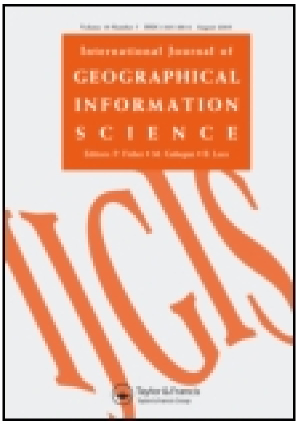


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# A modified particle swarm optimization algorithm for optimal allocation of earthquake emergency shelters

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Allocation for earthquake emergency shelters is a complicated geographic optimization problem because it involves multiple sites, strict constraints, and discrete feasible domain. Huge solution space makes the problem computationally intractable. Traditional brute-force methods can obtain exact optimal solutions. However, it is not sophisticated enough to solve the complex optimization problem with reasonable time especially in high-dimensional solution space. Artificial intelligent algorithms hold the promise of improving the effectiveness of location search. This article proposes a modified particle swarm optimization (PSO) algorithm to deal with the allocation problem of earthquake emergency shelter. A new discrete PSO and the feasibility-based rule are incorporated according to the discrete solution space and strict constraints. In addition, for enhancing search capability, simulated annealing (SA) algorithm is employed to escape from local optima. The modified algorithm has been applied to the allocation of earthquake emergency shelters in the Zhuguang Block of Guangzhou City, China. The experiments have shown that the algorithm can identify the number and locations of emergency shelters. The modified PSO algorithm shows a better performance than other hybrid algorithms presented in the article, and is an effective approach for the allocation problem of earthquake emergency shelters.

**Keywords:** discrete particle swarm optimization; constraint handling method; simulated annealing; optimal allocation; earthquake emergency shelters

## 1. Introduction

In recent decades, the population affected by various natural disasters has increased around the world, especially in disaster-prone cities with dense population (Hainesa *et al*. 2006, Srinivasa and Nakagawa 2008). Efficient disaster management plays a critical role in mitigating human suffering and damages from natural disasters. Currently, the main research work in disaster management focuses on transportation for the injured and delivery of relief material (Yi and Ozdamar 2007, Sheu 2007, 2010, Widerner and Horner 2011), relief resource allocation (Fiedrich *et al*. 2000, Rawls and Turnquist 2010), and evacuation planning under disaster conditions (Pidd *et al*. 1996, Chen *et al.* 2006a, Yuan and Han

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2010). But relatively little research has been conducted on shelter planning, which is an indispensable part of disaster management. Establishing emergency shelters provides great benefit for postdisaster relief work. About 250,000 people stayed in shelters after the Great Eastern Japan earthquake,[1] making the disaster-affected population much accessible by the government in rescue operations.

So far, much of the efforts in disaster shelter research have concentrated on the identification of designing criteria and location requirements (Liu *et al*. 2010) or on adaptability assessment (Bradford and Sen 2005, Ma *et al*. 2005, Ruang *et al*. 2006). Comparatively, only few literatures pertain to optimal shelter allocation. Huang *et al.* (2006) developed a fuzzy multi-objective model considering coverage maximization and distance balancing; Saadatseresht *et al.* (2009) proposed a bi-objective model minimizing maximum distance and capacity violation; Ng *et al.* (2010) brought forth a hybrid bi-level model considering minimizing total evacuation time and individual evacuation time; Li *et al.* (2008) put forward a model for minimizing the travel cost and keeping spatial continuity with capability constraint. These literatures have all considered distance and capacity factors, meanwhile ignoring minimizing the cost of construction and maintenance of shelters. In reality, however, disaster mitigation funds are often limited, and cost is an important factor to consider in planning emergency shelters. Moreover, the studies identified above have only considered large-scale and long-term shelters away from residential zones, with limited reference to community emergency shelter allocation. Emergency shelters in large urban areas are small open spaces near residential zones that provide immediate refuge services when disasters strike. They are especially important for areas with very high population density, such as many large cities in China. In fact, although a highly efficient early warning system is in place in Japan, it can only offer a 1 min or even several seconds of response time in advance of the quakes.[2] So the accessibility to available shelters plays an important role in improving the survival rate in disaster-affected areas.

The model proposed in this article is suitable for solving the optimal allocation problem of earthquake emergency shelter (OAEES problem) based on community-level units. It not only takes into account the capability constraint and distance constraint but also considers cost saving for shelter construction.

The OAEES problem is a complicated geographic optimization problem, because it involves strict constraints and a huge discrete feasible domain. Traditional brute-force method can obtain exact optimal solution by enumerating all possible combinations (Li *et al*. 2009). Unfortunately, the method cannot solve the problem within a reasonable time. As state-of-the-art models, artificial intelligent algorithms come into play, because they can improve the performance of location search by providing a suitable trade-off between solution quality and computation. In this article, a relatively new particle swarm optimization (PSO) algorithm is used, which improves effectiveness in solving the OAEES problem. PSO was first proposed by Kennedy and Eberhart in 1995, based on the metaphor of social interaction and communication of bird flocking. Similar to genetic algorithm (GA) and ant colony optimization (ACO), PSO is developed into an important tool for solving difficult optimization problems. It has powerful search capability by combining local search and global search (Xia and Wu 2006). Compared with simulated annealing (SA) and other heuristic algorithms, PSO has much stronger intelligent background. The implementation of PSO is more convenient than GA due to PSO's requirement for fewer parameters; and PSO is relatively easier to comprehend than ACO.

Standard PSO algorithms are easily trapped into local optima during the post-search period. Hybridization is an effective approach for overcoming this difficulty. It is proven to be of great robustness and efficiency, with the main merits of making full use of one approach to offset the drawbacks of the other and thus being superior to each single method. Some studies hybridizing PSO with other algorithms have been successfully applied to various optimization problems. For example, Shi *et al.* (2003) hybridized PSO and GA to find global optimum; Fan *et al.* (2004) incorporated the Nelder-Mead (NM) simplex search method into PSO for the multimodal function optimization problem; Afshinmanesh *et al.* (2005) combined binary coding PSO and artificial immune system to accelerate the convergence process; Shelokar *et al.* (2007) made a combination of PSO and ACO for highly non-convex optimization problems; Yin *et al.* (2007) solved a task allocation problem by incorporating a hill-climbing heuristic into PSO.

