed at candidate r; otherwise, 0
x_{ir}	1, if patient i is assigned to MRS r ; otherwise, 0
z_{crlk}	Quantity of medical supply k for patients with level l, required to be transported from medical deployment center c to MRS r

In this study, the sigmoid partial coverage function (Karasakal and Karasakal, 2004) is adopted to calculate the coverage ratio level CR_{irl}. The sigmoid partial coverage function $F(D_{ir}, \alpha_l, \beta_l)$ is defined as follows:

$$F(D_{ir}, \alpha_l, \beta_l) = \frac{1}{1 + e^{\delta(D_{ir} - (\alpha_l + \beta_l)/2)}} = CR_{irl} \ ,$$

where δ is a constant coefficient, α_l and β_l are the full and maximum partial coverage ranges for medical service level l, respectively. An MRS r fully covers all patients within the distance range of α_l and partially cover the patients in the distance range [α_l, β_l]. Those constants α_l and β_l can be chosen by the decision-maker considering the traffic conditions.

The proposed bi-objective mathematical programming model under consideration in this study is presented in the following.

Formulations

$$\text{Maximize } Z_1 = \sum_{i \in I} \sum_{r \in R} \sum_{l \in L} S_i \cdot CR_{irl} \cdot x_{ir} \quad (1)$$

$$\text{Minimize } Z_2 = \sum_{r \in R} \sum_{l \in L} CCF_{lr} \cdot y_{lr} + \sum_{r \in R} \sum_{l \in L} \sum_{c \in C} \sum_{k \in K} (CO_{lr} + CCV_{lr}) \cdot z_{crlk} + \sum_{r \in R} \sum_{l \in L} \sum_{c \in C} \sum_{k \in K} CP_k \cdot z_{crlk} + \frac{1}{\text{MV}} \sum_{r \in R} \sum_{l \in L} \sum_{c \in C} \sum_{k \in K} z_{crlk} V_k \cdot (CV + CT \cdot D_{lj}) \quad (2)$$

Subject to

$$\sum_{i \in I} A_k^{S_i} \cdot x_{ir} \leq \sum_{l \in L} \sum_{c \in C} z_{crlk} \qquad \forall k \in K, r \in R \quad (3)$$

$$\sum_{l \in L} \sum_{r \in R} z_{crlk} \leq MK_{kc} \qquad \forall\, k \in K, c \in C \quad (4)$$

$$z_{crlk} \leq Q \cdot y_{lr} \qquad \forall\, r \in R, l \in L \quad (5)$$

$$x_{ir} \cdot MSL_i \leq \sum_{l=0}^{L} l \cdot y_{lr} \qquad \forall\, r \in R, l \in L, i \in I \quad (6)$$

$$\sum_{i \in I} x_{ir} \leq 1 \qquad \forall\, r \in R \quad (7)$$

$$\sum_{r \in R} y_{lr} = P_l \qquad \forall\, l \in L \quad (8)$$

$$\sum_{l \in L} y_{lr} \leq 1 \qquad \forall\, r \in R \quad (9)$$

$$\sum_{l=1+SL_r}^{L} y_{lr} = 0 \qquad \forall\, r \in R \quad (10)$$

$$y_{lr} \in \{0,1\} \qquad \forall\, r \in R, l \in L \quad (11)$$

$$x_{ir} \in \{0,1\} \qquad \forall\, r \in R, l \in L \quad (12)$$

$$z_{crlk} \geq 0 \qquad \forall\, r \in R, l \in L, k \in K, c \in C \quad (13)$$

The objective function (1) maximizes the number of patients who get medical services at MRSs. The objective function (2) minimizes the total cost. Constraint (3) restricts the quantity of medical supplies k, transported from the medical deployment center c. This quantity must be greater than what is required for patients at the medical relief center r. Constraint (4) defines the maximum amount of medical supplies transported from medical deployment center c. Constraint (5) reflects that the capacity of MRS r with medical service level l can be allowed only when its candidate location is chosen for construction.

Similarly, constraint (6) indicates that the patient can be assigned to MRS r only when the MRS is constructed at candidate location r and the patient's required medical service level should be ensured by the MRS r. Constraint (7) indicates that a patient is assigned to only one MRS. Constraint (8) meets the restriction on the total number of allowed MRSs with different medical levels. Constraint (9) states that each MRS can only have a medical service level. Constraint (10) ensures that the constructed MRSs' medical service levels should be lower than the maximum medical service level provided by that medical relief candidate (each medical relief candidate has a maximum medical service level). Finally, constraints (11), (12), and (13) define the nature of decision variables.

3. SOLUTION METHOD

This section introduces the preliminary definitions and the proposed solution methods to solve the proposed MRS location problem. As explained in Section 2, the proposed model has two objective functions: minimizing the distribution costs and maximizing medical services to patients in need. The approaches to solving multi-objective optimization problems are different from the single-objective optimization problem. Multi-objective optimization problems do not necessarily have a single optimal solution that simultaneously optimizes all the objective functions. Therefore, important definitions are given in the following.

Definition 1: multi-objective optimization problem

Consider a multi-objective model with a set of conflicting objectives $F(\vec{x}) = [F_i(\vec{x}), \dots, F_k(\vec{x})]$ subject to $g_i(\vec{x}) \leq 0$, where $i = 1,2, \dots, k$, $\vec{x}$ denotes n-dimensional decision variables that can take real, integer, or Boolean value and $F(\vec{x})$ is a set of k objective functions. Its feasible solution space is Ω. Without loss of generality, we assume only maximization functions. The multi-objective model consists of finding a vector $\vec{x} \in \Omega$ that optimizes the vector function $F(\vec{x})$.

Definition 2: Pareto dominance

A vector $\vec{x}$ dominates $\vec{x}'$ (denoted by $\vec{x} \prec \vec{x}'$) if it is subject to (i) and (ii):

(i) $F_i(\vec{x}') \geq F_i(\vec{x}), \forall i = 1,2, \dots, k$

(ii) $\exists\ i \in \{1,2, \dots, k\}$: $F_i(\vec{x}') > F_i(\vec{x})$

Definition 3: Pareto optimal (Pareto efficiency or efficient solution)

A vector $\vec{x}^*$ is Pareto optimal if there does not exist a vector $\vec{x}' \in \Omega$ such that $\vec{x}' \prec \vec{x}^*$.

