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A HYBRID GENETIC ALGORITHM FOR MULTI-EMERGENCY MEDICAL SERVICE CENTER LOCATION-ALLOCATION PROBLEM IN DISASTER RESPONSE

Xuehong Gao, Yanjie Zhou, Muhammad Idil Haq Amir, Fifi Alfiana Rosyidah and Gyu M. Lee*

Department of Industrial Engineering, Pusan National University
Busan, Korea
*Corresponding author's e-mail: glee@pnu.edu

Temporary emergency medical service center provides an expeditious and appropriate medical treatment for injured patients in the post-disaster. As part of the first responders in quick response to disaster relief, temporary emergency medical service center plays a significant role in enhancing survival, controlling mortality and preventing disability. In this study, the final patient mortality risk value (injury severity) caused by both initial mortality risk value and travel distance (travel time) is considered to determine the location-allocation of temporary emergency medical service centers. In order to improve effective rescue task in post-disaster, two objectives of models are developed. The objectives include minimize the total travel time and the total mortality risk value of patients in the whole disaster area. Then, genetic algorithm with modified fuzzy C-means clustering algorithm is developed to decide locations and allocations of temporary emergency medical service centers. Illustrative examples are given to show how the proposed models optimize the locations and allocations of temporary emergency medical service centers and handle post-earthquake emergencies in the Portland area. Furthermore, comparisons of the results are presented to show the advantages of the proposed algorithm in minimizing the total travel time and the total mortality risk value for temporary emergency medical service centers in disaster response.

Keywords: emergency medical service; multi-facility location-allocation problem; hybrid genetic algorithm; fuzzy C-means

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1. INTRODUCTION

Quick and timely location-allocation of temporary emergency medical service (EMS) centers to the urgent needs of medical treatment in disaster areas is a significant issue for relieving the serious situation. The performance of temporary EMS center in the disaster area relies on the limited transportation and the medical resources. Besides, the most important and expeditious duties of the society mainly are rescuing human lives and helping all those injured patients who require medical attendance through life-saving operations (Badal, Vázquez-Prada *et al.* 2005). In this sense, a number of temporary EMS centers should be considered and located in the reasonable locations to satisfy the urgent needs of emergency recovery, reducing mortality and preventing health deterioration (Alsalloum and Rand 2006). On the other hand, many research show that higher mortality risk are significantly associated with higher injury severity scores (Baker, o'Neill *et al.* 1974, Deng, Tang *et al.* 2016, Gu, Zhou *et al.* 2016, Le, Orman *et al.* 2016). The injury severity should be considered as another critical factor to decide the survival of patients. Therefore, a feasible solution should be proposed to tackle multiple temporary EMS centers location-allocation problem from the perspectives of satisfying medical treatment care demands (Peña-Mora, Chen *et al.* 2010).

In the immediate aftermath of a disaster, a robust system for EMS should be established to decrease the travel time of injured patients and emphasize the priority of patient with higher mortality risk. At the scene of disaster, the temporary EMS center serves as a field hospital in the disaster area to enhance survival, control mortality and prevent disability (Kobusingye, Hyder *et al.* 2006). These temporary EMS centers are equipped with advanced utility vehicles and emergency medical equipment such as mobile emergency room and mobile emergency bed (Yoo, Park *et al.* 2003) and some other devices. In order to improve the performance of temporary EMS centers in hasty response to disaster relief, the location of the EMS centers and the allocation of the resources should be carried out effectively and efficiency.

There are two objectives in this study. The first one is to minimize the total travel time and the second one is to minimize the total mortality risk value of patients. The location-allocation of temporary EMS centers is a generalized multi-Weber problem, which is also known as an uncapacitated multi-facility location-allocation problem (MFLP) stated by Copper (Cooper 1963), and the problem can be interpreted as an enumeration of the Voronoi partitions of the customer set, which has been proven to be a NP-hard problem (Megiddo and Supowit 1984, Bischoff, Fleischmann *et al.* 2009).

In this study, we consider demand locations, travel distance, and available number of temporary EMS centers. Demand locations are composed of patient locations and injury severities triggered from the disaster. Patient locations and injury severities are known from civilian reporting system or local emergency management office. The Manhattan distance is used to approximately express the route distance between the injured patient and the temporary EMS center. Management of temporary EMS center in such an environment requires the patient to go to a designated temporary EMS center. And these temporary EMS centers are responsible for all emergency medical treatment task because all of the hospitals are damaged in the disaster.

The contents of the paper are organized in the following order. Section 2 provides the literature review of related works. In Section 3, the two main models formulations, proposed methodologies and process are provided. The data set is described in Section 4. Then, the experimental examples and results are presented and discussed in Section 5. Finally, Section 6 concludes this study with the contributions and further directions.

2. LITERATURE REVIEW

In this section, we present a literature review of relevant works in temporary EMS systems. Given the occurrence of a large-scale disaster emergency, a number of temporary EMS centers need to be applied to relieve the impact of the emergency disaster because EMS center is the first safety measure to provides medical treatment for people who have encountered emergency injuries. In this sense, the goal of temporary EMS centers location-allocation problem is to determine the locations of facilities to serve a given set of customers optimally (Esnaf and Küçükdeniz 2009).

In the past, quantities of methods have been proposed for solving various MFLPs. Jia *et al.* (Jia, Ordóñez *et al.* 2007) analyzed the characteristics of large-scale emergencies and proposed a general facility location model that was suited for large-scale emergencies. This general facility location model can be cast as a set covering model, a P-median model or a P-center model, and each of them suited for different needs in large-scale emergencies. Araz *et al.* (Araz, Selim *et al.* 2007) developed a multi-objective covering-based emergency vehicle location model considering the objectives of maximization of the population covered by one vehicle, maximization of the population with backup coverage and increasing the service level by minimizing the total travel distance from locations at a distance bigger than a pre-specified distance standard for all zones. Coskun and Erol (Coskun and Erol 2010) presented an integer optimization model to decide locations and types of service stations, regions covered by these stations under service constraints in order to minimize the total cost of the overall system. Sorensen and Church (Sorensen and Church 2010) developed a hybrid model, designated the local reliability-based maximum expected covering location problem, which combined the local-reliability estimates of maximum availability location problem with the original maximum expected coverage goal of maximum expected covering location problem. Başar *et al.* (Başar, Çatay *et al.* 2011) proposed a Tabu Search approach to solve the multi-period location planning problem of EMS stations. Hosseini and Ameli (Hosseini and Ameli 2011) presented a bi-objective mathematical model for the emergency services location-allocation problem on a tree network considering maximum distance constraint. Fares (Fares 2014) investigated the prospects of integrating data mining techniques and GIS simulation modeling in developing an innovative approach for modeling EMS systems, and a fuzzy K-means method was used in conjunction with GIS to model an EMS system. Chanta *et al.* (Chanta, Mayorga *et al.* 2014) proposed three bi-objective covering location models that directly considered fairness via a secondary objective in order to balance the level of first-response ambulatory service provided to patients in urban and rural areas by locating ambulances at appropriate stations. Chen and Yu (Chen and Yu 2016) applied integer programming and node-based K-medoids algorithm for location planning of temporary EMS facilities in disaster response.

