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Innovative Applications of O.R.

Evacuation planning using multiobjective evolutionary optimization approach

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ABSTRACT

In an emergency situation, evacuation is conducted in order to displace people from a dangerous place to a safer place, and it usually needs to be done in a hurry. It is necessary to prepare evacuation plans in order to have a good response in an emergency situation. A central challenge in developing an evacuation plan is in determining the distribution of evacuees into the safe areas, that is, deciding where and from which road each evacuee should go. To achieve this aim, several objective functions should be brought into consideration and need to be satisfied simultaneously, though these objective functions may often conflict with each other.

This paper aims to address the use of multiobjective evolutionary algorithms (MOEA) and the geographical information system (GIS) for evacuation planning. The paper proposes a three-step approach for evacuation planning. It explains that the last step, which corresponds to distribution of evacuees into the safe areas, is a spatial multiobjective optimization problem (MOP), because the objective functions and data required for solving the problem has a spatial component. To solve the MOP, two objective functions are defined, different algorithms for solving the problem are investigated, and the proper algorithm is selected. Finally, in the context of a case study project and based on the proposed approach and algorithm, evacuation planning is conducted in a GIS environment, and the results are tested. This paper is based on an ongoing research project in Iran.

1. Introduction

Evacuation is a common strategy for handling emergency situations. Evacuation is a process in which threatened people are displaced from dangerous places to safer places in order to reduce the health and life vulnerability of affected people. During disaster response, evacuation should be conducted accurately, and in a hurry. As a result, preparation, testing and training of a proper evacuation plan are required as a part of disaster preparedness. However, evacuation planning is a very complex problem involving many behavioral and management facets.

There are different studies in evacuation planning that work from different perspectives such as evacuee behaviors, traffic control strategies, sheltering site selection, and route finding for displacement. For example, Sherali et al. (1991) and Kongsomsaksakul and Yang (2005) studied the evacuation plan for hurricanes/floods with explicit consideration of the impact of shelter locations on evacuation time. The former formulated the problem as a nonlinear mixed integer programming problem, but the latter utilized a GA-based solution procedure to solve the problem. Feng and Wen (2003) studied various traffic control strategies for the earthquake-raided area in post earthquake periods and proposed some models to minimize the rescue time in a disaster area. Cova and Justin (2003) presented a network flow model for identifying optimal lane-based evacuation routing plans in a complex road network. A mixed-integer programming solver is used to derive routing plans for sample networks. Murray and Mahmassani (2003) added a consideration of household behavior into evacuation modeling. Yi and Özdamar (2007) proposed a dynamic logistics coordination model for evacuation and support in disaster response activities. Pursals and Garzon (2009) considered the building evacuation problem and developed a model for selecting the proper routs for movement of people in a building during an emergency situation.

Most of the data required for emergency management and evacuation planning have a spatial component or location that represents a significant opportunity to utilize geographical information systems (GIS) (Budic and Pinto, 1999; Mansourian et al., 2006). As a result, GIS-based emergency management and evacuation planning have gained popularity in recent years. Notable examples include Cova and Church (1997), who have presented a method for identifying neighborhoods that may face transportation difficulties during an evacuation. They used an integer programming model called the critical cluster model and demonstrated that a heuristic algorithm is able to produce efficient, high-quality solutions to this

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model in a GIS context. Pal et al. (2003) have discussed the development of a traffic simulation methodology using GIS and spatial data, which could be used for emergency evacuation planning purposes. This methodology seeks to give optimal evacuation alternatives in the form of safest and most efficient routes for evacuation of the population from the affected region. Vakalis et al. (2004) have developed a GIS-based forest fire simulation tool to manage wildfire crises based on a discrete contour propagation model for estimating fire consequences and a fuzzy/neural system for the estimation of fire spread. Zeng et al. (2007) used a heuristic GA method and GIS software in order to manage the risk of wind damage in forest planning. Mansourian et al. (2006) used spatial data infrastructure (SDI) concepts and Web-based GIS to facilitate disaster management. They used Web-based GIS to facilitate spatial data sharing among disaster management parties for better planning and decision-making.

Iannoni et al. (2009) present a method to optimize the configuration and operation of emergency medical systems on highways. This approach is based on embedding a well-known spatially distributed queueing model (hypercube model) into a hybrid Genetic Algorithm (GA) to optimize the decisions involved.

To develop an evacuation plan, it is important to first determine safe areas. Another significant job (and, in fact, a central challenge) involves determining the distribution of evacuees into the safe areas, that is, to answer: where should each evacuee go and from which route (ElDessouki, 1998)? To achieve a proper plan, a planner should consider *the capacities of the safe areas* and *the distance to the safe areas* as two important factors during the planning (Negreiros and Palhano, 2006; Wu and Zhang, 2006). In other words, in an evacuation plan, the distribution of evacuees into the safe areas should be based on the capacity of the safe areas, and, at the same time, each evacuee should go to the nearest safe area. Therefore, in evacuation planning, at least two objective functions should be satisfied simultaneously; the planners are faced with a multiobjective optimization problem (MOP). In addition, since objective functions and the relevant data for their determination has a spatial component (e.g., location of the safe areas, location of the building blocks in which evacuees are, and route map), evacuation planning can be defined as a spatial MOP (this has been also highlighted by Chow and Lui (2002), Georgiadou et al. (2006) and Yi and Kumar (2007)).

Although the potential role of GIS in evacuation planning has been noted by a number of studies, little work has been done in this area (Balram and Dragicevic, 2006). More specifically, there are very few studies integrating GIS and multiobjective techniques for evacuation planning (Balram and Dragicevic, 2006), particularly for the problem of this research With this in mind, this paper intends to address and present utilization of multiobjective optimization techniques and GIS as integrated frameworks for evacuation planning. The paper is based on a case study project in Tehran, the capital of Iran.

2. Methodology and materials

In response to this understanding, this paper proposes a three-step method for an optimized evacuation planning algorithm (Fig. 1). As illustrated in Fig. 1, in the first step appropriate safe places for evacuation are selected/designed. In the second step, by applying some constrains (such as a total distance constraint), appropriate candidate safe areas are chosen for each building block. Then, for each building block, optimum routes to its candidate safe areas are found. In the third step, by considering and optimizing different factors (such as distance from safe areas, the capacity of the safe areas, and the population of the building blocks), an optimum distribution of people to the safe areas is determined.

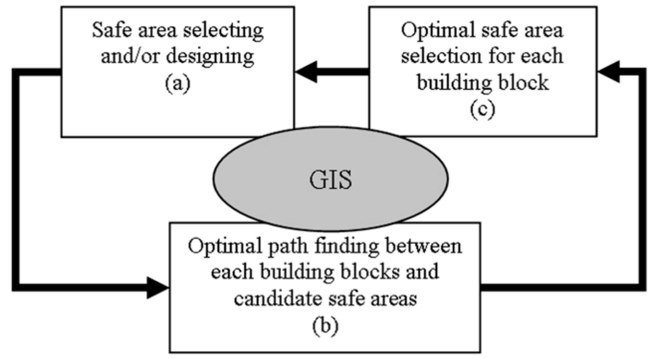

Fig. 1. The proposed evacuation planning procedure.

