Solving the earthquake disaster shelter location-allocation problem using optimization heuristics

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ABSTRACT

Earthquakes can cause significant disruption and devastation to populations of communities. Thus, in the event of an earthquake, it is necessary to have the right number of disaster shelters, with the appropriate capacity, in the right location in order to accommodate local communities. Mathematical models, allied with suitable optimization algorithms, have been used to determine the locations at which to construct disaster shelters and allocate the population to them. This paper compares the use of two optimization algorithms, namely a genetic algorithm and a modified particle swarm optimization, both of which have advantages and disadvantages when solving the disaster shelter location-allocation problem.

Keywords

Earthquake shelter location-allocation, multi-objective optimization, GA, MPSO.

INTRODUCTION

Natural disasters, such as floods, earthquakes and hurricanes, can result in significant losses in human life, along with serious injuries to people, as well as damage and disruption accounting for significant economic losses (EM-DAT, 2016). Natural disasters caused 23880 deaths in 2015 and 6860 deaths in 2016 (EM-DAT,2016). According to EM-DAT (2016), from 2000-2016, there has been 714654 deaths caused by earthquakes, 92191 deaths by floods, and 192748 deaths by storms, which indicates that natural disasters, in particular earthquakes, have a significant cost in terms of loss of life. In monetary terms, natural catastrophes caused economic losses of USD 74 billion in 2015 (Swiss Re, 2015) and USD 68 billion in the first half of 2016 (Swiss Re, 2016). In relation to the Nepal earthquake in 2015, more than 9,000 people lost their lives and an economic loss of more than USD 6 billion was estimated (Swiss, 2015). Other earthquake events, such as those that occurred in China in 2008 (Yuan, 2008; Zhang et al. 2010), Japan in 2011 (Norio et al., 2011) and Haiti in 2010 (Bilham, 2011), have led to loss of life and seriously affected the lives of others.

To reduce the damage caused by earthquakes, many engineering techniques have been proposed to enhance the resilience of buildings (Chen and Scawthorn, 2002). However, in cases where buildings cannot protect people, there is a need to ensure there are a sufficient number of disaster shelters, with adequate capacity, situated in locations that people can reach quickly. Constructing disaster shelters to be used in emergency situations is one of the most effective methods to help ensure people’s safety. For example, approximately 250,000 people were housed in emergency shelters after the 2011 earthquake and tsunami in Japan (BBC, 2011), which assisted the government in rescuing people quickly.

Selecting shelter locations, and establishing how a population can be allocated to these shelters, can provide assistance to government decision makers. Operations research offers a variety of methods and algorithms that can be used to solve the earthquake disaster shelter location-allocation problem. The purpose of this paper is to develop and compare the usage of a genetic algorithm (GA) and modified particle swarm optimiszation (MPSO) in solving the disaster shelter location and population allocation problem. Thus, the research reported can provide evidence and guidance in terms of how future work may be directed in developing a hybrid method, i.e. one which intelligently uses a GA and MPSO in combination to determine better solutions than is possible if each method were used independently.

The remainder of this paper is organised as follows. An overview of related work is presented followed by the mathematical model of the disaster shelter location and population allocation problem allied with two solution methods, namely a GA and MPSO. To aid the description of the solution methods, an overview of the case study used in this research is given. Next, some preliminary results using the GA and MPSO are presented, along with a comparison of their differences, based on real communities and candidate shelters data. Finally, the paper is concluded and an indication of the direction of future work is given.

RELATED WORK

In relation to construction schemes of disaster shelters, there are different approaches that can be used to select sites such as spatial analysis of geographical information systems (Gall, 2004; Yamada et al., 2004; Sanyal et al., 2009) and mathematical models. According to the particular optimization objectives of shelter site selection, mathematical models can be divided into single-objective models (Sherali et al., 1991; Berman et al., 2002; Dalal et al., 2007; Gama et al., 2013; Bayram et al., 2015; Kılcı et al., 2015), hierarchical models (Chang et al., 2007; Liu et al., 2009; Li et al., 2012 Li et al., 2011;), and multi-objective models (Huang et al., 2006; Doerner et al., 2009; Alçada Almeida et al., 2009; Saadatseresht et al., 2009; Barzinpour et al., 2014; Rodríguez-Espíndola et al., 2015). Optimization methods, such as GAs, PSO, and simulation annealing (SA), can be used to solve these mathematical models as most of them are NP-hard problems (Leeuwen et al., 1998) that cannot be solved using traditional methods such as linear programming (Schrijver, 1998). GAs have been used successfully to solve the shelter location selection problem. For example, Kongsomsaksakul et al. (2005) applied a GA to the flood shelter location selection problem with transportation problem, which is a hierarchical model. Also, Doener et al. (2009) and Hu et al. (2014) proposed their GAs to solve multi-objective models of hurricane and disaster shelter site selection problems respectively. As one of the most popular algorithms, PSO is viewed as being simpler than other algorithms as it has fewer parameters and has a simulation process that is easier to understand leading to its application in many fields (Jin et al., 2007; Shen et al., 2007; Yin et al., 2007; Ai et al., 2009). Furthermore, PSO has attracted the attention of researchers in using it to solve the shelter site selection problem (Hu et al., 2012). While research has been carried out using different optimization techniques and investigating how these perform, there remains a need to analyse and compare the performance of different algorithms in order to establish their advantages and disadvantages and how they can be combined as a hybrid algorithm capable of determining improved solutions to the disaster shelter location and population allocation problem.

MATHEMATICAL MODEL AND OPTIMIZATION METHODS

In this section, a mathematical model for the earthquake shelter location-allocation problem is developed. Furthermore, two optimization heuristic algorithms, used to solve the aforementioned problem, are described. To aid the description of the optimization heuristic algorithms, an overview of the case study considered in this research is presented.