However, PSO has not received much attention for solving geographic optimization problems. In this article, a modified algorithm based on PSO is proposed, in which three important methods are hybridized with PSO. First, the OAEES problem is an integer programming problem whose feasible solution domain is discrete. A new discrete PSO (NDPSO) algorithm proposed by Pan *et al.* (2008) is employed, which can let all particles move all around the discrete search space. Second, the OAEES problem is also a constrained optimization problem. Accordingly, utilizing constraint-handling technique becomes ineluctable. Owing to its simple logic, ease to implement, and effectiveness, the feasibility-based rule proposed by He and Wang (2007a) is used to deal with the constrained optimization problem. Third, to enhance the search capability, PSO is hybridized with SA to escape from local optima and focus computing effort upon the most promising solutions. Hybrid PSO and SA has been widely used in optimization problems of other fields (Zhao *et al*. 2007, Liu *et al*. 2008, Niknam *et al*. 2009). In other words, NDPSO provides the global search ability for discrete-coded particles and the feasibility-based rule makes all particles have tendency to the feasible solutions, but the DPSO and feasibility-based rule combination has the shortcoming of premature convergence. SA can help in converging to the global optimum, although it is sensitive to the initial point provided by NDPSO. Therefore, the modified PSO algorithm that hybridized NDPSO, the feasibility-based rule, and SA is proposed to tackle the OAEES problem. Compared with other hybrid algorithms, the modified PSO algorithm shows great effectiveness, and the feasible result also demonstrates that the algorithm is viable for solving the OAEES problem.

## 2. Standard PSO algorithm

PSO is an evolutionary algorithm based on mimicking simplified social behavior, such as bird flocking and fish schooling, whose goal is to find an optimal position for several objectives in a multidimensional space (Kennedy and Eberhart 1995, Eberhart and Shi 2001). In PSO, each intelligent individual searching for an optimal position is called a particle. Each particle represents a candidate solution that can be evaluated by a preset evaluation function. Flying in a $D$-dimensional search space, a particle changes its velocity dynamically based on its own flying experience and the flying experience of its colleagues. The PSO algorithm begins with randomly initializing a swarm of particles, then iteratively adjusts the flying trajectory of each particle toward its personal best position (called local optimum) and toward the best particle of swarm (called global optimum), and finally achieves an optimal solution.

In the $D$-dimensional search space, the $a$th particle's position in the $u$th generation is represented as $X_a(u) = \{x_{a1}(u), x_{a2}(u), \ldots, x_{aD}(u)\}$; similarly, the velocity can be represented as $V_a(u) = \{V_{a1}(u), V_{a2}(u), \ldots, V_{aD}(u)\}$. The velocity and position of each particle can be updated according to Formula (1) and Formula (2), respectively:

$$v_{ad}(u+1) = \omega(u)v_{ad}(u) + c_1r_1\left(X_a^P(u) - x_{ad}(u)\right) + c_2r_2\left(X^G(u) - x_{ad}(u)\right) \quad (1)$$

$$x_{ad}(u+1) = x_{ad}(u) + v_{ad}(u+1) \quad (2)$$

where $A$ denotes population size and the variable $a = 1, 2,\ldots, A$; $U$ denotes maximum number of generations and the variable $u = 1, 2,\ldots, U$; $D$ denotes the dimension of a particle, the variable $d = 1, 2,\ldots, D$; $X_a^p$ and $X^G$ denote local optimum and global optimum; $c_1$ and $c_2$ are learning factors; $r_1$ and $r_2$ are the uniform random numbers generated between 0 and 1; and $\omega(u)$ is inertia weight.

In Formula (1), the first part represents a particle's inheritance of previous velocity, reflecting the particle's confidence with current state of motion; the second part represents the particle's cognition, namely, independent thinking; the third part is the social part, expressing the information sharing and mutual cooperation between particles. Formula (2) also conveys the information sharing mechanism.

## 3. Optimal allocation model for earthquake emergency shelters

Before building the model for the OAEES problem, for simplicity two assumptions are made as follows:

(1) The population of a community is concentrated at its centre point. The residents prefer to follow the shortest path when they evacuate to the assigned shelter.
(2) The physical locations of all candidate shelters are predetermined and all residents in a given community can only be assigned to one shelter.

Appropriate shelter allocation is propitious for evacuation in reasonable time and adequate shelter capacity can provide sufficient refuge service for all people in disaster areas. Therefore, all feasible solutions should comply with the following two strict constraints.

(1) Distance constraint: To ensure safety, it is necessary for residents to evacuate to a nearby shelter in a short time when disaster happens. Hence, the distance between each community and its assigned shelter should be within the shelter's maximal service distance, which is the most important constraint and should be given priority.
(2) Capacity constraint: In each shelter, to meet the basic needs for living, the number of residents should not exceed the maximum capacity of the shelter.

Apart from these two important aspects, shelter allocation should also emphasize cost saving due to the limits in funding for disaster mitigation. To save the total construction cost by supposedly having the same construction fee for each shelter, the number of locating emergency shelters should be minimized after satisfying the two constraints, which is the objective of the proposed model for the OAEES problem.