A MFLP is defined as a special clustering problem if the sets of customers served by the same facility are considered as clusters (Küçükdeniz and Büyüksaatçi 2008) where K-means (Zhou and Lee 2017) and fuzzy C-means (FCM) clustering methods are widely used. Žalik (Žalik 2006) proposed that FCM was used to minimize the mean squared distance from each data point to its nearest center. Sheu (Sheu 2006, Sheu 2007) developed different versions of a hybrid fuzzy clustering method to group the customer order demands. Esnaf and Kucukdeniz (Esnaf and Küçükdeniz 2009) presented a fuzzy clustering-based hybrid method for a MFLP which assumed that the capacity of each facility was unlimited. Ozdamar and Demir (Ö zdamar and Demir 2012) described a multi-level clustering algorithm that grouped demand nodes into smaller clusters at each planning level, enabling the optimal solution of cluster routing problems. Chen *et al.* (Chen, Yeh *et al.* 2014) considered the Euclidean distance in seeking of potential locations of temporary EMS facilities by clustering EMS demands previously. Moreover, heuristic algorithms are widely used for various EMS facility location models. Jaramillo et al. (Jaramillo, Bhadury *et al.* 2002) built a genetic algorithm (GA) algorithm which was tested on two standard data sets. The solutions obtained from GA were slightly better, compared with a Lagrangian heuristic followed by a substitution procedure.

In order to improve the performance of clustering algorithm, the combination of the clustering algorithm and GA was used to achieve data clustering. And genetic algorithm clustering was the algorithm that achieves data clustering by genetic algorithm (Ou, Cheng *et al.* 2004). Many research used GA with the FCM algorithm to assign patterns or data into different clusters for soft partitioning. Ding and Fu (Ding and Fu 2016) proposed a kernel-based fuzzy C-means (KFCM) to optimize FCM clustering result based on the GA optimization. In the algorithm, the improved adaptive GA is used to optimize the initial clustering center firstly, and then the KFCM algorithm is availed to guide the categorization, so as to improve the clustering performance of the FCM algorithm. Yang *et al.* (Yang, Kuo *et al.* 2015) proposed a non-dominated sorting genetic algorithm using fuzzy membership chromosome for categorical data clustering based on K-modes method which combined fuzzy genetic algorithm and multi-objective optimization to improve the clustering quality on categorical data.

From the research above, we can see that genetic fuzzy clustering algorithm (Gong and Guo 2007) combined the advantages of GA and FCM to overcome the defect that FCM was sensitive to the noise of isolated data and the initial clustering center. And FCM enhanced the local search capabilities of GA, which had a good effect on the clustering result. In this study, a GA with modified FCM clustering algorithm (GA-MFCM) is proposed to tackle the multi-temporary EMS center location-allocation problem in disaster area. Patients are assigned to uncapacitated temporary EMS centers considering their geographical locations and final mortality risk value. We first have patient locations and injury severities. Then, travel distance is taken into account for each patient which worsens the mortality risk value of patient. Furthermore, each patient would be assigned to a single temporary EMS center exactly based on the biggest membership value, which is used to split demands into several groups. Finally, each group is considered as a single facility location problem. Therefore, patients are grouped by GA-MFCM in respect to individual mortality risk and geographical location.

3. PROBLEM DESCRIPTION AND METHODOLOGY

The methodology for achieving the research objectives is presented in this section. First, integer programming formulations for multi-facility locations are presented for two different models M1 and M2. The GA-MFCM is later introduced to improve the objective performance. The main different between M1 and M2 is whether we take individual injury severity into consideration when we determine the optimal locations for temporary EMS centers.

2.1 Problem Description

The model (M1) is a multi-facility location problem, where the set of facility locations depends on the locations of patients. The objective of M1 is to minimize the total travel time. In the model, given the total number of patients L, the parameter K indicates the number of temporary EMS centers to be established. In the model, $\left|P_{lx}-\frac{\sum_{l=1}^{L} w_{lk}P_{lx}}{\sum_{l=1}^{L} w_{lk}}\right|+\left|P_{ly}-\frac{\sum_{l=1}^{L} w_{lk}P_{ly}}{\sum_{l=1}^{L} w_{lk}}\right|$ is the Manhattan distance between patient P_l and temporary EMS center C_k. $V_0 = 60\text{km/h}$ is the travel speed (Harewood 2002). The decision variable w_{lk} is a binary variable, which represents assignment of patient P_l and temporary EMS center C_k.

Model M1:

$$\text{Min} \sum_{k=1}^{K}\sum_{l=1}^{L} w_{lk}\cdot\frac{\left|P_{lx}-\frac{\sum_{l=1}^{L} w_{lk}P_{lx}}{\sum_{l=1}^{L} w_{lk}}\right|+\left|P_{ly}-\frac{\sum_{l=1}^{L} w_{lk}P_{ly}}{\sum_{l=1}^{L} w_{lk}}\right|}{V_0} \tag{1}$$

s.t.

$$\sum_{k=1}^{K} w_{lk} = 1 \qquad \forall\, l \in \{1,2,\dots,L\} \tag{2}$$

$$\sum_{l=1}^{L} w_{lk} > 0 \qquad \forall\, k \in \{1,2,\dots,K\} \tag{3}$$

$$w_{lk} = \begin{cases} 1 & \text{if } P_l \text{ is assigned to } C_k \quad \forall\, l \in \{1,2,\dots,L\}, k \in \{1,2,\dots,K\} \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

The following model (M2) is also a multi-facility location problem, where the set of facility locations depends on the locations and mortality risk value of patients. The objective of M2 is to minimize the total mortality risk value. In the model, $\left|P_{lx}-\sum_{l=1}^{L}\frac{w_{lk}\cdot M_{lk}^{I}}{\sum_{l=1}^{L} w_{lk}\cdot M_{lk}^{I}}\cdot P_{lx}\right|+\left|P_{ly}-\sum_{l=1}^{L}\frac{w_{lk}\cdot M_{lk}^{I}}{\sum_{l=1}^{L} w_{lk}\cdot M_{lk}^{I}}\cdot P_{ly}\right|$ is the Manhattan distance between patient P_l and temporary

EMS center C_k. And the parameter M_{lk}^I is the initial mortality risk value of patient P_l assigned to temporary EMS center C_k. Parameter $\alpha = 0.02$ is a coefficient (Nicholl, West *et al.* 2007).

Model M2:

$$\text{Min} \sum_{k=1}^{K}\sum_{l=1}^{L} w_{lk} \cdot M_{lk}^I \cdot \left[1 + \alpha \cdot \left(\left|P_{lx} - \sum_{l=1}^{L} \frac{w_{lk} \cdot M_{lk}^I}{\sum_{l=1}^{L} w_{lk} \cdot M_{lk}^I} \cdot P_{lx}\right| + \left|P_{ly} - \sum_{l=1}^{L} \frac{w_{lk} \cdot M_{lk}^I}{\sum_{l=1}^{L} w_{lk} \cdot M_{lk}^I} \cdot P_{ly}\right|\right)\right] \tag{5}$$

s.t.

$$\sum_{k=1}^{K} w_{lk} = 1 \qquad \forall\, l \in \{1,2,\dots,L\} \tag{6}$$

$$\sum_{l=1}^{L} w_{lk} > 0 \qquad \forall\, k \in \{1,2,\dots,K\} \tag{7}$$

$$w_{lk} = \begin{cases} 1 & \text{if } P_l \text{ is assigned to } C_k \qquad \forall\, l \in \{1,2,\dots,L\}, k \in \{1,2,\dots,K\} \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

where objective function (1) minimizes the total travel time of injured patients and objective function (5) minimizes the total mortality of risk value of patients. Constraints (2) and (6) determine that one patient can only be assigned to a temporary EMS center in M1 and M2 respectively. Constraints (3) and (7) guarantee that at least one patient P_l should be assigned to temporary EMS center C_k. Constraints (4) and (8) are decision variables in M1 and M2 respectively.