Mathematical model

Many types of models have been proposed to solve the shelter site selection problems, such as the P-median model (Bayram et al., 2015; Gama et al., 2015), the P-center model (Kılcı et al., 2015), the covering model (Dala et al. 2007; Gama, 2013), the hierarchical model (Widener, 2009; Widener, 2011) and the multi-objective model（Rodríguez-Espíndola and Gaytán, 2015). In the preliminary study reported in this paper, a multi-objective model has been selected; the same as proposed by Zhao et al. (2015). The two objectives are minimising total shelter area (TSA) (see equation (1)) and minimising total weighted evacuation time (TWET) (see equation (2)) subject to a capacity constraint (CC) (see equation (3)) and a time constraint (see equation (4)). Equation (5) expresses that a community can be allocated to only one shelter.

$$f_1 = \min \sum_{k=1}^{N} Y_k \times S_k \qquad \forall k = 1, 2, \ldots\ldots, N \tag{1}$$

$$f_2 = \min \sum_{j=1}^{M} \sum_{k=1}^{N} \frac{d_{jk}}{v_j} \times \frac{P_j}{W_{jk}} \times B_{jk} \qquad \forall k = 1, 2, \ldots\ldots, N \quad \forall j = 1, 2, \ldots\ldots, M \tag{2}$$

$$\sum_{j=1}^{M} P_j L B_{jk} - S_k Y_k \leq 0 \qquad \forall k = 1, 2, \ldots\ldots, N \tag{3}$$

$$d_{jk} B_{jk} - D_j \leq 0 \qquad \forall k = 1, 2, \ldots\ldots, N \quad \forall j = 1, 2, \ldots\ldots, M \tag{4}$$

$$\sum_{k=1}^{N} B_{jk} Y_k = 1 \qquad \forall j = 1, 2, \ldots\ldots, M \tag{5}$$

where N is the total number of candidate shelters, Y_k indicates if candidate shelter k is allocated as a shelter (1 if allocated, 0 if not allocated), S_k is the area of candidate shelter k, M is the total number of communities, d_{jk} is the length of the shortest path between community j and candidate shelter k, and v_j is the evacuation speed of the people in community j calculated as:

$$v_j = (2 \times p_c \times v_c + (p_a - p_c) \times v_a + p_o \times v_o) \times \rho \tag{6}$$

where v_c, v_a and v_o represent the speed of a community's children, adults and elderly people as defined by Gates (2006), and p_c, p_a, and p_o are the proportions of the different categories of people respectively, and ρ is an adjustment parameter of the evacuation speed relative to the ordinary speed (set to 1 in this study). Furthermore, P_j is the number of people to be evacuated in community j, W_{jk} is the mean width of the evacuation path from community j to candidate shelter k, B_{jk} indicates if candidate shelter k is allocated to community j (1 if allocated, 0 if not allocated; note that all people within a particular community are allocated to the same shelter), L is the smallest refuge area per capita (1 m^2/person (Beijing Municipal Institute of City Planning & Design, 2007)), and D_j is the maximum evacuation distance for the people in community j, which is equal to the product of $Tmax_j$ and v_j, with $Tmax_j$ being the maximum evacuation time for community j.

Case study

Figure 1 indicates the location of the geographical area considered in the study presented in this paper, namely Jinzhan, Chaoyang, Beijing, China. More specifically, Figure 1(a) shows the location of Beijing in China and Figure 1(b) shows the location of Jinzhan within Chaoyang in Beijing.

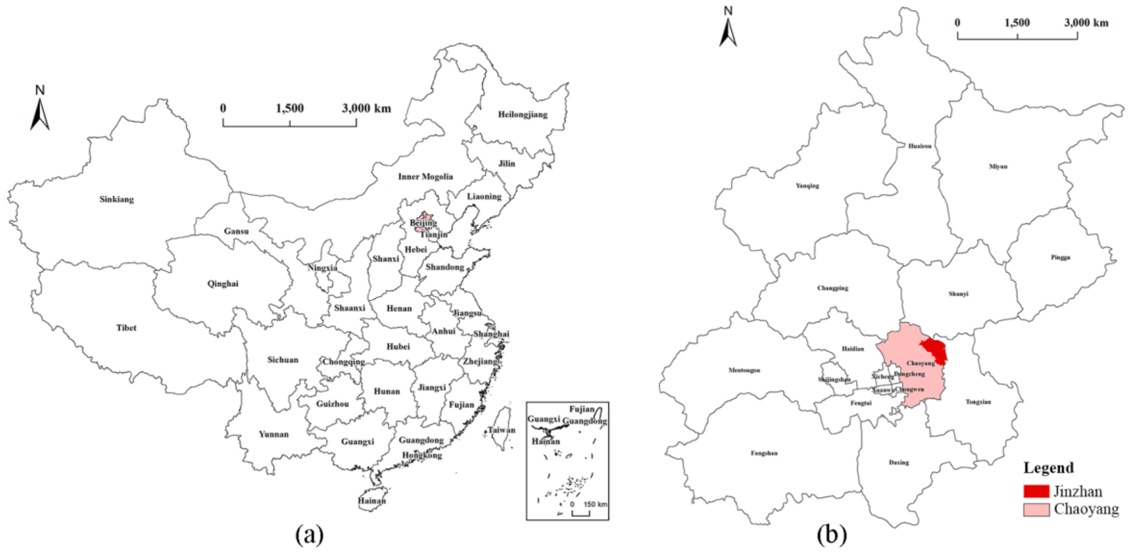

Figure 1. Location of Jinzhan, Chaoyang, Beijing, China

Figure 2(a) presents a map of communities, shelters and evacuation path network, which was provided by the Key Laboratory of Environmental Change and Natural Disaster of Ministry of Education, Beijing Normal University. Furthermore, Figure 2(a) indicates the locations of 10 candidate shelters and 15 communities that need to be allocated to the selected shelters. The locations of candidate shelters were determined in consideration of the requirement that these should be at least a distance of 500m from the earthquake faults (Hu et al., 2014). In the model presented in this paper, it is assumed that sheltering assets are able to be delivered to those shelters selected when solving the location-allocation problem. Figure 2(b) shows population data which was provided by the Beijing Bureau of Civil Affairs. Table 1 indicates the area of each of the 10 candidate shelters, the number of people in each of the 15 communities and the distance between communities and shelters.

