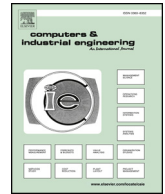




Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

Medical relief shelter location problem with patient severity under a limited relief budget

Jeongmin Gu^a, Yanjie Zhou^a, Amrit Das^a, Ilkyeong Moon^b, Gyu M. Lee^{a,*}

^a Department of Industrial Engineering, Pusan National University, Republic of Korea

^b Department of Industrial Engineering, Seoul National University, Republic of Korea

ARTICLE INFO

Keywords:

Disaster management
Medical relief shelters
Medical deployment centers
Location problem
Injury severity

ABSTRACT

It is an essential but difficult problem to provide effective and efficient medical or relief services to people in areas impacted by various anthropogenic and natural disasters. This study proposes a mathematical programming model to determine the locations of temporary medical relief shelters, as well as provide the required medical supplies from medical deployment centers effectively and efficiently under a limited relief budget. The severities and geographical locations of patients are considered in the problem. A mixed integer programming formulation has been proposed. The proposed model is hard to solve using a commercially available solver in a reasonable amount of time, especially for the problems of larger sizes. Hence, a greedy algorithm is proposed to solve the problem to generate good solutions in comparison with the solution obtained by LINGO. The computational results demonstrate the effectiveness and efficiency of the proposed methodology. Computational results under different scenarios are provided as well to demonstrate the validity of the proposed algorithm for various situations.

1. Introduction

Anthropogenic and natural disasters may cause the loss of lives, injuries, property damage, social and economic disruptions, and environmental degradation, and such disasters have become regular occurrences. The Haiti earthquake caused about 500,000 casualties on January 12, 2010 (Yonhap News, 2017). The earthquake in Sichuan on May 12, 2008, killed approximately 69,000 people and injured 374,000 people (United States Geological Survey, 2008). It also damaged the assets of more than 40 million people. Typhoon Haiyan in 2013 was responsible for an estimated 7300 deaths (Inverse, 2015). Cyclone PAM took place in March 2015 in Vanuatu and Port Vila. In Vanuatu's capital, over the 80% of houses were damaged, and 3300 victims had to be evacuated to 37 evacuation centers (Hankookilbo, 2015). In recent years, not only natural disasters but also manmade disasters such as terrorism, fire accidents and nuclear disasters have been increasing. One of the most recent major manmade disasters is the Fukushima nuclear accident. The tsunami and earthquake that occurred in Japan in March 2011 damaged nuclear power plants in Fukushima, which leaked dangerous radioactive materials. It resulted in numerous victims and prolonged damage to Japan, as well as serious concerns in neighboring countries for the environment, health, and safety.

Quick response can reduce the number of the deaths. Effective and

efficient disaster management is needed for quick response. In emergency medical services (EMS), it is essential to recognize the severity and distribution of patients to establish medical relief shelters and transport them for appropriate medical treatments by considering the location of medical deployment centers that provide medical supplies and personnel. Medical staff are also considered as a type of medical supply in this study without loss of generality.

Research on disaster management is needed to reduce the impact of disasters. The area of operations research and management science (OR/MS) is one of the most important research areas in disaster management for making efficient and effective decisions during disasters. Altay and Green (2006) investigated the literature to find potential research directions in disaster operation management. They studied disaster operation management in terms of OR/MS and discussed the four typical activities: mitigation, preparedness, response, and recovery.

This paper looks at the response operations during a disaster. Both evacuation and humanitarian logistics are discussed from the perspective of OR/MS. Humanitarian logistics is a branch of logistics that specializes in organizing the delivery and warehousing of supplies during natural or manmade disasters or complex emergencies. In the event of a disaster, appropriate plans are needed to provide EMS, such as medical shelters and ambulance services when mass casualties occur.

* Corresponding author.

E-mail address: glee@pnu.edu (G.M. Lee).

EMS provides emergency care and ambulances to patients. In terms of disaster management, EMS is one of the most important factors for providing quick medical care for disaster victims and minimizing deaths.

EMS in emergency disaster situations is divided into hospitals and on-site responses. This paper considers the locations of temporary medical relief shelters to provide on-site medical services by finding the best locations of medical relief shelters. The paper is organized as follows. A literature review is provided in Section 2. In Section 3, a variant of the maximal covering location problem (MCLP) is presented. The severity of patients and distance from individual patient to temporary medical shelter are considered, as well as the allocation of medical supplies. The proposed algorithm is introduced in Section 4, and computational results are provided in Section 5. Finally, the conclusions are given in Section 6.

2. Literature review

Balcik and Beamon (2008) considered facility location decisions for a humanitarian relief chain responding to quick-onset disasters. They developed a model that determines the number and locations of distribution centers in a relief network, as well as the amount of relief supplies to be stocked at each distribution center to meet the needs of people affected by the disasters. Afshar and Haghani (2011) presented a mathematical model that controls the flow of several relief commodities from sources through the supply chain and until they are delivered to recipients. Day, Melnyk, Larson, Davis, and Whybark (2012) studied humanitarian and disaster relief supply chains within the broad field of supply chain management. Sheu and Pan (2015) provided a novel relief supply collaboration approach to address the supply-demand imbalance issue of post-disaster relief in emergency logistics operations.

In this study, the locations of medical relief shelters are determined by considering the severity and distribution of patients and locations of medical deployment centers. The facility location problem concerns the optimal placement of facilities to minimize transportation cost while considering various factors. The medical facility location problem determines the medical facilities' locations and the optimal allocation of the impacted patients and is a practical and challenging problem. Jia, Ordóñez, and Dessouky (2007a) studied a maximal covering facility location model that efficiently finds locations to satisfy the tremendous demands of medical services in emergency situations. Jia, Ordóñez, and Dessouky (2007b) studied the characteristics of large-scale disasters and presented a model of large-scale emergency situations. They shortly reviewed the traditional facility models for emergency services: covering models, p-median models, and p-center models.

Farahani and Hakmatfar (2009) explained the basic concept of a variety of facility location problems, including p-median, p-center, and covering problems. Mete and Zabinsky (2010) proposed a stochastic optimization approach for emergency and non-emergency cases to select the storage locations of medical supplies and required inventory levels for each type of medical supply under a wide variety of possible disaster types and magnitudes to prepare for the disaster. Farahani, Asgari, Heidari, Hosseini, and Goh (2012) presented an extensive review on the covering problem in facility location. They introduced a variety of maximal covering location problems (MCLP), such as planar maximal covering and capacitated MCLP.

