



Presenting a New Method for Earthquake Relief Center Location Allocation Based on Whale Optimization Algorithm

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ABSTRACT

Despite the regulations set for the reinforcement of structures, many buildings in the world are vulnerable to earthquakes. Local governments try to be prepared to cope with this possible crisis through establishing earthquake relief centers. Considering the budget provision for creating n relief centers in a certain region, the main problem is yet in which place these centers should be constructed in order to achieve the highest speed and quality in rescuing after an earthquake. The enormous number of points that need relief, and of the many locations that could be candidates for constructing a relief center have caused this problem to be considered as an NP-Complete problem. In this article, there is a focus on solving the location allocation of the earthquake relief center problem. In order to find a reasonable solution, Whale Optimization Algorithm has been used. Classic Whale functions have been modified for this research dedicatedly. Results of the algorithm implementation and its execution on the map of region 1 of the city of Tehran show that with 9 relief centers, the average distance between each point and the center is roughly equal to 760 meters, showing almost 1.9% optimization compared to the best recent articles.

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1. INTRODUCTION

Disasters affecting human societies increase almost every year. Correct management of these disasters could have a great role in preserving human life. Disaster management is divided into 4 main phases. These phases consist of preventing disaster, preparation for the occurrence, responding properly to the disaster and reconstructing afterwards [1]. Among these 4 phases, proper response is the only one that runs immediately and very shortly after the disaster. Proper response to disasters includes all the work that is done immediately after a disaster in order to save the life of civilians and protect their property [2]. In other words, a proper response mission is somehow simultaneous with the disaster. Therefore, time and human resources management are very important in it. Cooperation and

coordination between various parts is also one of the essential requirements for succeeding in the response phase [3,4]. This phase of disaster management has been focused on in this article.

In order to succeed in responding to disaster, conducting two sets of measures is necessary. The first set of tasks includes supplying suitable hardware equipment for providing relief after disaster. This equipment includes food, fire prevention equipment, safety equipment and medical equipment. The second set of tasks includes decisions that must be taken in advance in order to provide the best relief when responding. These decisions consist of location allocation of relief centers and shelters, highlighting relief paths and careful planning for commuting [4-8].

One of the painful disasters that threatens many people's lives is the earthquake. For reducing an earthquake effect, all disaster management phases should be applied. One of the most important effects of earthquakes is mass destruction of buildings in a region.

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A major challenge in responding to earthquakes is location allocation of temporary relief centers in the earthquake zone. Relief centers must be placed in locations in which all points can be serviced with maximum speed. This problem is known as the Location Allocation or LA problem. The main objectives in the LA problem are reducing "relief providing time" and "rescuer dispatching cost" as much as possible [9].

The LA problem is a hard and complicated problem that doesn't have any solution in polynomial time. Having enormous points and conditions has caused finding the best solution to be impossible through classical and structural algorithms. Various complexities have been defined for this problem in different articles. In some articles, the problem of objective incompatibility has been mentioned. In other articles, having too many points has been talked about. A number of articles consider objective function complexities and limitations as the main reason of difficulty in this problem. Moreover, uncertainty and high volume of data are a couple of reasons for further complicating the problem [10,11].

As mentioned above, a problem in such a level of hardness and complexity cannot be solved by means of a classical algorithm, hence this problem, like any other NP-Complete problem, is solved by optimization methods. In optimization methods that are implemented based on heuristic algorithms, there is not only one definite answer. Moreover, the produced solution is not necessarily the optimum answer. However, these kinds of algorithms produce a certain solution in each execution that is close to the optimum answer in an acceptable extent. Therefore, the quick and reliable output of an optimization method can be an appropriate basis for the system's decision makers [12].

Nowadays, using metaheuristic methods in hard problem optimization has become common more than ever. The reasons of using these algorithms can be mentioned in a few main points: The first reason is that these algorithms are based on simple concepts and their implementation is rather easy. The second reason is that they don't need precise information about classical solutions of the problem. The third reason is that they can easily cope with local optimums. Metaheuristic algorithms are inspired by natural and physical phenomena. Take genetic-based algorithms for example, or algorithms that have been designed by inspiration from gravity. Another group of algorithms are particle based methods [13]. These algorithms have been inspired by mass movement of particles for hunting or reaching a certain goal. The most famous particle-based algorithm is PSO. This algorithm has been inspired by the hunting process in birds. In solving problems by this method, each particle is a random solution for the problem. By means of a certain function

called the "fitness function," closeness of each solution to the best answer is calculated [14]. One of the newest particle-based algorithms is the Whale Optimization Algorithm or WOA [13].

In this article, WOA was used for solving the LA problem. Since location allocation is a NP-hard problem and WOA has never been used in it, one of the motivations of this research is modifying the WOA algorithm in order to solve the problem. Thanks to characteristics and novelty of this algorithm it was anticipated that the results would be satisfactory. According to this, WOA was applied to GIS information of a group of points in a certain map in order to find the best locations for constructing relief centers. The proposed method was evaluated by means of region 1 of the city of Tehran. The main goal of this article is adjusting WOA in order to find the best locations for earthquake relief centers. The proposed method was assessed and then compared with previous studies.

In this project, all of the points were extracted from a GIS map. In this method, all points in a map could be a candidate to become a relief center. Due to some managerial reasons, if just some of these points are candidates to become relief centers, there won't be any trouble to the whole method, but the problem space will be more limited and its solving will become even easier. After determining the points, each of which could be a relief center, WOA is applied to them. This algorithm was dedicatedly modified and adjusted to solve the LA problem. The algorithm parameters were calibrated by a simple hypothetical map. After calibration, the proposed method was evaluated by a complicated map and a real map from region 1 of Tehran.

The rest of the article is organized as follows. The second section reviews previous work done in this area. The third section presents an overall introduction of WOA. In the fourth section, the proposed algorithm was introduced thoroughly and all of its parts have been explained. In the fifth section, the proposed method was implemented and evaluated from many aspects. In the last section, there is a summary, conclusion and some suggestions for future studies.

2. PREVIOUS STUDIES

For the first time, the LA problem was formulated in 1964. In this formulation, complexities of the problem, like getting stuck in local optimum and lack of convergence in objective function, were demonstrated. In the same research, efficiency of heuristic functions in solving the LA problem was highlighted [15,16]. After defining the problem, much research was done to solve it. A method was proposed by Badri [17] to solve the LA problem in a general case. In this method, a

combination of the Analytic Hierarchy Process and Goal Programming was used.

Wesolowsky et al. [18] solved a special version of the LA problem. In this version, there is an ability to move facilities in certain periods of times. For solving the problem, two different methods are presented. The first one was implemented by Mixed-Integer Programming and is suitable for small-scale problems. In the second, Dynamic Programming was used. By means of the second method, large-scale problems can be solved. In various articles, some other methods, like Fuzzy Logic and the Stochastic Model were used to solve the problem as well [19,20].

After introducing and studying some of the solutions for LA, those versions of LA will be reviewed that are used for location allocation of earthquake relief centers. Due to the considerable importance of the problem, much research was conducted. Some algorithms have used direct optimization and some others have solved the problem by means of metaheuristic methods. First, direct optimization methods will be introduced. Berladi et al. [21] have developed a probabilistic algorithm for finding optimum location of relief centers. In this algorithm, relief centers are located in a non-deterministic environment. Another method was proposed in 2007 that uses a multi-dimension model for locating relief centers. In this method, parameters like cost, response time and responsibility have been considered [22]. Hooshangi and Alesheikh [23] defined a new algorithm for a disaster zone that assigns tasks to relief centers.