Definition 4: Pareto optimal set

Given a multi-objective model in definition 1, the Pareto set is defined as $\mathrm{P}^* = \{\vec{x}^* \in \Omega\}$.

Definition 5: Pareto front

Given a multi-objective model in definition 1 and its Pareto set P^*, the Pareto front is defined as $\mathrm{PF}^* = \{F(\vec{x}) \mid \vec{x} \in \mathrm{P}^*\}$.

Pareto efficiency or Pareto optimality is defined as a situation where one objective function cannot be improved without making at least another objective function or any loss. It takes place when the resources are most optimally used.

The Pareto frontier or Pareto front is the set of all Pareto efficient solutions. Therefore, this study tries to find Pareto efficient solutions by implementing NSGA-II and the modified NSGA-II (mNSGA-II) with a fine-tuned parameters using the Taguchi method.

In genetic algorithms, chromosome representation plays an important role in the performance of the algorithms. It must be simple and straightforward because the efficiency of the algorithms is determined by crossover and mutation operations that work on the chromosome structure. The solution to the MRS problem in this study consists of two parts: (1) the MRS locations with some medical service levels to be constructed and (2) the assignments and patients and medical supplies to be assigned to those MRSs. We explain the chromosome representation and how to construct the solutions using the proposed chromosome representation in the following.

Step 1) MRS locations with specific medical service levels

The MRS locations and their medical service levels are determined by satisfying the two following constraints:

a) Each candidate location for an MRS has a maximum level of medical service it can offer to patients. This level is limited by the pre-defined maximum medical service level for all MRSs.
b) The number of MRSs constructed is no more than the maximum number of allowed MRSs with the pre-defined medical service levels.

Considering these two constraints (a) and (b), the chromosome of an individual in a population is represented by a binary string with a length equal to $\sum_{r\in R}|R| \cdot SL_r$, where $|R|$ denotes the maximum number of MRSs. The shaded binary string in Table 1 shows an example of chromosome representation. Table 1 illustrates the explanation of this chromosome representation. There are 4 candidate locations of MRSs, and the maximum medical service level for each candidate location is 3. One MRS with each medical service level is constructed. Candidate locations r_1, r_2, and r_3 have newly-constructed MRSs with medical service levels 2, 1, and 3, respectively. Candidate location r_4 does not have a new construction. Binary numbers 0 and 1 in the shaded row of Table 1 indicate whether a MRS with the corresponding level is constructed at the corresponding candidate location. The first three genes (0, 1, 0) of the chromosome corresponds to candidate location r_1 and it indicates that a MRS is constructed there with medical service level 2. The second three genes (1, 0, 0) means that there is an MRS with medical service level 1 at candidate location r_2. The thrd three genes (0, 0, 1) represent an MRS with medical service level 3 at candidate location r_3. The last three genes (0, 0, 0) corresponds to candidate location r_4, which has no construction for a MRS.

Table 1. An example of chromosome representation.

Candidate locations for MRSs	r_1			r_2			r_3			r_4		
Medical service level	1	2	3	1	2	3	1	2	3	1	2	3
Chromosome	0	1	0	1	0	0	0	0	1	0	0	0

Through the proposed chromosome representation, the locations of newly-constructed MRSs are determined.

Step 2) Assignments and patients and medical supplies

Once the locations of MRSs and their medical service levels are determined, the patients must be assigned to the appropriate MRSs to receive the appropriate medical services, and the medical supplies also need to be transported to MRSs. These are achieved using a set of greedy approaches on the top of solutions in Step 1. Firstly, MRSs choose the nearest medical deployment centers from their locations. Secondly, Patients need to be assigned to MRSs in a greedy principle of the shorter distance to an MRS and the higher priority on patients with the higher severity level. This idea was originally from Gu *et al.* (2018). They used an objective function that ensures this principle. The following approach has been used in this paper. The coverage ratio level CR_{irl} for patient i, MRS r, and medical service level l are calculated using sigmoid partial coverage function $F(D_{ir}, \alpha_l, \beta_l)$. Then, values of $S_i * CR_{irl}$ of patient i for all MRSs with the medical service level required by patient i are calculated and sorted into a list in descending order. Each value is associated with patient *i* and MRS *r*, which indicates the assignments. Once a patient is assigned, we removed all its $S_i * CR_{irl}$ values from the list. This completes the assignment of a patient. This process is repeated until all patients are assigned to MRSs. Thirdly, the medical supplies to be transported from medical deployment centers to MRSs are determined by adding up the amounts of medical supplies to be used to treat assigned patients with their medical service levels.

Once Steps 1 and 2 are completed, two objective functions Z_1 and Z_2 can be calculated. In other words, we can used them as the fitness functions in NSGA-II and mNSGA-II.

We explain the genetic operations that are used in our implementation of NSGA-II and mNSGA-II. A binary tournament selection method has been used to select the parents for the crossover operation because it is simple and effective. Many previous studies have adopted this parent selection method to generate the mating pool, and two parents are randomly selected from the mating pool for reproduction (Deb *et al.*, 2002; Wang *et al.*, 2017). A multi-point crossover (De Jong and Spears, 1992) is chosen for the crossover operator, and it is an enhanced crossover operation based on a one-point crossover by swapping alternated segments of chromosomes between two parents to generate new off-springs, as shown in Figure 3. As mentioned above, the genes of a chromosome have binary numbers to represent whether an MRS is established at the corresponding location or not. Therefore, the chromosome designed in this paper is very suitable to adopt a bit-flip mutation (Chicano *et al.*, 2015), which randomly selects one or more genes and flips the selected genes, as shown in Figure 4.