3.2 Modified FCM Algorithm

The FCM clustering algorithm is developed by Dunn (Dunn 1973), and later on improved by Bezdek (Bezdek and Dunn 1975). In the beginning of the algorithm, the number of clusters should be pre-determined. Then, the algorithm tries to assign each of the data points to one of the clusters. The difference between FCM and K means clustering algorithm is that FCM does not decide the absolute membership of a data point to a given cluster and its main procedures are the calculation of membership degree and the update of cluster centers, which starts with two and designated. Hence, data points are allowed to belong to several clusters with different degrees of membership. The membership degree is used to represent the extent to belong to each cluster, and this information is also used to update the cluster centers. The FCM can be seen as the fuzzified version of K-means algorithm and is based on the minimization of an objective function called C-means function (Bezdek and Dunn 1975, Kenesei, Balasko *et al.* 2006).

In this study, a modified FCM clustering algorithm based on FCM clustering algorithm is proposed to tackle this multi-temporary EMS center location-allocation problem considering patient's geographical locations and initial mortality risk value. The modified FCM is different from the classical FCM because it introduces parameter M_{lk}^I, initial mortality risk value, to calculate C-means function and update temporary EMS centers.

For the modified FCM clustering algorithms, there are three input parameters needed to run this function including the number of clusters K; the fuzziness exponent m> 1; the termination tolerance ϕ> 0. Given the data points L that includes geographical X and Y coordinates and initial mortality risk value. And the algorithm tracks the following steps.

3.2.1 FCM function

The minimization of an objective function called FCM function:

$$J = \sum_{k=1}^{K}\sum_{l=1}^{L} u_{lk} \cdot M_{lk}^I \cdot D_{(P_l, C_K)} \tag{9}$$

Here, C_K is the center vector; u_{lk} is the degree of membership for patient P_l in temporary EMS center C_k; the norm $D_{(P_l, C_K)}$ which is the Manhattan distance measures the similarity (or closeness) of the patient P_l to the center vector C_K. Note that, in each iteration, the algorithm maintains a center for each of the clusters.

3.2.2 Degree of membership

For a given patient P_l, the degree of membership to the cluster C_k is calculated as follows:

$$u_{lk} = \frac{1}{\sum_{q=1}^{K}\left(\frac{D_{(P_l,C_k)}}{D_{(P_l,C_q)}}\right)^{\frac{2}{m-1}}} \tag{10}$$

where, m is the fuzziness coefficient, and the center $C_k(C_{kx}, C_{ky})$ is calculated as follows:

$$C_{kx} = \frac{\sum_{l=1}^{L}(u_{lk})^m \cdot M_{lk}^I \cdot P_{lx}}{\sum_{l=1}^{L}(u_{lk})^m \cdot M_{lk}^I} \tag{11}$$

$$C_{ky} = \frac{\sum_{l=1}^{L}(u_{lk})^m \cdot M_{lk}^I \cdot P_{ly}}{\sum_{l=1}^{L}(u_{lk})^m \cdot M_{lk}^I} \tag{12}$$

In the equation above, u_{lk} is the value of the degree of membership calculated in the previous iteration; M_{lk}^I is initial mortality risk value. Note that at the start of the algorithm, the degree of the membership for the data point P_l to the cluster C_k is initialized with a random value $\vartheta_{lk}, 0 \leq \vartheta_{lk} \leq 1$, such that $\sum_{k=1}^{K} u_{lk} = 1$. The fuzziness coefficient $1 < m < \infty$ measures the tolerance of the required clustering.

3.2.3 Termination condition

The required accuracy of the objective function value J determines the number of iterations completed by the FCM clustering algorithm. This measure of accuracy is calculated using J from one iteration to the next.

If we represent the measure of accuracy iteration n with J^n, we calculate termination tolerance value ϕ as follows:

$$\phi = |J^{n+1} - J^n| \tag{13}$$

3.3 GA-MFCM

The FCM based on the objective function is widely applied because of its strong ability of local search and its fast convergence speed. However, FCM algorithm has two defects (Ding and Fu 2016). The first one is that the sum of the membership degree for all of the categorizations, which makes it sensitive to the noise and isolated data. The second one is that FCM is sensitive to the initial clustering center and easy to converge to a local extremum.

Aim at the problems existed in the FCM clustering algorithm, a modified FCM is proposed to optimize FCM clustering by changing the FCM function and updating the center vector. On the other hand, GA is global, parallel, stochastic search methods, founded on Darwinian evolutionary principles. During the last decade GA has been applied in a variety of areas, with varying degrees of success (Ding and Fu 2016). In this sense, we develop GA-MFCM which is combined of the GA and modified FCM clustering algorithm. Then a center-based string encoding, nonlinear ranking select measurement, adaptive crossover and mutation strategy (Wikaisuksakul 2014) are employed in GA-MFCM. In the GA-MFCM algorithm, the adaptive GA is used to optimize the clustering center and MFCM algorithm provides the categorization of the data, so as to improve the result of clustering algorithm.

Fitness is the standard to judge and evaluate the individual. The final criteria are the maximum evolution generation or the average fitness convergence. Genetic operators that are responsible for the search process are detailed in the following parts.

3.3.1 Chromosome Design

FCM is easy for cluster centers to fall into local extreme points. Thus, in this study, cluster centers coding method is used to represent the chromosome, which is center-based string encoding for the clustering centers. Firstly, each individual of cluster centers is arranged in the chromosome and each gene contains the center location information. We use a letter with index number to present the each of individual cluster centers. If there are K cluster centers, each cluster center is called a gene and index number goes from 1 to K (Figure 1).

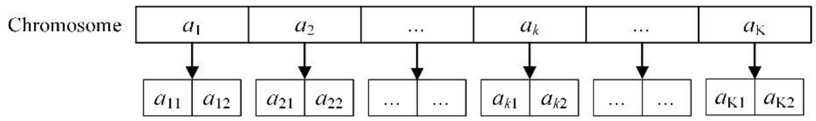


Figure 1. Center-based string encoding for cluster centers

For a given number of cluster centers K, we have cluster vector $\{C_1,\ C_2, \dots\ C_k \dots C_K\}$. And each gene C_k in chromosome has geographical X coordinate C_{k1} and Y coordinate C_{k2}.

3.3.2 Fitness function

In a modified FCM clustering algorithm, the results of clustering are measured by the objective function.