Another approach used for the LA relief center problem concerns metaheuristic methods. Shortages and limitations in classical methods lead researchers to use metaheuristic algorithms. These algorithms have a high ability in searching for the problem space and solving hard problems. A research conducted by Yi and Kumar [24] used PSO to solve the problem. In this research, a new method was proposed to organize the rescue mission. The mission was divided to two phases. In Phase 1, relief paths are characterized, and in the second phase a material distribution pattern was determined [24]. Ghasemi and Khalili-Damghani [25] proposed a robust method for pre-disaster location allocation inventory planning. Their method is based on a mathematical method which can be optimized by meta-heuristic methods [25]. In another paper, Ghasemi et al. [26] proposed a method multi-period multi-vehicle location allocation model for earthquake evacuation planning. They combined an exact model with a meta-heuristic model to tackle the problem. They applied their method to the Tehran city (Iran) [26]. Paul et al. [27] presented a robust method for location allocation network design. They used an optimization model to reach a better solution. Their method was checked by the data of the Northridge in the California, USA [27].

Saedian et al. [2] focused on a new method for location allocation of relief centers. In their research, GA and BA algorithms have been used. In this method, parcels in a GIS map have been used as input of the algorithm. The algorithm has been evaluated on region 1 of Tehran [2]. Based on parcel data and region 1 of Tehran, another algorithm has been developed as well. It is a hybrid method that has combined GA and BA with clustering methods and TOPSIS [28].

Metaheuristic methods are used to solve a wide range of problems. The main ability of these methods is searching problem space and finding reasonable answers. Therefore, in problems which do not have a classical solution, the best approach is using metaheuristic methods [29]. There are various kinds of metaheuristic methods. Some of them, like GA, have been designed based on genetic science [30]. Some other algorithms, like SA, have been invented by inspiration from physical phenomena [31]. A well-known group of metaheuristic methods are particle-based algorithms. There is a wide range of particle-based algorithms. Algorithms like PSO, BA, GOA and ACO are all particle-based [14,32,33,34]. One of the newest algorithms that was proposed in recent years is WOA or Whale Optimization Algorithm. WOA gets inspiration from mass hunting of humpback whales [13]. In this article, WOA has been used for the earthquake relief center location allocation problem.

WOA was used to solve many problems in recent years. Mirjalili et al. [34] have used WOA for feature selection in data mining. They combined WOA with SA to manage to select the best features [35]. In other research, WOA was used to optimize the weight of edges in ANN [36]. Moreover, WOA has been applicable in image processing. For example, in 2017 a new segmentation method was designed based on WOA [37]. WOA is also usable in multi-objective problems. Wang et al. [38] proposed a new method for wind speed forecast based on WOA. Researchers have also used WOA in scheduling problems. In 2018, an algorithm based on WOA was proposed to solve the Flow Shop problem [39]. In this article, WOA was applied to solve the earthquake relief center location allocation problem.

Selecting WOA to solve the LA problem has some sensible reasons. The first reason is that WOA is a rather new algorithm that has never been used for the LA problem so far. Therefore, using WOA can lead to new results for the problem. The second reason is that in recent years, WOA was used in many areas of science and has had good results as well. These successes have motivated authors of the article to use WOA in the LA problem. The third reason goes back to inherent characteristics of WOA. WOA has a good convergence speed and can truly transmit from the exploration phase to exploitation phase. It has a high ability to escape from local optimum. Given the above reasons, it feels

that WOA can be an effective tool to solve the LA problem.

3. WHALE OPTIMIZATION ALGORITHM

Whale Optimization Algorithm was created based on the mass movement of humpback whales during hunting. It is classified as a particle-based algorithm. The performance of a whale in WOA is just like a particle in PSO. Two different types of movement toward prey have been considered for whales. One of them is Spiral, in which a whale goes toward prey through a spiral path. Another movement is called Shrinking. In Shrinking, every whale goes directly toward prey. In fact, group Shrinking causes the mass of whales to contract. Each whale is a random solution for

the LA problem. Apart from Spiral and Shrinking, another function, called Searchprey also exists. This function adds some of the genetic-based algorithm's characteristics to WOA. Basic WOA is a continuous algorithm. To use this algorithm in the LA problem, which is a discrete problem, Spiral, Shrinking and Searchprey functions have been redefined with a new performance [13].

The values of a , A , l and p , are parameters of this algorithm. The parameter p has a value in $[0,1]$ and through it, either Spiral or Shrinking will be selected to run. The parameter a varies from 2 to 0 in order for parameter A to be made. The parameter A transmits the algorithm from the exploration to exploitation phase. The parameter l is for rotation angle that has been explained in the next section. Figure 1 illustrates the execution process of Whale Optimization Algorithm.