The proposed model for the OAEES problem includes the following variables and sets: $M$ represents the total number of communities in a study area; $J$ denotes the set of communities and $j$ is community index; $P_j$ denotes the population of community $j$; $N$ represents the number of candidate shelters; $I$ denotes the set of candidate shelters and $i$ is shelter index; $S_i$ denotes the area of candidate shelter $i$; $L$ denotes the smallest refuge area per capita, which is preset as 1 $m^2$/person; $d_{ji}$ represents the length of the shortest path between community $j$ and candidate shelter $i$; and $D_{max}$ represents the maximum service distance of an emergency shelter, which is preset as 450 m. The two decision variables are as follows:

$$Y_i = \begin{cases} 1, \text{the } i\text{th candidate shelter is selected as the designated shelter} \\ 0, \text{otherwise} \end{cases}$$

$$B_{ji} = \begin{cases} 1, \text{ the residents in the } j\text{th community are assigned to the } i\text{th candidate shelter} \\ 0, \text{otherwise} \end{cases}$$

$$\text{minimize } Z = \sum_{i=1}^{N} Y \qquad \forall i = 1,\ 2,\ \ldots,\ N \tag{3}$$

Subject to

$$\sum_{j=1}^{M} P_j L B_{ji} - S_i Y_i \leq 0 \qquad \forall i = 1,\ 2,\ \ldots,\ N \tag{4}$$

$$d_{ji} B_{ji} - D_{\max} \leq 0 \qquad \forall i = 1,\ 2, \ldots,\ N \qquad \forall j = 1,\ 2, \ldots,\ M \tag{5}$$

$$\sum_{i=1}^{N} B_{ji} Y_i = 1 \qquad \forall j = 1,\ 2,\ \ldots,\ M \tag{6}$$

$$B_{ji} \in (0, 1) \qquad Y_i \in (0, 1) \tag{7}$$

Formula (3) denotes the objective function and $Z$ denotes the objective function value (OFV); Formula (4) represents the capacity constraint; Formula (5) denotes the distance constraint; Formula (6) expresses that all residents in a community can only be assigned to one shelter; and Formula (7) restricts all the values of decision variables $B_{ji}$, $Y_i$ to the binary numbers 0 and 1.

## 4. The modified PSO algorithm

### *4.1. A new discrete PSO algorithm*

Standard PSO algorithm was initially developed for continuous optimization problems, and its continuous nature prevents it from working with discrete optimization problems. To overcome this limitation, some discrete methods were put forward. Kennedy and Eberhart (1997) proposed a binary-coded PSO, in which the binary-valued position of a particle is generated from its real-valued velocity by employing a sigmoid function with a random probability. But this method is inconvenient to use due to the encoding and decoding process. Chen *et al.* (2006b) adopted a quantum DPSO algorithm developed by Yang *et al.* (2004) to solve the vehicle routing problem. However, the dimension of particle will be huge by using the encoding method in this work. Jin *et al.* (2007) and Xia and Wu (2006) proposed other DPSO algorithms by rounding off real optimum values to the nearest integer numbers. But the discrete value near the real optimal value may fall outside the feasible region and is usually not the optimal solution. Kitayama and Yasuda (2006) created a multimodal augmented objective function by treating the discrete variables in terms of a penalty function. However, the method needs a large amount of computation and has difficulty in determining whether the sufficient local optima have been found.

To the OAEES problem, the integer-coded PSO will be more suitable. Based on the above analysis, we adopt a new discrete method first proposed by Pan *et al.* (2008). In our application, different mutation operator and crossover operator are created to fit the OAEES problem.

### *4.1.1. Position representation*

The traditional idea on location planning is to find $N$ optimal sites for siting a facility. Different from this idea, in this article, the number and location of shelters are identified through finding the optimal evacuation assignment scheme. One of the most important issues in applying PSO algorithm to OAEES problem depends on associating particle positions with evacuation assignment schemes and relating them to the problem domain in an efficient way.

The position of a particle can be expressed as an $M$-dimensional vector:

$$X = (x_1, x_2, \ldots, x_j, \ldots, x_M) \tag{8}$$

where $x_j$ denotes the $j$th ($j = 1, 2, \ldots, M$, the same below) dimension of the position; $M$ is the total number of dimensions of the position.

In this article, the position of a particle $X$ represents a candidate evacuation assignment scheme, corresponding to a candidate shelter allocation scheme. The dimension of position $M$ represents the total number of communities. The value of $j$th dimension of the position $x_j$ is the serial number of a candidate shelter where the residents of $j$th community are to be assigned to.

The serial numbers of candidate shelters are consecutive integers and can be any integer between 1 and $N$. However, considering the distance constraint, it is obvious that the $j$th community is only covered by several candidate shelters that are within a shelter's maximum service distance, whose corresponding serial numbers are inconsecutive, that is, the particles fly between a set of inconsecutive integers. To simplify the problem, we renumber the candidate shelters that cover the $j$th community so that the particles can fly in a new set of consecutive integers.

The renumbering process for candidate shelters is as follows:

(1) Calculating the shortest distance matrix

According to the geographic locations of communities and candidate shelters, based on the evacuation route network, the real shortest distances between communities and candidate shelters, denoted as distance($j$, $i$) ($j = 1, 2, \ldots, M$; $i = 1, 2, \ldots, N$), can be calculated. Then, the shortest distance matrix $DI = [\text{distance}(j, i)_{M \times N}]$ is obtained (see Table 1).

(2) Calculating the coverage matrix

By comparing each element distance ($j$, $i$) of $DI$ with the maximum service distance, the coverage matrix $Q = [q(j, i)_{M \times N}]$ is obtained (see Table 2).

Table 1. The shortest distance matrix.

| | Communities | | | | |
|---|---|---|---|---|---|
| Candidate shelters | 1 | 2 | 3 | ... | $M$ |
| 1 | 733 | 663 | 450 | ... | 733 |
| 2 | 152 | 426 | 395 | ... | 447 |
| 3 | 409 | 984 | 709 | ... | 303 |
| ... | ... | ... | ... | ... | ... |
| $N$ | 731 | 881 | 482 | ... | 731 |

Table 2. The coverage matrix of candidate shelters.

| | Communities | | | | |
|---|---|---|---|---|---|
| Candidate shelters | 1 | 2 | 3 | ... | $M$ |
| 1 | 0 | 0 | 1 | ... | 0 |
| 2 | 1 | 1 | 1 | ... | 1 |
| 3 | 1 | 0 | 0 | ... | 1 |
| ... | ... | ... | ... | ... | ... |
| $N$ | 0 | 0 | 0 | ... | 0 |

The calculation rule is as follows:

If distance $(j, i) \leq 450$, then $q(j, i) = 1$;
If distance $(j, i) > 450$, then $q(j, i) = 0$.