Hu, Yang, Hu, and Wang (2017) considered the optimization of shelter service area demarcation and post-disaster evacuation route planning simultaneously to improve the efficiency of current shelter operation and reduce disaster risk. Mohamadi and Yaghoubi (2017) introduced a bi-objective stochastic optimization model to determine the location of transfer points and medical supply distribution centers in a triage system network. Boonmee, Arimura, and Asada (2017) conducted a survey on the facility location problems related to emergency humanitarian logistics and examined pre- and post-disaster situations with respect to the location of distribution centers,

warehouses, shelters, debris removal sites, and medical centers. They also presented real world applications.

Huang, Kim, and Menezes (2010) described a variation of the p-center problem with an additional assumption that the facility at a node fails to respond to the demands from the node. To solve it, they used a dynamic programming approach to develop an efficient algorithm for optimal locations in a general network. Beraldi and Bruni (2009) looked at the formulation and solution of a probabilistic model for determining the optimal locations of facilities in congested emergency systems under uncertainty. A new stochastic programming method was used to solve the uncertainty problem, and results were obtained by an exact solution method and different tailored heuristics.

In this study, it is assumed that candidate locations of medical relief shelters are determined in advance before the disaster impact. It is also assumed that the severity and distribution of the patients in the impacted areas are known via emergency call centers or estimation. Two categories of patients are assumed: emergency and non-emergency patients. The emergency patients are determined using a threshold of severity. Normally, seriously injured people need high-priority care. Emergency patients require immediate medical services and need to be transported to the nearest medical shelters quickly. It is assumed that more medical supplies are required for emergency patients. The proposed mathematical programming model can be easily extended to accommodate different numbers of patient types and different ways to determine them.

The main objective of this study is to maximize the number of patients medicated at multiple medical relief shelters under a limited relief budget while considering the severity of patients and distances to the shelters. The cost related to establishing temporary medical relief shelters, occupying them, and transportation of the medical supplies including medical staff are subjected to the total relief budget. The cost of constructing medical relief shelters involves variable construction costs that are proportional to the capacity of shelters, in addition to the fixed construction cost. The quantity of required medical supplies at a medical relief shelter is determined based on the number and type of patients assigned to it. Medical deployment centers provide medical staff and medical supplies to medical relief shelters and have their own maximum capacities for each supply. Transportation cost includes vehicle costs and variable costs.

Nicholl, West, Goodacre, and Turner (2007) surveyed the relationship between the distance to a hospital and patient death in emergencies. Naturally, fast evacuation is crucial for saving human lives. Najafi, Eshghi, and Dullaert (2013) studied a multi-objective, multi-mode, multi-commodity, and multi-period stochastic model to manage the logistics of both commodities and injured people in earthquake response. They minimized the total unserved patients and the unsatisfied demands during the planning horizon. In our study, the optimal locations of temporary medical relief shelters are determined from candidate locations that can be pre-selected before disasters occur. In addition, the objective function in the proposed mathematical programming model assigns as many patients as possible considering the severity, proximity, and the relief budget. Hence, the problem considered in this study is a variant of the MCLP in a disaster situation.

It is urgent to plan a response for administrations for disaster situations. However, it is very time-consuming to obtain the optimum solution using commercially available solvers due to the computational complexity of the problem, especially for large problems. In this study, a greedy algorithm is proposed by defining different rules to assign patients and allocate medical supplies. A computational experiment shows that the proposed problem can be solved in an acceptable amount of time.

3. Problem description and formulations

To save as many lives as possible, it is essential to recognize the severity and distribution of the patients, establish medical relief

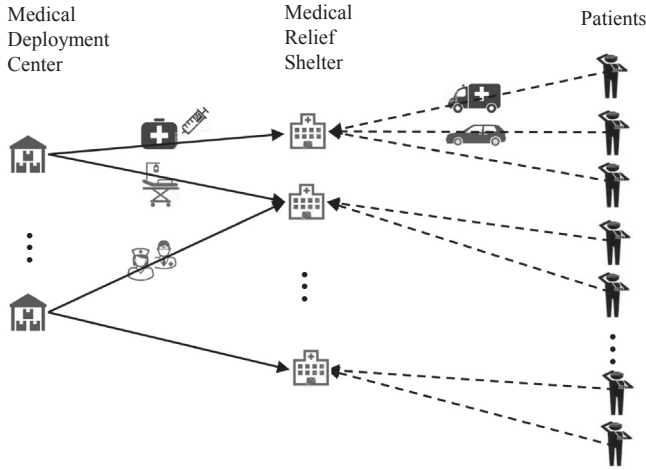


Fig. 1. Illustration of the proposed model.

shelters, and transport patients for appropriate medical treatments. It is also important to consider the locations of medical deployment centers that provide the medical supplies and staff. In addition, a reasonable amount of relief budget needs to be reserved to reduce the avoidable deaths.

Fig. 1 shows an overview of the evacuation and humanitarian logistics. The patients are assigned and transported to appropriate medical shelters while their severities are considered. Depending on these assignments, the necessary medical supplies should be provided from the medical deployment shelters, which are large hospitals or relief chain distribution centers. The required medical staff must be dispatched as well to cope with the patient assignment. For this operation, logistics cost will be incurred, and the total logistics cost cannot exceed the limited relief budget.

A variant of MCLP is presented to maximize the number of patients who receive medical services at newly established medical relief shelters under a limited relief budget, while considering the severity of patients and distances to medical relief shelters. A list of assumptions for the problem is provided. The parameters and decision variables are also presented.

Problem assumptions

- The severity of injury and the locations of patients are known.
- Patients are classified as emergency and non-emergency patients using a pre-set threshold of severity.
- Emergency and non-emergency patients require different quantities of medical supplies.
- The medical deployment centers provide medical supplies to medical relief shelters at the maximum of pre-set quantities.
- Each type of medical supply has a fixed volume, and a vehicle transporting medical supplies has the maximum volume capacity.
- The maximum budget that can be used for medical relief operations is limited, including the construction and operating costs of medical relief shelters and the procurement and transportation costs of medical supplies from medical deployment centers.