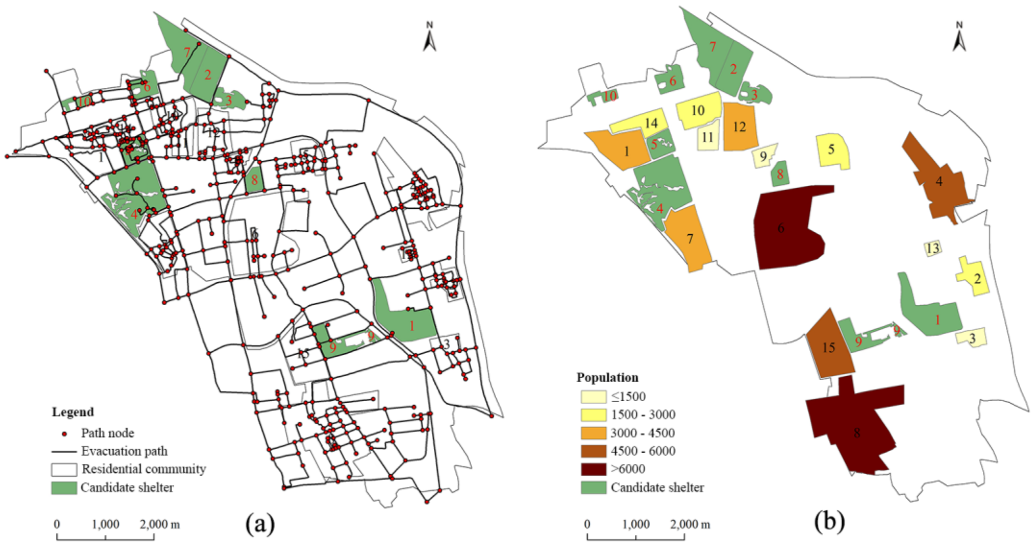

Figure 2. Location of communities, shelters, evacuation paths and distribution of population

Table 1. Area of candidate shelters, population of community and distance between communities and candidate shelters

			Candidate shelter index									
			1	2	3	4	5	6	7	8	9	10
		Area(m^2) / Population	803385	502342	203617	1114636	232884	236840	741967	157105	357538	112152
Community index	1	3848	10575.4	2920.6	4410.4	3397.1	1565.1	2351.1	3687.6	3691.3	8080.5	1981.5
	2	1650	1411.0	8488.5	7679.4	9096.8	9489.1	10647.4	11320.5	6626.0	4438.1	11370.7
	3	956	1392.9	9112.8	8303.7	8965.4	9885.3	11075.8	11944.8	7250.3	2703.3	11799.1
	4	5874	3492.6	7451.5	6642.4	8149.5	8452.1	9610.4	10283.4	5589.0	5841.1	10333.7
	5	2157	5600.8	3583.2	2774.1	4455.3	4583.8	5742.1	6415.2	1540.3	5142.3	6465.4
	6	10937	6170.0	5173.8	5733.4	4966.2	5886.1	7076.7	8004.3	3676.7	3147.5	7800.0
	7	4251	8158.2	3875.9	4672.0	1576.7	2821.8	4012.3	5271.3	2565.4	5135.7	4735.6
	8	12858	5375.1	8509.0	8690.2	8082.5	9002.4	10193.0	11339.5	7011.9	2575.6	10916.3
	9	868	7501.7	1771.6	2125.1	3275.6	2772.2	3930.5	4603.5	360.6	5389.5	4653.8
	10	2716	9820.4	1167.3	3151.2	3341.2	2074.2	1989.5	2270.7	2936.2	7491.3	2773.2
	11	1276	8902.9	1329.4	2814.2	2856.1	1589.1	2539.8	3053.7	2018.7	6573.8	3264.3
	12	3452	8376.2	627.4	1929.2	3598.1	2664.4	3168.2	3459.3	1492.1	6169.6	3945.5
	13	455	1949.2	7778.8	6969.6	8476.7	8779.4	9937.7	10610.7	5916.2	4976.3	10661.0
	14	2084	10581.3	2235.9	4246.3	3435.2	1753.1	1552.8	2918.4	3697.2	8118.6	2104.7
	15	4618	4801.5	6798.6	6851.1	6540.3	7460.2	8650.8	9629.1	5231.5	736.5	9374.1

Optimization heuristics

Different approaches can be taken to solve optimization problems involving multiple objectives such as that considered in this paper, i.e. minimising total shelter area (TSA) and minimising total weighted evacuation time (TWET). One approach is to convert the multi-objective problem into a single objective problem. This can be achieved by summing the weighted values of each of the multiple objectives to give a single value. However, the weight assigned to each objective can be difficult to set due to the lack of prior information on the relative importance of each one. Thus, this approach can involve performing a sensitivity analysis in which the weights assigned to each of the multiple objectives are varied. An alternative approach, referred to as Pareto-based (Pareto, 1896), involves a set of optimal solutions in which, for each solution, no increase can be achieved in any of the objectives without resulting in a simultaneous decrease in at least one of the remaining objectives.

In the preliminary work reported in this paper, both approaches have been used and compared. For the weight-based approach, the objective function, to be minimised, is defined as the sum of the weighted objective value of TSA and TWET,

$$f = (\alpha \times TSA) + (\beta \times TWET) \tag{7}$$

where α and β are the weight of TSA and TWET respectively. These weights represent the relative importance of each objective and, thus, each varies between 0 and 1 and they sum to unity.

For the Pareto-based approach, any feasible solution which is non-dominated in terms of the two objectives, i.e. TSA and TWET, is defined as a solution in the Pareto optimal set.

In this paper, MPSO, which is assisted by a SA algorithm during the search for local optima, and a GA have been used to solve the earthquake shelter location-allocation problem. Flowcharts of the MPSO and GA are shown in Figure 3(a) and 3(b) respectively.