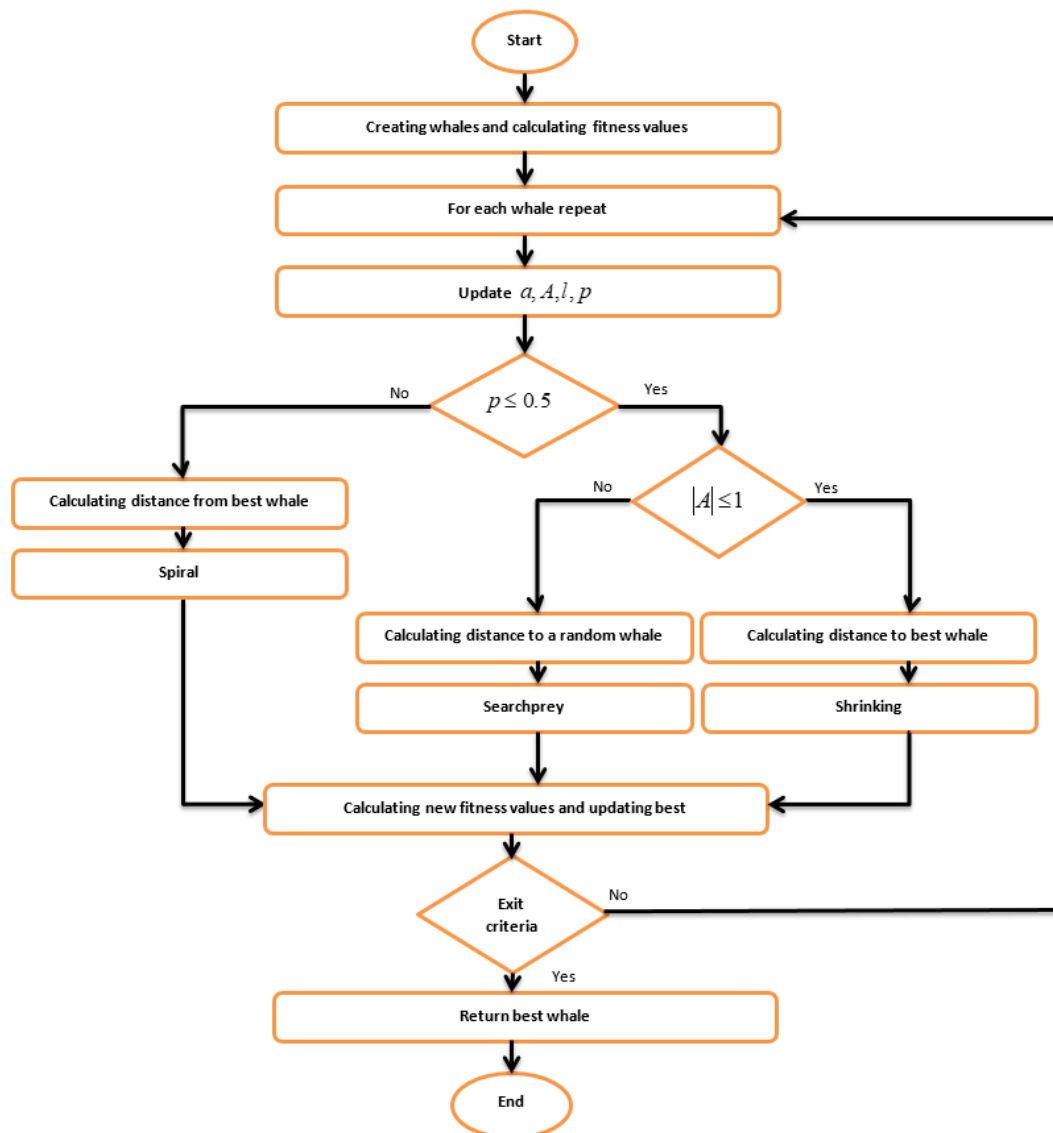


Figure 1. Structure of WOA in the proposed method

4. THE PROPOSED METHOD

In this section, the proposed method is explained thoroughly. Before explanation of the proposed method, an overall schematic flow diagram is illustrated in Figure 2. As it is shown in Figure 2, GIS maps of a region enter the algorithm as an input. Another implicit input that is considered number of relief centers. Following, more details of the designed algorithm are explained.

4. 1. Structure of a Whale In the proposed method, each whale represents a solution for locating relief centers. An analogy can be drawn between a whale in WOA, a particle in PSO and a chromosome in GA. Initially, whales are created randomly, and in the execution process, they are optimized by designed functions. Before describing designed WOA, whale structure and its design pattern should be explained. Data structure of each whale is a dynamic array whose length is specified by the number of relief centers. Each index of this array consists of a certain coordinate that indicates the proposed location for a relief center. Table 1 shows an example of whales that was created for a problem with 5 relief centers. In this whale, the first index indicates location of the first center; the second index indicates location of the second center; and so on.

4. 2. Objective Function The objective function or fitness function is a function that indicates worthiness

TABLE 1. An example of whales with 5 centers

Whale	Center ₁	Center ₂	Center ₃	Center ₄	Center ₅
X	1287	755	1065	356	790
Y	280	799	1899	521	1572

of each whale. By calculating each whale's fitness value, it could be possible to move whales and optimize the solutions. Before explaining fitness function, it is worth mentioning that parcels are assigned to relief centers by the Euclidean method. In other words, the duty of servicing to a parcel should be done by the nearest relief center. Logically, a shorter distance between parcels and centers leads to faster relief. Therefore, the first notion to design a fitness function comes from the Euclidean distance between parcels and centers. This function is calculated by Equation 1. In this equation, *whale* is a whale whose fitness value is calculated. The variable *n* indicates number of parcels on the map. *parcel_i* is a parcel on the map. *center_i* shows the assigned center to *parcel_i*. This function has been designed in a way that lower value of fitness indicates higher quality of whale. In fact, whale optimization problem searches for lessening fitness value.

$$fitness(whale) = \frac{\sum_{i=1}^n distance(parcel_i, center_i)}{n} \tag{1}$$

There is a major weakness in the fitness function of Equation (1). The major weakness is that load-balancing in centers has been overlooked. The only factor that affects this function is the distance between parcels and points. This property causes too many parcels to be assigned to a single center in crowded areas. On the other hand, in dispersed areas, the number of parcels in each center would be very low. This weakness leads to overhead in some centers and waste of facilities in some other. To solve the problem, a penalty function has been defined. This function tries to assign a grade to each whale based on load-balancing. The more balance in centers we have, the better grades would be produced. The best state is a completely balanced distribution of parcels. Equation (2) shows the penalty function. In this equation, variable *n* indicates the number of parcels on the map. *parcel_i* is a parcel on the map. *center_i* shows the assigned center to *parcel_i*. And *k* is the number of centers.

$$penalty(center_i) = \begin{cases} 1 & parcels_i < \frac{n}{k} \\ 0 & O.W. \end{cases} \tag{2}$$

Now, the fitness function of Equation 1 can be improved by the penalty function. Equation 3 shows the

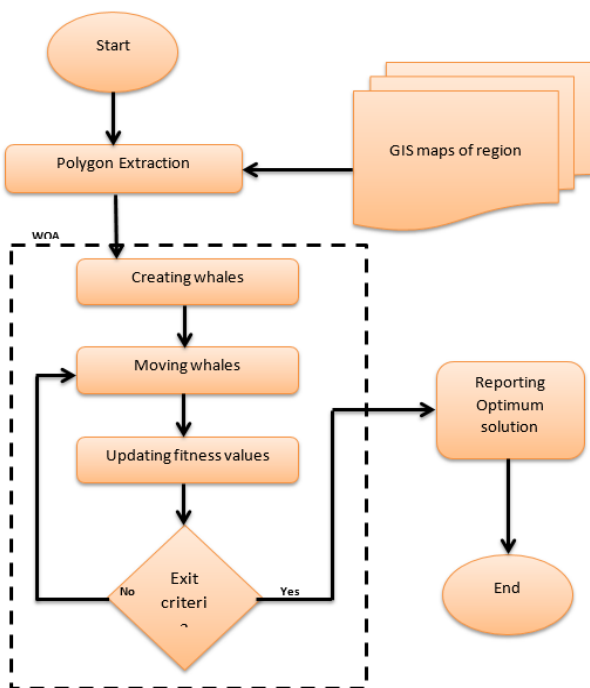


Figure 2. Overall schema of the proposed method

new fitness function. In this function, both factors of closeness to centers and load balancing will be effective.

$$fitness(whale) = \frac{\sum_{i=1}^n distance(parcel_i, center_i)}{\sum_{j=1}^k penalty(center_j)} \quad (3)$$

4. 3. Definition of Distance One of the most important concepts in WOA is the distance between whales. In basic WOA, distance is calculated by a subtraction. For this problem, the distance should be redefined. In the proposed algorithm, the distance between two whales is in the form of an array. The length of the array equals length of whale. Each index contains a number that is calculated by Euclidean distance. The distance of a center from the closest center in the other whale is considered as a value in the array. After calculating this value for all array cells, we will have the complete distance array. Algorithm 1 shows the computation of the distance array.

```

Algorithm 1 : whaleDistance
Input :  $w_a, w_b$ 
Output :  $disVector, nearest$ 


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 $k = length(w_a)$ 
 $disVector = array\ with\ length\ k, initialize\ by\ +\infty$ 
 $selected = array\ with\ length\ k, initialize\ by\ zero$ 
 $nearest = array\ with\ length\ k, initialize\ by\ zero$ 
for  $i = 1$  to  $k$ 
    for  $j = 1$  to  $k$ 
        if  $distance(w_a(i), w_b(j)) < disVector(i)$  and  $not(selected(j))$ 
             $disVector(i) = distance(w_a(i), w_b(j))$ 
             $tmp = j;$ 
             $nearest(i) = j;$ 
        end
    end
     $selected(tmp) = 1;$ 
end

```

Figure 3 shows an example of two whales. The red points show the centers of the first whale, and the black points show those of the second. Apart from the sequence of centers, the distance of each center in the first whale is calculated with the closest center in the second.