By following these three steps, *proper safe area* and *the optimum path to get into the safe area* are determined for each building block. The result can then be presented on a map, which is known as an evacuation plan. In order to implement the proposed method, several models, theories, and tools are utilized. These are described as follows.

2.1. Safe area designation

Available vacant lands as well as green and open areas are generally considered as safe areas during an emergency. These areas should have some specifications such as: enough space for evacuees, basic living requirements (water, toilet, electricity, etc.), and not being threatened by any hazard. Through different techniques such as aerial/satellite image processing, field work, and using available maps, appropriate places are identified and then prepared to be usable as a safe area. For the case study of this research, in the context of a comprehensive plan for Tehran disaster management, JICA and TDMMC (2004) had already designed potential evacuation safe areas, so we adopted these areas for our research.

2.2. Optimum path finding

At this step, for each building block, initial candidate safe areas are selected. The selection is based on the nearness of the available safe areas to the building blocks. In this research, in order to find candidate safe areas, three data layers (namely, building blocks, safe areas, and route network of the case study area) were loaded in a geographical information system (GIS). Then, using a buffering tool, a buffer zone was created for each building block. The buffering distance was set based on the experiences of Iranian disaster managers in administrating different disasters such as Manjil (1990), Ghazvin (2002), Bam (2003), and Boroujerd (2006). After this, candidate safe areas for each building block were determined by overlaying the buffer areas with safe areas. In the last stage, optimum paths between each building block and the relevant candidate safe areas were determined using a GIS network analysis tool. The optimum paths were determined by choosing the shortest path satisfying traffic and safety constrains.

2.3. Optimal safe area selection for each building block

The last step of the proposed methodology is to select the proper safe area for the evacuation of each building block. To solve this problem, several factors should be brought into consideration and optimized simultaneously. The two decisive factors are the "distance of building block from assigning safe area" and the "capacity of the safe area". With this in mind, two objective functions, U and V, were defined (Eq. (1)) here. Of these, U models the capacity criterion, while V models the distance criterion.

Objective functions

$$U = \sum_j \left| \frac{\sum_i p_{ij}}{C_j} - 1 \right| \Rightarrow \min \quad V = \sum_j \sum_i d_{ij} p_{ij} \Rightarrow \min \tag{1}$$

where p_{ij}: population of the ith building block that should be evacuated to the jth safe area, d_{ij}: distance between the ith building block and the jth safe area (along the optimum path), C_j: capacity of the jth safe area.

The optimization problem in Eq. (1) is a kind of spatial grouping in which, for any safe area, building blocks are assigned as follows:

- U: The total population assigned to each safe area should be equal or less than its capacity. The absolute sign for U indicates whether the total population of evacuees is more than the total capacity of the safe areas, the overload should be divided among the safe areas while trying to minimize the overload capacity for each safe area.
- V: Building blocks with a greater population have priority to be assigned to the nearest safe area. Thus, more people can reach the safe areas in the shortest possible time.

Since the two objective functions (U and V) have spatial components[1] and should be satisfied simultaneously, the optimization problem that the research aims to solve is a spatial MOP. Therefore, the problem can be solved with more flexibility and better visualization via loosely coupled integration of MOP solutions and GIS.

2.3.1. Multiobjective optimization problems

The MOP is defined as the problem of finding a vector of decision variables that satisfies constraints and optimizes a vector function whose elements represent the objective functions. These functions form a mathematical description of performance criteria which are usually in conflict with each other. Hence, the term "optimize" means finding a solution that would give values for all of the objective functions that are acceptable to the decision maker (Coello Coello, 2002). MOPs are a very important research topic because of the multiobjective nature of most real-world decisions (such as the case of this research). The general MOP can be formally defined as illustrated in Eq. (2):

The general MOP

$$\begin{aligned}
&\text{Find the vector } x^* = [x_1^*, x_2^*, \ldots, x_n^*]^{\mathrm{T}} \text{ which will satisfy:}\\
&\text{the } m \text{ inequality constraints } g_i(x) \geqslant 0\\
&\text{where } i = 1, 2, \ldots, m \ (x \text{ is a vector}),\\
&\text{the } p \text{ equality constraints } h_i(x) = 0\\
&\text{where } i = 1, 2, \ldots, p \ (x \text{ is a vector}), \text{ and}\\
&\text{will minimize the vector function}\\
&f(x) = [f_1(x), f_2(x), \ldots, f_k(x)] \rightarrow \min \ (x \text{ is a vector})
\end{aligned} \tag{2}$$

Traditionally, there are several methods available in the operational research literature for solving MOPs, such as goal attainment (Wilson and Macleod, 1993), weighted averaging (Coello Coello, 2003), and Pareto front optimization (Zitzler and Thiele, 1998).

The concept of a goal is somewhat different from that of an objective. A goal is usually considered as a planned objective. Therefore the optimality is measured, in the case of goal-based methods, in terms of the amount of deviation from the planned levels (Abbass and Sarker, 2002). None of the goal-based methods treat all of the objectives simultaneously (Coello Coello, 2003) and are thus not suitable for solving the problem of this research.

In the weighted average optimization method, the user assigns a weight to each function (after normalizing the objective functions). Then, the multiobjective problem is converted into a single scalar function, usually through a linear combination of the normalized weighted objectives. The scalar function can be solved by conventional methods, such as gradient-based approaches (if the scalar function has a convex shape with a global optimum) or heuristic search algorithms (if the function has several local optima). This optimization method, however, has three main drawbacks that make it unsuitable as the problem solving approach of this research (Coello Coello, 2002):

- The final optimum depends on the weights and normalization method, so, for each selected weight set, the result is only one of the global optimum solutions.
- Determining the weights at the beginning of problem solving is a difficult task, if one has no idea about the results.
- If all global optimum solutions perform a concave set, principally it is not possible to reach some global optimum solutions by selecting different weights.

In the Pareto front optimization method, all individual objective functions are simultaneously considered in the optimization process, and a complete set of global optima is calculated. After this, the user can decide and select the best optimal solution based on the problem conditions, constraints and his/her experiences (Zitzler and Thiele, 1998). In other words, there is no single optimal solution in MOP analysis, but rather a set of alternative solutions. These solutions are optimal in the wider sense that no other solutions in the search space are superior to (dominate) them when all objectives are simultaneously considered (Abbass and Sarker, 2002). They are known as Pareto optimal solutions. The Pareto front technique is expected to provide flexibility for the human decision maker in multiobjective optimization. Given all of this, the Pareto front technique was selected as a suitable method for solving the research problem here.