Parameters

I	Set of individual patients, $i \in I$
K	Set of different types of medical supplies, $k \in K$
L_R	Set of candidate locations for medical relief shelters, $j \in L_R$
L_S	Set of medical deployment centers, $l \in L_S$
A_k^e	Quantity of medical supply k required for an emergency patient

A_k^n	Quantity of medical supply k required for non-emergency patient
MK_{lk}	Maximum quantity of medical supply k at medical deployment center l
V_k	Volume of medical supply k
MV	Maximum capacity of a vehicle in volume
S_i	Severity of patient i
D_{ij}	Distance between the location of patient i and medical relief shelter j
CV	Vehicle cost per vehicle
CT	Transportation cost per vehicle per unit distance
CCF_j	Fixed construction cost for a medical relief shelter at candidate location j
CCV_j	Variable construction cost per additional capacity of a medical relief shelter at candidate location j
CO_j	Operating cost of a medical relief shelter at candidate location j
CP_k	Procurement cost of medical supply k
B	Total relief budget
M	A large number
E_i	$\begin{cases} 1 & \text{if patient } i \text{ is in emergency condition} \\ 0 & \text{otherwise} \end{cases}$

Decision variables

y_j	$\begin{cases} 1 & \text{if a medical relief shelter is constructed at candidate location } j, \text{ for } j \in L_R \\ 0 & \text{otherwise, for } j \in L_R \end{cases}$
cy_j	Capacity of medical relief shelter at candidate location j
z_{ljk}	Quantity of medical supply k , required to be transported from medical deployment center l to medical relief shelter j , $l \in L_S$
x_{ij}	$\begin{cases} 1 & \text{if a patient is assigned to medical relief shelter } j \\ 0 & \text{otherwise} \end{cases}$

The proposed mixed integer mathematical formulation for the problem is presented in the following.

Formulations

$$\text{Maximize} \quad \sum_i \sum_j \frac{S_i}{D_{ij}} x_{ij} \quad (1)$$

$$\text{Subject to} \quad \sum_i x_{ij} \leq cy_j \quad \forall j \in L_R \quad (2)$$

$$A_k^e \sum_i x_{ij} E_i + A_k^n \sum_i x_{ij} (1-E_i) \leq \sum_l z_{ljk} \quad \forall k \in K, \quad \forall j \in L_R \quad (3)$$

$$\sum_j z_{ljk} \leq MK_{lk} \quad \forall k \in K, \quad \forall l \in L_S \quad (4)$$

$$\begin{aligned} & \sum_j CCV_j cy_j + \sum_j CCF_j y_j + \sum_j CO_j cy_j + \sum_l \sum_j \sum_k CP_k z_{ljk} \\ & + \frac{1}{MV} \sum_l \sum_j \sum_k z_{ljk} V_k (CV + CT * D_{lj}) \leq B \end{aligned} \quad (5)$$

$$cy_j \leq My_j \quad \forall j \in L_R \quad (6)$$

$$x_{ij} \leq y_j \quad \forall j \in L_R, \quad \forall i = 1, \dots, n \quad (7)$$

$$\sum_i x_{ij} = 1 \quad \forall j \in L_R \quad (8)$$

$$y_j \in \{0,1\} \quad \forall j \in L_R \quad (9)$$

$$x_{ij} \in \{0,1\} \quad \forall j \in L_R, \quad \forall i = 1, \dots, n \quad (10)$$

$$cy_j \geq 0, z_{ljk} \geq 0 \quad \forall k \in K, \quad \forall j \in L_R, \quad \forall i = 1, \dots, n \quad (11)$$

Objective function (1) maximizes the number of patients who obtain

medical services at multiple medical relief shelters under a limited relief budget while considering severity and distances. Constraint (2) indicates that the total number of assigned patients in a medical relief shelter cannot exceed its capacity. Constraint (3) restricts the quantity of medical supplies k transported from medical deployment center l , which must have more than the quantity required for the emergency and non-emergency patients at medical relief shelter j . Constraint (4) defines the maximum amount of medical supplies that can be transported from medical deployment center l . The maximum relief budget is limited in constraint (5), including fixed construction, variable construction, operating, procurement, vehicle, and transportation costs. Constraint (6) reflects that a capacity of medical relief shelter j is available only if its candidate location is chosen for construction. Similarly, constraint (7) indicates that a patient can be assigned to medical relief shelter j only if the medical relief shelter has been constructed at the candidate location. Constraint (8) indicates that a patient is assigned to only one medical relief shelter. Finally, constraints (9)–(11) define the nature of decision variables.

4. The proposed greedy algorithm

In emergency circumstances, quick responses are absolutely imperative for saving human lives. However, our experimental results show that LINGO cannot solve the proposed mathematical model within 3 h when there are more than 15 candidate locations for medical relief shelters and more than 300 patients. It is very time consuming to solve the problem using commercial solvers, so a heuristic that can find good solutions in a reasonable time was designed.

The mathematical model contains many considerations. A constraint for the relief budget is included, which can be considered as an objective, and the proposed problem can be modeled as a bi-objective problem. A balance of considerations between the cost for relieving patients and the number of relieved patients is needed. We have to consider where medical relief shelters are constructed in many candidate locations, how many medical relief shelters are needed, and how many people can be assigned in each shelter. Also, decisions are needed to find the best strategy between the construction of new medical relief shelters and increasing the capacity of a medical relief shelter to reduce the construction cost and assign more people, even if the distance to each medical relief shelter is increased.

The k-means algorithm (Lloyd, 1982) is first used to cluster the patients. The algorithm makes k groups using data. The objective of clustering in the algorithm is to minimize the variation of the differences in distance. However, the objective of the proposed clustering method is to maximize the total severity of patients and to minimize the total distance in each group. Patients cluster and assigned to medical relief shelters in such a way to maximize the total $\frac{S_i}{D_{ij}}$ value of all relieved patients ($\forall j \in L_R, \forall i = 1$). The number of groups is the same as the number of candidate locations of medical relief shelters.

After clustering all of the patients in the candidate locations of shelters, a greedy algorithm is used to choose the best candidate locations. The proposed greedy algorithm tends to choose the locations to save closer and more severe patients. The greedy algorithm is an approximate method for finding a feasible solution. It chooses the best solution at each stage and reaches a final solution. The final solution does not guarantee global optimality but it is a straight-forward method to find good solutions quickly as far as decision criteria are carefully chosen.