4. 4. Whale Move Function Whales move through three different functions. These functions have been rewritten for earthquake relief center LA problem. The functions have been designed in a way that carries the concepts of basic WOA. This section describes these functions.

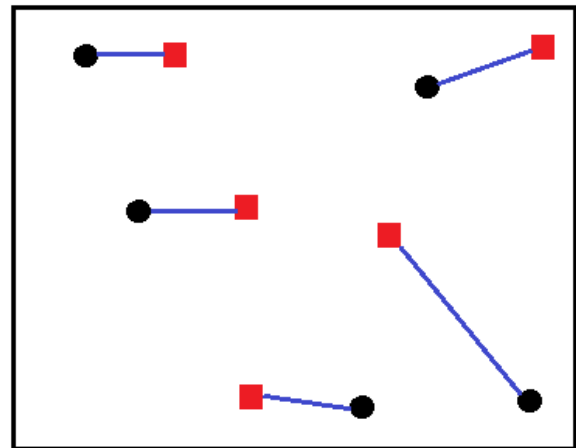


Figure 3. Distance of red and black whales by blue line

4. 4. 1. Spiral In some states of the algorithm, the whales should spiral around the best whale. The Spiral function simulates this movement. Spiral is a controlled and smooth movement toward the prey. For Spiral movement, first, the distance array should be calculated. Then a random variable in $[-1, +1]$, called l , is produced. By means of $2\pi l$, the rotation angle is calculated. Assuming that centers of the whale w_1 should move toward the best whale, for each pair of centers, a random point is produced on an imaginary line of w_1 toward the best whale. Then, the point turns clockwise with a random point as center and $2\pi l$ as rotation angle. In this way, Spiral is a function with a kind of rotation toward the prey. Figure 4 illustrates an example of Spiral. The rotation angle is assumed to be 45 degrees. The red point is the random point between two whales, and the green point is destination of rotation. This operation should be done for all centers. To simplify the figure, just one move has been illustrated.

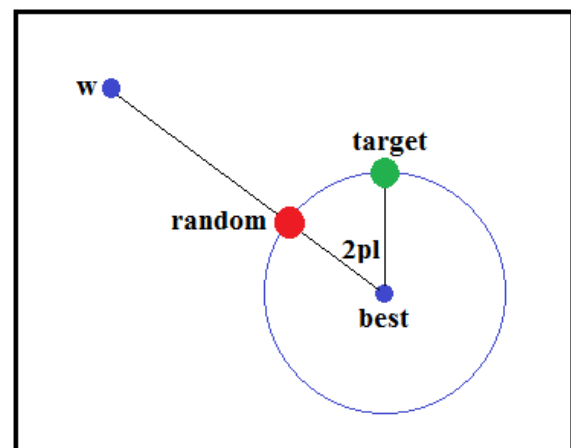


Figure 4. An example of Spiral

Algorithm 2 shows the pseudocode of the Spiral function. In this pseudocode, *point* is the random point, *destination* is the new location of a center and *w* is the new whale after Spiral movement.

Algorithm2: Spiral

Input: w₁: a whale for spiral, best: the best whale

Output: w: spiraled whale

$l = \text{a random number in } [-1, +1];$

$\theta = 2\pi; // \text{rotation angle}$

for $i = 1$ *to* $\text{len}(w)$

$\text{point} = \text{a random location on line}(w_1, \text{best});$

$\text{destination} = \theta \text{ sized roundClock rotation centered by best};$

$w(i) = \text{destination};$

end

4. 4. 2. Shrinking The shrinking function simulates directed movement toward the best whale. This function has two parameters. The first one is a typical whale and the second one is the best whale. As a result of Shrinking, a typical whale moves toward the best whale. For the whale that is supposed to move, first the distance array should be calculated. Then random points are produced on the imaginary line between centers of the whale and the best whale. At the end, the centers are transferred to random points. The big difference between Shrinking and Spiral is that in Shrinking, we don't have rotation angle. In fact, Shrinking simulates a direct and fast move. Algorithm 3 shows the pseudocode of Shrinking.

Algorithm3: Shrinking

Input: w₁: a whale for spiral, best: the best whale

Output: w: shrunked whale

for $i = 1$ *to* $\text{len}(w)$

$\text{destination} = \text{a random location on line}(w_1, \text{best});$

$w(i) = \text{destination};$

end

4. 4. 3. Searchprey The Searchprey function adds the ability of finding new solutions to the proposed method. This function does not need the best whale and works with typical whales. Execution of this function leads to better exploration of the problem space. Algorithm 4 shows the pseudocode of Searchprey.

As it can be seen in Algorithm 4, three different functions are used in the algorithm. One of the functions is Shrinking, and the others are the Join and Randomwalk function. These two functions are similar to mutation and crossover in genetics.

4. 5. Parameter α Parameter α is one of the most important values in WOA. The formula of

Algorithm4: searchprey

Input: w₁: a whale for shrinking, w₂: a randomly selected whale

Output: w: a new whale

$\text{distance} = \text{whaleDistance}(w_1, w_2);$

$\text{tmp} = \text{a random number in } [0, 1];$

if $\text{tmp} < 0.25$

$w = \text{shrinking}(w_1, w_2);$

elseif $\text{tmp} < 0.25$

$w = \text{join}(w_1, w_2);$

else

$w = \text{randomwalk}(w_1);$

end

producing α creates descending values in $[2, 0]$. In other words, in the beginning of the algorithm, α equals 2, but its value gradually decreases. Eventually, α would be a number around zero. Equation 4 shows the production formula of α . In this equation, k is maximum number of whale movements, and i is the current number of whale movements.

$$\alpha = 2 \times \left(\frac{k-i+1}{k} \right)^2 \quad (4)$$

Assuming $k = 1000$, Figure 5 shows the changes in α with blue color. Given this changing pattern in, the likelihood of Searchprey at the beginning of the algorithm and that of Shrinking at the end, are very high. In fact, the proposed algorithm produces new random solutions in the beginning and optimizes the produced solutions at the end.

In order to create a little bit of a random condition in the exploitation phase, a new parameter, called A is created by α . Most of the times, the value of A is close to α . The last decision about Shrinking or Searchprey will be made by A . Equation 5 shows the calculation of A . r is a random number with normal distribution in $[0, 2]$. Figure 5 shows the changes in A with red color.

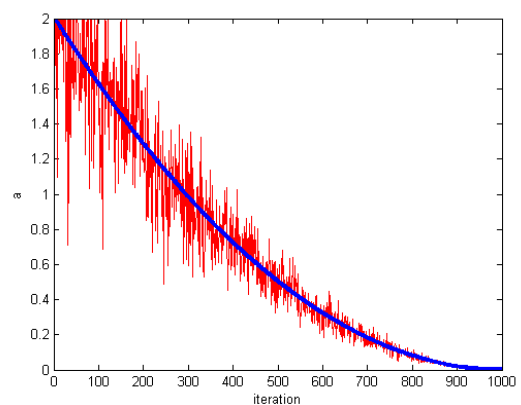


Figure 5. Changing procedure in α for $k = 1000$

$$A = 2ar - a \quad (5)$$

5. EVALUATION OF THE PROPOSED METHOD

In this section, the proposed method has been implemented and evaluated. Matlab software has been used for implementation. After calibration, the proposed method was tested by hypothetical maps and region 1 of Tehran's map. Input of the algorithm is parcels of polygon that can be extracted from GIS maps.