2.3.2. Pareto front optimization

According to Coello Coello (2002), for a given minimization problem, a vector of decision variables $\vec{x}^* \in F$ is Pareto optimal if there does not exist another $\vec{x} \in F$ such that $f_i(\vec{x}) \leqslant f_i(\vec{x}^*)$ for all $i = 1, \ldots, k$ and $f_j(\vec{x}) < f_j(\vec{x}^*)$ for at least one j. Here, F denotes the feasible region of the problem (i.e., where the constraints are satisfied). This definition says that $\vec{x}^*$ is Pareto optimal if there exists no feasible vector of decision variables $\vec{x} \in F$ that would decrease some criterion without causing a simultaneous increase in at least one other criterion. Unfortunately, this concept almost always gives not a single solution, but rather a set of solutions called the Pareto optimal set. The vectors $\vec{x}^*$ corresponding to the solutions included in the Pareto optimal set are called non-dominated. The plot of the objective functions whose non-dominated vectors are in the Pareto optimal set is called the Pareto front.

Evolutionary algorithms (EAs) are found useful for determining Pareto fronts in MOPs since EAs have some advantages over traditional operational research techniques. For example, they are population-based, and also considerations for convexity, concavity, and/or continuity of functions are not necessary in EAs, whereas they form a real concern in traditional operational research techniques (Abbass and Sarker, 2002). Given this, we chose a Pareto front based multiobjective evolutionary algorithm (MOEA) to solve the research problem here.

[1] In an MOP, if objective functions and corresponding data for determining them have a spatial component, the MOP is known as a spatial MOP. In short, spatial data are items of information that can be related to a location on the earth and are presented in the form of maps, satellite imageries, etc. GIS is known as the best tool for managing, storing, retrieving, and presenting spatial data.

2.3.3. Multiobjective evolutionary algorithms

EAs are search methods inspired by "natural selection" and "survival of the fittest" in the biological world. EAs differ from more traditional optimization techniques because they involve a search from a "population" of solutions, rather than from a single point. Each iteration of an EA involves a competitive selection that removes poor solutions. The solutions with high "fitness" are "recombined" with other solutions by exchanging parts of a solution with another. Solutions are also "mutated" by making a small change to a single element of the solution. Recombination and mutation are used to generate new solutions that are biased towards regions of the space for which good solutions have already been seen.

In the last two decades, roughly a dozen MOEAs have been demonstrated to give more of the Pareto front with a lower computation cost. VEGA (Schaffer, 1985), FFGA (Fonseca and Fleming, 1993), NSGA (Srinivas and Deb, 1995), and SPEA (Zitzler and Thiele, 1998) are examples of such MOEAs. As all of these methods are the extended states of Genetic Algorithms (GA), they have the following difficulties (Horn et al., 1994; Zitzler et al., 1999):

- Since GA utilizes a population of n points to explore the search space, it is possible to find n points of the Pareto front. If one needs to identify more parts of the Pareto front, he/she needs a larger population size, thus incurring a higher computational cost.
- GA generally suffers from early convergence of population in a local optimum area, due to the duplication of strong solutions (with high fitness) in the population.

Zitzler et al. (1999) conducted a comparison study among the mentioned MOEAs and highlighted the good performance of NSGA and SPEA as compared with the others. There were still some complexities, however, with respect to parameter initialization and adaptation of the algorithms. To be more specific, multiobjective evolutionary algorithms that use NSGA have been mainly criticized for their:

- $O(mN^3)$ computational complexity (where m is the number of objectives and N is the population size);
- non-elitism approach (i.e., the experience of the current generation will not transfer to the next one);
- the need for specifying a sharing parameter.

To solve this problem, NSGA-II was then proposed by Deb et al. (2002). The NSGA-II solution avoids the conventional problems of evolutionary algorithms such as the early uniformity in population during generations. NSGA-II resolves the problem by applying a crowding distance constraint. In addition, the Elitism Effect (Deb et al., 2002) of NSGA-II keeps the best individuals through sequential generations. As a result, the performance of the algorithm is qualified considerably. NSGA-II is currently known as a very famous MOEA among the others (KanGAL, 2005). With these facts in mind, the NSGA-II was utilized for solving the MOP of this research.

2.3.4. NSGA-II

A number of different modules form part of NSGA-II (Deb et al., 2002):

- A fast non-dominant sorting approach, by comparing each solution with every other solution in the population to find if it is dominated.
- Density estimation using the average distance.
- A crowded comparison operator ($\geqslant_n$), which guides the selection process at the various stages of the algorithm towards a uniformly spread Pareto-optimal front.

The main loop of the NSGA-II algorithm is presented in Fig. 2 (Deb et al., 2002). Initially, a random parent population P_0 is created. The population is sorted based on the non-domination. Each solution is assigned a fitness equal to its non-domination level (1 is the best level). Thus, minimization of fitness is assumed. Binary tournament selection, recombination, and mutation operators are used to create a child population Q_0 of size N. From the first generation onward, the procedure is different. The elitism procedure for $t \geqslant 1$ and for a particular generation is shown in the following.

As Fig. 2 shows, a combined population $R_t = P_t \cup Q_t$ is first formed. The population R_t will be of size $2N$. Then, the population R_t is sorted according to non-domination. The new parent population P_{t+1} is formed by adding solutions from the first front until the size exceeds N. Thereafter, the solutions of the last accepted front are sorted according to $\geqslant_n$ and the first N points are picked. This is how the population P_{t+1} of size N is constructed. This population of size N is now used for selection, crossover and mutation to create a new population Q_{t+1} of size N. It is important to note that a binary tournament selection operator is used, but the selection criterion is now based on the crowded comparison operator $\geqslant_n$.

3. Practical tests: A case study

A practical test was conducted over a 150 ha area of Tehran, the capital of Iran, in order to solve an evacuation problem. Fig. 3 shows the test area including 118 building blocks with a total population of 22,000 and 7 safe areas with a total capacity of 20,000 persons.

As Fig. 3 shows, several roads surround a building block. A building in a block generally has access to one of the surrounding roads depending on its location in the building block. In order to reduce the complexity of the modeling, each building block was approximated by four points, each representing an access point for some building to a certain road (Fig. 4). Additionally, the coordinates of the centroid of the safe areas were considered as their location (Fig. 4).

$R_t = P_t \cup Q_t$	combine parent and children population
$F = \text{FAST-NONDOMINATED-SORT}(R_t)$	$F = (F_1, F_2, \ldots)$ all non-dominated fronts of R_t
until $\lvert P_{t+1} \rvert < N$	till the parent population is filled
$\quad \text{CROWDING-DISTANCE-ASSIGNMENT}(F_i)$	calculate crowding distance in F_i
$\quad P_{t+1} = P_{t+1} \cup F_i$	include i-th non-dominated front in the parent pop
sort $(P_{t+1}, \geq n)$	sort in descending order using $\geq n$
$P_{t+1} = P_{t+1}[0:N]$	choose the first N elements of P_{t+1}
$Q_{t+1} = \text{MAKE-NEW-POP}(P_{t+1})$	use selection, crossover and mutation to create a new population Q_{t+1}
$t = t + 1$	

Fig. 2. NSGA-II Algorithm (Deb et al., 2002).