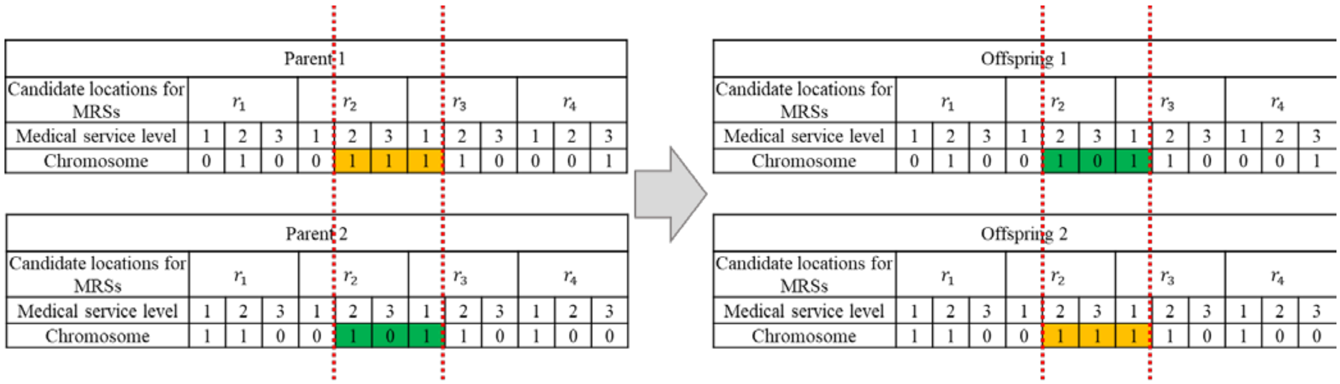

Figure 3. A multi-point crossover operation

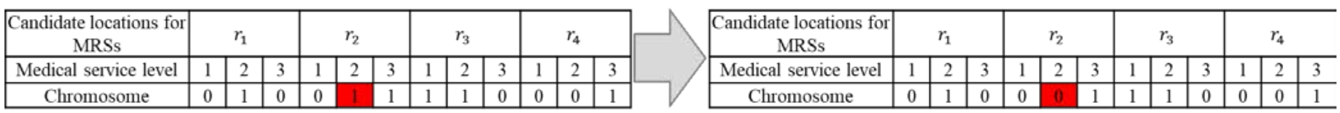

Figure 4. A bit-flip mutation operation

The study of Gu *et al.* (2018) proposed a mathematical model for an MRS location problem with a limited budget constraint and a single objective function and solved their model using a LINGO solver. Their experimental results showed that the MRS location problem is challenging to solve and time-consuming. The problem considered in this paper has two objective functions, making it belong to multi-objective optimization problems. Effective and efficient algorithms for multi-objective optimization problems are considered to solve the proposed MRS location problem. NSGA-II (Deb *et al.*, 2002), which consists of three essential cores including fast non-dominated sorting, fast crowding distance estimation, and simple crowding comparison operator, is one of the most popular multi-objective evolutionary algorithms and has been used to solve multi-objective problems, such as engineering design problems and medical treatments. Based on the proposed chromosome representation and evolutionary algorithm operators. A new algorithm, mNSGA-II (Wang *et al.*, 2017), a variation of NSGA-II hybrid with a memetic algorithm, is effective and efficient than the NSGA-II. This paper developed the mNSGA-II and NSGA-II for the proposed MRS location problem.

4. COMPUTATIONAL EXPERIENCES

This section presents the computational experiences and the discussion.

4.1. Test problems

To our best knowledge, there was no benchmark problem for the proposed MRS location problem in this study. Therefore, the problem generator from Gu *et al.* (2018) was extended to generate the severities and the locations of patients for the test problems.

In our experiments, the maximum number of medical service levels is assumed to be 3, as Lee and Lee (2010) also used levels 1, 2, and 3 in their study. That is, the cardinality $|L|$ is set to 3. The number of medical deployment centers $|C|$ is set to 2. The locations of patients and the medical deployment centers, and the candidate locations for MRSs are generated within a two-dimensional Euclidian space. The maximum X and Y coordinates are 100, respectively. The fixed construction costs of MRSs are randomly generated within the range [20000, 25000], [25000, 30000], and [30000, 35000] for levels 1, 2, and 3, respectively. The variable construction cost per additional patient is \$50 per assigned patient. The operating cost of MRS per patient is \$100. The vehicle cost is \$1,000 per vehicle, and the transportation cost per unit distance is \$10. The procurement costs of three different types of medical supplies are \$30, \$50, and \$30, respectively. The volumes for the three types of medical supplies are 2, 3, and 5, respectively. The capacitated vehicle can load the medical supplies of 20 in volume.

Table 2 shows the characteristics of randomly generated test problems, i.e., the input parameters for the problem generator. For test problem e1 in Table 2, the number of patients $|I|$ is set to 100 and the number of candidate locations for MRS $|R|$ is set to 15. The maximum number P_l of MRSs is allowed to be constructed at each level is set to 1, 2, and 3 for medical service levels 1, 2, and 3, respectively. The fourth column $|SL_r{=}1|$ indicates the number of candidate locations to establish MRSs with medical service level 1. Similarly, $|SL_r{=}2|$ and $|SL_r{=}3|$ are given.

Table 2. Characteristics of the randomly generated test problems.

Test problem	$\lvert I\rvert$	$\lvert R\rvert$	Number of MRS candidate locations for medical service level l			P_l		
			$\lvert SL_r{=}1\rvert$	$\lvert SL_r{=}2\rvert$	$\lvert SL_r{=}3\rvert$	P_1	P_2	P_3
e1	100	15	4	5	6	1	2	3
e2	100	15	4	5	6	2	3	4
e3	100	15	4	5	6	3	4	5
e4	200	20	5	7	8	1	2	3
e5	200	20	5	7	8	2	3	4
e6	200	20	5	7	8	3	4	5
e7	300	25	6	9	10	1	2	3
e8	300	25	6	9	10	2	3	4
e9	300	25	6	9	10	3	4	5
e10	400	30	7	11	12	1	2	3
e11	400	30	7	11	12	2	3	4
e12	400	30	7	11	12	3	4	5

As explained, the sigmoid coverage function was used to calculate CR_{irl}, where δ were set to 5. The full coverage range α_l is set to 20, 30, and 40 for medical service levels 1, 2, and 3, respectively. The partial coverage range β_l is set to 30, 40, and 50 for medical service levels 1, 2, and 3, respectively.