5.1. Calibration

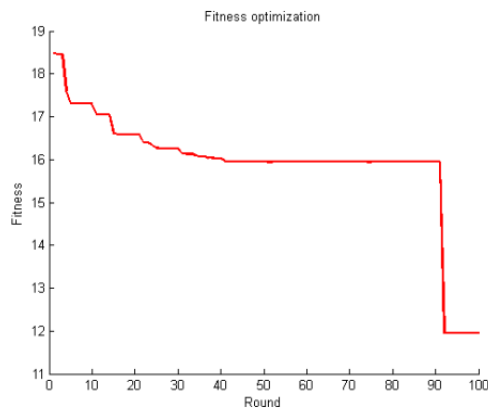
The proposed method has multiple parameters that could have various values. Parameters like number of movements and number of whales can considerably affect the algorithm. In this section, by means of an even map whose solution is obvious, the optimum value of parameters has been found. The scale of the map is 250 in 250. Parcels are distributed in chess form at a distance of five. In fact, the map has 2500 parcels. The optimum solution for this map is segmenting the map and locating each relief center in the center of segments. In this section, this

problem has been solved with four centers. The number of whales and movements increase gradually in order to find the best value of parameters. Results of various runs have been listed in Table 1. The number of whales are 20, 30 and 40. Also, the number of movements is between [60, 100]. As it can be seen in Table 1, the best answer is the 9th row that has 40 whales and 100 moves. Executions with movements below 100 and whales below 40 have produced weaker solutions. In terms of runtime, the 9th row is the worst. The reason is obvious; to create more whales and more movements, more time is needed. In fact, by spending more time, we can explore the problem space more carefully.

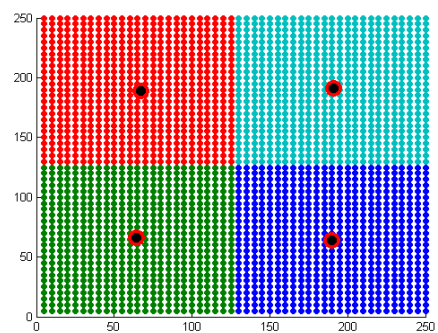
For better evaluation of the optimizing process in the 9th row of Table 2, the chart of fitness is given in Figure 6a. As it can be seen, optimization in the first rounds is satisfactory. At around the 45th round, the optimization was stopped and the best solution did not change until the 90th round. In final rounds, by a slight change, considerable optimization has been achieved. Figure 6b shows the location of centers in the final solution. This figure highlights that the optimum answer has been found.

TABLE 2. Results of the proposed method with different parameters

Row#	Whale#	Move#	Center1	Center2	Center3	Center4	fitness	Time(m)
1	20	60	512	580	669	739	21	2.5
2	20	80	643	599	572	686	19.5	4
3	20	100	602	535	711	652	19	5
4	30	60	699	605	614	582	19	6
5	30	80	615	641	610	634	18	7
6	30	100	637	620	618	625	16.5	8
7	40	60	621	625	630	624	16	5.5
8	40	80	621	625	630	624	16	7
9	40	100	625	625	625	625	12	9.5



(a) Fitness chart



(b) Location of centers

Figure 6. results of calibration (checkered environment with 4 centers)

5. 2. Evaluation with Hypothetical Maps

In the hypothetical map, there are 2000 parcels in a 2000 in 2000 coordinate. Concentration of parcels in location (0,0) and around it is more, and by getting away from this point, the density of parcels would be less. It is expected that relief centers are more likely to be in congested areas. Figure 7 shows this map.

Location allocation in this map has been solved with 40 whales and 100 movements. The number of centers equals six. Evaluation of results shows that centers in congested areas are denser. Because of the ability of the fitness function, despite the fact that the map is heterogeneous, location allocation is rather balanced. Table 3 shows the results of the algorithm for both fitness functions. The first row belongs to Equation (1),

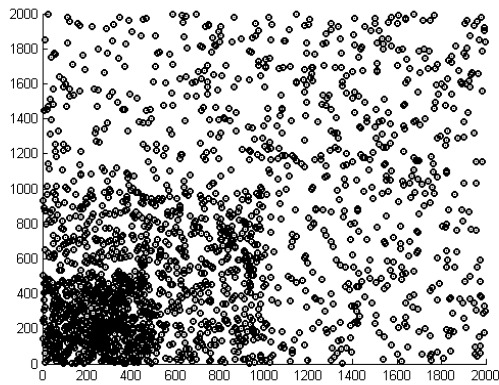


Figure 7. Heterogeneous map

TABLE 3. Results in the heterogeneous map

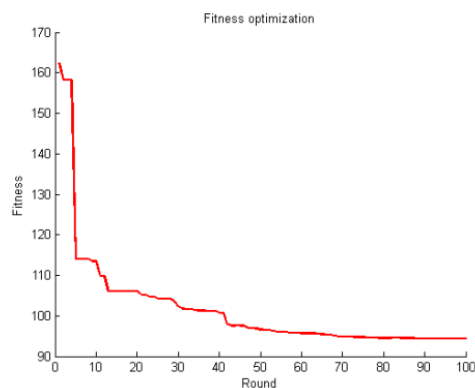
fitness	Center1	Center2	Center3	Center4	Center5	Center6	Avg_dis
(1)	201	288	728	354	176	253	272
(3)	251	318	317	317	590	207	283.5

and the second to Equation (3). Comparison of results shows that with a slight increase in distance, we managed to achieve better load balancing. In the first row, the biggest number is 728, and the smallest number is 176. Whereas, in the second row, the biggest number is 590 and the smallest number is 176. Decreasing distance between the two numbers shows that load balancing has been considered. Low average in the first row shows that Equation (1) focuses on Euclidean distance.

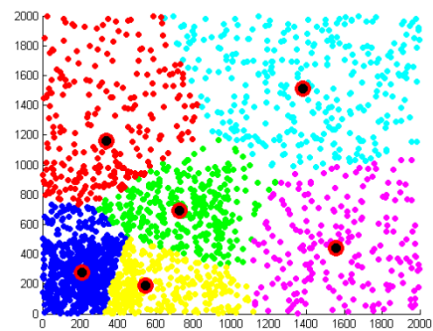
Figure 8a illustrates the fitness chart of this problem. The optimization process indicates that the proposed algorithm has passed a sensible path to reach the final solution. At the beginning, the optimization speed is very high, whereas at the end, optimization is rare and in low speed. This kind of progress is completely matched with evolutionary algorithm’s philosophy. Figure 8b shows the location of centers in the final solution. It can be easily seen that the distance between the centers in disperse parts of the map is more.

5. 3. Evaluation with Tehran's Map

Iran is a country which has suffered from earthquakes quite a lot of times. Meanwhile, Tehran, which is the biggest and most populated city in the country, is an earthquake-prone city [40]. Region 1 of Tehran, as one of the most earthquake-prone regions of the city, has a population of nearly 400000, and covers an area of more than 64 square km. To locate relief centers, parcel's location should be clear. Therefore, among the layers of the GIS map, the parcel layer has been used. Figure 9 illustrates the parcels. This map has roughly 35000 parcel [2].