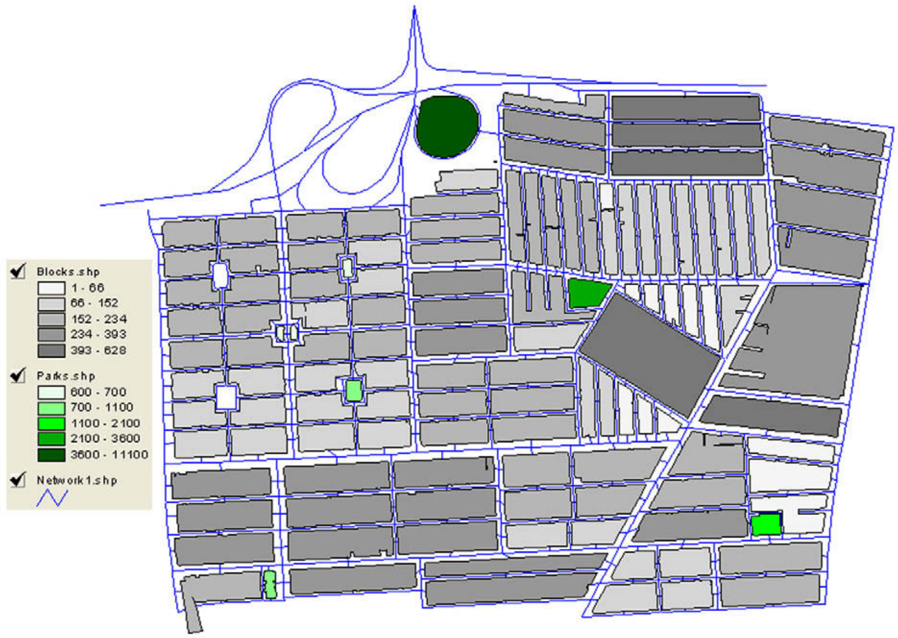

Fig. 3. The case study area.

The three-step approach, which has been proposed in this paper (Fig. 1), was adopted for evacuation planning. For the first step, as highlighted earlier, the pre-designed safe areas for Tehran (JICA and TDMMC, 2004) were utilized. Then, in the second step, the candidate safe areas for each building group (represented by gray points in Fig. 4) were determined in GIS, and the optimum path between the building groups and the relevant candidate safe areas were found. In the last step, the MOP was solved. To solve the MOP, The NSGA-II was coded in MATLAB software. The coordinates of building blocks and the safe areas as well as the length of optimum paths between the building groups and the relevant candidate safe areas were extracted from GIS and exported to a file, which was then used as the input for the NSGA-II. Finally, the results were exported to and presented in a GIS environment.

In order to solve the MOP of this research, a population with $N = 1000$ individuals was evolved in 200 sequential generations using NSGA-II to get the optimum solutions of the final Pareto front. Fig. 5 illustrates the optimization of U and V, as the capacity and nearness objective functions, respectively, through the evolution process. In Fig. 5, the upper graph shows the first Pareto set size (vertical axes) for each generation (horizontal axis). The first Pareto set includes the best individuals in the population which dominate all other individuals. As the graph shows, the number of the best individuals increases through generations until including the whole population in the set.

The other graphs in Fig. 5 illustrate the optimization process of U and V objective functions. In each graph, three solutions for the best (red), the worst (green) and the moderate (blue) individuals, in each generation, are presented. As the graphs show, from the 150th generation onward, there was no significant improvement in the optimization process, thus indicating that the algorithm has achieved the approximate global opti-

Fig. 4. The point model of the case study area.

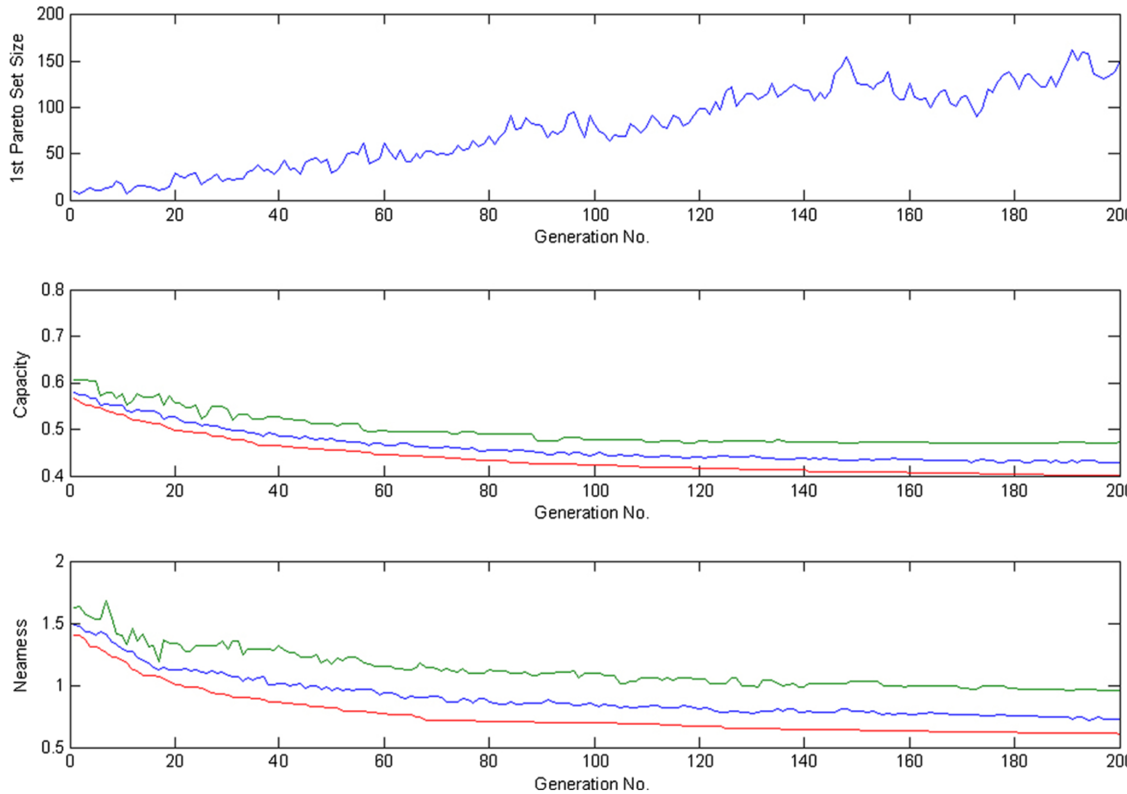

Fig. 5. The first Pareto set size (upper), capacity (middle) and nearness (bottom) in optimization process by NSGA-II approach.

mums. Although the final solution may not be the exact optimum, it satisfies the *U* and *V* objective functions. The satisfaction level depends on the number of generations and improves on a logarithmic scale.