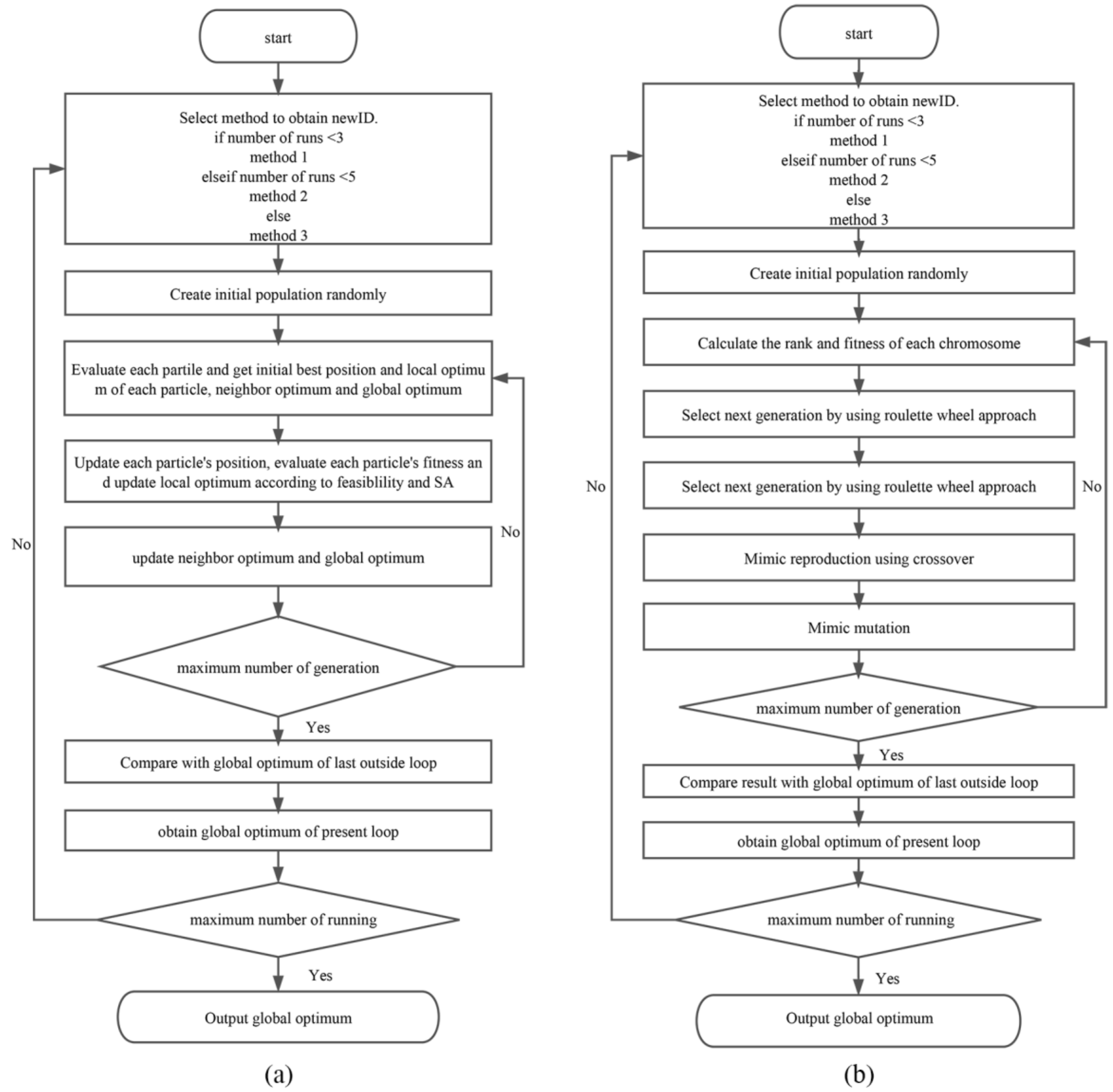

Figure 3. Flowcharts of (a) MPSO and (b) GA

Although the MPSO and GA are different in many aspects, both need to generate an initial population, which traditionally is done randomly. In order to investigate the effect of the initial population on the final 'optimized' solutions obtained, three different methods have been used to account for the indexing of the ten shelters to which the fifteen communities must be allocated. All three methods involve allocating each community, in turn, to one of the ten candidate shelters providing each allocation does not violate the capacity constraint or time constraint referred to in relation to equations (3) and (4) respectively. That is, not all communities can be allocated to every shelter. The number of shelters to which a community can be allocated is summarized in the vector {8, 2, 2, 2, 8, 5, 9, 2, 9, 8, 8, 8, 2, 8, 3}, where, for example, community 1 can be allocated to only 8 of the 10 shelters, community 2 can be allocated to only 2 shelters and so on. Method 1 assigns indices to candidate shelters, to which a community can be allocated, according to those indicated in Figure 2, then as communities are allocated to shelters these indices are reset from 1 to the number of remaining potential shelters to which a community can be allocated. Method 2 assigns indices to candidate shelters according to the time for a community to reach the possible candidate shelters such that the nearest shelter to the community is given an index of 1, the next nearest shelter to the community is given an index of 2 and so on. As each community is allocated to a candidate shelter, indices are reset from 1 to the number of remaining potential shelters to which a community can be allocated. Method 3 assigns indices to candidate shelters according to the area of each possible candidate shelter to which a community can be allocated such that the candidate shelter with the smallest area capable of housing the community is assigned an index 1 and so on. Again, as each community is allocated to a candidate shelter, indices are reset from 1 to the number of remaining potential shelters to which a community can be allocated. As an example, taking community 1 which can be allocated to only 8 of the 10 shelters, namely {2, 3, 4, 5, 6, 7, 8, 10}, the indices set according to the three methods are shown in Table 2.

Table 2. Community 1's candidate shelter indices set according to the three methods

	Candidate shelter indices							
Original	2	3	4	5	6	7	8	10
Method 1	1	2	3	4	5	6	7	8
Method 2	6	7	5	3	2	8	1	4
Method 3	6	3	8	4	5	7	2	1

The MPSO algorithm used has been described as detailed in the work of Zhao et al. (2015). In the GA that has been developed, each solution's chromosome, which corresponds to a location and allocation plan, consists of fifteen genes, one per community, $\{g_1, g_2, g_3, \ldots, g_{15}\}$ with each gene represented as a binary number with four digits. For example, a chromosome could be represented as follows by using Method 1,

{0011, 0001, 0010, 0001, 1000, 0100, 0010, 0001, 0100, 1000, 0001, 0011, 0001, 0111, 0010}.