The proposed algorithm uses the hierarchical approach: shelter construction stage and patient assignment stage. In this algorithm, the value of $\frac{S_i}{D_{ij}}$ for $\forall j \in L_R, \forall i = 1, \dots, n$ is an important measure as it is used in the objective function in the proposed formulation in Section 3. In the shelter construction stage, an individual patient can calculate its values to each of candidate locations. Patient i is assigned to the candidate location with the highest value of $\frac{S_i}{D_{ij}}$, for $\forall j \in L_R$. Then start to

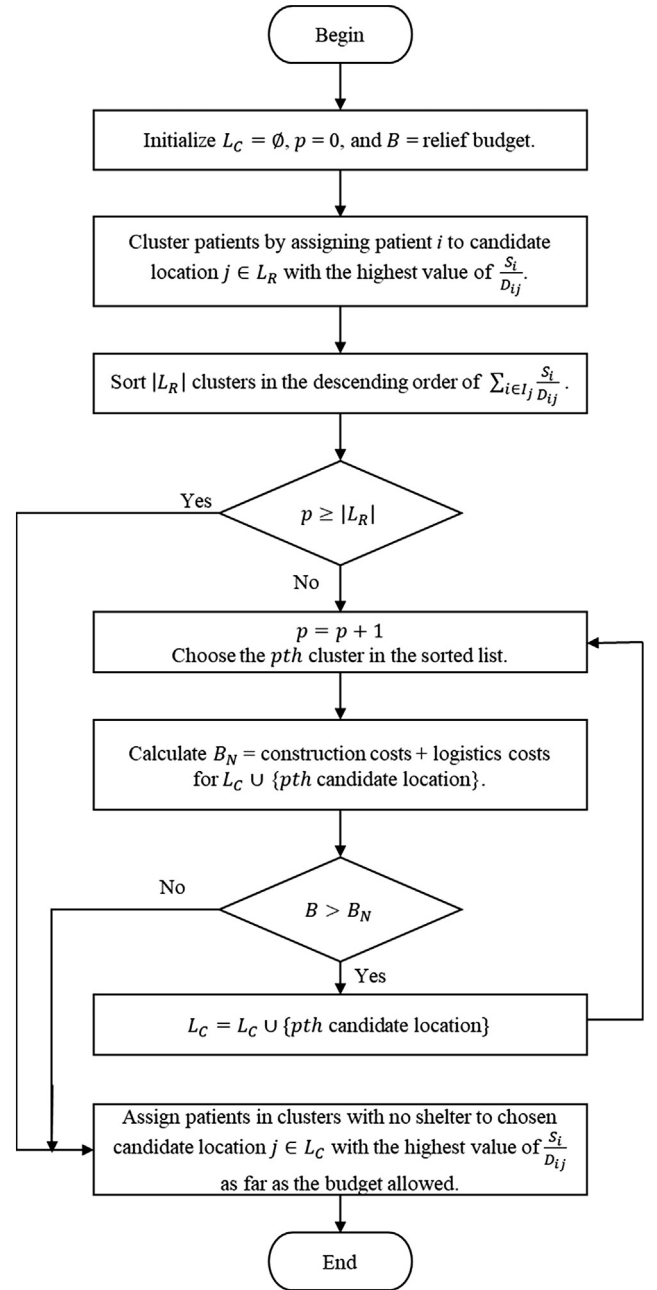


Fig. 2. Flowchart of the proposed greedy algorithm.

choose candidate locations with the highest value of $\sum_{i \in I_j} \frac{S_i}{D_{ij}}$, for $\forall j \in L_R$ and I_j , which is the index set of patients assigned to candidate location j , as far as the relief budget is allowed. In this stage, only patients assigned to the chosen candidate locations are considered and the construction and logistics costs are considered.

When the relief budget does not allow any additional shelter construction, the second stage starts to assign patients with the highest value of $\frac{S_i}{D_{ij}}$ in unchosen candidate locations to the chosen ones in the previous stage. In this stage, additional logistics cost is considered.

A flowchart of the greedy algorithm is shown in Fig. 2, and the procedures are detailed in the following.

- Step 1. Initialize the parameters: counter p , set L_C of chosen candidate locations for construction and relief budget B
- Step 2. Cluster all patients with candidate locations centered by assigning patient i to candidate location j with the highest value of $\frac{S_i}{D_{ij}}$, for $\forall j \in L_R$.

Step 3. Sort all clusters (or candidate locations) in the descending order of $\sum_{i \in I_j} \frac{S_i}{D_{ij}}$, for $\forall j \in L_R$ and I_j , which is the index set of patients assigned to candidate location j

Step 4. Check if $p \geq |L_R|$. If yes, go to Step 9. Otherwise, go to Step 5.

Step 5. Increase p by 1 and choose the p th cluster from the sorted list in Step 3 for constructing additional medical relief shelter.

Step 6. Calculate the total cost including construction cost for shelters at chosen candidate locations $L_C \cup \{p\text{th candidate location}\}$ and logistics cost for all patients in the corresponding clusters.

Step 7. Check if $B > B_N$. If yes, go to Step 8. Otherwise, go to Step 5.

Step 8. Update $L_C = L_C \cup \{p\text{th candidate location}\}$ and go to Step 5.

Step 9. Assign the patients in clusters with no shelter to chosen candidate location $j \in L_C$ with the highest value of $\frac{S_i}{D_{ij}}$ as far as the budget allowed. Then, terminate the algorithm.

5. Computational results

The proposed mathematical model and greedy algorithm were tested with problems of various sizes under different scenarios. The proposed formulation was modeled and implemented in LINGO on a PC with a 3.60-GHz Intel core i7-4790 CPU and 16 GB of RAM. A problem generator (Gu, Zhou, & Lee, 2016) was used to generate the locations of patients (x, y) , where $0 \leq x, y \leq 100$, and the severity is random in the range of 0–100. The program generator can accept customized values, such as the number of patients impacted, distribution ranges, severity ranges, the threshold for emergency patients, candidate locations for medical relief shelters, and locations medical deployment centers.

For simplicity, the Euclidian distance is used. The fixed construction cost of a medical relief shelter and the variable construction cost per additional capacity are \$20,000 and \$50, respectively. The operating cost of a medical relief shelter per patient is \$100. The vehicle cost is \$1000, and the transportation cost per unit distance is \$10. The procurement costs of the three types of medical supplies are \$30, \$50, and \$30 (staff, equipment, and medicine, respectively). The respective volumes for the types of medical supplies are 2, 3, and 5. The volume capacity of a vehicle is 20. All cost parameters used in the following experiments are summarized in Table 1.

5.1. Experiment 1

An example is used to conduct an experiment for the relief budget using 100 randomly distributed patients with their own severities, 5 candidate locations for medical relief shelters, and 2 medical deployment centers. There are 3 types of medical supplies. It is assumed emergency patients require quantities of 3, 2, and 4 for the three types, and non-emergency patients require one of each type. Three scenarios with different relief budgets of \$300,000, \$250,000 and \$200,000 are considered to validate the proposed model. This experiment looks at the number of patients assigned (or relieved) and the locations of established medical relief shelters. The results under different relief budgets are summarized in Table 2. Note that the relieved patients decrease with larger relief budgets. With a relief budget of \$300,000, all patients were assigned to medical relief shelters.