And it is small when the result is good. The objective function is:

$$h = \sum_{k=1}^{K}\sum_{l=1}^{L} w_{lk} \cdot M_{lk}^{I} \cdot \alpha \cdot \left(\left| P_{lx} - \sum_{l=1}^{L} \frac{w_{lk} \cdot M_{lk}^{I}}{\sum_{l=1}^{L} w_{lk} \cdot M_{lk}^{I}} \cdot P_{lx} \right| + \left| P_{ly} - \sum_{l=1}^{L} \frac{w_{lk} \cdot M_{lk}^{I}}{\sum_{l=1}^{L} w_{lk} \cdot M_{lk}^{I}} \cdot P_{ly} \right| \right) \tag{14}$$

$$w_{lk} = \begin{cases} 1 & \text{if } u_{lk} = \max(u_{l1}, u_{l2}, \dots, u_{lk}, \dots, u_{lK}) \qquad \forall\, l \in \{1,2,\dots,L\}, k \in \{1,2,\dots,K\} \\ 0 & \text{otherwise} \end{cases} \tag{15}$$

In genetic algorithm, fitness is the standard to judge and evaluate the individual. The individual with bigger fitness value is finer and has a greater probability to survive. So the reciprocal objective function is considered as the fitness function to evaluate that an evolutionary individual is excellent or inferior. The fitness formulation is calculated as follows:

$$f = \frac{10^8}{1 + h} \tag{16}$$

3.3.3 Genetic operator

(1) Selection operator
The constant ratio selection method is adopted to choose some chromosomes to undergo genetic operations. In order to avoid the current best individual being destroyed by crossover or mutation operation, the optimal preservation strategy is taken in this paper. In other words, the fittest individual will be selected among the certain number S of random selected individuals, which indicates that the fitter the individual, the higher the probability to survival. Although one individual has the highest fitness, there is no guarantee that it can be selected.

(2) Crossover operator
We generates a random number p between [0, 1], if $p < P_c$ (P_c is a given crossover probability), then two patients implement crossover and generate two new children in each time. The crossover operator adopted in GA-MFCM is single-point crossover operator. A random integer number k belonging to [1, K-1] is generated, which is considered as the crossover point. The crossover process is shown in the Fig. 2.

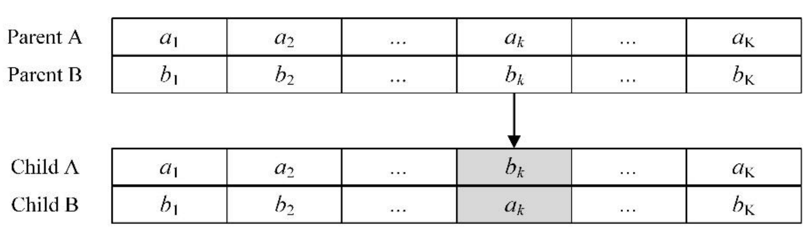


Figure 2. Crossover operation for two individuals

(3) Mutation operator
Each individual generates a random number q between $[0,1]$, if $q < P_m$ (P_m is a given mutation probability), then the chromosome mutates. Before the mutation operator, an integer k between $[1,K]$ is generated in advance, then a random geographical location $C_k^*(C_{k1}^*, C_{k2}^*)$ is used to replace the kth gene. The mutation process is shown in the Fig. 3.

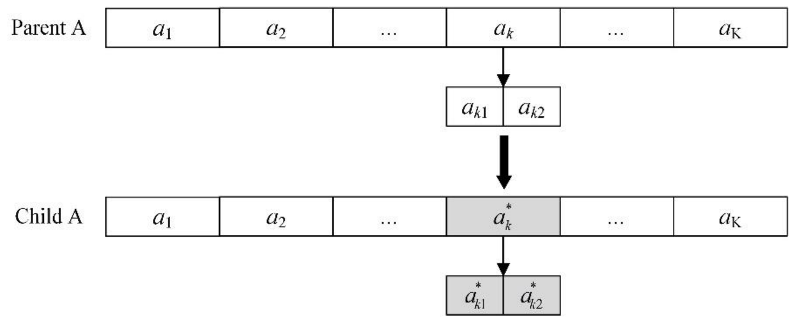


Figure 3. Mutation operation for one individual

3.3.4 GA-MFCM clustering algorithm steps
The flowchart of GA-MFCM is illustrated in the Fig. 4 and GA-MFCM tracks the following steps.
Step 1: Set the parameters
Set the number of clusters K; population number L with injury severities; generation number G; crossover probability P_c; mutation probability P_m; fuzziness value m and termination tolerance value ε.

Step 2: Population and membership initialization.
For each individual, we generate random $L \times K$ numbers, and the degree of the membership u_{lk} for data point P_K to center vector C_K is initialized with a random value $\vartheta_{lk}, 0 \leq \vartheta_{lk} \leq 1$.

$$u_{lk} = \frac{\vartheta_{lk}}{\sum_{t=1}^{K} \vartheta_{lt}} \tag{17}$$

Step 3: Set the individual chromosome
In the practical application, each individual has a chromosome with K cluster centers which are stored in a one dimension array. Thus, each row index number of the array can be regard as a gene of cluster center from 1 to K.

Step 4: Genetic operation.
Each individual with K serial index numbers is considered as the cluster center. Then, fitness function value can be calculated for each of individuals. Genetic operations, including selection, crossover and mutation operator are used to improve genetic diversity, which avoids falling into local optimal value.

Step 5: Optimal preservation.
After the mutation operation of each generation, fitness function value which is based on FCM clustering algorithm is calculated for each of individuals. And individuals with higher fitness function value are more likely to be selected for survival, and the worst individuals are replaced by the better ones.

Step 6: Termination condition
Termination condition of testing adopts the combination of MFCM clustering algorithm and GA. If it is satisfied then the evolution stops, otherwise go to step 3. In this study, the termination consideration is the number of evolutionary generations G or the variance of the total individual fitness function value ε. POP_{C} is the number of population.

$$\varepsilon = \sum_{p=1}^{POP_{\mathrm{C}}} \left(f_p - \frac{\sum_{p=1}^{POP_{\mathrm{C}}} f_p}{POP_{\mathrm{C}}} \right)^2 \tag{18}$$