(a) Fitness chart



(b) Location of centers

Figure 8. Results of heterogeneous map with 6 centers

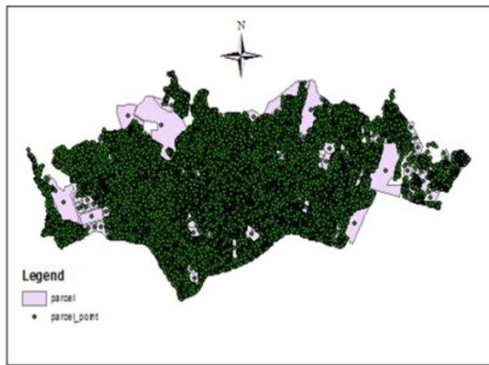


Figure 9. Parcels in region 1 of Tehran

In this section, the proposed algorithm has been applied to region 1 of the Tehran map. The number of whales is 40, and the number of movements is 100. Region 1 of Tehran has roughly 34000 parcels. 9 relief centers are supposed to be created, then parcels distributed among them. Figure 10a shows the fitness chart for 100 movements. Figure 10b illustrates the final location of relief centers. This result belongs to the fitness function that considers load balancing. Parcels of each center are distinguished by a certain color, and the relevant center can be seen in the center of parcels.

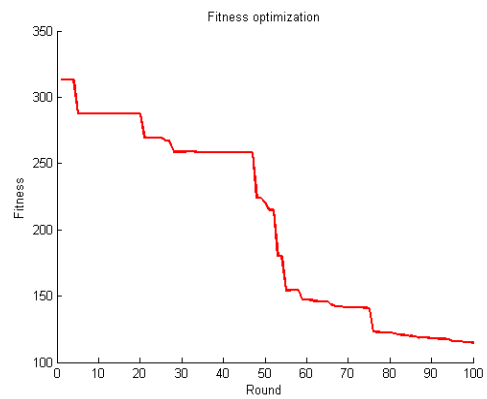
For better evaluation, details of the results have been listed in Table 4. The first row belongs to load balancing fitness function, and the second row shows the results of distance fitness function. The last column includes the average distance of parcels with their center. Comparison of values in the last column shows that the distance fitness function is better. However, focusing on the number of parcels in each center shows that the load balancing method has a more reasonable distribution of parcels. In this case, no center is overloaded, whereas, in distance function, there is a considerable distance between number of parcels. Center 1 has 4732 parcels, while center 8 has 2746.

5. 4. Stability of the Algorithm The proposed method has been designed based on an evolutionary algorithm. The main difference between this algorithms and classical methods is that optimization in evolutionary algorithms is quite random. In other words, in evolutionary algorithms, after each run, we have different solutions. Stability is one of the challenges in this algorithm. To assess stability, the proposed method was run for 35 times. Both fitness functions have been

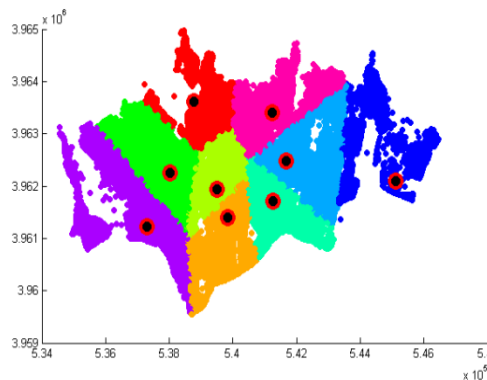
used. Figure 11 illustrates the results. The average of results is almost close to the best solution. For example, in Tehran’s map with load balancing function (Figure 10c), the average is 933 and standard deviation is 13, whereas the best answer is 918. In distance function (Figure 10d) the average is 782 and standard deviation is 17, whereas the best answer is 760.

5. 5. Comparison

One of the maps that the proposed method has been evaluated with is the Tehran map’s region 1. Since Saeidian et al. [2] has used region 1 of the Tehran map as well, we can compare the proposed algorithm with literature [2]. Table 5 shows the comparison results. The first column includes average distance of parcels with their centers. The second column lists the total distance of providing



(a) Fitness chart

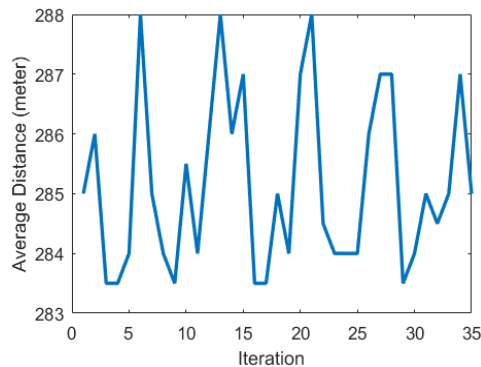


(b) Location of centers

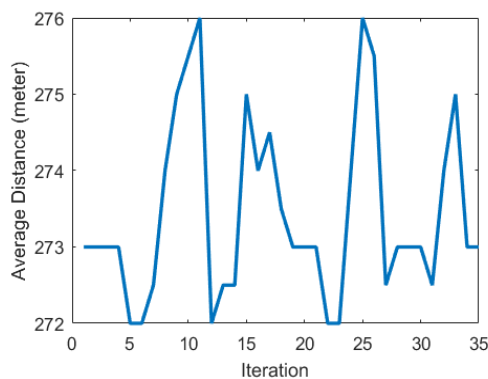
Figure 10. Result of the Tehran map (region 1) with 9 centers

TABLE 4. Details of results for Tehran (region 1)

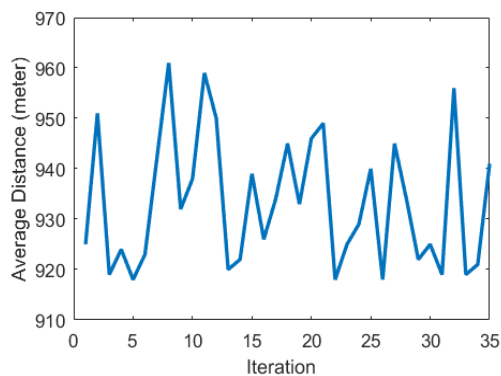
fitness	Center1	Center2	Center3	Center4	Center5	Center6	Center7	Center8	Center9	Avg_dis (meter)
Balance(3)	3757	3855	350	3922	3654	3836	3893	3959	3662	918
Mean(1)	4732	3918	4956	2873	3157	3491	4284	2746	3941	760



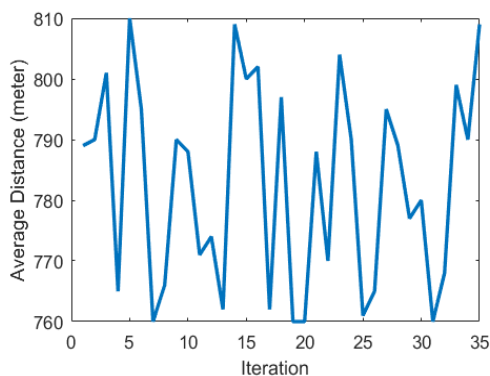
(a) Load balancing function with the hypothetical map



(b) Distance function with the hypothetical map



(c) Load balancing function with the Tehran map



(d) Distance function with the Tehran map

Figure 10. results of 35 run**TABLE 5.** Comparison

fitness	Avg_dis (meter)	KM
Balance (3)	918	31.3
Mean (1)	760	25.9
[2]	775	26.4

relief. As it can be seen, the distance function (row 2) produced a better solution than literature [2] (760 vs. 775). However, by the load balancing function (row 3) the answer is weaker (918 vs. 775). Increasing in average distance is because the function wants to provide load balancing.