Fig. 6 illustrates the evolution process in six different generations to get to the final Pareto front. As Fig. 6 shows, more improper individuals exist in the first generation population. The number

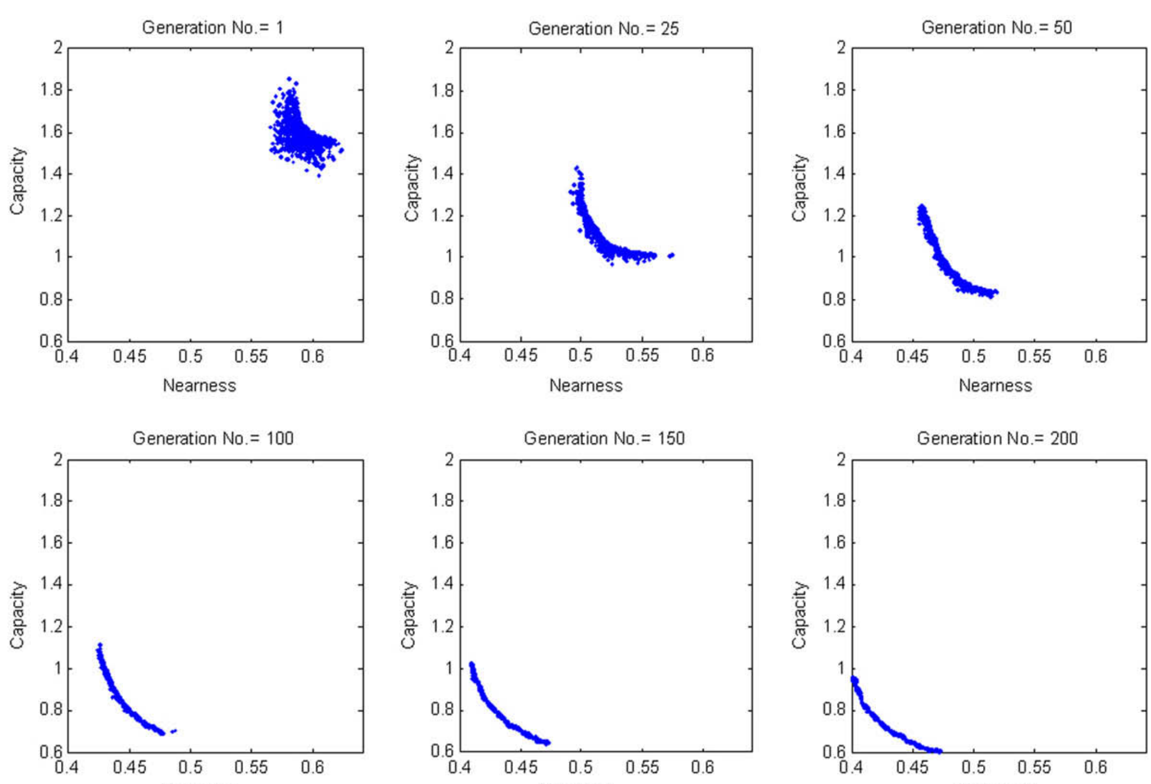

Fig. 6. Multiobjective *U* and *V* optimization process by NSGA-II.

of proper individuals increases with generations, and the first Pareto front moves toward the global optimum.

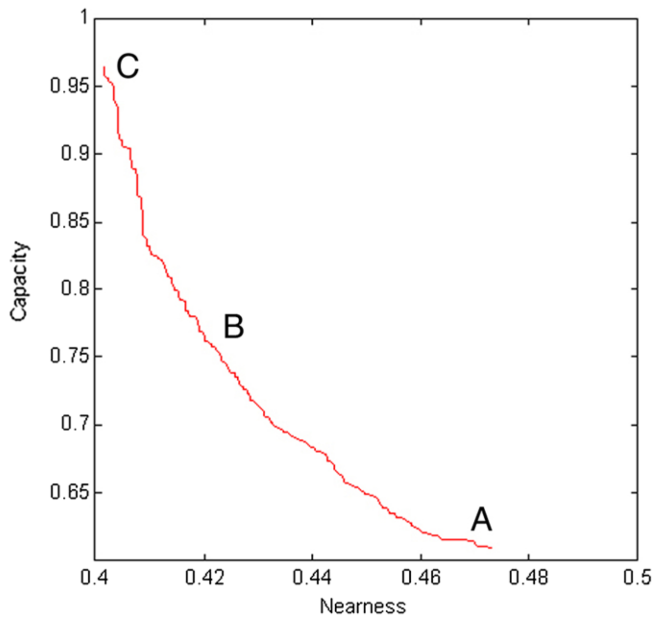

Fig. 7. The final Pareto front.

The evolution of sequential generations will attain the final Pareto front, which includes the global optimum points. By joining these points, a line can be drawn (Fig. 7) that shows the Pareto optimality of the evacuation problem. Every point on the line indicates a global optimum point, giving values for the *U* and *V* functions.

As Fig. 7 shows, all points, such as 'A', 'B' or 'C', are in the final Pareto front. Any point on the Pareto front offers a trade-off between a specific value of *V* and a specific value of *U*. It should be noted that, by selecting 'A' or 'C', optimization is conducted by giving the first priority on the nearness or capacity criteria, respectively. The 'B' point represents a case in which a similar priority has been given to both the nearness and the capacity criteria.

Considering the point 'B' (in Fig. 7) as the optimum point of the research problem, Fig. 8 illustrates the search process over different generations, which assigns buildings to the safe areas (each line indicates allocated buildings, represented by gray points in Fig. 4, to a safe area). As Fig. 7 shows, the grouping becomes more optimal in such a way as to bring the last generations into a star pattern with the safe areas at the center and buildings at the end point of lines. We also note that, before the 150th generation, the optimization and changes in the grouping process are considerable. However, only minor change/optimization is observed from the 150th generation to the next.

Fig. 9 illustrates a comparison among different optimization solutions when A, B and C (see Fig. 7) are selected as optimum points.