Table 1
Costs for the computational experimentations.

Cost	Value
The fixed construction cost of medical relief shelter	\$20,000
The variable construction cost per additional capacity	\$50
The operating cost of medical relief shelter per patient	\$100
Unit vehicle cost	\$1000
Transportation cost per unit distance	\$10
The procurement costs of medical supplies for three types	\$30, \$50, \$30
The volume for three medical supplies	2, 3, 5
The capacity of vehicle in volume	20

Table 2

Numbers of relieved patients under different relief budgets.

	Relief budgets		
	\$300,000	\$250,000	\$200,000
Number of constructed medical relief shelters	5	5	4
Candidate location 1	12	12	11
Candidate location 2	23	11	0
Candidate location 3	18	16	17
Candidate location 4	22	19	18
Candidate location 5	25	15	13
Total number of relieved patients	100	73	59

5.2. Experiment 2

Another example is shown in Fig. 3 for the coastal areas of Busan, Korea. It includes 20 patients, 5 candidate locations for medical relief shelters, and 2 medical deployment centers. The circles denote patients, black triangles denote medical deployment centers, and black rectangles denote candidate locations for medical relief shelters. The numbers on the sides of candidate locations indicate the indices. The patients are distributed on the waterfront since it is assumed that a disaster like a tsunami has occurred in this area. The relief budget in this example is \$50,000. The fixed construction cost of a medical relief shelter and the variable construction cost per additional capacity are \$8000. Other parameters are kept the same as in the example for the relief budget experiment.

In this example, three scenarios with different degrees of impact by the disasters are considered to observe the changes in the situations after the disaster. It is natural to assume that a stronger impact by disasters will lead to more aggravating situations, where the severities of patients become higher. In the three scenarios, the ranges of severity are 20–60, 30–80, and 40–100, respectively. Since emergency patients are assumed to require more medical supplies, there is higher urgency for medical treatments and higher costs.

As shown in Table 3, the numbers of relieved patients in the three different scenarios are 20, 19, and 15, respectively. These numbers decreased as the severity of patients increased under the fixed relief budget. Depending on the cost information, it is advisable to decide whether the budget would be more wisely spent on transportation or the construction of additional medical relief shelters. Additional experiments were performed to see the effects of the quantities of medical supplies required for emergency and non-emergency patients. If the required quantities are identical for emergency and non-emergency patients, the objective function places higher priority on emergency patients, and there is more flexibility to relieve more patients.

5.3. Experiment 3

The proposed greedy algorithm was coded in C++ and compiled with Visual Studio 2013. We considered a benchmark set of random instances that was produced by a problem generator (Gu et al., 2016) using the parameters presented in Table 4. Each case has different numbers of patients, candidate locations of medical relief shelters, medical deployment centers, and relief budgets. This study compares the results with those from LINGO by using the same parameters.

The results are shown in Table 5. The proposed model is a mixed-integer mathematical formulation, so LINGO uses primal and dual simplex solvers in a linear model and searches for feasible solutions using preprocessing and “cut” generation routines. We experimented with 15 test problems that have various parameter values. Cases e1-1 ~ e1-6 have 200 patients, 10 candidate locations of medical relief shelters, and 6 medical deployment centers. LINGO found a feasible solution in 3 h. However, the proposed algorithm can find feasible solutions in a few seconds in all cases. To compare the characteristics related to

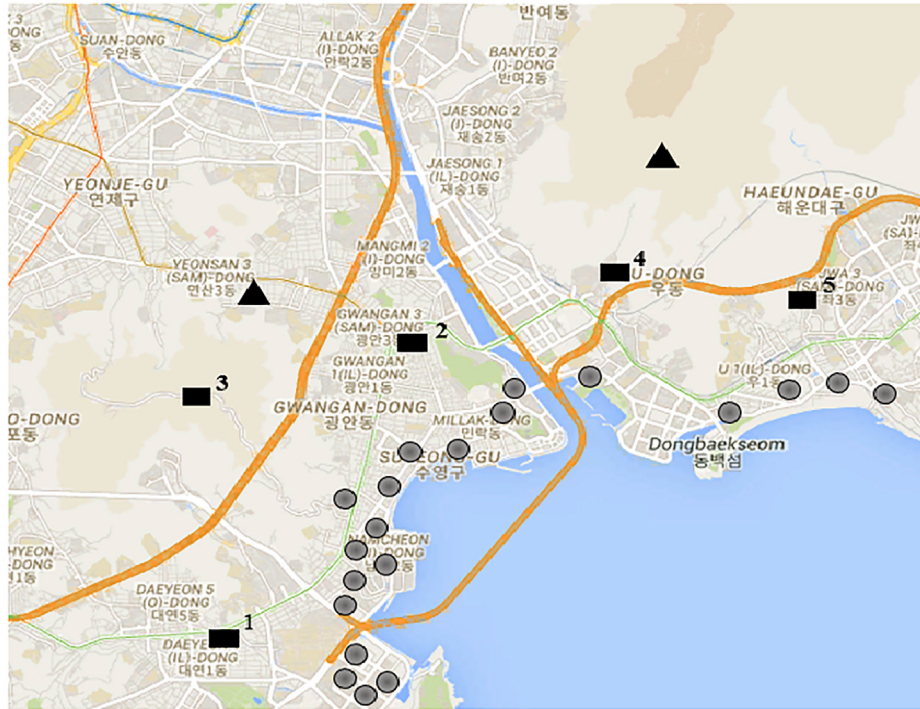


Fig. 3. Coastal areas of Busan, Korea.

Table 3
Computational results for scenarios with different degrees of impact.

	Degrees of impact		
	20–60	30–80	40–100
Number of constructed medical relief shelters	3	2	2
Candidate location 1	13	14	15
Candidate location 2	3	0	0
Candidate location 3	0	0	0
Candidate location 4	0	0	0
Candidate location 5	4	5	0
Total number of relieved patients	20	19	15

Table 4
Benchmark set of random instances.

Case	Number of medical relief shelter	Number of patients	Number of medical deployment center	Relief budget (\$)
e1-1	5	100	2	200,000
e1-2	5	100	2	250,000
e1-3	5	100	2	300,000
e1-4	10	200	6	200,000
e1-5	10	200	6	250,000
e1-6	10	200	6	300,000
e1-7	15	300	10	200,000
e1-8	15	300	10	250,000
e1-9	15	300	10	300,000
e1-10	20	400	15	200,000
e1-11	20	400	15	250,000
e1-12	20	400	15	300,000
e1-13	30	500	20	200,000
e1-14	30	500	20	250,000
e1-15	30	500	20	300,000

the solutions, the following notations are defined. The covering ratio is denoted by CR and is defined as the ratio of the relieved patients to the total number of the patients. The computation time is indicated by CT and is recorded in seconds. F_{tc} and F_{obj} indicate the total cost and the

objective value. CM represents the ratio of the number of candidate locations of medical relief shelters to the number of constructed medical relief shelters.