(3) Renumbering the candidate shelters

Let Num($j$) denote the number of candidate shelters that cover the $j$th community ($j = 1, 2,. . ., M$); Cov($j$) denote the set of candidate shelters that cover the $j$th community, with $k_j$ as its index ($k_j = 1,2,. . ., \mathrm{Num}(j)$); New($k_j$) denote the new serial number of these candidate shelters, with the index $k_j$; and Ori($k_j$) denote the original serial number of these candidate shelters, with the index $k_j$.

The candidate shelters that cover the $j$th community are renumbered by a new set of consecutive integers from 1 to Num($j$), so that the particles can fly in this set of consecutive integers. The new serial numbers New($k_j$) of those candidate shelters are equal to their corresponding index $k_j$ in Cov($j$). Simultaneously, the new serial number New($k_j$) also corresponds to a unique original serial number Ori($k_j$). For example, in Table 2, the three candidate shelters numbered 2, 3, and 6 that cover Community 1 are renumbered as 1, 2, and 3, respectively, as shown in Figure 1.

Through the renumbering process, all positions found by the particles comply with the distance constraint and the search space is greatly reduced. The search range of $x_j$ is re-identified as from 1 to Num($j$) in the new set of consecutive integers.

### *4.1.2. Position update method*

With the standard PSO algorithm, a particle's behavior is a trade-off among three directions, that is, at its own position, toward its personal best position, and toward the

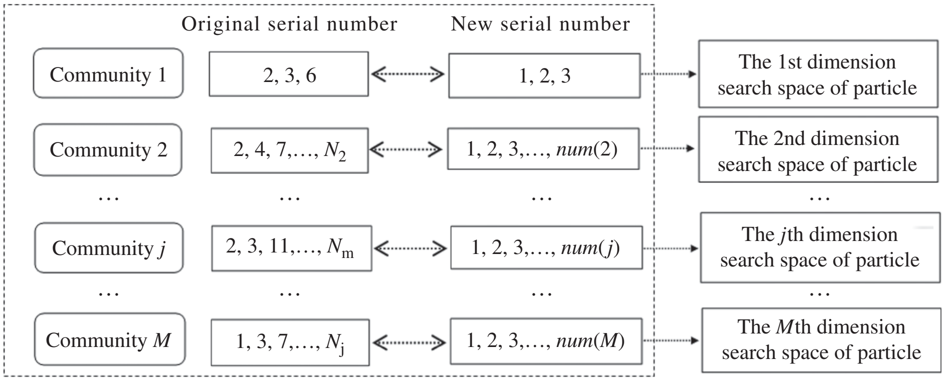


Figure 1. Conversion between original serial numbers and new serial numbers of candidate shelters and the search space of each dimension of the particles.

best position of the particles in the whole swarm population. Therefore, the $a$th particle's position in the $u$th generation can be updated as follows (Pan *et al*. 2008):

$$X_a(u+1) = c_2 \otimes F_3 \left\{ c_1 \otimes F_2 \left[ w \otimes F_1 \left( X_a(u) \right), X_a^P(u) \right], X^G(u) \right\} \tag{9}$$

The position update is realized through the following three steps:

(1) In the first step, $\lambda_a(u+1) = w \otimes F_1 \left( X_a(u) \right)$ ($\lambda_a$ is a $D$-dimensional variable and $\lambda_a = (\lambda_{a1}, \lambda_{a2}, \ldots, \lambda_{aj}, \ldots, \lambda_{aD})$), representing a particle's inheritance of previous position and reflecting the particle's confidence with current state of motion. $F_1$ represents the mutation operator for each dimension of the particles with the probability of $w$. The mutation operator is performed as follows:

$$\lambda_{aj}(u+1) = \begin{cases} \hat{x}, & \text{if } r < w \\ x_{aj}(u), & \text{otherwise} \end{cases} \tag{10}$$

Note that $\hat{x}$ is integer$\in [1, \mathrm{num}(j)]$ and $\hat{x} \neq x_{aj}(u)$. The uniform number $r$ is randomly generated and is between 0 and 1.

(2) In the second step, $\delta_a(u+1) = c_1 \otimes F_2 \left( \lambda_a(u+1), X_a^P(u) \right)$ ($\delta_a$ is a $D$-dimensional variable and $\delta_a = (\delta_{a1}, \delta_{a2}, \ldots, \delta_{aj}, \ldots, \delta_{aD})$), representing the particle's cognition, that is, independent thinking of the particle itself. $F_2$ represents the crossover operator with the probability of $c_1$. If $r$ is larger than $c_1$ then $\delta_a(u+1) = \lambda_a(u+1)$, otherwise $\lambda_a(u+1)$ and $X_a^P(u)$ will be the first and second parents for the crossover operator, respectively. The crossover operator is performed as follows and two offspring are generated:

$$\delta_{aj}^1(u+1) = \begin{cases} \lambda_{aj}(u+1), & \text{if } j \leq b \\ X_{aj}^P(u), & \text{otherwise} \end{cases} \tag{11}$$

$$\delta_{aj}^2(u+1) = \begin{cases} X_{aj}^P(u), & \text{if } j \le b \\ \lambda_{aj}(u+1), & \text{otherwise} \end{cases} \quad (12)$$

Note that $b$ is the crossover position, which is an integer value between 1 and $M - 1$.

(3) In the third step, $X_a(u+1) = c_2 \otimes F_3(\delta_a(u+1), X^G(u))$, representing the social part of the particle, namely, the collaboration among particles. $F_3$ represents the crossover operator with the probability of $c_2$. If $r$ is larger than $c_2$ then $X_a(u+1) = \delta_a(u+1)$, otherwise $\delta_a(u+1)$ and $X^G(u)$ will be the first and second parents for the crossover operator, respectively. The crossover operator is the same as the second step.