4.2. Performance metrics

Performance metrics used for assessing multi-object algorithms are different from those used for assessing single-objective algorithms. This study uses the five criteria for assessing and comparing performances of NSGA-II and mNSGA-II (Tavakkoli-Moghaddam *et al.*, 2007; Behnamian *et al.*, 2009; Karimi *et al.*, 2010; Asefi *et al.*, 2014). These performance metrics are classified into qualitative and quantitative metrics.

1. Qualitative metrics:

- **Number of Pareto solutions (NPS)**: The cardinality of the Pareto solution set is denoted as NPS, which refers to the number of solutions that exist in the Pareto solution set. This performance criterion is calculated by counting the number of nondominated solutions obtained **from** each algorithm. Intuitively, a larger number of NPS is preferred because of the flexibility of decision-making.

- **Diversity**: Zitzler and Thiele (1999) defined $D_{Diversity}$ to evaluate the range of the values covered by the Pareto solutions, i.e., the diversity of Pareto solutions. The formula of $D_{Diversity}$ is shown in the following, and a bigger value indicates a better spread of solutions.

$$D_{Diversity} = \sqrt{\left(\max_{i\le \mathrm{NPS}} f_i^1 - \min_{i\le \mathrm{NPS}} f_i^1\right)^2 + \left(\max_{i\le \mathrm{NPS}} f_i^2 - \min_{i\le \mathrm{NPS}} f_i^2\right)^2}$$

- **Spacing:** Schott (1995) proposed a metric called spacing to evaluate the variance of each solution's range (distance) to its closest neighboring solution. The formula of the measure is given in the following:

$$S_{spacing} = \frac{1}{\text{NPS}-1}\sum_{i=1}^{\text{NPS}}\left(\bar{d}-d_i\right)^2,$$

where $d_i = \min_{j\le \text{NPS}, j\ne i}\{|f_i^1 - f_j^1| + |f_i^2 - f_j^2|\}$ and $\bar{d} = \frac{1}{\text{NPS}}\sum_{i=1}^{\text{NPS}} d_i$. The distance d_i is the minimum Manhattan distance between the *i*-th solution and the others from Pareto solutions. The smaller value of $S_{spacing}$ indicates a better solution.

2. Quantitative metrics:

- **Mean ideal distance (MID)**: Karimi *et al*. (2010) defined it to measure the nearness or closeness between Pareto solutions and the ideal point. MID is defined as follows:

$$\text{MID} = \frac{\sum_{i=1}^{\text{NPS}} C_i}{\text{NPS}},$$

where $C_i = \sqrt{f_i^1 * f_i^1 + f_i^2 * f_i^2}$ and f_i^1 and f_i^2 are the values of the ith Pareto optimal solution for the first and second objective functions, respectively. The lower the value of MID is, the better performance of the algorithm is.

- **Computation time (CT)**: Computation time is a very common metric to evaluate the performance of algorithms, and time is usually considered the most critical resource in disaster circumstances. So, in this study, computation time is adopted as a metric, and the unit for time is "second."

These five performance metrics are used as criteria to compare the effectiveness and efficiency of NSGA-II and mNSGA-II for the proposed MRS location problem in this study.

4.3. Taguchi method for parameter tuning

Two algorithms designed for multi-objective optimization problems are implemented using NSGA-II and mNSGA-II, where various parameters significantly impact the performances. Therefore, the efforts to optimize the parameter choices of the algorithms for the concerned problems are necessary. To obtain the suitable parameters of NSGA-II and mNSGA-II in this study, the Taguchi method (León *et al.*, 1987) has been adopted. The Taguchi method is a powerful and easy way to set parameters for algorithms, and it has been applied to many engineering problems (Asefi *et al.*, 2014).

For this parameter tuning, test problem e10 in Table 2 was used because of its problem size. In addition, assuming the parameters of our interests have a similar influence to both NSGA-II and mNSGA-II because of their similar procedures, only an algorithm, NSGA-II was used to conduct the parameter tuning. These tuned parameters through the Taguchi method are used by both algorithms for comparison purposes. To apply the Taguchi method, four parameters of our interests are chosen to be tuned. They are population size, crossover rate, mutation rate, and maximum generations as the terminal condition. Through the experimental runs of the algorithms, the five different levels are chosen as potential optimal levels for parameters. Those levels are summarized in terms of parameters in Table 3.

Table 3. Parameter levels for NSGA-II.

Level	Parameters			
	Population size	Crossover probability	Mutation probability	Maximum generation
1	60	0.5	0.05	50
2	80	0.6	0.1	70
3	100	0.7	0.15	90
4	120	0.8	0.2	110
5	140	0.9	0.25	130

The L_{25} orthogonal array of the Taguchi method is adopted to design the experimentation. The L_{25} orthogonal array with corresponding parameter settings is presented in Table 4.

Table 4. Experimental layout for NSGA-II: Taguchi L_{25} orthogonal array.

Experiment	Parameters			
	Population size	Crossover probability	Mutation probability	Maximum generation
1	60	0.5	0.05	50
2	60	0.6	0.1	70
3	60	0.7	0.15	90
4	60	0.8	0.2	110
5	60	0.9	0.25	130
6	80	0.5	0.1	90
7	80	0.6	0.15	110
8	80	0.7	0.2	130
9	80	0.8	0.25	50
10	80	0.9	0.05	70
11	100	0.5	0.15	130
12	100	0.6	0.2	50
13	100	0.7	0.25	70
14	100	0.8	0.05	90
15	100	0.9	0.1	110
16	120	0.5	0.2	70
17	120	0.6	0.25	90
18	120	0.7	0.05	110
19	120	0.8	0.1	130
20	120	0.9	0.15	50
21	140	0.5	0.25	110
22	140	0.6	0.05	130
23	140	0.7	0.1	50
24	140	0.8	0.15	70
25	140	0.9	0.2	90

An optimal signal of the performance is also important for the best results of the tuning because it would directly impact the performance of the algorithms. Because the five performance metrics are chosen to compare two algorithms in this study, we have used a utility function aggregating five criteria to evaluate the quality of the solution (Asefi *et al.*, 2014). For simplicity, the utility function in this study is defined as follows:

$$UF = \text{MID} + S_{spacing} - D_{Diversity} + CT - \text{NPS}.$$

To determine the optimal levels of the parameters of the NSGA-II, the signal-to-noise (S/N) ratio with the smaller-the-better rule is adopted for the Taguchi method. The S/N ratio is defined in the following:

$$S/N = -10Log_{10}\left(\frac{\sum_{i=1}^{n}\widetilde{UF}_i^2}{n}\right),$$

where $\widetilde{UF}_i = UF_i + |min\{UF_1, \ldots, UF_n\}|$ and UF_i denotes the value of utility function at i-th experimental run and n denotes the number of experimental runs. In this study, the NSGA-II implementation was run 10 times under the same settings of the L_{25} orthogonal array in Table 4. The experimental results produce the plot of the mean S/N ratio for different levels of the parameters for test problem e10 using NSGA-II, as given in Figure 5.