For the proposed models, LINGO did not provide the optimal solution due to the inherent complexity of the model and a shortage of computer memory, as shown in Table 5. The symbol ‘-’ indicates that LINGO did not find the optimal solutions within 3 hours. As shown in the table, the computation times for the problems grow rapidly as the problem size increases in LINGO.

The proposed algorithm finds the feasible solutions in all 15 cases in one second, even if the problem size is large. Comparing the results of the proposed algorithm and LINGO, it is noted that more patients were assigned to the constructed medical relief shelters using the proposed algorithm while the mathematical programming approach constructs more shelters, finding a higher objective value in a few cases. Fig. 4 shows a detailed comparison of the computational results between the methods.

The computational results show that the proposed algorithm is faster than LINGO and can solve large problems. In Cases e1-2 and e2-3, all of the patients are assigned to the medical relief shelters in both the proposed algorithm and LINGO. But in large problems, many patients are not assigned to the medical relief shelters because of the limited relief budget. Therefore, we must also discuss the relationship between the relief budget and the number of constructed medical relief shelters.

As shown in Table 5, LINGO constructs more medical relief shelters in all cases. Therefore, CR in the proposed algorithm is higher than in LINGO because we can assign more patients by reducing construction costs with a limited relief budget. But LINGO has a higher F_{obj} , which means that more emergency patients who have higher severity or closer patients are assigned to newly constructed medical relief shelters. Fig. 4(a) shows the number of assigned patients in constructed medical relief shelters, and Fig. 4(b) shows the value of F_{obj} from the proposed algorithm and LINGO for the different cases. In Table 5, the range of relief budget is the same for both small and large cases, so more than half of the patients in large cases are not assigned to medical relief shelters.

Table 5
Computational results and performance of the proposed algorithm and LINGO.

Case	The proposed algorithm					LINGO				
	F_{tc}	CR	F_{obj}	CT	CM	F_{tc}	CR	F_{obj}	CT	CM
e1-1	199,258	83/100	591.6	0.00024	4/5	199,987	78/100	625.2	358	5/5
e1-2	236,905	100/100	645.2	0.00012	5/5	248,518	100/100	647.0	1	5/5
e1-3	236,905	100/100	651.3	0.00011	5/5	248,023	100/100	647.0	1	5/5
e1-4	199,879	97/200	558.4	0.00647	4/10	200,000	76/100	675.3	3393	8/10
e1-5	249,632	115/200	681.4	0.00495	5/10	249,999	104/200	784.9 ^b	7200	9/10
e1-6	299,996	144/200	740.5	0.00370	5/10	299,997	126/200	876.1	3820	10/10
e1-7	199,257	115/300	550.8	0.03888	4/15	— ^a	—	—	—	—
e1-8	249,892	140/300	690.1	0.03395	5/15	—	—	—	—	—
e1-9	299,525	167/300	800.7	0.02789	6/15	—	—	—	—	—
e1-10	199,603	105/400	955.9	0.15715	4/20	—	—	—	—	—
e1-11	249,985	132/400	1133.9	0.14124	5/20	—	—	—	—	—
e1-12	299,901	158/400	1403.7	0.12732	7/20	—	—	—	—	—
e1-13	199,801	101/500	1384.0	0.54794	5/30	—	—	—	—	—
e1-14	249,848	124/500	1757.4	0.51471	7/30	—	—	—	—	—
e1-15	299,702	156/500	1830.6	0.47502	7/30	—	—	—	—	—

^a The symbol “—” indicates that LINGO did not find a feasible solution in 3 hours.

^b Best feasible solution after 2 h from LINGO.

5.4. Experiment 4

In Tables 4 and 5, Cases e1-10, e1-11 and e1-12 considered 400 patients, 20 candidate locations and 15 medical deployment centers under 3 different amounts of relief budget. In order to understand the behavior of CR and F_{obj} against the budget changes, additional experiments have been conducted.

In Table 6, the relief budget is increased by \$50,000 with other parameters same in Cases e1-10, e1-11, and e1-12. The relief budget is increased by \$10,000 in the range of \$750,000–800,000 to observe the impact of the construction of a medical relief shelter. We also look at how the installation of additional medical relief shelters affects the objective value.

As shown in Table 6, as the relief budget is increased, the number of constructed medical relief shelters, objective values, and number of patients assigned to constructed medical relief shelters increase. In addition, when the relief budget increases by \$10,000, the number of assigned patients increases even if there is no additional medical relief shelter. When the relief budget is \$770,000 in Case e2-14, all 400 patients are assigned to medical relief shelters. However, when the relief budget is increased to \$780,000, an additional medical relief shelter is constructed, so that the objective value increases. This means that when additional medical relief shelters are constructed, the distance between patients and medical relief shelters decreases, and the objective value increases. If the relief budget is \$790,000 or \$800,000, there is no

Table 6

Computational results for various relief budgets with 20 medical relief shelter candidate locations.

Case	Relief budget (\$)	CR	CM	F_{obj}	F_{tc}
e2-1	200,000	105/400	4/20	955.9	199,603
e2-2	250,000	132/400	5/20	1133.9	249,985
e2-3	300,000	158/400	7/20	1403.7	299,901
e2-4	350,000	186/400	8/20	1478.5	349,828
e2-5	400,000	215/400	8/20	1615.6	399,932
e2-6	450,000	239/400	10/20	1764.42	449,926
e2-7	500,000	264/400	11/20	1945.72	499,714
e2-8	550,000	295/400	12/20	2049.9	549,571
e2-9	600,000	322/400	13/20	2195.7	599,297
e2-10	650,000	346/400	14/20	2367	649,896
e2-11	700,000	368/400	16/20	2516.2	699,354
e2-12	750,000	390/400	18/20	2633.9	749,778
e2-13	760,000	392/400	19/20	2654.7	759,862
e2-14	770,000	400/400	19/20	2678.6	769,493
e2-15	780,000	400/400	20/20	2693.5	777,340
e2-16	790,000	400/400	20/20	2693.5	777,340
e2-17	800,000	400/400	20/20	2693.5	777,340

further change in all of the outcomes.