If neither the second step nor the third step implemented the crossover operator, then only one offspring is generated; if only one step implemented the crossover operator, then two offspring are generated; if the crossover operator was implemented twice, then four offspring are generated. For the two latter cases, one of the offspring is chosen randomly as a new position with an equal probability.

The position update method used in this article is suitable for the discrete optimization problem due to a number of remarkable advantages. First, the position of a particle is a rational integer value throughout the whole update process, which makes it convenient to map a particle's position to an evacuation assignment scheme. Second, the mutation and crossover operators are employed to maintain the diversity of particles in swarm population so that the global search ability of the algorithm is enhanced. Moreover, the direction of a particle's evolution is toward its personal best position and toward the best position in the whole swarm, which accelerates the convergence of the particles. In addition, it need not consider the velocity of a particle.

#### *4.1.3. Parameter selection*

*4.1.3.1. Population size.* Population size has much influence on the convergence and computation of the PSO algorithm. If a population size is too large, the algorithm will take a long time to calculate; if it is too small, the algorithm will easily converge to local optima. For general optimization problems, the algorithm achieves best solution when the population size is between 30 and 50 (Kennedy and Eberhart 1995).

*4.1.3.2. Initialization of position.* In the new set of consecutive integers, the initial position of the $a$th particle on each dimension, denoted as $X_{aj}(0)$, is given by Formula (13):

$$X_{aj}(0) = \mathrm{INT}(r \times \mathrm{num}(j) + 1) \quad \forall j = 1, 2, \ldots, M \quad \forall a = 1, 2, \ldots, A \quad (13)$$

where $r$ denotes the random decimal between 0 and 1 and INT is the function for deriving the integer value.

*4.1.3.3. Mutation probability.* The mutation probability is equal to the inertia weight in standard PSO, whose change strategy is given by Shi and Eberhart (1999):

$$\omega = 0.9 - \frac{0.9 - 0.4}{U} \times u \tag{14}$$

where $\omega$ denotes the mutation probability; $U$ denotes the maximum number of generations and $u$ denotes the current generation. $\omega$ decreases linearly with the increasing number of generations. At the beginning of the run, $\omega$ should be of a high value to render higher global search capability, whereas at the end of the run, $\omega$ should be of a low value to give higher local search capability. So $\omega$ can balance exploration and exploitation by controlling the impact of previous velocity on current velocity.

*4.1.3.4. Crossover probabilities.* From the sociopsychological point of view, individual cognition and social interaction play significant parts in learning (Yin *et al*. 2007). Crossover probabilities are equal to the learning factors in standard PSO, which determine the influences of a particle's own experiment and the social experiment on the trajectory of particles. In this article, crossover probabilities $c1$ and $c2$ are both assigned the same constant value 0.5.

*4.1.3.5. Maximum number of generations.* The procedure of PSO algorithm calculation will stop at a specified maximum number of generations (Eberhart and Shi 2001, Naka *et al.* 2003) that is determined experimentally. The experiment can start at 100 with an increment of 50 and stop at 1000. We consider the algorithm has converged and obtain the parameter value when the global optimum has not changed for a specified number of generations (Jin *et al*. 2007), for example, 300.

### 4.2. *Combining with the feasibility-based rule*

The model for the OAEES problem includes distance constraint and capability constraint. The first constraint is solved in Section 4.1.1 and the second constraint will be tackled by a constraint-handling technique. Penalty function approach is the most popular constraint-handling technique because it is simple and easy to implement. But its shortcoming lies in setting the suitable penalty parameter. To remedy this drawback, other methods have been developed. Deb (2000) proposed penalty parameter-less approach with infeasible solutions compared only according to constraint violations (CVs). But when the maximum of OFV and CVs have different orders of magnitude, it is difficult to find the optimal solution. He and Wang (2007b) proposed a co-evolutionary PSO algorithm, where two types of swarms representing solutions and penalty parameters evolve interactively. But this method requires *a priori* knowledge of the domain of penalty parameter and a large number of fitness evaluations that are costly. Deb and Datta (2010) combined a bi-objective evolutionary approach and penalty function method. But this method is sensitive to the domain definition of feasible solutions.

Through the analysis of these existing techniques, we chose the feasibility-based rule proposed by He and Wang (2007a) to solve the OAEES problem.

Solution evaluation mainly depends on the OFV and capability CV. The OFV can be calculated by the following equation:

$$\mathrm{OFV} = \sum_{i=1}^{N} Y_i \quad \forall i = 1, 2, \ldots, N \tag{15}$$

And the capability CV can be calculated as follows (note that CV is normalized to avoid the influence of orders of magnitude):

$$\mathrm{CV} = \begin{cases} 0, & \text{if } g \leq 0 \\ \frac{g}{g_{\max}}, & \text{if } g \geq 0 \end{cases} \tag{16}$$

$$g = \sum_{i=1}^{N} \left( \sum_{j=1}^{M} P_j LB_{ji} - S_i Y_i \right), \quad \forall i = 1, 2, \ldots, N; \forall j = 1, 2, \ldots, M \tag{17}$$

The feasibility-based rule is used to evaluate any solutions and guides the particle update, described as follows (He *et al*. 2007a):

(1) Any feasible solution is preferred to any infeasible solution.
(2) Between two feasible solutions, the one having better OFV is preferred.
(3) Between two infeasible solutions, the one having smaller CV is preferred.

According to this rule, the penalty parameters are not employed by considering OFVs and CVs separately (He *et al*. 2007a). Moreover, the search direction is toward the feasible region in the first and third cases and toward good solutions of feasible region in the second case, which makes the search algorithm find good feasible solutions in a short time. In addition, compared with other constraint-handling techniques, the feasibility-based rule is simple and easy to understand and implement.