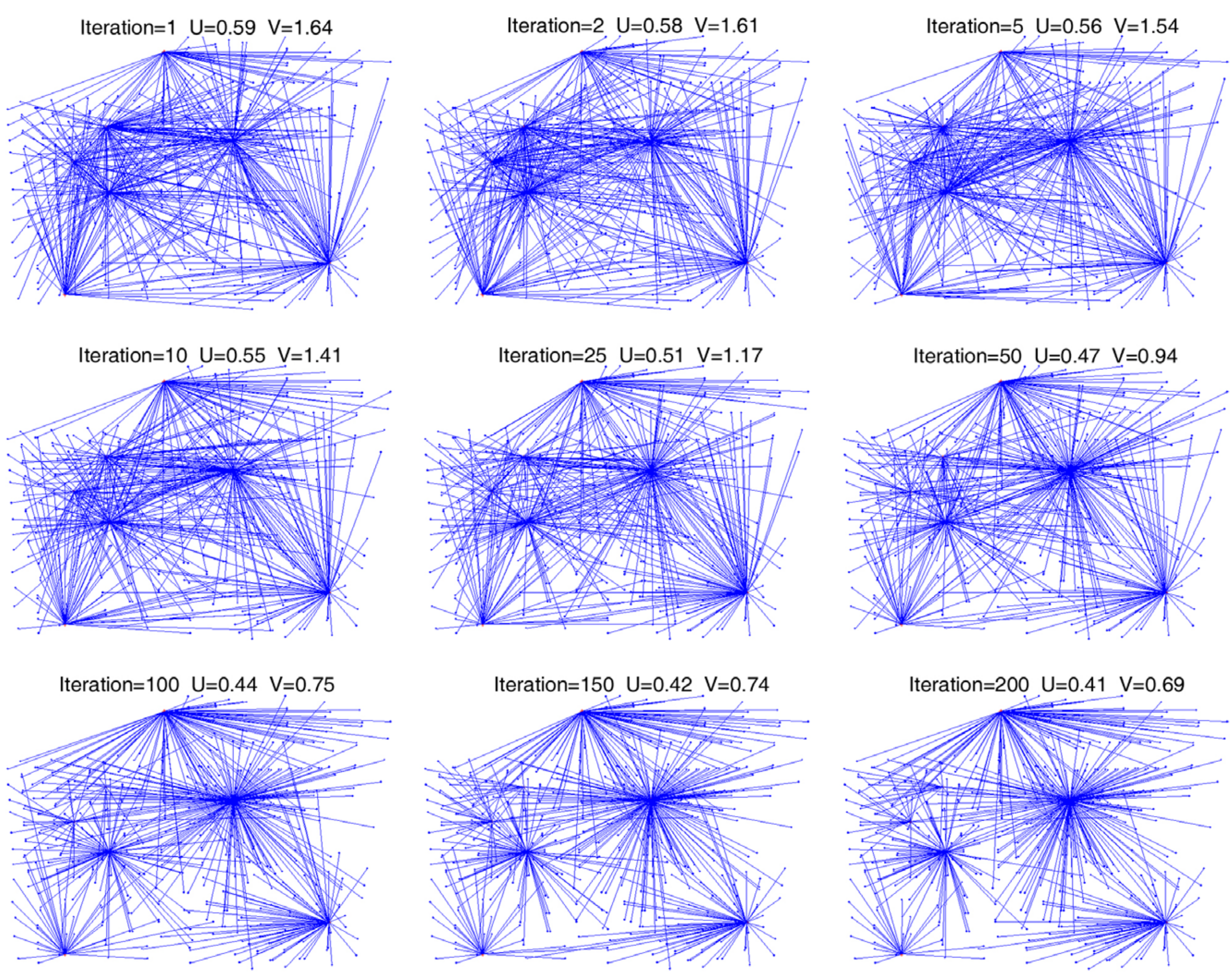

Fig. 8. The improvement of optimum solution of case 'B' through generations.

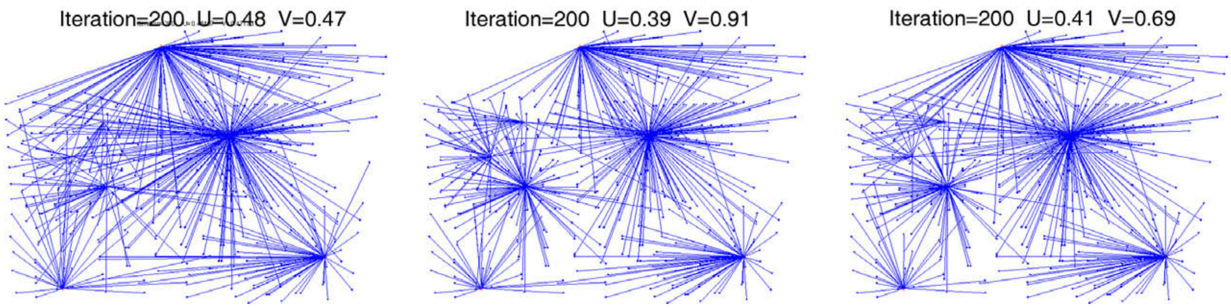

Fig. 9. The global optimum solutions for different cases A, B and C, from left, respectively.

For case ‘C’, the capacity criterion has a higher priority in comparison to the nearness criterion, for assigning buildings to safe areas, so the grouping of buildings moves toward a complex shape. On the other hand, for case ‘A’, the nearness criterion has a higher priority in comparison to the capacity criterion, so the grouping of buildings moves toward a regular star shape. Case ‘B’ gives similar priority to the capacity and nearness criteria, so its corresponding pattern does not exhibit the complexity of case ‘C’. It is also a little bit different from ‘A’.

Fig. 10a shows star shape of assigned buildings to a safe area, and Fig. 10b shows the same assignment along the routing network. In other words, the optimum path that victims should use to get into the relevant safe area has been illustrated in Fig. 10b.

4. Analyses of the results

4.1. Investigate the repeatability of the algorithm

In Heuristic search methods, the results will change when the algorithm is run again. This is due to the effect of random elements in the search process. Therefore, in order to investigate the rate of such changes in the results of this research, the algorithm was run five times with the same parameters: population size 500 and number of generations 200. Table 1 and Fig. 12 show the results.

As Fig. 11 and Table 1 show, there is not a significant difference between derived U and V fitness values in different runs. Existing differences indicate that the problem has several important local optimal solutions to which the algorithm sometimes re-converges. Meanwhile, it is notable that the same results are obtained from the 1st and the 3rd runs. A more detailed investigation was conducted on the results, and it was concluded that the average repeatability of the algorithm is about 72%.

Table 1
Repeatability test of the algorithm

No.	Population size	Number of generations	Number of solutions in 1st Pareto front	*V*	*U*
1	500	200	102	0.6751	0.4196
2	500	200	99	0.6794	0.4141
3	500	200	102	0.6751	0.4196
4	500	200	113	0.6328	0.4164
5	500	200	117	0.6025	0.4311

It was also observed that buildings that have been assigned to different safe areas in different repetitions of the algorithm have the following characteristics that indicate that such changes are not large enough to be critical for the planning process:

- they have a lower population than other buildings and/or
- their distances from the candidate safe areas are approximately equal.