It is necessary to reduce the distance between patients and medical relief shelters by constructing more shelters in special cases, such as when some areas have much damage from a disaster that results in

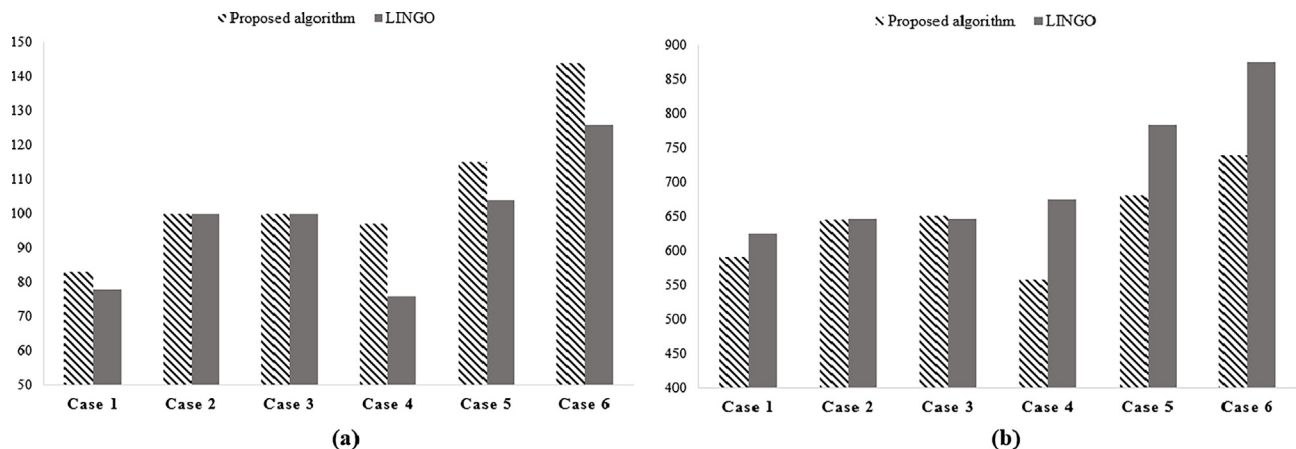


Fig. 4. (a) Numbers of relieved patients and (b) objective values by the proposed algorithm and LINGO.

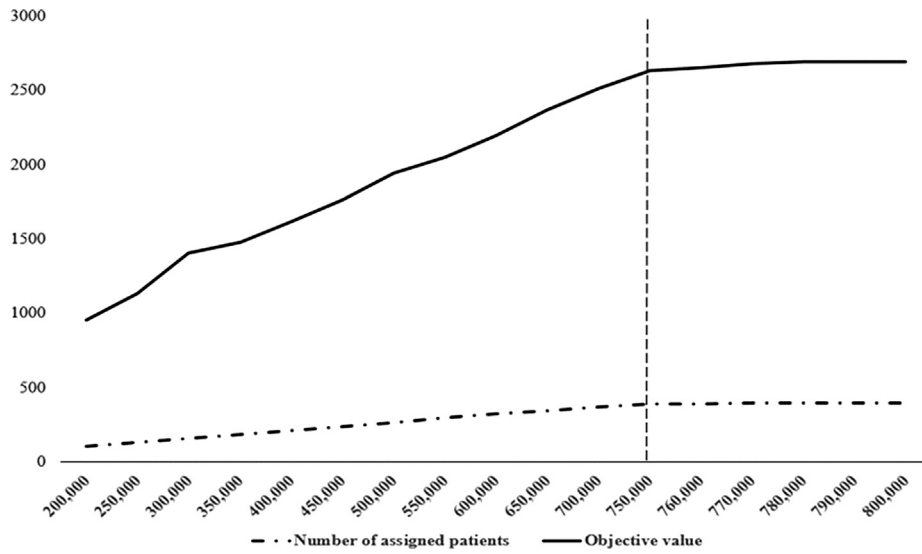


Fig. 5. The number of assigned patients and objective value with various relief budgets.

many emergency patients. Generally, we can make assumptions about how many patients will occur in disasters by using data such as population, topographic information, and so on. Therefore, before a disaster occurs, the proposed methodology can help governments and municipalities to make decisions about how many medical relief shelters should be constructed in a certain place with a proper relief budget.

Fig. 5 illustrates the computational results in Table 7. The number of assigned patients and objective value increased when the relief budget increased, but at \$750,000, the results are almost unchanged. Therefore, at least \$750,000 of relief budget is needed to obtain the maximal objective value when there are 400 patients, 20 candidate locations of medical relief shelters, and 15 medical deployment centers. The number of constructed medical relief shelters affects the objective value, so further experiments on the construction cost are needed. Therefore, we changed the number of candidate locations for medical relief shelters to 10 to see how much the construction cost affects the solutions. These experiments could help to make decisions that are tailored to the purposes of each local government.

As shown in Case e3-12, when the candidate locations of the medical relief shelters are reduced to 10, a relief budget of only \$689,587 is needed to assign all patients. When the number of candidate locations is 20 in Case e2-14, at least \$769,493 is required to assign all patients to constructed shelters. However, when all patients are assigned in Case e2-15, the maximal objective value is 2693.5, whereas in Case e3-12, the maximal objective value is reduced to 1885.9, which is about 30% lower. However, the relief budget is reduced by only 10%. Thus, even

when considering the additional construction costs, it would be a better decision to increase the number of candidate locations for medical relief shelters to provide more efficient and effective emergency medical services to patients in disasters.

6. Conclusion

Natural disasters and anthropogenic disasters have become more frequent in recent years. In such emergency situations, authorities need to augment their medical response capabilities by using scarce medical resources to provide emergency medical care. Therefore, in this study, a variant of the MCLP model was proposed to manage the logistics of both medical supplies and patients.

The locations of medical relief shelters were determined by considering the severity and distribution of patients and the locations of medical deployment centers. The cost information and other input parameters had a great influence on the decisions that should be made for some important factors, such as finding the appropriate places to establish medical relief shelters, choosing the supplier of medical relief centers, determining the capacity of the shelters, and keeping sufficient resources for emergency and non-emergency patients. Therefore, it is important to have a concrete decision-making model to support authorities in emergency situations.

In an emergency management system, the planners want to serve as many injured people as possible and dispatch scarce medical resources as quickly as possible with the lowest cost. The objective of this study was to maximize the number of patients who obtain medical services at multiple medical relief shelters with a limited relief budget while considering the severity of patients and distances to medical relief shelters.