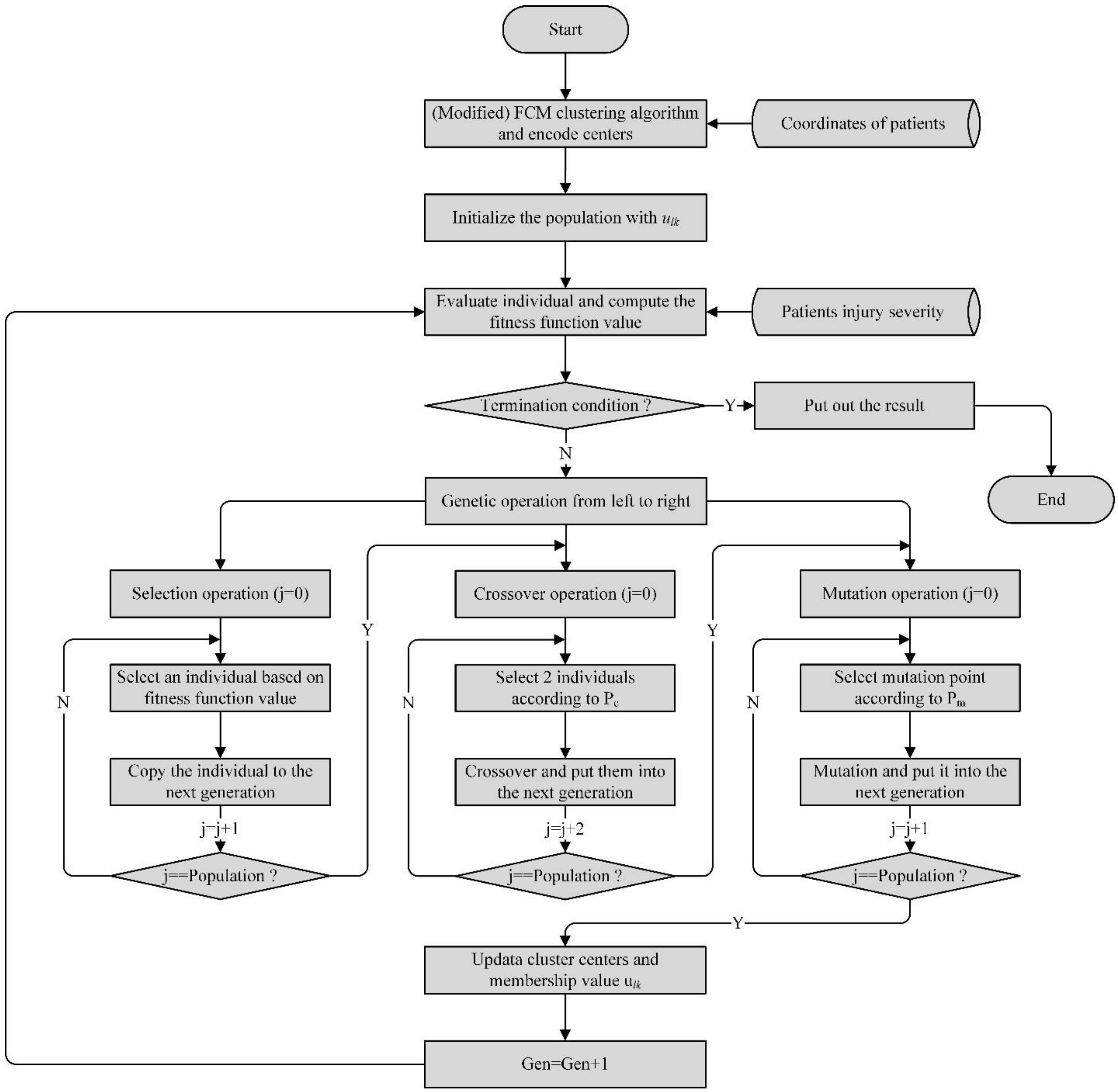


Figure 4. Flowchart of GA-MFCM

Step 7: Output result

If the termination condition is satisfied, the best individual generated by genetic algorithm is obtained. Then, the cluster centers are obtained by decoding that individual.

4. DATA SET

In this study, a specific disaster type is taken into consideration because the types of disaster result in different outcomes of damages and casualties. Here we consider an earthquake as our post-disaster environment and a specific level of earthquake leads to a certain number of casualties. For instance, the earthquake magnitude can destroy almost every facility of the city.

The data set we used in the computational experiments is a real-world data of Portland (America) which has a population of 1.6 million and provides people geographical coordinates locations (Marathe and Eubank). As shown in the Fig. 5 (143×130 (km^2)), we transform the earth coordinate of Portland into 2D coordinate. Then, the proposed methodology is applied in this area considering patient's injury severities and geographical locations.

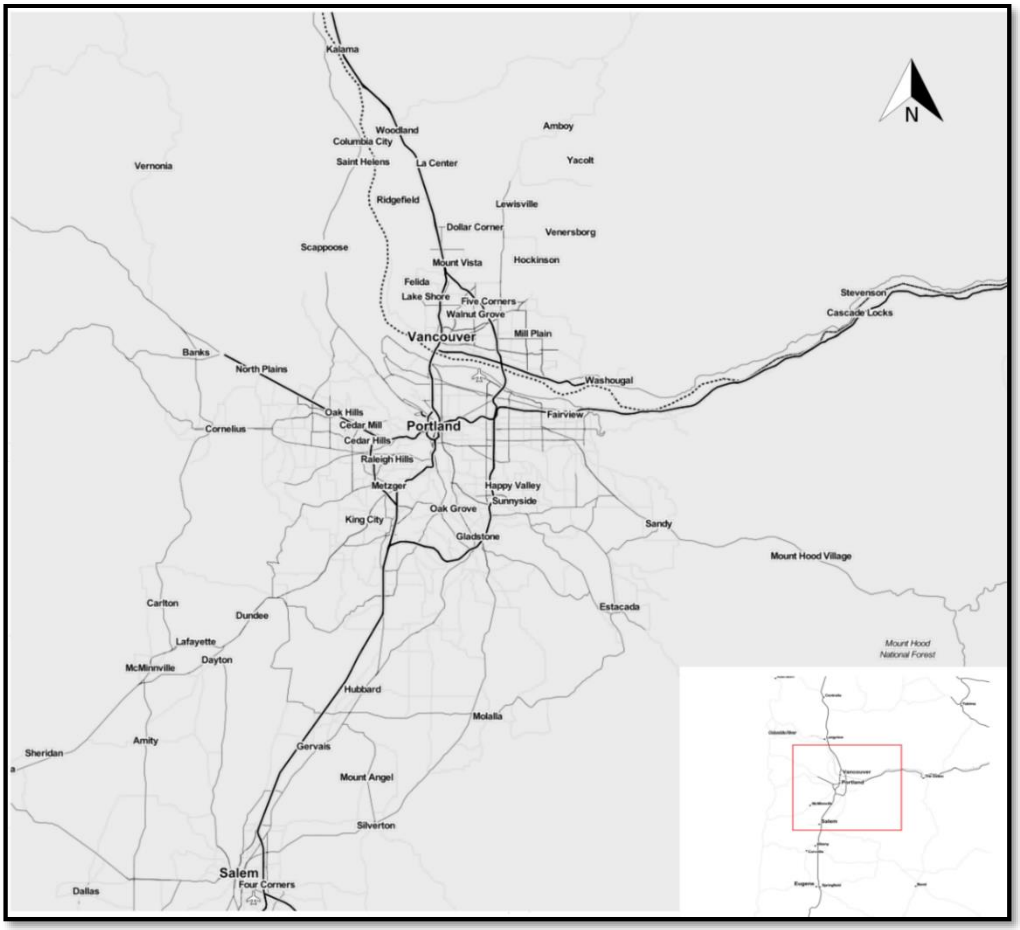


Figure 5. Geographical location of Portland (America)

We use the conclusion that the total deaths and injured people are *log-linear* with the earthquake magnitude in a certain area when the depth $h \leq 60$km. The proposed method is based on a quantitative model that combines earthquake magnitude S and population density PD to calculate the number of human losses N_S in regression equations (SAMARDJIEvA and OIKE 1992, Badal, Vázquez-Prada *et al.* 2005).

$$\log N_S(PD) = \kappa(PD) \cdot S + \eta(PD) \tag{19}$$

where the coefficients κ and η are regression parameters that depend on the average population density of the affected area. Here, $\eta = -3.15$ and $\kappa = 0.97$ according to the average population density of Portland ($PD > 200 \text{people/km}^2$). And the expected number of injured people N_I can be calculated by the method of Christoskov and Samardjieva (Christoskov and Samardjieva 1984).

$$\log(N_I/N_S) = \tau \cdot S + \varphi \tag{20}$$

where the coefficients $\tau = 0.21$ and $\varphi = -0.99$ are parameters. Note that for a fixed earthquake magnitude S, N_I is directly proportional to N_S (Christoskov and Samardjieva 1984, Samardjieva and Badal 2002, Badal, Vázquez-Prada *et al.* 2005).