6. CONCLUSION

In this article, a new method has been proposed to locate relief centers. The proposed method is based on WOA and can solve the problem on any map. This method has been evaluated with many maps and eventually applied to Tehran's map. A new fitness function has been designed that has the ability of load balancing. The average distance of relief centers with parcels is 760 meter which is 1.9% better than previous work. In load balancing function the average distance has increased to 918, however the method did this sacrifice in order to improve the load balancing. Advantages of the proposed method are the following:

- Quick convergence and local optimum avoidance
- Using a new objective function for load balancing
- Dynamic of the proposed method in location of centres
- Ability of combining the proposed method with other algorithms

Based on limitations of the proposed method, the future works may include the following:

- Using other layers of maps, such as roads
- Considering the level of relief in calculations
- Considering the building vulnerability parameter in calculations

7. REFERENCES

1. Beiki, H., Seyedhosseini, S. M., Ghezavati, V. R., and Seyedaliakbar, S. M., "A location-routing model for assessment of the injured people and relief distribution under uncertainty", *International Journal of Engineering, Transactions A: Basics*, Vol. 33, No. 7, (2020), 1274-1284. <https://doi.org/10.5829/IJE.2020.33.07A.14>
2. Saeidian, B., Mesgari, M. S., and Ghodousi, M., "Evaluation and comparison of Genetic Algorithm and Bees Algorithm for location-allocation of earthquake relief centers", *International*

- Journal of Disaster Risk Reduction*, Vol. 15, (2016), 94-107. <https://doi.org/10.1016/j.ijdr.2016.01.002>
3. Kondaveti, R., and Ganz, A., "Decision support system for resource allocation in disaster management", In 2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, (2009), 3425-3428, <https://doi.org/10.1109/IEMBS.2009.5332498>
 4. Rolland, E., Patterson, R. A., Ward, K., and Dodin, B., "Decision support for disaster management", *Operations Management Research*, Vol. 3, No. 1-2, (2010), 68-79. <https://doi.org/10.1007/s12063-010-0028-0>
 5. Altay, N., and Green III, W. G., "OR/MS research in disaster operations management", *European Journal of Operational Research*, Vol. 175, No. 1, (2006), 475-493. <https://doi.org/10.1016/j.ejor.2005.05.016>
 6. Lin, Y. H., Batta, R., Rogerson, P. A., Blatt, A., and Flanigan, M., "Location of temporary depots to facilitate relief operations after an earthquake", *Socio-Economic Planning Sciences*, Vol. 46, No. 2, (2012), 112-123. <https://doi.org/10.1016/j.seps.2012.01.001>
 7. Najafi, M., Eshghi, K., and Dullaert, W., "A multi-objective robust optimization model for logistics planning in the earthquake response phase", *Transportation Research Part E: Logistics and Transportation Review*, Vol. 49, No. 1, (2013), 217-249. <https://doi.org/10.1016/j.tre.2012.09.001>
 8. Tzeng, G. H., Cheng, H. J., and Huang, T. D., "Multi-objective optimal planning for designing relief delivery systems", *Transportation Research Part E: Logistics and Transportation Review*, Vol. 43, No. 6, (2007), 673-686. <https://doi.org/10.1016/j.tre.2006.10.012>
 9. Jing, Wang, Zhu Jianming, Huang Jun, and Zhang Min., "Multi-level emergency resources location and allocation.", In 2010 IEEE International Conference on Emergency Management and Management Sciences, 202-205. IEEE, (2010), <https://doi.org/10.1109/ICEMMS.2010.5563466>
 10. Aerts, J. C., and Heuvelink, G. B., "Using simulated annealing for resource allocation", *International Journal of Geographical Information Science*, Vol. 16, No. 6, (2002), 571-587. <https://doi.org/10.1080/13658810210138751>
 11. Zheng, Y. J., and Ling, H. F., "Emergency transportation planning in disaster relief supply chain management: a cooperative fuzzy optimization approach", *Soft Computing*, Vol. 17, No. 7, (2013), 1301-1314. <https://doi.org/10.1016/j.ejor.2005.05.016>
 12. Aerts, J. C., Goodchild, M. F., and Heuvelink, G. B., "Accounting for spatial uncertainty in optimization with spatial decision support systems", *Transactions in GIS*, Vol. 7, No. 2, (2003), 211-230. <https://doi.org/10.1111/1467-9671.00141>
 13. Mirjalili, S., and Lewis, A., "The whale optimization algorithm", *Advances in Engineering Software*, Vol. 95, (2016), 51-67. <https://doi.org/10.1016/j.advengsoft.2016.01.008>
 14. Kennedy, J., "Particle swarm optimization", *Encyclopedia of Machine Learning*, (2010), 760-766. <https://doi.org/10.1109/ICNN.1995.488968>
 15. Cooper, L., "Heuristic methods for location-allocation problems", *SIAM Review*, Vol. 6, No. 1, (1964), 37-53. <https://doi.org/10.1137/1006005>
 16. Cooper, L., "Location-allocation problems", *Operations Research*, Vol. 11, No. 3, (1963), 331-343. <https://doi.org/10.1287/opre.11.3.331>
 17. Badri, M. A., "Combining the analytic hierarchy process and goal programming for global facility location-allocation problem", *International Journal of Production Economics*, Vol. 62, No. 3, (1999), 237-248. [https://doi.org/10.1016/S0925-5273\(98\)00249-7](https://doi.org/10.1016/S0925-5273(98)00249-7)
 18. Wesolowsky, G. O., and Truscott, W. G., "The multiperiod location-allocation problem with relocation of facilities", *Management Science*, Vol. 22, No. 1, (1975), 57-65. <https://doi.org/10.1287/mnsc.22.1.57>
 19. Zhou, J., and Liu, B., "New stochastic models for capacitated location-allocation problem", *Computers & Industrial Engineering*, Vol. 45, No. 1, (2003), 111-125. [https://doi.org/10.1016/S0360-8352\(03\)00021-4](https://doi.org/10.1016/S0360-8352(03)00021-4)
 20. Zhou, J., and Liu, B., "Modeling capacitated location-allocation problem with fuzzy demands", *Computers & Industrial Engineering*, Vol. 53, No. 3, (2007), 454-468. <https://doi.org/10.1016/j.cie.2006.06.019>
 21. Beraldi, P., and Bruni, M. E., "A probabilistic model applied to emergency service vehicle location", *European Journal of Operational Research*, Vol. 196, No. 1, (2009), 323-331. <https://doi.org/10.1016/j.ejor.2008.02.027>
 22. Tzeng, G. H., Cheng, H. J., and Huang, T. D., "Multi-objective optimal planning for designing relief delivery systems", *Transportation Research Part E: Logistics and Transportation Review*, Vol. 43, No. 6, (2007), 673-686. <https://doi.org/10.1016/j.tre.2006.10.012>
 23. Hooshangi, N., and Alesheikh, A. A., "Agent-based task allocation under uncertainties in disaster environments: An approach to interval uncertainty", *International Journal of Disaster Risk Reduction*, Vol. 24, (2017), 160-171. <https://doi.org/10.1016/j.ijdr.2017.06.010>
 24. Yi, W., and Kumar, A., "Ant colony optimization for disaster relief operations", *Transportation Research Part E: Logistics and Transportation Review*, Vol. 43, No. 6, (2007), 660-672. <https://doi.org/10.1016/j.tre.2006.05.004>
 25. Ghasemi, P., and Khalili-Damghani, K., "A robust simulation-optimization approach for pre-disaster multi-period location-inventory planning", *Mathematics and Computers in Simulation*, Vol. 179, (2020), 69-95. <https://doi.org/10.1016/j.matcom.2020.07.022>
 26. Ghasemi, P., Khalili-Damghani, K., Hafezalkotob, A., and Raissi, S., "Uncertain multi-objective multi-commodity multi-period multi-vehicle location-allocation model for earthquake evacuation planning", *Applied Mathematics and Computation*, Vol. 350, (2019), 105-132. <https://doi.org/10.1016/j.amc.2018.12.061>
 27. Paul, J. A., and Wang, X. J., "Robust location-allocation network design for earthquake preparedness", *Transportation research part B: Methodological*, Vol. 119, (2019), 139-155. <https://doi.org/10.1016/j.trb.2018.11.009>
 28. Saeidian, B., Mesgari, M., Pradhan, B., and Ghodousi, M., "Optimized Location-Allocation of Earthquake Relief Centers Using PSO and ACO, Complemented by GIS, Clustering, and TOPSIS", *ISPRS International Journal of Geo-Information*, Vol. 7, No. 8, (2018), 292. <https://doi.org/10.3390/ijgi7080292>
 29. Kahrizi, M. R., and Kabudian, S. J., "Projectiles Optimization: A Novel Metaheuristic Algorithm for Global Optimization", *International Journal of Engineering, Transactions A: Basics*, Vol. 33, No. 10, (2020), 1924-1938. <https://doi.org/10.5829/IJE.2020.33.10A.11>
 30. Koza, J. R., "Genetic programming", *Search Methodologies*, (1997), 127-164. https://doi.org/10.1007/0-387-28356-0_5
 31. Kirkpatrick, S., Gelatt, C. D., and Vecchi, M. P., "Optimization by simulated annealing", *Science*, Vol. 220, No. 4598, (1983), 671-680. <https://doi.org/10.1126/science.220.4598.671>
 32. Yang, X. S., "A new metaheuristic bat-inspired algorithm. In Nature inspired cooperative strategies for optimization", NCSO 2010, (2010), 65-74. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-12538-6_6