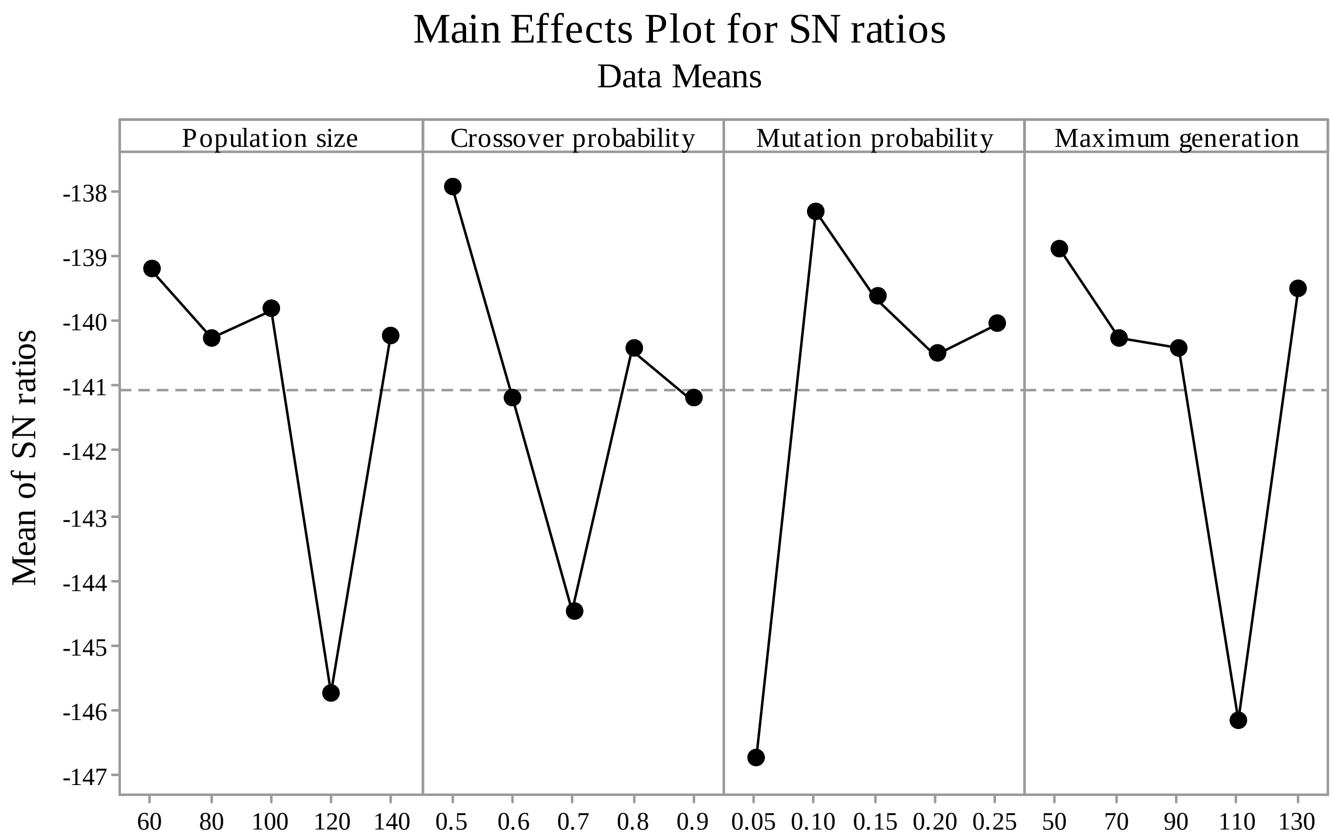

Figure 5. The mean S/N ratio plot for different levels of the parameters for test problem e10.

4.4. Comparisons and Discussions of NSGA-II and mNSGA-II

This section compares the effectiveness and efficiency of NSGA-II and mNSGA-II for the proposed MRS location problem using the performance metrics 4.2. Both algorithms solve the test problems introduced in Section 4.1 using the optimized parameters in Section 4.3.

These two algorithms are developed in the C++ programming language and implemented on a PC with an Intel Core i7-4792 CPU at 3.6 GHz and 16 GB of memory. Since the evolutionary algorithms belong to the Monte-Carlo approach, any experiment to solve each test problem using NSGA-II and mNSGA-II is repeated 10 times to obtain the average performance for five performance metrics.

The twelve test problems (instance) were solved 10 times using NSGA-II and mNSGA-II to produce the Pareto solutions. Then, five metrics are calculated from the solutions at each run. Then we take the average of five performance metrics. The experiment results of those five average performance metrics are compared in Figure 6.

Figure 6(a) shows the calculation times of NSGA-II and mNSGA-II to solve the Pareto solutions. For test problems of relatively small sizes, the calculation times of both algorithms were very similar. Interestingly the calculation times of mNSGA-II are significantly larger than that of NSGA-II for the test problems of larger sizes. It is conjectured that the proposed MRS location problem's combinatorial nature signifies the additional computational burden of mNGSA-II.

For diversity of the Pareto solutions, mNSGA-II produces a similar or slightly better performance than NSGA-II, as shown in Figure 6(b). The mean ideal distance (MID) in Figure 6(c) shows similar results as the diversity metic were obtained as mNSGA-II shows a similar or slightly shorter MID than NSGA-II. Then, Figure 6(d) shows that mNSGA-II generates more Pareto solutions (or Pareto front) than NSGA-II, making mNSGA-II performance superior to NSGA-II.