When earthquake magnitude S is 7.0, the total human losses $N_S = 11419$ that are chosen from 1.6 million people randomly. Then, we set the injury severity threshold value $T = 6.0$ of death which is given by the author. Because the injury severity G_{lk} approximately follows exponential distribution (Hutchinson 1976, Hutchinson 1976, Hutchinson and Lai 1981), the mean injury severity λ can be calculated as.

$$\lambda = \frac{T}{lnN_S - lnN_I} \tag{21}$$

Finally, we select 3973 injured patients who have injury severity ranging from 2.0 to 6.0 because injury severity less than 2.0 can hardly be life-threatening.

Based on the injury severity, we can calculate initial mortality risk value M_{lk}^{I} according to the following quadratic regressions (Weaver, Barnard *et al.* 2013).

$$M_{lk}^{I} = \varrho \cdot G_{lk}^{2} + \nu \cdot G_{lk} + \xi \qquad (22)$$

where the coefficients ϱ, ν and ξ are regression parameters depending on the collected data. Here, $\varrho = 0.07$, $\nu = -0.33$ and $\xi = 0.40$ while $R^2 = 0.88$.

In the following experiments, the parameters of the GA-MFCM are shown in Table 1.

Table 1 Parameters of the GA-MFCM in experiments

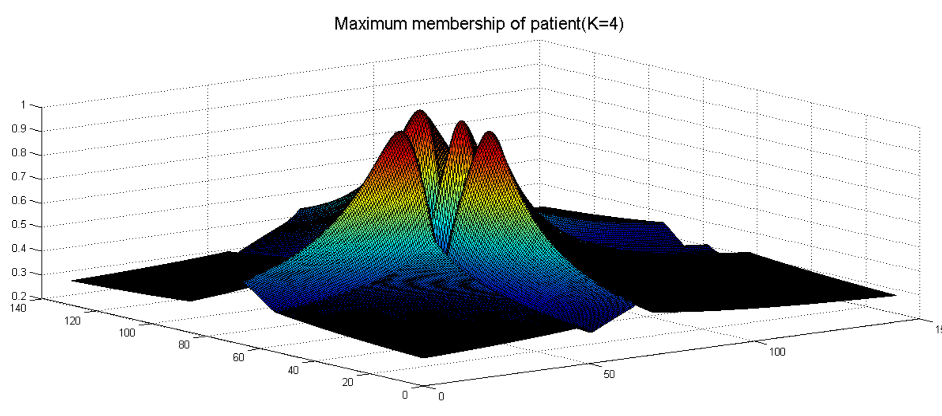
Parameters	Value
Fuzziness exponent: m	2
Initial population number: POP_{I}	50
Next population number: POP_{C}	80
Number of selected individuals: S	5
Mutation probability: P_m	0.5
Crossover probability: P_c	0.1
Variance of fitness value: ε^{*}	10^{-5}

5. EXPERIMENTAL RESULTS

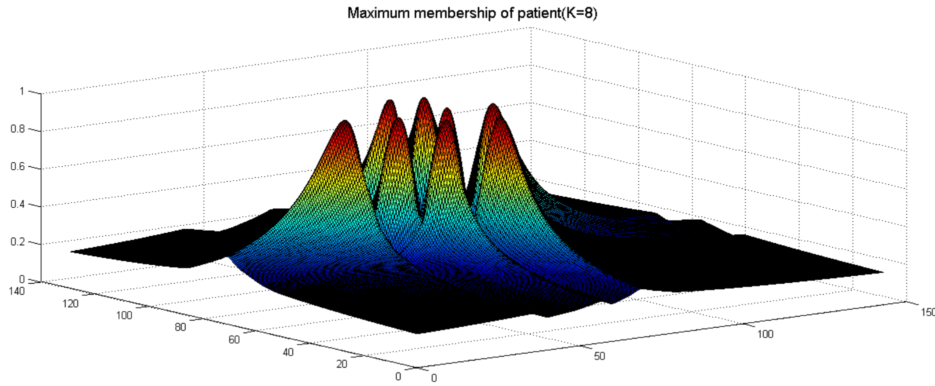
Here, the data set is applied in M1 and M2 with two different number of clusters K=4 and K=8. And the injured patients with higher injury severities are given in the right side of the area because of different radius to the earthquake epicenter. In the experimental results, big red points stand for temporary EMS centers and small points in diverse colors stand for patients. Beside, small points in the same color indicate that they belong to the same cluster.

5.1 Results of M1

A certain earthquake with the magnitude $S = 7.0$ is tested in two different number of clusters (K=4 and K=8 respectively) to minimize the total travel time of patients. The maximum membership of each patient corresponding to the geographical location is shown in Fig. 6 and temporary EMS centers maps are shown in the Fig. 7.

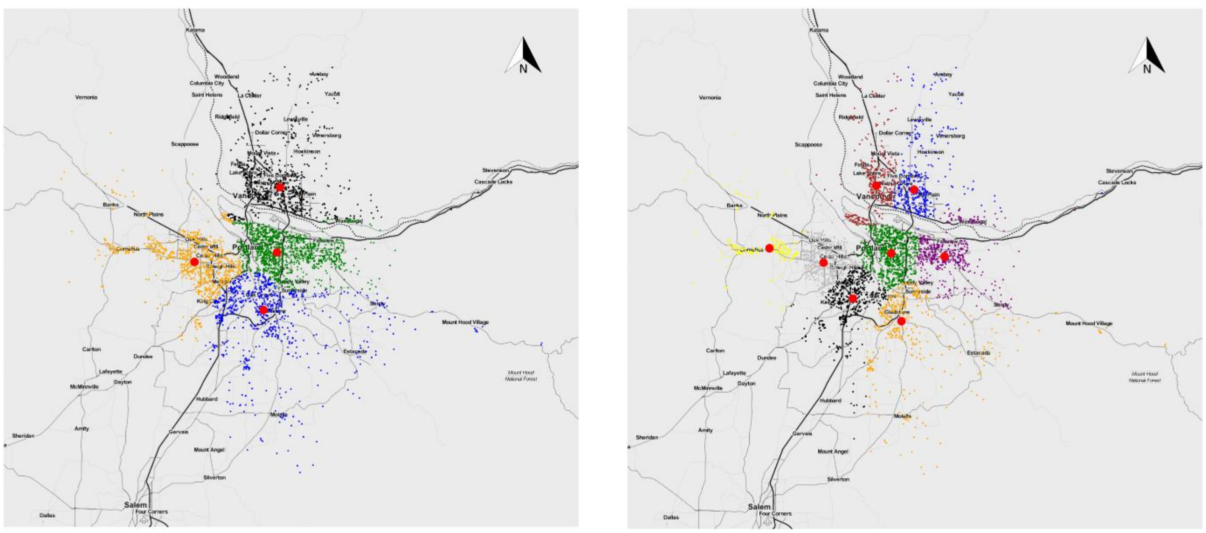


(a) K=4



(b) K=8

Figure 6. Maximum membership of each patient with different number of clusters in M1