### *4.3. Incorporation of SA algorithm*

While the feasibility-based rule can guide particles to find good feasible solutions quickly, strictly complying with the rule leads to premature convergence. SA is incorporated to offset this drawback. SA, a famous meta-heuristic local search algorithm, can effectively avoid premature convergence and focus computing effort upon the most promising solutions. First introduced by Kirkpatrick *et al.* (1983), SA can be seen as an analog of an algorithm employed in statistical physics for imitating the solids' annealing procedure that is similar to the tactic for solving optimization problems (van Laarhoven *et al*. 1992). SA not only accepts the better solutions but also accepts worse solutions with certain probabilities (Hasan and Osman 1995), so that it can escape from the local optima and balance between exploration and exploitation.

The conventional way of incorporating SA into PSO is to apply SA as a local search for global optimum in the whole swarm (Zhao *et al*. 2007, Liu *et al*. 2008, Niknam *et al*. 2009). Different from that approach, in this article, we use SA as a local search for each particle's local optimum, which can enlarge information throughput and find better solutions.

In SA, $T_0$ denotes initial temperature, which is usually assigned a high value; $T_u$ denotes the temperature in the $u$th generation; $T_{\min}$ denotes the minimum temperature; $K$ denotes the annealing rate; $X_a(u)$ denotes the position of the $a$th particle in the $u$th generation and $\mathrm{sum}Z_a(u)$ denotes its OFV and $\mathrm{sum}G_a(u)$ denotes its CV; $XP_a(u)$ denotes the position of local optimum currently acquired by the $a$th particle and $\mathrm{sum}Zp_a(u-1)$ denotes its OFV and $\mathrm{sum}Gp_a(u-1)$ denotes its CV; Prob denotes the acceptable probability of a newly generated position; $\varepsilon$ denotes the uniform randomly generated number, which is between 0 and 1. The local searching process for each particle's local optimum can be controlled by the cooling schedule (Aerts and Heuvelink 2002, Li *et al*. 2010).

The implementation of SA combining with the feasibility-based rule is in two steps.
Step1:

For each particle's newly generated position in each generation:

(1) If $\text{sum}G_a(u) = 0$ and $\text{sum}Gp_a(u-1) > 0$, then prob = 1

(2) If $\text{sum}G_a(u) > 0$ and $\text{sum}Gp_a(u-1) = 0$, then prob = 0

(3) If $\text{sum}G_a(u) = 0$ and $\text{sum}Gp_a(u-1) = 0$, then

$\Delta E = \text{sum}Z_a(u) - \text{sum}Zp_a(u-1)$, prob $= \min\{1, \exp[\Delta E/T_u]\}$

(4) If $\text{sum}G_a(u) > 0$ and $\text{sum}Gp_a(u-1) > 0$, then

$\Delta E = \text{sum}G_a(u) - \text{sum}Gp_a(u-1)$, prob $= \min\{1, \exp[\Delta E/Tu]\}$

In cases (3) and (4),

If prob $= \exp[\Delta E/T_u]$, then $T_u = K \times T_{u-1}$, otherwise $T_u = T_{u-1}$

If $T_u < T_{\min}$, then $T_u = T_{\min}$

Step 2:

If prob $< \varepsilon$, then $\text{sum}Gp_a(u) = \text{sum}G_a(u)$; $\text{sum}Zp_a(u) = \text{sum}Z_a(u)$; $XP_a(u) = X_a(u)$ otherwise $\text{sum}Gp_a(u) = \text{sum}Gp_a(u-1)$; $\text{sum}Zp_a(u) = \text{sum}Zp_a(u-1)$; $XP_a(u) = X_a(u-1)$

Therefore, the flow of the modified PSO algorithm is as in Figure 2:

## 5. Case study

### 5.1. Study area

Guangzhou, the capital city of the Guangdong Province in China, is the center of the Pearl River Delta economic zone. Although no catastrophic earthquake has occurred in recorded history, the city was built on several earthquake faults where destructive earthquakes have occurred in the past (Ou *et al*. 2008). Meanwhile, Guangzhou is a densely populated city with highly developed economy. Therefore, the city is at high risk of earthquake losses. Many instances have proved that shelter provision would greatly help to reduce casualties during natural disasters such as an earthquake (Yi and Ozdamar 2007). Presently, only three long-term shelters have been built in Guangzhou, which are distant from the local communities and capable of providing refuge services for only about 60,000 people, far short of the current refuge demand. Hence, it is important to plan emergency shelters before an earthquake strikes the region. In this research, Zhuguang Block in the south of the Yuexiu District in Guangzhou was selected as the case study area. It is at 113°16′E and 23°7′N and comprises 18 administrative communities, with a total area of 0.89 km$^2$. The total population was 71,672 and the population density was 80,530 persons/km$^2$ in 2006.

### 5.2. Data preprocessing

#### 5.2.1. Candidate shelter data

Open spaces in the study area such as parks, playgrounds, and green spaces can be viewed as candidate shelters. The candidate shelter sites were interpreted from a Landsat TM