33. Dorrani, Z., Farsi, H., and Mohamadzadeh, S., "Image Edge Detection with Fuzzy Ant Colony Optimization Algorithm", *International Journal of Engineering, TransactionC: Aspects*, Vol. 33, No. 12, (2020), 2464-2470. <https://doi.org/10.5829/IJE.2020.33.12C.05>
34. Mirjalili, S. Z., Mirjalili, S., Saremi, S., Faris, H., and Aljarah, I., "Grasshopper optimization algorithm for multi-objective optimization problems", *Applied Intelligence*, Vol. 48, No. 4, (2018), 805-820. <https://doi.org/10.1007/s10489-017-1019-8>
35. Mafarja, M. M., and Mirjalili, S., "Hybrid whale optimization algorithm with simulated annealing for feature selection", *Neurocomputing*, Vol. 260, (2017), 302-312. <https://doi.org/10.1016/j.neucom.2017.04.053>
36. Aljarah, I., Faris, H., and Mirjalili, S., "Optimizing connection weights in neural networks using the whale optimization algorithm", *Soft Computing*, Vol. 22, No. 1, (2018), 1-15. <https://doi.org/10.1007/s00500-016-2442-1>
37. El Aziz, M. A., Ewees, A. A., and Hassanien, A. E., "Whale optimization algorithm and moth-flame optimization for multilevel thresholding image segmentation", *Expert Systems with Applications*, Vol. 83, (2017), 242-256. <https://doi.org/10.1016/j.eswa.2017.04.023>
38. Wang, J., Du, P., Niu, T., and Yang, W., "A novel hybrid system based on a new proposed algorithm—Multi-Objective Whale Optimization Algorithm for wind speed forecasting", *Applied Energy*, Vol. 208, (2017), 344-360. <https://doi.org/10.1016/j.apenergy.2017.10.031>
39. Abdel-Basset, M., Manogaran, G., El-Shahat, D., and Mirjalili, S., "A hybrid whale optimization algorithm based on local search strategy for the permutation flow shop scheduling problem", *Future Generation Computer Systems*, Vol. 85, (2018), 129-145. <https://doi.org/10.1016/j.future.2018.03.020>
40. Ibrion, M., Mokhtari, M., and Nadim, F., "Earthquake disaster risk reduction in Iran: Lessons and "lessons learned" from three large earthquake disasters—Tabas 1978, Rudbar 1990, and Bam 2003", *International Journal of Disaster Risk Science*, Vol. 6, No. 4, (2015), 415-427. <https://doi.org/10.1007/s13753-015-0074-1>

Persian Abstract

چکیده

با وجود قوانین تعیین شده برای مقاوم‌سازی سازه‌ها، ساختمان‌های زیادی در دنیا در برابر زلزله آسیب‌پذیر هستند. از این رو وقوع زلزله در بسیاری از نقاط جهان موجب ایجاد بحران خواهد شد. به همین دلیل یکی از سرفصل‌های مدیریت بحران، مدیریت امداد و نجات بعد از زلزله است. دولت‌های محلی با ایجاد مراکز امداد زلزله سعی می‌کنند برای مقابله با این بحران احتمالی آماده شوند. بودجه محدود و هزینه بالای ایجاد مراکز امداد زلزله موجب شده تا مکان‌یابی این مراکز به یک مسئله مهم تبدیل شود. با فرض تأمین بودجه برای احداث n مرکز زلزله در یک منطقه، مسئله اصلی این است که این مراکز در چه مکانی ساخته شود تا بالاترین سرعت و کیفیت امدادسانی بعد از زلزله را داشته باشد. تعداد بیشمار نقاطی که به امداد نیاز دارند و تعداد زیاد مکان‌هایی که می‌تواند کاندیدای احداث مرکز امداد باشد موجب شده این مسئله در مجموعه مسائل np -complete قرار گیرد. برای حل چنین مسائلی باید از روش‌های اکتشافی و تکاملی استفاده کرد. در این مقاله روی حل مسئله مکان‌یابی مراکز امداد زلزله تمرکز شده است. برای یافتن یک پاسخ از الگوریتم تکاملی نهنگ استفاده شده است. الگوریتم نهنگ یک الگوریتم فرااکتشافی است که با الهام از شکار دسته‌جمعی نهنگ‌های کوهان‌دار طراحی شده است. توابع کلاسیک نهنگ برای حل این مسئله به‌طور اختصاصی بازنویسی شدند. دو تابع برازندگی مختلف در نظر گرفته شده است. تابع اول یک تابع کلاسیک در این مسئله است که روی کاهش فاصله تمرکز دارد و تابع دوم توازن بار را هم در نظر می‌گیرد. نتایج پیاده‌سازی الگوریتم و اجرای آن روی نقشه منطقه 1 تهران نشان می‌دهد که در صورت وجود نه مرکز امداد میانگین فاصله هر نقطه تا مرکز 760 متر می‌باشد که نسبت به بهترین مقالات قبلی حدود دو درصد بهبود را نشان می‌دهد.