(a) K=4   (b) K=8

Figure 7. Temporary EMS center maps with different number of clusters in M1

5.2 Results of M2

The same data is used to find the performance of M2 in two different number of clusters (K=4 and K=8 respectively) in minimizing the total mortality risk value of patients. The maximum membership value of each patient corresponding to the geographical location is shown in Fig. 8, and temporary EMS centers maps are shown in the Fig. 9.

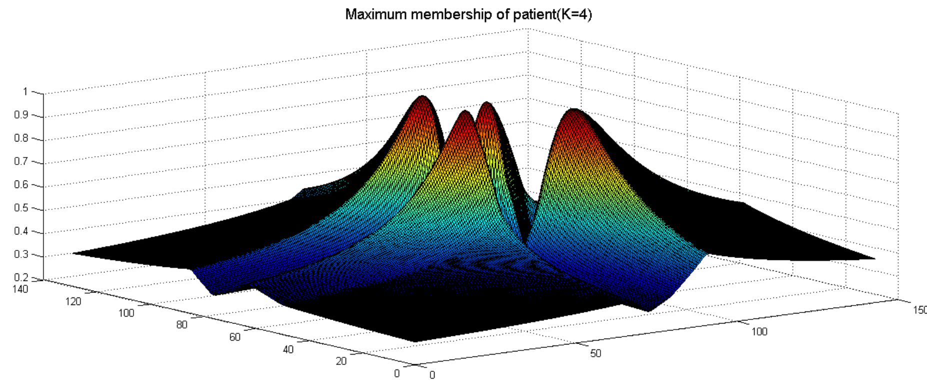
5.3 Comparison of M1 and M2

The total travel time and the total mortality risk value in first 50 generations are shown for both M1 and M2. Fig. 10 illustrates the total travel time per stage of generation with different number of centers in M1 and M2. Fig. 11 presents the total mortality risk value per stage of generation with different number of centers in M1 and M2. It is remarkable that both the total travel time and the total mortality risk value present decreasing trends with the growing number of centers which indicates more centers enable to improve the efficiency of rescue task.

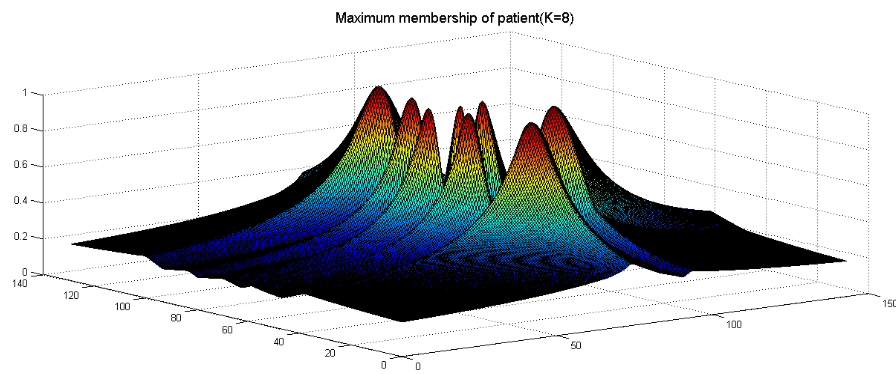
Table 2 provides detailed information for the performance of M1 and M2 under different number of temporary EMS centers. Geographical coordinates, generation number, the total travel time and the total mortality risk value are also given in the Table 2, which shows that M1 has lower total travel time than M2, whereas M1 has larger total mortality risk value than M2. We can find that a smaller total mortality risk value can be obtained at the expense of longer total travel time and vice versa.

5.4 Discussion

5.4.1 Effects of travel time

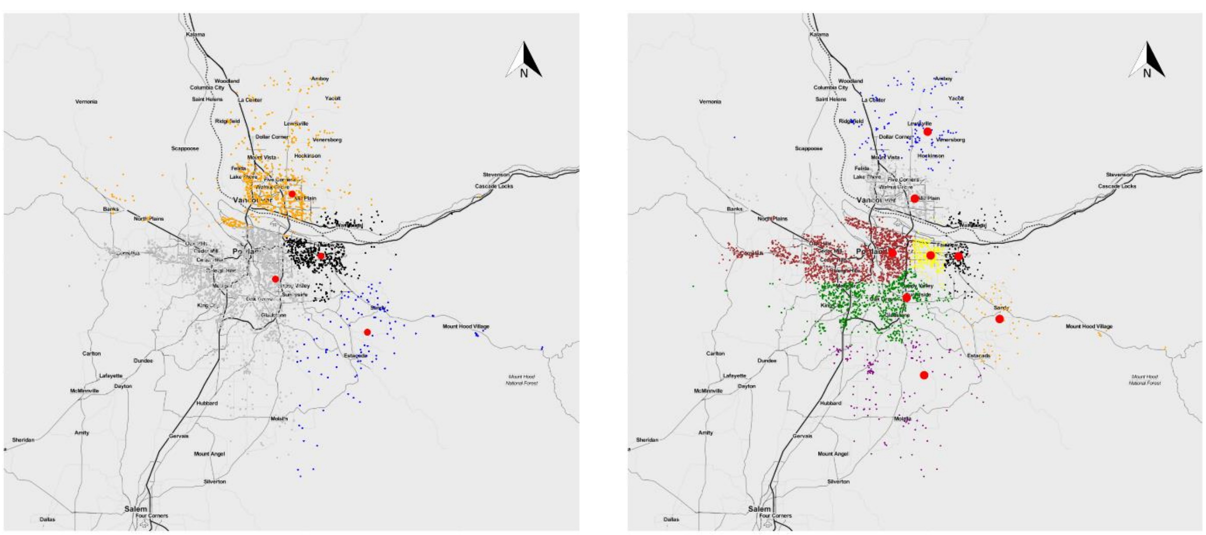


(a) K=4



(a) K=8

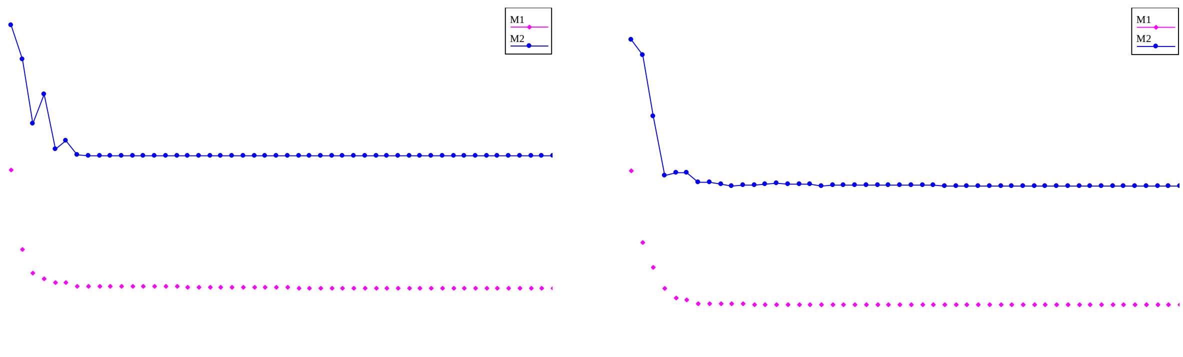
Figure 8. Maximum membership of each patient with different number of clusters in M2