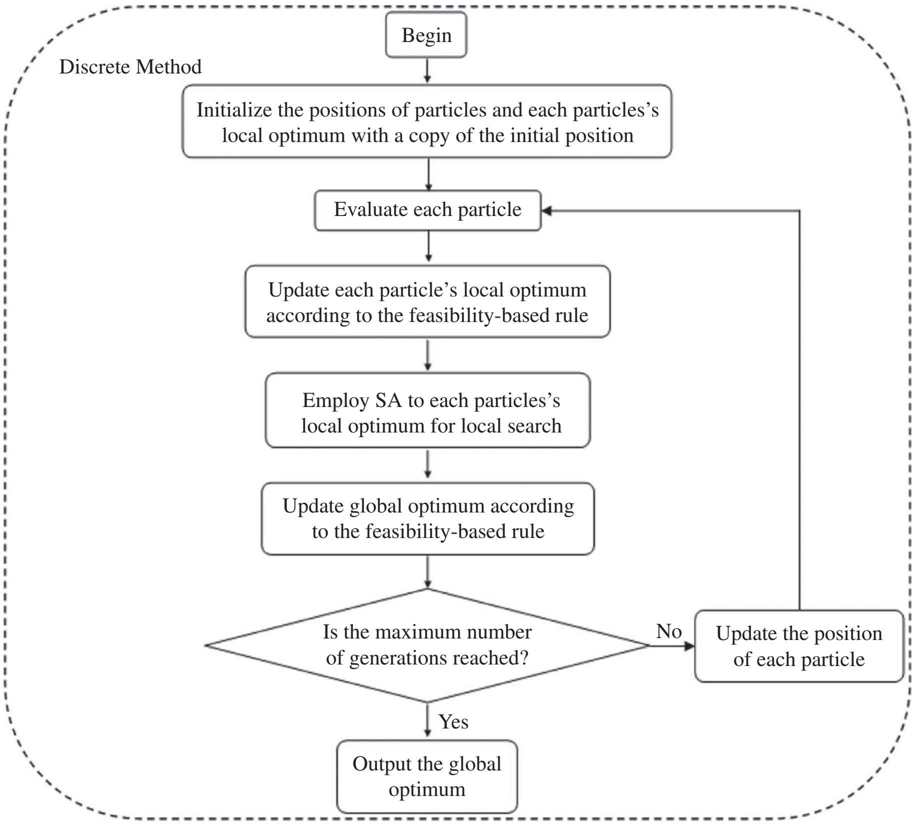


Figure 2. The flow diagram of modified PSO algorithm.

image (pixel size 30 m × 30 m, acquired on 23 November 2005, downloaded at http://glcfapp.glcf.umd.edu).

#### 5.2.2. *High-risk candidate shelter elimination*

Slope was calculated through the Digital Elevation Model (DEM) data downloaded at http://glcfapp.glcf.umd.edu. Data on earthquake fault zones were acquired from Ou *et al.* (2008), and disaster-prone areas were identified by the Geological Disaster Prevention Program of Yuexiu District in 2008. Based on these data, the open spaces with high risk, that is, those with slopes greater than 20°, less than 500 m away from earthquake fault zones, and less than 500 m away from disaster-prone areas, were excluded from the list of candidate shelters.

#### 5.2.3. *Estimate the local population in each community*

The population size of Zhuguang Block was extracted from the Economic and Social Development Statistics Yearbook of the Yuexiu District of Guangzhou in 2007. Assuming that the population of the Zhuguang Block is evenly distributed in its built-up areas, the population of each community can be calculated by Formula (18):

$$PJ_j = \frac{SJ_j}{SR} \times PR \tag{18}$$

where $PJ_j$ denotes the population of the $j$th community; $SJ_j$ denotes the built-up area of the $j$th community; $PR$ denotes the population of the Zhuguang Block; and $SR$ denotes the total built-up area of the Zhuguang Block, interpreted from the TM image.

#### *5.2.4. Calculating the distances between shelters and communities*

The evacuation route data layer was acquired by digitizing the city center map of Guangzhou (Xi'an Map Press 2009). In ARCGIS 9.3, based on the actual evacuation routes, the computational procedure of the distances between communities and shelters (all represented by their central points) was as follows: First, let the routes share the same node where they intersect, as in Figure 3. Then the evacuation route network connectivity was constructed by the '*any vertex*' connectivity policy. Finally, the distances were calculated by the *OD Cost Matrix* of the Network Analysis module.

### *5.3. Results and analysis*

To solve the OAEES problem, the modified PSO algorithm is employed. In this modified PSO, three types of algorithms as shown in Table 3 are explored, with the aim of comparing different discrete methods and constraint-handling techniques, as well as testing the local search effectiveness of SA. Meanwhile, the parameters of SA are studied. All computer programs used in this research were developed on the VB developer platform, combining with secondary development of the MapObject components in geographic information system. The experimental environment was an Intel Core2 2.1 GHz PC with 2GB memory.

Figure 4 and Table 4 present the result of shelter allocation based on the competing algorithms. In Figure 4, the green polygons represent the candidate shelters, distributed throughout the whole block; the red spots represent residents in the corresponding community; the blue lines represent the actual evacuation route network; and the red straight lines that link communities and emergency shelters display the final evacuation assignment scheme.

Table 4 indicates that the modified PSO algorithm obtains the best feasible solutions with relatively small OFV. By a systematic procedure of trial and error, all parameters of competing algorithms are determined (Table 5). We will analyze all competing algorithms in detail.

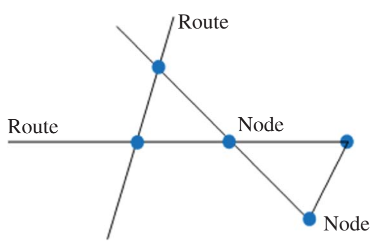


Figure 3. Node sharing between routes that intersect.

Table 3. Hybridization among various algorithms.

| | Discrete method | | | Constraint-handling techniques | | | The local search mechanism of SA | |
|---|---|---|---|---|---|---|---|---|
| Hybridization | NDPSO | Round-based DPSO | GA | Feasibility-based rule | Penalty parameter-less approach | Penalty function approach | SA for guiding local best update | SA for guiding global best update |
| A1 | | ○ | | ○ | | | ○ | |
| A2 | | | ○ | ○ | | | ○ | |
| B1 | ○ | | | | | ○ | ○ | |
| B2 | ○ | | | | ○ | | ○ | |
| C1 | ○ | | | ○ | | | | |
| C2 | ○ | | | ○ | | | | ○ |
| D | ○ | | | ○ | | | ○ | |

Notes: NDPSO, new discrete particle swarm optimization; GA, genetic algorithm; SA, simulated annealing.
○ denotes that the method is included in the corresponding hybridization algorithm.

### *5.3.1. The comparison between different discrete methods*

Three algorithms involving different discrete methods (the rounding-based DPSO algorithm hybridized with feasibility-based rule and SA (A1), GA hybridized with feasibility-based rule and SA (A2), NDPSO hybridized with feasibility-based rule and SA (D)) were compared. Changes of OFV and CV in the generation process of the three algorithms are displayed in Figure 5.