In this example, the indices of candidate shelters selected to allocate each community are {3, 1, 2, 1, 8, 4, 2, 1, 4, 8, 1, 3, 1, 7, 2}. Thus, the original indices can be obtained using Table 2, which indicates that community 1 is allocated to candidate shelter 4, community 2 is allocated to candidate shelter 1, and so on.

At each generation, for each solution's chromosome, the TSA and TWET objective values are calculated. For example, consider the five solutions' chromosomes, C_1 to C_5, generated, say, using Method 1,

C_1 = {0111, 0001, 0001, 0010, 0110, 0100, 0111, 0001, 0100, 1000, 0101, 0111, 0001, 0101, 0010}

C_2 = {0111, 0010, 0010, 0010, 0001, 0101, 0101, 0010, 0111, 0111, 0010, 0100, 0010, 1000, 0011}

C_3 = {0101, 0001, 0001, 0010, 0111, 0100, 1000, 0001, 0101, 0101, 0111, 0110, 0001, 0110, 0011}

C_4 = {0100, 0010, 0001, 0001, 0111, 0101, 1001, 0010, 0001, 0101, 1000, 0101, 0010, 0001, 0011}

C_5 = {0101, 0010, 0001, 0010, 0010, 0100, 0111, 0010, 0010, 0101, 0100, 0010, 0010, 0101, 0001}

In C_1, community 1 is allocated to candidate shelter 8 (using the mapping given in Table 2), communities 2 and 3 are both allocated to candidate shelter 1 since it is capable of housing both communities (using a mapping not given in this paper), and so on. For the five solutions' chromosomes shown, the TSA and TWET objective values are (1542368, 10688895.5), (2103524, 8954749.6), (2296837, 10443330.5), (2402250, 9527582.7) and (2493715, 9921918.0) respectively. These values of TSA and TWET are obtained using equation 1 and 2 respectively, along with the data presented in Table 1. Based on these values, each solution is ranked according to how many other solutions in the population dominate it. That is, if a solution is non-dominated, i.e. no other solution has 'better' (lower) values for both TSA and TWET objectives, then it is ranked 1 as it is Pareto-optimal. From the five example chromosomes shown, it can be seen that C_1 and C_2 are non-dominated so have rank R = 1, C_3 and C_4 are dominated by C_2 so have rank R = 2, and C_5 is dominated by C_2 and C_4 so has rank R = 3. Based on these ranks, the fitness of each solution is calculated according to a fitness function

$$F_i = (n + 1 - R_i)^{\gamma} \tag{8}$$

where n is the number of solutions in a population and γ is a coefficient set to unity in this work. Again referring to the five example chromosomes shown, the fitness values are 5, 5, 4, 4 and 3 respectively. Based on fitness values, the next generation is obtained via a roulette wheel approach in which fitter solutions are more likely to be selected. Also, within the GA, crossover and mutation are used. In relation to the crossover operation, based on chromosomes being selected according to a crossover probability, single point crossover has been selected for use after it was shown, in the problem domain considered in this paper, to outperform two-point crossover and bitwise crossover. The mutation operation, using a mutation probability, involves probabilistically selecting chromosomes for mutation then randomly selecting genes in which the four digit binary number is altered. A sensitivity analysis revealed that for the earthquake shelter location-allocation problem under consideration, better optimized solutions were obtained using a crossover and mutation probability of 0.84 and 0.009 respectively.

PRELIMINARY RESULTS AND DISCUSSION

This section presents comparisons of the performance of MPSO and GA, using the three methods to set the indices of candidate shelters to which the fifteen communities must be allocated. Furthermore, these comparisons are considered using a Pareto-based approach and then the weight-based approach (converting the multi-objective problem into a single objective problem) as described in the previous section. In all runs of the MPSO and GA, the population size and number of generations were both set to 100.

Pareto-based approach

Figure 4 shows the Pareto solutions obtained by the GA (Figure 4(a)) and MPSO (Figure 4(b)) using the three methods to set the indices of candidate shelters. In Figure 4(a), using the GA, it can be observed that the three methods result in noticeably different sets of Pareto solutions. Furthermore, the majority of the non-dominated solutions were obtained using Method 2; however one non-dominated solution, with lower TSA, stems from Method 3. As shown in Figure 4(b), for MPSO, the spread of Pareto solutions is similar using Methods 2 and 3, although it is observed that all non-dominated solutions were obtained via Method 2.

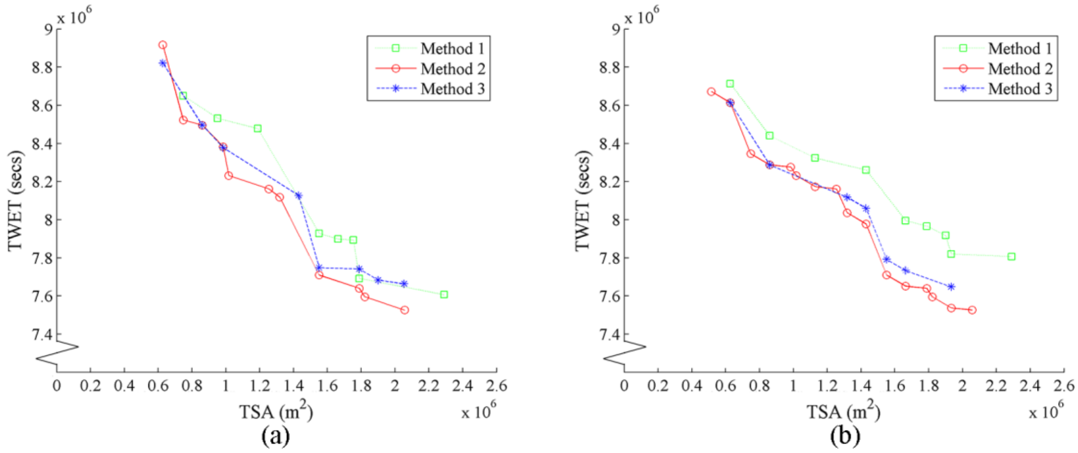

Figure 4. Pareto solutions obtained via the methods for setting candidate shelter indices using (a) GA and (b) MPSO

Figure 5 presents a direct comparison between the results obtained using the GA and MPSO with each of the three methods to set the indices of candidate shelters. In Figure 5(a), using Method 1, it can be seen that MPSO and the GA perform better than each other in different regions of the search space. In contrast, MPSO performs better than the GA using Methods 2 and 3 as shown in Figures 5(b) and 5(c) respectively.