(a) K=4 (b) K=8

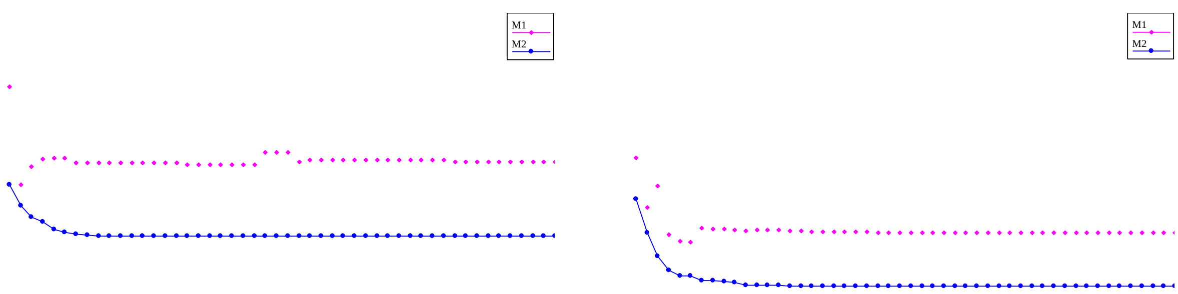
Figure 9. Temporary EMS center maps with different number of clusters in M2

In order to reduce the total mortality risk value and emphasize the importance of patient with higher mortality risk, additional mortality risk based on initial mortality risk and travel distance is taken into account. Besides, each patient selects the temporary EMS center according to its maximum membership value and arrives at the temporary EMS center personally or by vehicle provided by local government. Because there are so many injured patients after huge earthquake that the number of ambulances cannot meet the demands. Finally, the location of temporary EMS center can be placed closer to the worst-hit areas (Fig. 9 and Table 2) to reduce the total mortality risk value.



(a) K=4 (b) K=8

Figure 10. The total travel time with different number of centers in M1 and M2



(a) K=4 (b) K=8

Figure 11. The total mortality risk value with different number of centers in M1 and M2

5.4.2 Effects of the earthquake magnitude

According to the research above, the total deaths and injured people present positive relationships with earthquake magnitude when the depth $h \leq 60$km. However, an estimation of casualties of the population in the region is a key factor to determine whether the emergency medical service task could be completed successfully and effectively. For example, Taiwan earthquake loss estimation system (TELES) (Christoskov and Samardjieva 1984, Chen, Lu *et al.* 2015), which provides the estimation of casualties of the population in the region. This is achieved by combining the EMS demands forecast in usual conditions and the estimated impacted demands from TELES in New Taipei City. Finally, location-allocation of temporary EMS centers can be resolved based on the estimation collected by TELES.

5.4.3 Effects of number of temporary EMS centers

As shown in the Table 2, more temporary EMS centers should be assigned to disaster areas while reducing the total mortality risk value. However, the number of temporary EMS centers cannot exceed the specific number or there will be not enough doctors and nurses to guarantee temporary EMS center normal operation and complete rescue medical task in collaboration with each other.

Table 2 Comparison of the total travel time and mortality risk value of each model

Models								
	M 1				M 2			
Number of centers k	K=4		K=8		K=4		K=8	
	C_{kx}	C_{ky}	C_{kx}	C_{ky}	C_{kx}	C_{ky}	C_{kx}	C_{ky}
1	68.9237	85.0459	56.3154	57.7532	78.9972	69.0748	82.5230	69.0127
2	64.8495	54.6462	71.4446	84.6345	90.4770	50.1744	74.8230	99.9354
3	47.7250	66.5846	68.3519	52.1823	71.8424	84.4759	92.6904	53.4614
4	68.1878	68.9337	49.0388	66.6346	67.7336	63.3490	71.6270	83.3226
5	--	--	79.0373	68.1365	--	--	73.9615	39.5058
6	--	--	35.6238	70.1666	--	--	75.5745	69.2376
7	--	--	62.1129	85.6270	--	--	66.1018	69.8029
8	--	--	65.8279	68.9410	--	--	69.6160	58.7328
Number of Generations	500		1000		500		1000	
Total Travel Time	729.853		526.349		1000.53		798.961	
Total Mortality Risk Value	1250.437		1175.894		1175.074		1119.893	

5.4.4 Decision making of location and allocation

The proposed algorithm is a self-adaptive searching method to identify the locations and allocations of temporary EMS centers. It combines the advantages of GA and FCM to overcome the defects that FCM is sensitive to the noise of isolated data and the initial clustering center which avoids falling into local extreme point easily. And FCM enhances the local search capabilities of GA, which has a good effect on the clustering result. Hence, GA-MFCM provides a solution for location-allocation of temporary EMS centers decision making from the perspectives of reducing the total mortality risk value of temporary EMS centers. On the other hand, each patient has K degrees of membership, which enables to provide alternative strategy for patient.

6. CONCLUSION AND FURTHER DIRECTIONS

Location-allocation models are imperative in geographical modeling of health-care service. In this paper, we applied GA-MFCM clustering algorithm to solve location-allocation of EMS centers considering the dynamic patient mortality risk and travel distance (travel time) in quick response to the disaster relief. Given the data of geographical location and injury severity in the disaster, the locations and allocations of temporary EMS centers are identified. Numerical examples showed the performances of the proposed algorithm in different number of centers. The performances were demonstrated on whether considering the initial injury severity in the disaster affected area. By comparing M1 and M2 models, the M2 model has better performance in reducing the total mortality risk value of temporary EMS centers and M1 is good at decreasing the total travel time. Besides, both the total travel time and the total mortality risk value present decreasing trends with the increasing number of temporary EMS centers. Furthermore, for each temporary EMS center, the location of center is inclined to the worst-hit areas in M2, which emphasizes the patient with higher injury severity and enables to reduce mortality.

Finally, it is expected that the proposed model M2 can produce several benefits not only for reducing the total mortality risk value of temporary EMS centers, but also emphasizing the patient with higher injury severity. The proposed model has a highly instructive significance and time efficiency to temporary EMS centers locations and allocations decision making. For further research directions, we will focus on developing a robust transportation model considering traffic volumes and traffic congestion when the huge disaster happens, which intends to decline the travel time of patients. Additionally, improving the operational efficiency of temporary EMS center system by redesigning service procedure is another key factor to reduce the mortality and rescue time.

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