4.2. Investigating the effect of parameters setting on the algorithm

Although NSGA-II algorithms do not use most of the parameters that are usually set in evolutionary algorithms, two parameters should be still set: the number of generations and the number of individuals in each generation (population size). The product of

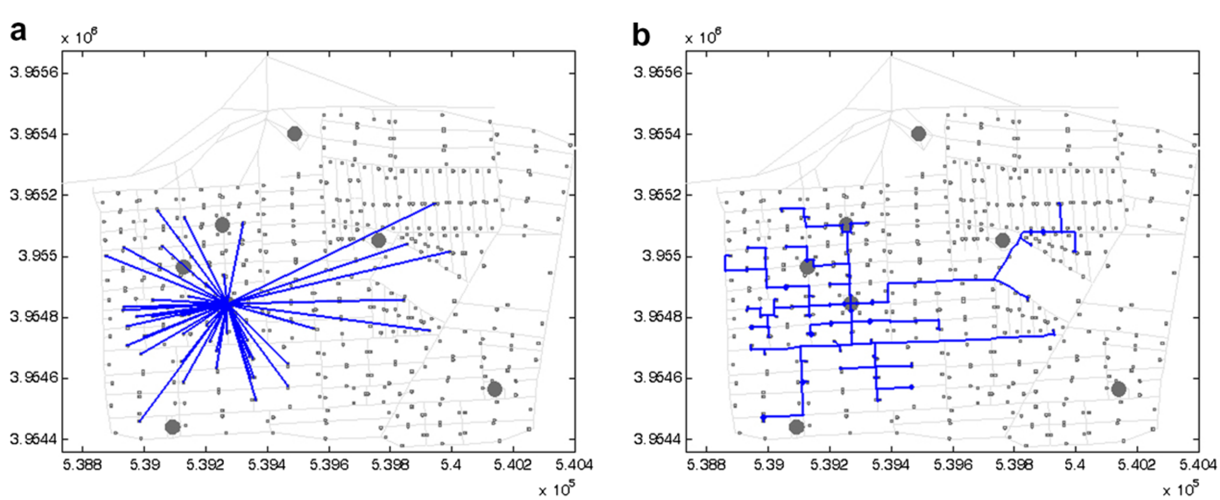

Fig. 10. Assigned building blocks to a safe area: (a) a star shape presentation; (b) presentation along the routing network.

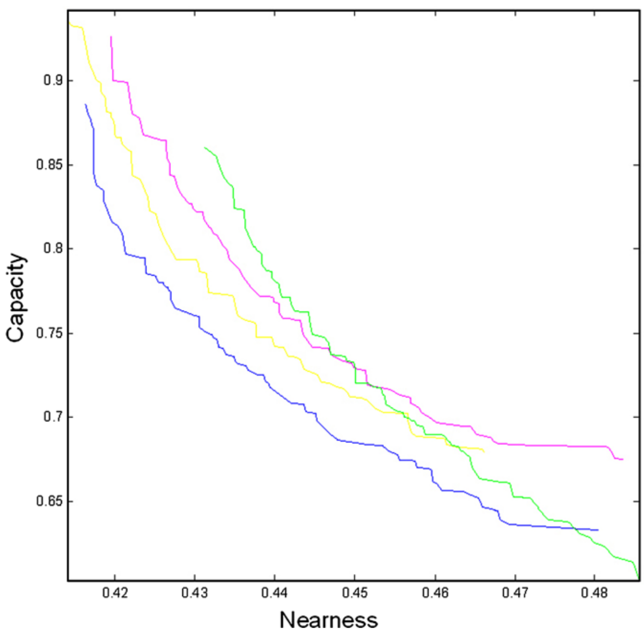

Fig. 11. Representation of Pareto fronts in repeatability investigation.

Table 2
Effect of parameter settings on the algorithm

No.	Population size	Number of generations	Number of solutions in 1st Pareto front	*V*	*U*
1	500	200	102	0.6751	0.4196
2	500	200	99	0.6794	0.4141
3	500	200	102	0.6751	0.4196
4	500	200	113	0.6328	0.4164
5	500	200	117	0.6025	0.4311

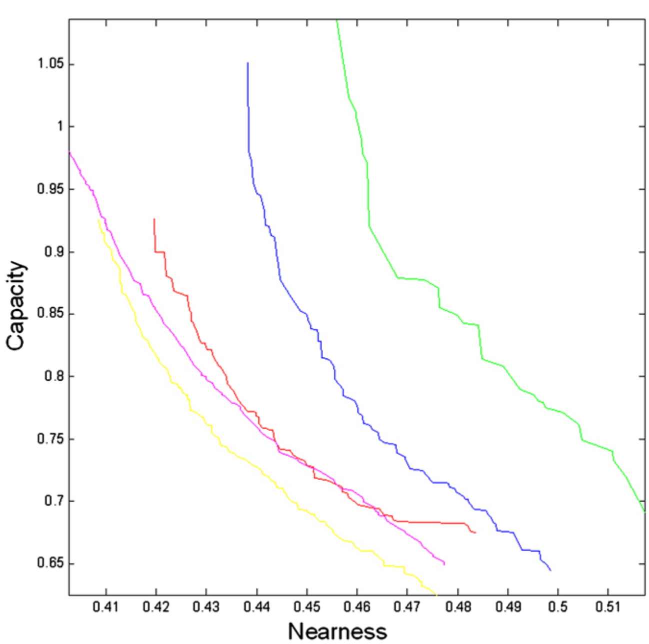

Fig. 12. Representation of Pareto fronts in parameters setting investigation.

the multiplying these two parameters is a factor which is known as "function evaluation". The "function evaluation" represents the complexity of the algorithm. To investigate the effect of different settings of the parameters in the algorithm, the value for function evaluations should be fixed.

To investigate the effect of various parameter choices, the function evaluation value was experimentally set to 100,000, similar to the repeatability test. The algorithm was run five times, with different settings on the population size as well as the number of generations (Table 2 and Fig. 12).

As illustrated in Table 2 and Fig. 12, by decreasing the population size, in spite of increasing the number of generations, a more optimum Pareto Front is generally achieved. In addition, it can be seen that the changing rate of fitness value *V* is irregular with the change of parameter settings, implying that *V* is more sensitive than *U*. Given this, we expect that, for different numbers of generations and population sizes, the better result is usually achieved for *U*.

5. Conclusion and future trends

Determining how to distribute people to the available safe areas is one of the major steps of evacuation planning in disaster management. This paper proposed a three-step approach for evacuation planning. It was highlighted that, for the third step, different factors should be simultaneously optimized in order to achieve the best distribution pattern of people to the safe areas. Of these, the distance of people from the safe areas and the capacity of the safe areas were taken as the two most important. With this in mind, the paper highlighted that the third step of evacuation planning is a kind of spatial MOP. In the context of a case study project, the proposed three-step approach was utilized in order to investigate the proposed approach and also to address the use of MOP for evacuation planning. Two objective functions were defined, and then the spatial MOP was solved using the NSGA-II algorithm in a GIS environment. The results showed that spatial MOP can facilitate evacuation planning by finding a proper pattern for assigning people to the safe areas by simultaneous optimization of affecting criteria.

In planning activities allocation is traditionally conducted based on the zoning method. However, zoning planning can make some aggregation errors affecting the results. These errors occur due to the two following facts: (i) by aggregating required data in a zone, it is assumed that there is not any variance within the zone; (ii) planners often use a single point to represent a zone for distance calculations, etc. In the proposed method of this paper, we use finer resolution data (building blocks), indicating the spatial distribution of evacuees, to remove the errors associated with zoning planning.