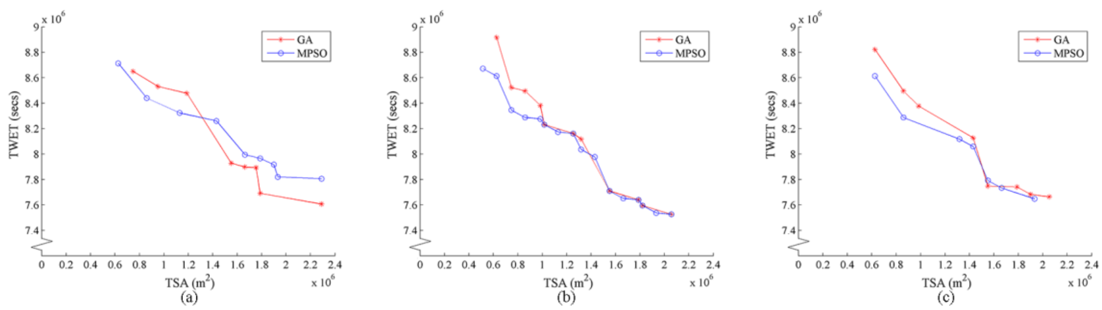

Figure 5. Pareto solutions obtained by the GA and MPSO using (a) Method 1, (b) Method 2 and (c) Method 3

Based on multiple runs using all three methods, Figure 6(a) presents the 'best' Pareto solutions obtained from the GA and MPSO in solving the specific location-allocation problem considered in this paper. In this figure it is apparent that the Pareto solutions generated by MPSO are better than those generated by the GA. Taking the solutions at various locations on the Pareto front marked 'A', 'B', and 'C' in Figure 6(a) as examples, Figure 6(b), (c) and (d) show the location of the candidate shelters selected and an indications of how the fifteen communities are allocated to them. It is noted that for the three Pareto solutions highlighted, different numbers of shelters are selected for the fifteen communities to be allocated. Specifically, Pareto solutions 'A', 'B' and 'C' utilize five (numbered 1, 2, 6, 8, 9), three (numbered 1, 8, 9) and two (numbered 8, 9) candidate shelters respectively. It is observed that for all three Pareto solutions highlighted, candidate shelters 8 and 9 are always utilized. Indeed, for Pareto solution 'C', which corresponds with a low value of TSA and high value of TWET, only candidate shelters 8 and 9 are utilized. However, for Pareto solution 'B', with a greater value of TSA and lower value of TWET, candidate shelter 1 is also utilized. Also, for Pareto solution 'A', with a high value of TSA and low value of TWET, candidate shelters 2 and 6 are utilized in addition to 1, 8 and 9. Another observation for all three Pareto solutions highlighted is that communities 1, 5, 6, 7, 9 and 11 are always allocated to candidate shelter 8 while communities 8 and 15 are always allocated to candidate shelter 9.

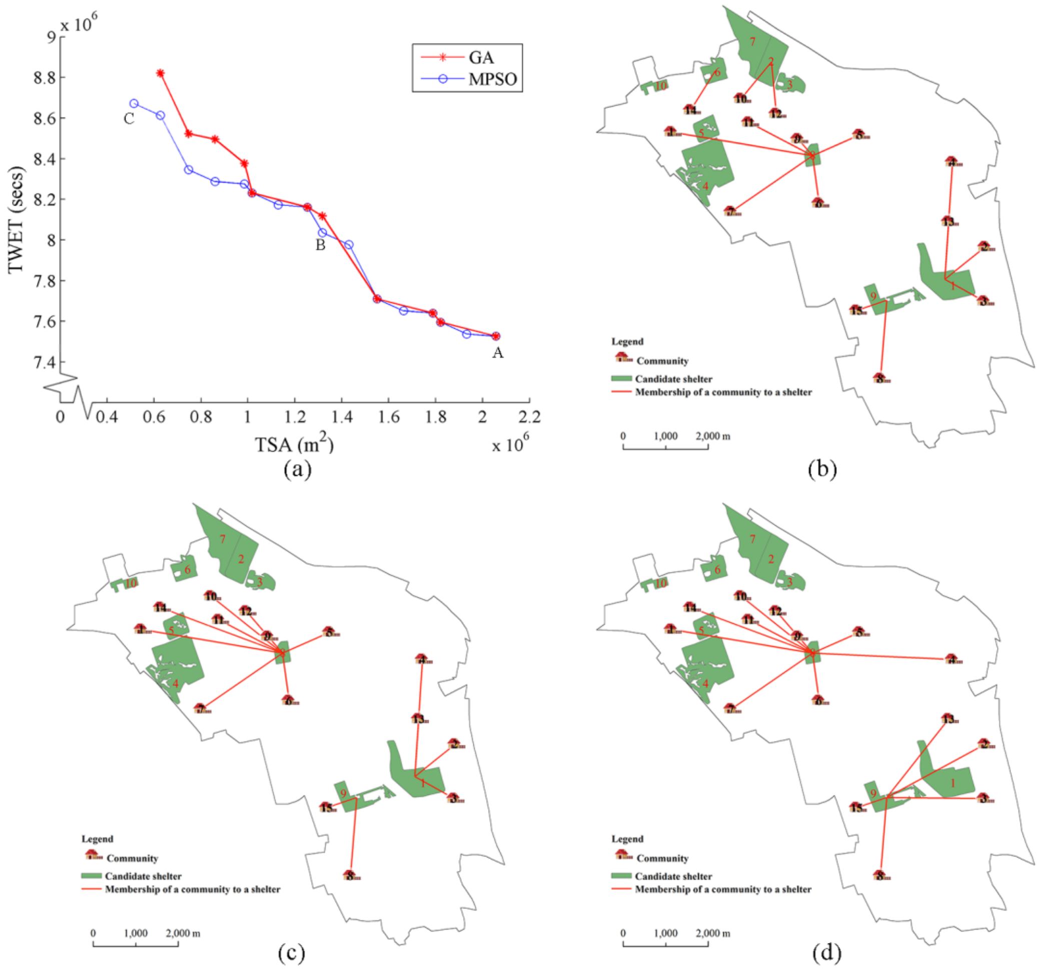

Figure 6. (a) 'Best' Pareto solutions obtained using the GA and MPSO and (b) (c) and (d) illustrate the Pareto 'location-allocation' solutions corresponding to point A, B and C respectively