The proposed model produces the optimal solutions quickly, and the results varied significantly in accordance with the input parameters. Timely response to disasters is very important. The proposed mathematical model is hard to solve for larger case problems in a reasonable time. To obtain a feasible solution, a greedy algorithm was proposed. The effectiveness and efficiency of the proposed solution method were demonstrated using randomly generated problems, and the results showed that the proposed algorithm can generate feasible solutions in a reasonable time. Future studies should consider the multiple time periods that may lead to the computational intractability, hierarchical medical relief shelters that can provide different levels of services, and vehicle routing problems (Zhou & Lee, 2017) to pick up patients.

Table 7

Computational results for various relief budgets with 10 medical relief shelter candidate locations.

Case	Relief budget (\$)	CR	CM	F_{obj}	F_{ic}
e3-1	200,000	117/400	2/10	557.5	199,562
e3-2	250,000	147/400	3/10	778.4	249,359
e3-3	300,000	175/400	3/10	859.7	299,539
e3-4	350,000	204/400	4/10	1074.4	349,603
e3-5	400,000	234/400	4/10	1075.6	399,843
e3-6	450,000	266/400	6/10	1290.3	449,699
e3-7	500,000	294/400	6/10	1409.0	499,454
e3-8	550,000	322/400	7/10	1548.2	549,972
e3-9	600,000	350/400	8/40	1639.4	599,675
e3-10	650,000	376/400	9/10	1783.9	649,881
e3-11	680,000	398/400	9/10	1830.1	679,217
e3-12	690,000	400/400	10/10	1885.9	689,587
e3-13	700,000	400/400	10/10	1885.9	689,587

Acknowledgements

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (No. 2015R1A2A1A10054253, 2017R1A2B2007812 and No. 2018R1A2B3008890).

References

- Afshar, A., & Haghani, A. (2011). Modeling integrated supply chain logistics in real-time large-scale disaster relief operations. *Socio-Economic Planning Sciences*, 46(2), 327–338.
- Altay, N., & Green, W. G. (2006). OR/MS research in disaster operations management. *European Journal of Operational Research*, 175(1), 475–493.
- Balcik, B., & Beamon, B. M. (2008). Facility location in humanitarian relief. *International Journal of Logistics Research and Applications*, 11(2), 101–121.
- Beraldi, P., & Bruni, M. E. (2009). A probabilistic model applied to emergency service vehicle location. *European Journal of Operational Research*, 196(1), 323–331.
- Boonmee, C., Arimura, M., & Asada, T. (2017). Facility location optimization model for emergency humanitarian logistics. *International Journal of Disaster Risk Reduction*. <http://dx.doi.org/10.1016/j.ijdr.2017.01.017> (in press).
- Day, J. M., Melnyk, S. A., Larson, P. D., Davis, E. W., & Whybark, D. C. (2012). Humanitarian and disaster relief supply chains: A matter of life and death. *Journal of Supply Chain Management*, 48(2), 21–36.
- Farahani, R. Z., Asgari, N., Heidari, N., Hosseini, N., & Goh, M. (2012). Covering problems in facility location: A review. *Computers & Industrial Engineering*, 62(1), 368–407.
- Farahani, R. Z., & Hakmatfar, M. (2009). *Facility location: Concept, model, algorithm and case studies* (2009th ed.). Physica.
- Gu, J., Zhou, Y., & Lee, G. M. (2016). Medical relief shelter location considering the severity of patients under limited relief budget. In: *The 46th international conferences on computers and industrial engineering*.
- Hankooklibo (2015). < <http://hankooklibo.com/m/v/4361af128c3c4a208ad710e59a56ed6c> > . Accessed on Feb. 2, 2018.
- Hu, F., Yang, S., Hu, X., & Wang, W. (2017). Integrated optimization for shelter service area demarcation and evacuation route planning by a ripple-spreading algorithm. *International Journal of Disaster Risk Reduction*. <http://dx.doi.org/10.1016/j.ijdr.2017.06.006> (in press).
- Huang, R., Kim, S., & Menezes, M. B. (2010). Facility location for large-scale emergencies. *Annals of Operations Research*, 181(1), 271–286.
- Inverse (2015). < <https://www.inverse.com/article/7348-hurricane-patricia-is-the-strongest-western-hemisphere-storm-on-record> > . Accessed on Feb. 2, 2018.
- Jia, H., Ordóñez, F., & Dessouky, M. M. (2007a). Solution approaches for facility location of medical supplies for large-scale emergencies. *Computers & Industrial Engineering*, 52(2), 257–276.
- Jia, H., Ordóñez, F., & Dessouky, M. (2007b). A modeling framework for facility location of medical services for large-scale emergencies. *IEE Transactions*, 39(1), 41–55.
- Lloyd, S. (1982) Least squares quantization in PCM. *Special issue on quantization, IEEE Trans. Inform. Theory*, 28, 129–137.
- Mete, H. O., & Zabinsky, Z. B. (2010). Stochastic optimization of medical supply location and distribution in disaster management. *International Journal of Production Economics*, 126(1), 76–84.
- Mohamadi, A., & Yaghoubi, S. (2017). A bi-objective stochastic model for emergency medical services network design with backup services for disasters under disruptions: An earthquake case study. *International Journal of Disaster Risk Reduction*, 23, 204–217.
- Najafi, M., Eshghi, K., & Dullaert, W. (2013). A multi-objective robust optimization model for logistics planning in the earthquake response phase. *Transportation Research Part E: Logistics and Transportation Review*, 49(1), 217–249.
- Nicholl, J., West, J., Goodacre, S., & Turner, J. (2007). The relationship between distance to hospital and patient mortality in emergencies: An observational study. *Emergency Medicine Journal*, 24(9), 665–668.
- Sheu, J. B., & Pan, C. (2015). Relief supply collaboration for emergency logistics responses to large-scale disasters. *Transportmetrica A: Transport Science*, 11(3), 210–242.
- United States Geological Survey (2008). Magnitude 7.0 – Eastern Sichuan, China and Hong Kong. <https://web.archive.org/web/20080916024447/http://earthquake.usgs.gov/eqcenter/recenteqsww/Quakes/us2008ryan.php>. Accessed on Feb. 2, 2018.
- Yonhap News (2017). < <http://www.yonhapnews.co.kr/bulletin/2017/11/22/0200000000AKR20171122065600054.HTML?input=1195m> > . Accessed on Feb. 2, 2018.
- Zhou, Y., & Lee, G. M. (2017). A Lagrangian relaxation-based solution method for a green vehicle routing problem to minimize greenhouse gas emissions. *Sustainability*, 9, 776.