To be realistic, we note that evacuee behaviors and traffic control strategies highly affect evacuation planning. Modeling these factors in the proposed method is a subject for further research. In addition, more work should be done for simultaneous mobilization of evacuees to the determined safe areas in terms of prioritization of the evacuee groups and departure scheduling of the groups aimed at reducing traffic congestion.

References

Abbass, H.A., Sarker, R., 2002. The Pareto differential evolution algorithm. International Journal on Artificial Intelligence Tools 11 (4), 531–552.
Balram, S., Dragicevic, S. (Eds.), 2006. Collaborative Geographic Information Systems. Idea Group Inc., New York, p. 364.
Budic, Z.D., Pinto, J.K., 1999. Interorganizational GIS: Issues and prospects. The Annals of Regional Science 33 (2), 183–195.
Chow, W.K., Lui, C.H., 2002. Numerical studies on evacuation design in a karaoke. Building and Environment 37, 285–294.
Coello Coello, C.A., 2003. A comprehensive survey of evolutionary-based multi-objective optimization techniques. Knowledge and Information Systems 1 (3), 269–308.
Coello Coello, M.A., 2002. Introduction to Evolutionary Multi-objective Optimization, lecture notes, Depto. de Ingenier'ıa El'ectrica, Secci'on de Computaci'on, Instituto Polit'ecnico Naciona, MEXICO.

Cova, T.J., Church, R.L., 1997. Modelling community evacuation vulnerability using GIS. International Journal of Geographical Information Science 11 (8), 763–784.

Cova, T.J., Justin, P.J., 2003. A network flow model for lane-based evacuation routing. Transportation Research Part A 37, 579–604.

Deb, K., Pratap, A., Agarwal, S., Meyarivan, T., 2002. A fast and elitist multi-objective genetic algorithm: NSGA-II. IEEE Transaction on Evolutionary Computation 6 (2), 181–197.

ElDessouki, W.M., 1998, Some Developments in Transportation Network Analysis and Design with Application to Emergency Management Problems. Ph.D. Dissertation, North Carolina State University.

Feng, C.M., Wen, C.C., 2003. Traffic control management for earthquake-raided area. Journal of the Eastern Asia Society for Transportation Studies 5, 3261–3275.

Fonseca, C.M., Fleming, P.J., 1993. Genetic algorithms for multi-objective optimization: Formulation, discussion and generalization. In: Proceedings of the Fifth International Conference on Genetic Algorithms. Morgan Kauffman, San Mateo, CA, pp. 416–423.

Georgiadou, P.S., Papazoglou, I.A., Kiranoudis, C.T., Markatos, N.C., 2006. Modeling emergency evacuation for major hazard industrial sites. Reliability Engineering and System Safety. doi:10.1016/j.ress.2006.09.009.

Horn, J., Nafploitis, N., Goldberg, D.E., 1994. A niched Pareto genetic algorithm for multi-objective optimization. In: Proceedings of the First IEEE Conference on Evolutionary Computation. IEEE Service Center, Piscataway, NJ, pp. 82–87.

Iannoni, A.P., Morabito, R., Saydam, C., 2009. An optimization approach for ambulance location and the districting of the response segments on highways. European Journal of Operational Research 195 (2), 528–542.

JICA and TDMMC, 2004. The comprehensive master plan study on urban seismic disaster prevention and management for the Greater Tehran Area in the Islamic Republic of Iran, Final Report, August 2004, Pacific Consultants International. OYO Cooperation.

KanGAL, 2005. Kanpur Genetic Algorithms Laboratory, http://www.iitk.ac.in/kangal/index.shtml, visited on September 2007.

Kongsomsaksakul, S., Yang, C., 2005. Shelter location-allocation model for flood evacuation planning. Journal of the Eastern Asia Society for Transportation Studies 6, 4237–4252.

Mansourian, A., Rajabifard, A., Valadan Zoej, M.J., Williamson, I.P., 2006. Using SDI and web-based systems to facilitate disaster management. Journal of Computers and GeoSciences 32 (6), 303–315.

Murray, P.M., Mahmassani, H.S., 2003. Model of household trip chain sequencing in an emergency evacuation. Presented at 82nd Annual Meeting of the Transportation Research Board, Washington, DC.

Negreiros, M., Palhano, A., 2006. The capacitated centered clustering problem. Computers and Operations Research 33 (6), 1639–1663.

Pal, A., Graettinger, A.J., Triche, M.H., 2003. Emergency evacuation modeling based on geographical information system data. TRB 2003 Annual Meeting.

Pursals, S.C., Garzon, F.G., 2009. Optimal building evacuation time considering evacuation routes. European Journal of Operational Research 192 (2), 692–699.

Schaffer, J.D., 1985. Multiple objective optimization with vector evaluated genetic algorithms. In: Proceedings of an International Conference on Genetic Algorithms and their Applications, pp. 93–100.

Sherali, H.D., Carter, T.B., Hobeika, A.G., 1991. A location-allocation model and algorithm for evacuation planning under hurricane/flood conditions. Transportation Research Part B 25 (6), 439–452.

Srinivas, N., Deb, K., 1995. Multi-objective function optimization using non-dominated sorting genetic algorithms. Evolutionary Computation 2 (3), 221–248.

Vakalis, D., Sarimveis, H., Kiranoudis, C., Alexandridis, A., Bafas, G., 2004. A GIS based operational system for wildland fire crisis management. I. Mathematical modelling and simulation. Applied Mathematical Modelling 28 (4), 389–410.

Wilson, P.B., Macleod, M.D., 1993. Low implementation cost IIR digital filter design using genetic algorithms. IEE/IEEE workshop on Natural Algorithms in Signal Processing, 1–8.

Wu, L.Y., Zhang, X.S., 2006. Capacitated facility location problem with general setup cost. Computers and Operations Research 33 (5), 1226–1241.

Yi, W., Kumar, A., 2007. Ant colony optimization for disaster relief operations. Transportation Research Part E. doi:10.1016/j.tre.2006.05.004.

Yi, W., Özdamar, L., 2007. A dynamic logistics coordination model for evacuation and support in disaster response activities. European Journal of Operational Research 179 (2007), 1177–1193.

Zeng, H., Pukkala, T., Peltola, H., 2007. The use of heuristic optimization in risk management of wind damage in forest planning. Forest Ecology and Management 241 (1–3), 189–199.

Zitzler, E., Deb, K., Thiele, L., 1999. Comparison of Multi-Objective Evolutionary Algorithms: Empirical Results. TIK-Report No. 70, Institut fur Technische Informatik und Kommunikationsetze, EYH Zurich, Gloriastrasse 35, ETH-Zentroom, CH-8092 Zurich, Switzerland, February 12, 1999.

Zitzler, E., Thiele, L., 1998. Multiobjective optimization using evolutionary algorithms – A comparative case study. In: Eiben, A.E., Ɓack, T., Schoenauer, M., Schwefel, H.-P. (Eds.), Parallel Problem Solving from Nature, vol. V. Springer, Berlin, Germany, pp. 292–301.