The utilized and non-utilized shelter areas associated with the Pareto solutions obtained are presented in Figure 7(a) and (b) for the GA and Figure 7(c) and (d) for MPSO. It can be seen that utilized areas of the selected shelters are significantly less than the non-utilized areas. Thus, each selected shelter has sufficient room to house relief workers and volunteers, along with relief assets, and for the evacuees to move around.

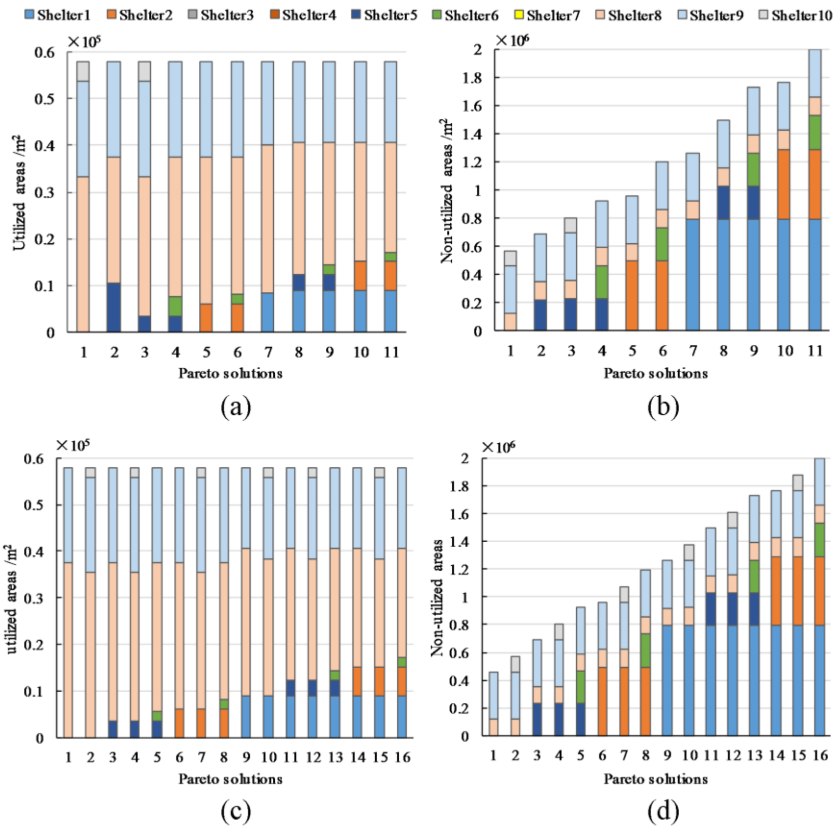

Figure 7. Utilized and non-utilized shelter areas associated with the Pareto solutions for the GA (see (a) and (b)) and MPSO (see (c) and (d))

Weight-based approach

In converting the multi-objective problem to a single objective problem, weights of 0.5 were assigned to α and β. Thus, equation (7) to evaluate the objective function, to be minimized, can be written as

$$f = (0.5 \times TSA) + (0.5 \times TWET) \quad (9)$$

Figure 8 presents the convergence of the objective function using the GA (Figure 8(a)) and PSO (Figure 8(b)) with the three methods to set the indices of candidate shelters. In Figure 8(a), for the GA, it can be observed that using Method 1 results in better solution being found than the other two methods. In addition, convergence using Methods 1 and 2 is similar, both being quicker than Method 3. For MPSO, Figure 8(b) shows that Method 2 leads to better solution than the other two methods. Also, Methods 2 and 3 show similar convergence, both doing so more quickly than Method 1.

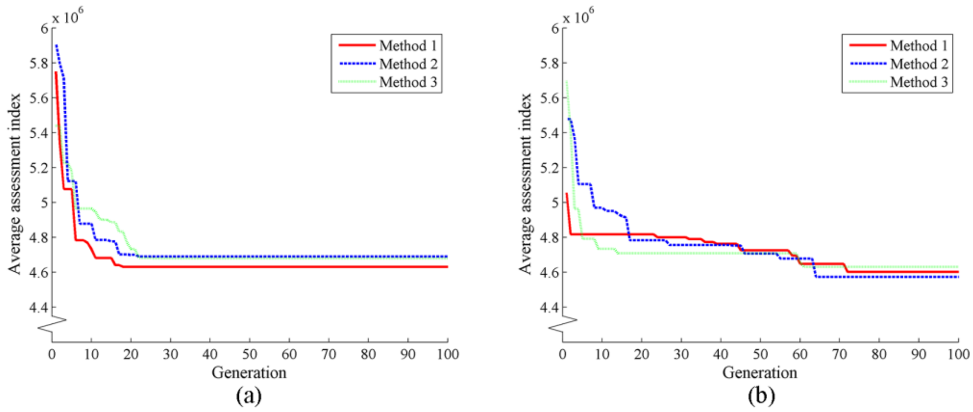

Figure 8. Convergence of objective function obtained via the methods for setting candidate shelter indices using (a)

GA and (b) MPSO

Figure 9 presents a direct comparison of the results obtained using MPSO and GA with each of the three methods to set the indices of candidate shelters. In Figure 9(a) it can be seen that using Method 1, the GA outperforms MPSO for the majority of generations (approximately 70). However, beyond approximately 70 generations, the MPSO yields better solutions than the GA. Similar observations can be made using Methods 2 and 3 as shown in Figures 9(b) and 9(c) respectively. The best solution generated by the GA and MPSO, in terms of the location of the candidate shelters selected and how the fifteen communities are allocated to them, are shown as Figure 10(a) and Figure 10(b) respectively.