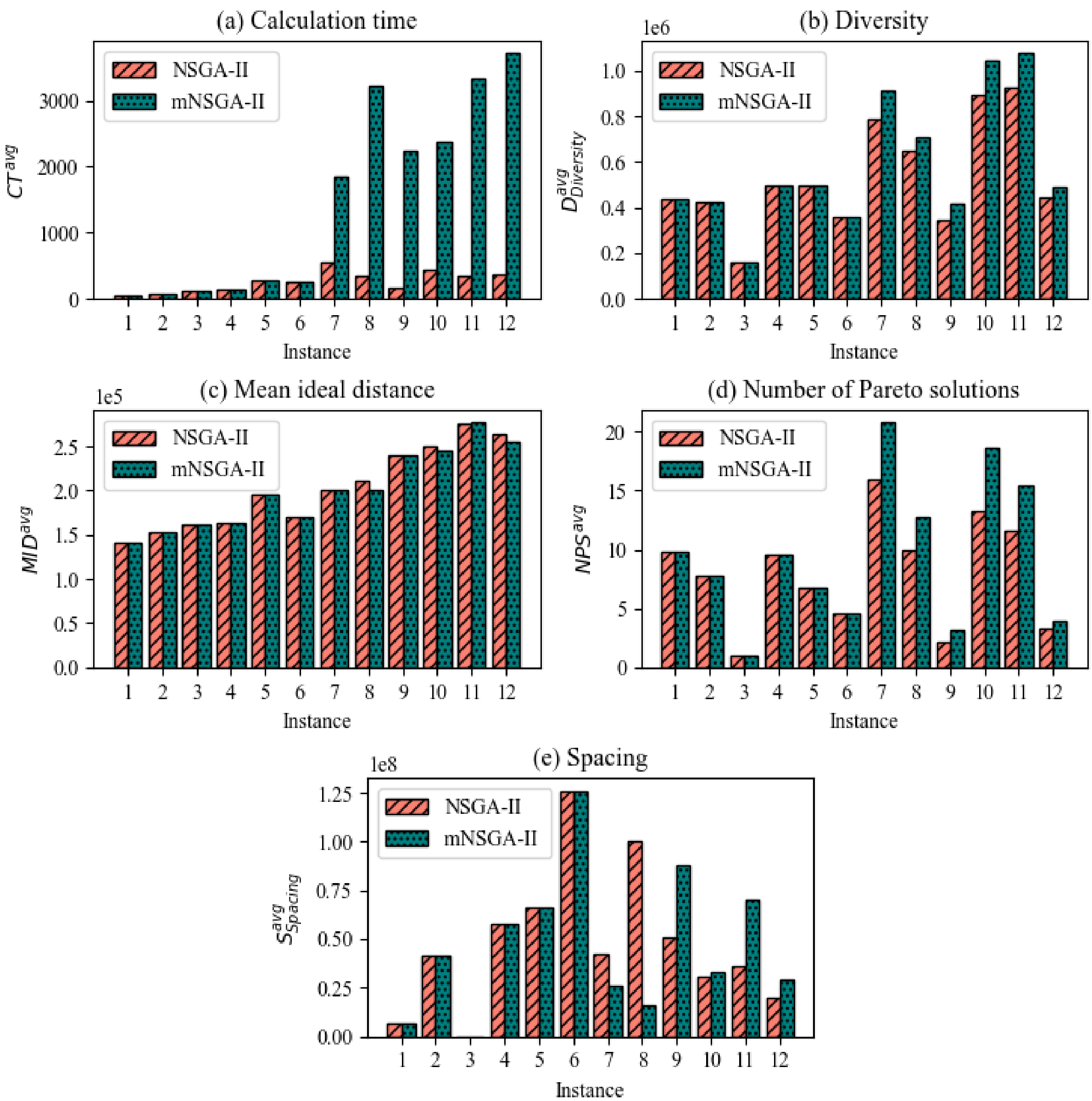

Figure 6. The average value of the five criteria obtained by mNSGA-II and NSGA-II.

Regarding the spacing metric, one can observe that there is no dominating algorithm. It is observed that the performance of the two algorithms depends on the test problems in terms of the spacing metric.

Descriptive statistics are calculated further to illustrate our evaluation and comparison regarding the performance of NSGA-II and mNSGA-II in terms of five performance metrics. 7 shows the boxplot of the five average performance metrics from the 10 experimental results of test problem e10. The dashed line in the box denotes the median, and the small circle denotes the statistical outlier. Figure 5 shows mNSGA-II outperforms NSGA-II for 4 performance metrics, including diversity, mean ideal distance, the number of Pareto solutions, and spacing. NSGA-II completes the execution of the algorithms much quicker than mNSGA-II on average.

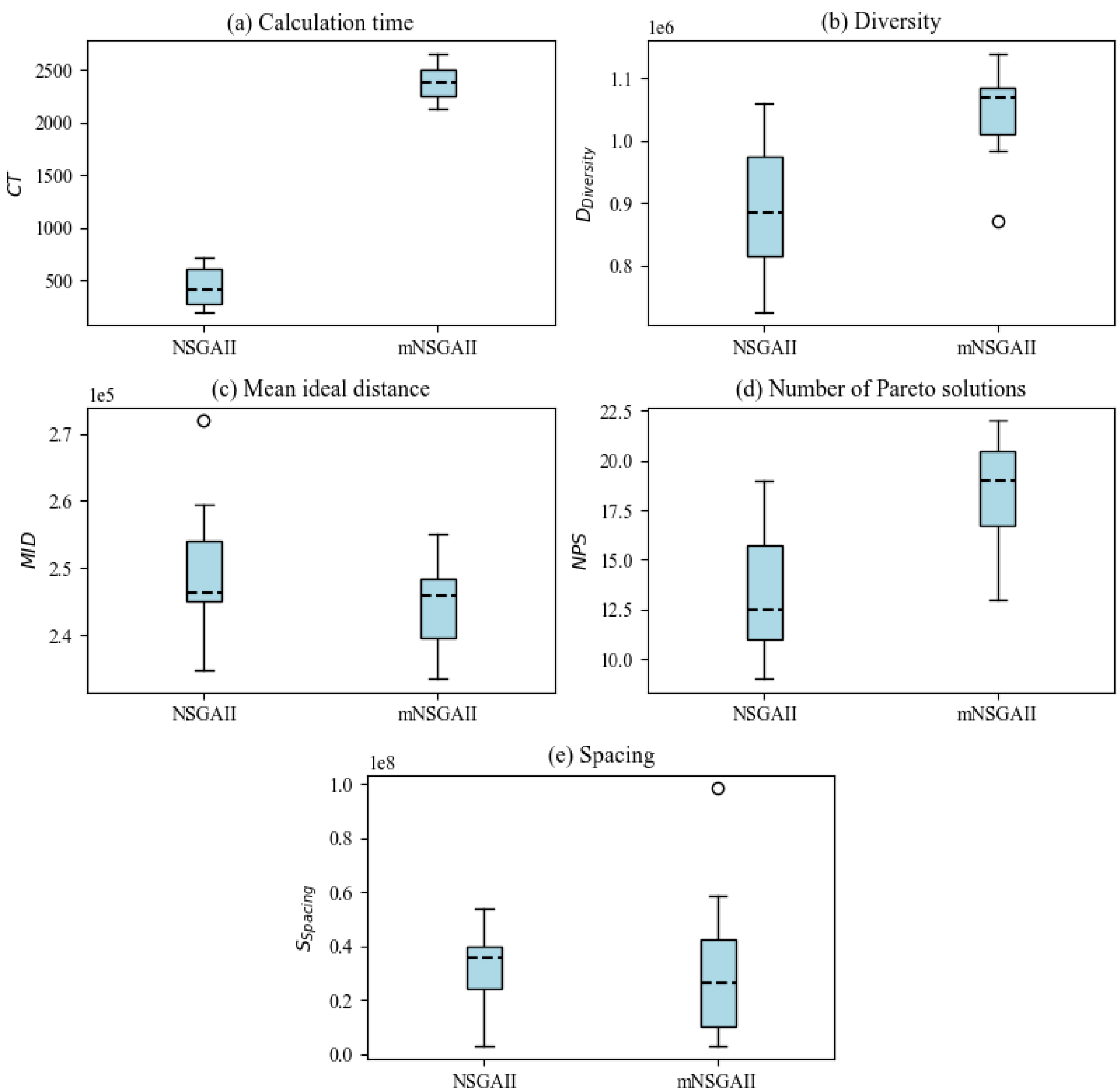

Figure 7. Boxplot of the five performance metrics for mNSGA-II and NSGA-II on test problem e10.

Additional analysis and discussion on the Pareto solutions (or Pareto front) are given here. The Pareto front obtained by NSGA-II and mNSGA-II for test problem e10 is visualized in Figure 8. The Pareto front from both algorithms for 10 runs is given. The red circles and blue crosses denote the Pareto front obtained by NSGA-II and mNSGA-II, respectively. The proposed model in this study has two objective functions of maximizing Z_1 and minimiziing Z_2 simultaneously. Therefore, preferred solutions are located at the lower-right area of the Z_1- Z_2 graphs in Figure 8. In addition, the widespread of the Pareto solutions indicates the higher diversity, offering various options of choice for the decision-makers.

A numerical analysis has been completed to compare the results of both algorithms, using the Pareto dominance. Overall, the Pareto solutions obtained by the mNSGA-II have a stronger tendency to be located at the lower-right area of the graph than those by the NSGA-II. We can observe them in Figure 8. In Figure 6(a), mNSGA-II generates 19 Pareto solutions while NSGA-II produces 16 Pareto solutions. In addition, 14 Pareto solutions by NSGA-II are dominated by the Pareto solutions by mNSGA-II. Only two Pareto solutions by NSGA-II are not dominated, as shown as two Pareto solutions near 3000 and 4000 of Z_1 values. in Figure 6(a). In Figures 8(i) and 8(j), mNSGA-II obtained 19 Pareto solutions, and NSGA-II obtained 11 Pareto solutions. Those of mNSGA-II dominate all the Pareto solutions obtained by NSGA-II. Therefore, it is concluded that mNSGA-II finds more Pareto solutions than NSGA-II. The solutions obtained by mNSGA-II dominates most of the solutions obtained by NSGA-II.

In terms of the diversity of Pareto solutions, it was observed that the Pareto solutions generated by mNSGA-II are located over the wide ranges in all 10 runs, as shown in Figure 8. It is concluded that mNSGA-II generates better Pareto solutions than NSGA-II.