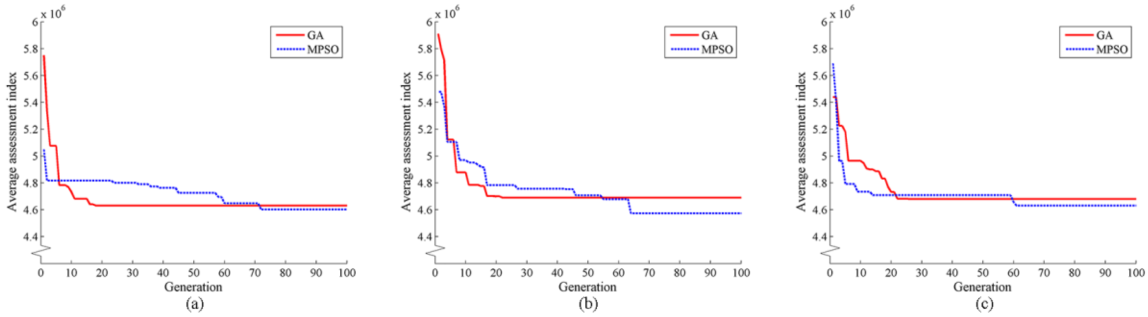

Figure 9. Convergence of objective function with the GA and MPSO using method 1 (a), 2 (b) and 3 (c)

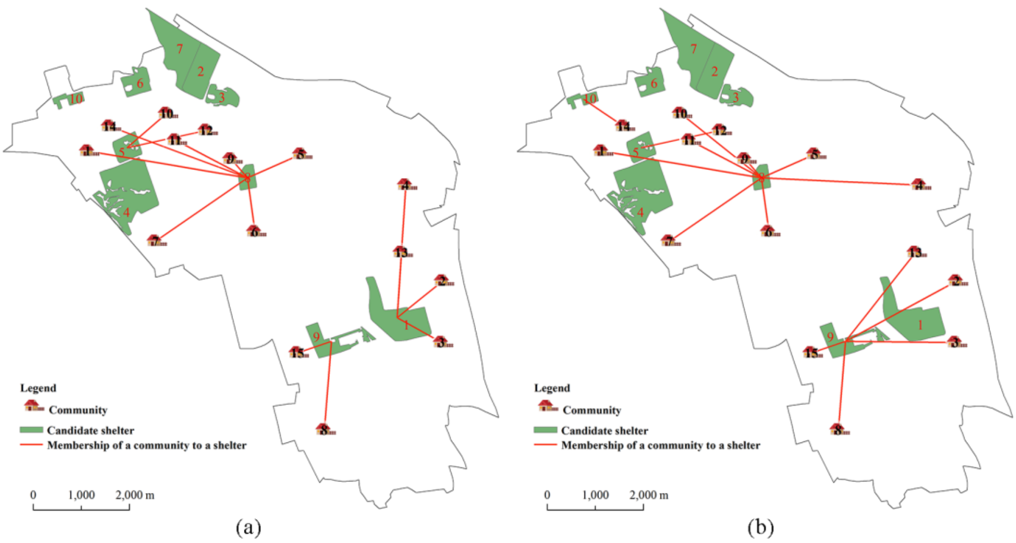

Figure 10. Best 'allocation-location' solutions generated using the (a) GA and (b) MPSO

Comparison of approaches

The Pareto-based and weight-based approaches offer two different ways of solving the multi-objective problem described in this paper. The Pareto-based approach yields a set of 'best' (non-dominated) solutions, whereas the weight-based approach produces a single 'best' solution which depends on the weights assigned to each of the multiple objectives. Consequently, it is not possible to compare the 'best' solutions obtained using the two approaches. However, it is possible to consider an example Pareto solution and compare this with the 'best' solution produced via the weight-based approach (with both weights set at 0.5). For example, compare the Pareto solution marked 'B' in Figure 6(a), which is also illustrated in terms of the location of the candidate shelters selected and how the communities are allocated to them in Figure 6(c), and the MPSO's weight-based solution shown in Figure 10(b). The Pareto solution utilized candidate shelters 1, 8 and 9 with a TSA of 1318028 m^2 (determined from Table 1) and TWET of 8035780 seconds. In contrast, the 'best' solution via the weight-based approach utilized candidate shelters 5, 8, 9 and 10 with a TSA of 859679 m^2 and TWET of 8287234 seconds. As such, the 'best' solution via the weight-based approach is not dominated by the Pareto solution.

CONCLUSION

The aim of this paper was to present preliminary work in evaluating the performance of two optimization heuristics, namely a GA and MPSO, in solving the earthquake disaster shelter location-allocation problem considered. This preliminary work will support the direction of future work regarding how a hybrid optimization algorithm, using a GA and MPSO in combination, can be developed to improve solutions to the earthquake shelter location and allocation problem, which will inform disaster management strategies.

In this paper, a comparison has been undertaken of the performance of a GA and MPSO, using three different methods to determine the initial population, according to a Pareto-based approach and a weight-based approach. It was found that all three methods mentioned have advantages and disadvantages and thus it is proposed that an appropriate direction of the next stage of our research is to combine their use. However, when the weighted method is used, the convergence process is clear, which highlights that MPSO is better in the early and final stages of the optimization process; in contrast the GA performs better than MPSO over the majority of generations between the early and final stages of the optimization process. Although a GA and MPSO have been compared and the results give some information regarding how to combine them to obtain better optimized solutions more quickly, the simple GA developed to date requires further work to include aspects such as niching and elitism. Also, in terms of further work, a number of improvements will be made to the mathematical model. For example, damage to the shelters and evacuation roads caused by an earthquake will be considered. In addition, the possibility of evacuees belonging to the same community being divided and allocated to multiple shelters will be considered. Finally, results generated from this research will be presented to practitioners involved in managing earthquake disasters, which is viewed as an important aspect of this work.

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