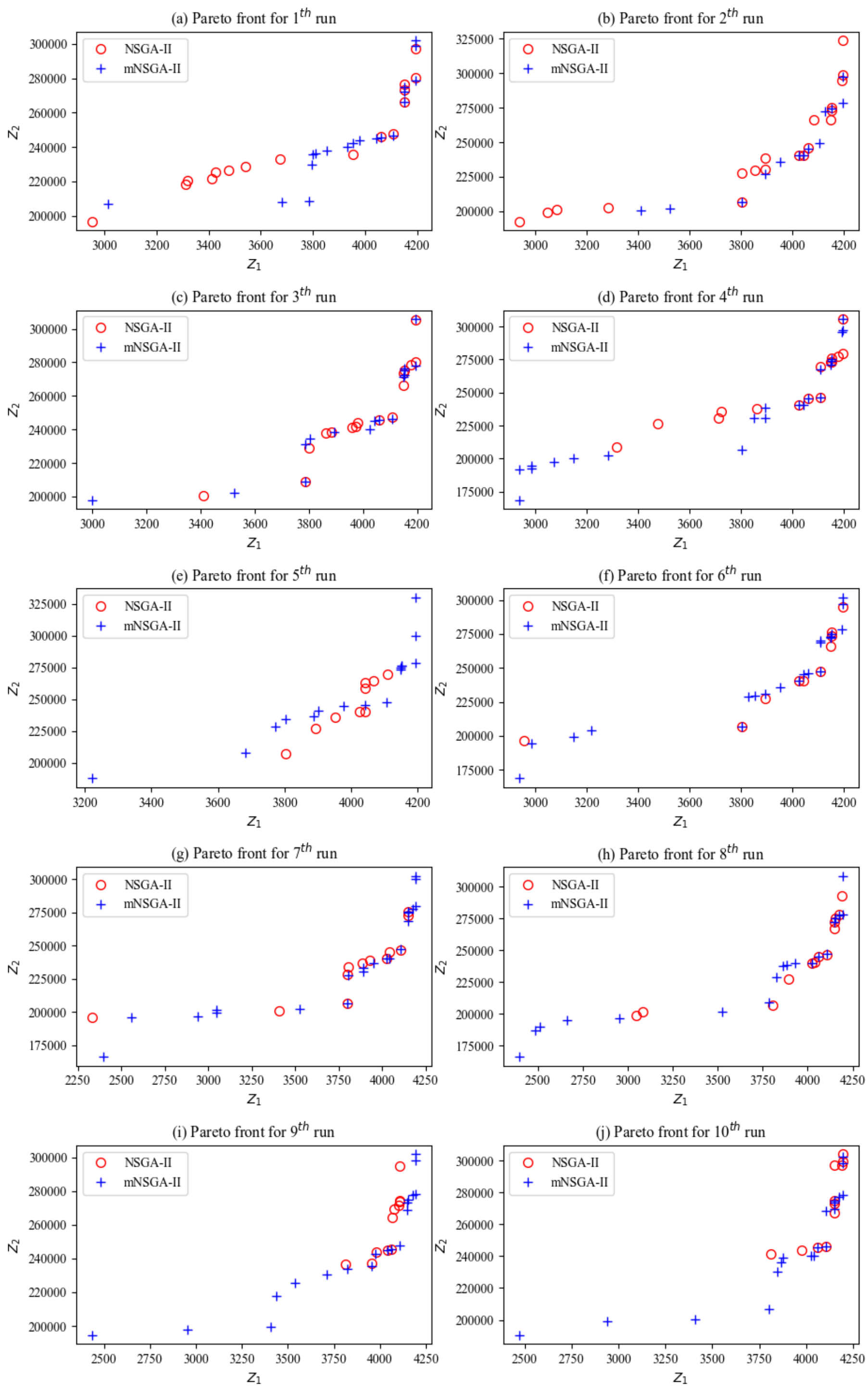

Figure 3. Pareto front obtained by NSGA-II and mNSGA-II for test problem e10

Table 6 presents the number of Pareto solutions obtained by NSGA-II and mNSGA-II for test problem e10 in each run. The results show that mNSGA-II produces more Pareto solutions than NSGA-II except for run 2, where both algorithms generate the same number of Pareto solutions.

Table 6. Number of Pareto solutions obtained by NSGA-II and mNSGA-II for test problem e10 in each run.

Algorithms	Runs									
	1	2	3	4	5	6	7	8	9	10
NSGA-II	16	19	16	15	9	10	12	13	11	11
mNSGA-II	19	19	16	22	16	22	21	19	19	19

This result indicates that mNSGA-II provides more informative and various decisions of choice to the decision-makers for selecting MRS locations. It reveals that mNSGA-II outperforms NSGA-II in the proposed MRS location problem.

Decision-making in response to disasters is complex (Horita *et al.*, 2018). Many influential factors, including external and internal factors, incur the dynamics of disaster, which increase the difficulty of disaster responses. In the context of a disaster, providing more candidate solutions will help the decision-makers to make good responses. Usually, decision-makers need to consider the preferences, hopes, and opinions before responding to a disaster, when decision-makers adopt priori methods (Miettinen 1998) to solve multi-objective optimization problems under disaster context. The information provided by the mNSGA-II could enhance the preferences, hopes, and opinions.

The experimental results in this section find a trade-off between computational time and solution quality for NSGA-II and mNSGA-II. NSGA-II converges faster than the mNSGA-II. However, the solution quality obtained by the NSGA-II is worse than the solutions obtained by the mNSGA-II. The trade-off between computational time and solution quality is widespread in solving industrial problems, such as scheduling problems and routing problems. This paper mainly explores the performances of NSGA-II and mNSGA-II by comparing different performance metrics, including the number of Pareto solutions, mean ideal distance, spacing, diversity, and computation time. This discussion helps decision-makers choose an appropriate solution method based on the acceptable computation time under the disaster emergency circumstance. After obtaining the Pareto front, the decision-maker must select one preferred solution from the Pareto front, considering the pre-defined selection criteria. Choosing one solution from the Pareto front is also a challenging problem too. It is beyond the scope of this paper. Many previous studies (Wang and Rangaiah, 2017) investigate how to select one solution from the Pareto front. The decision-maker can select a selection method as a criterion or design a new method for determining one solution from the Pareto front.

5. CONCLUSIONS

In emergencies such as typhoons, earthquakes, or terrorist attacks, quick responses are imperative for the administrations. The administrations need to augment their medical response capability by using scarce medical resources to provide emergency medical service. In an emergency management system, the planner aims to serve as many affected people as possible with a minimum budget concerning the emergency relief logistics. Therefore, in this study, we proposed a bi-objective mathematical programming model to minimize the total cost associated with the logistics of medical supplies and maximize the total number of patients who get appropriate medical services at multiple MRSs.

This study considers the severity levels of patients and medical service levels of MRSs. The patients are assumed to be located in the impacted areas, and the candidate locations or buildings are pre-determined ahead of the disaster strike. Patients can be served by temporary MRSs whose medical service level is equal to or higher than the severity levels of patients. The locations of MRSs are determined in consideration of the distribution of patients of various severities and the locations of medical deployment centers.

Because the proposed MRS location problem has bi-objective functions, five different performance metrics has been chosen to measure the performance of solution methods. Those include the number of Pareto solutions, mean ideal distance, spacing, diversity, and computation time.

To solve the multi-objective optimization model, NSGA-II and an mNSGA-II are implemented. The algorithm parameters were tuned for the best performance using the Taguchi method. Extensive computational experiments are conducted to compare and evaluate the performance of NSGA-II and mNSGA-II. The experimental results show that mNSGA-II outperforms NSGA-II in terms of solution quality.

Future studies should consider the following aspects: (1) considering vehicle routing problems to pick-up patients; (2) multi-time period will be incorporated, which may lead to computational intractability.

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