The CVs obtained by A1 and A2 did not converge to zero, that is, all solutions obtained by these two algorithms are infeasible solutions. By contrast, the solution obtained by D is feasible. A1 always found the discrete solution nearest to the real optimal value, so it is difficult to reach the optimal yet feasible solution. GA in A2 is widely regarded as an appropriate method for discrete optimization problems because it can be coded directly using discrete variable. But its search direction is not clear compared with D, leading to low convergence speed and difficulty in finding the optimal solution. D can let all particles fly in a rational integer value domain. Meanwhile, the mutation and crossover operators maintain the diversity of particles. Therefore, it is obvious that D is more suitable for the discrete optimization problem.

### *5.3.2. The comparison between different constraint-handling techniques*

Three algorithms involving different constraint-handling techniques (NDPSO hybridized with penalty function approach and SA (B1), NDPSO hybridized with penalty parameter-less approach and SA (B2), and D) were compared. Changes of CV in the generation process of the three algorithms are illustrated in Figure 6.

In B1, the penalty parameter is assigned the value of 150 by the trial and error procedure. Figure 6 shows that the convergence speed of B1 is faster than that of B2, and the CV of its optimal solution is lower than that of B2. But all solutions found by B1 are infeasible because B1 is sensitive to the penalty parameter. The fitness function in B2 is composed of maximum OFV and CV when the solutions are infeasible. As shown in Figure 6, in B2 particles fly toward the feasible region at a fast speed in the beginning, but the movement is at a

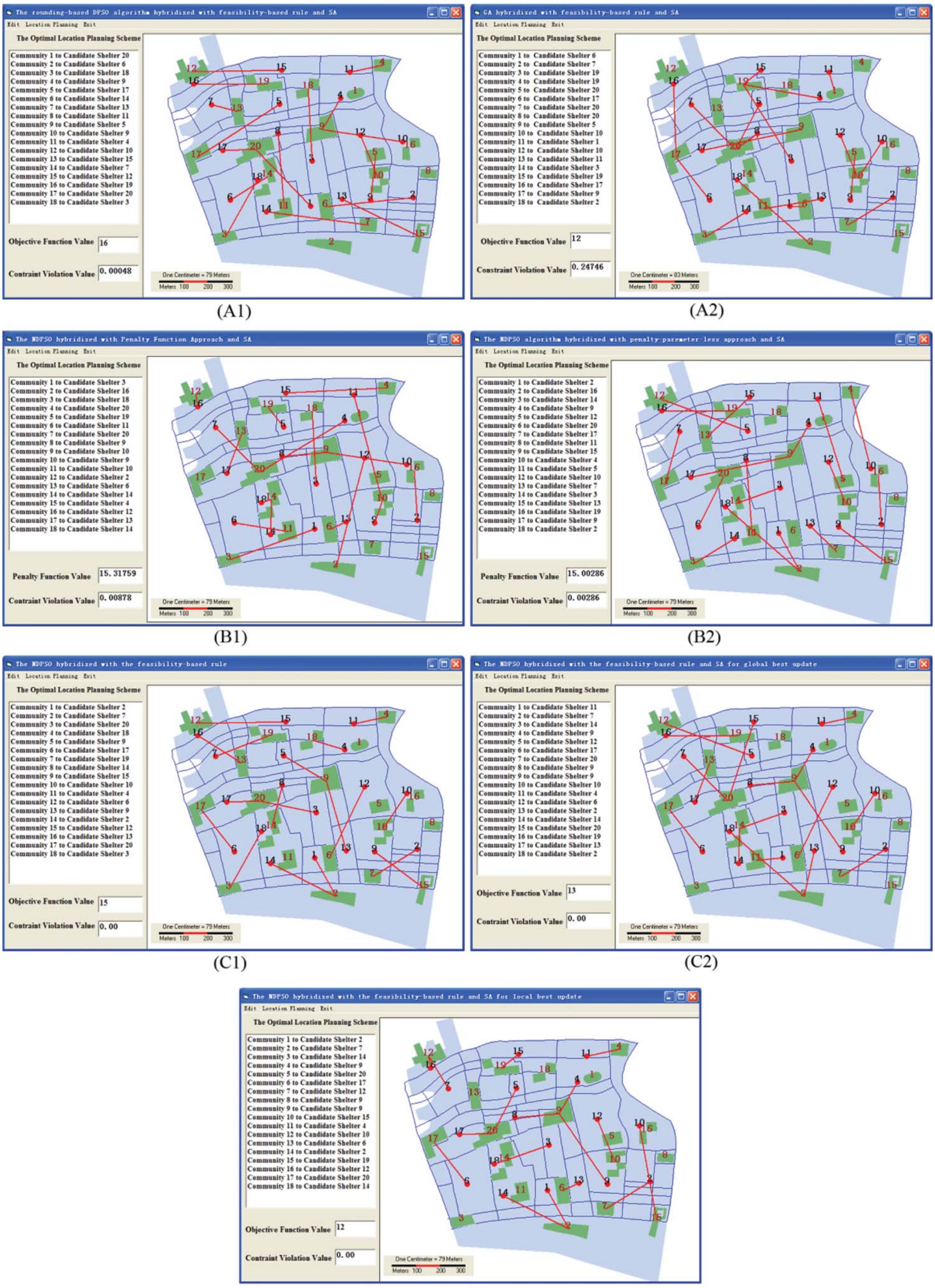


Figure 4. Optimal allocation results of earthquake emergency shelters in the Zhuguang Block based on the completing algorithms. (A1) Result based on the rounding-based DPSO algorithm hybridized with feasibility-based rule and SA. (A2) Result based on GA hybridized with feasibility-based rule and SA. (B1) Result based on the NDPSO algorithm hybridized with penalty function approach and SA. (B2) Result based on the NDPSO algorithm hybridized with penalty parameter-less approach and SA. (C1) Result based on the NDPSO algorithm hybridized with feasibility-based rule. (C2) Result based on the NDPSO algorithm hybridized with feasibility-based rule and SA for global optimum. (D) Result based on the NDPSO algorithm hybridized with feasibility-based rule and SA for local optimum.

Table 4. The result of the competing algorithms.

| The hybrid algorithms | Objective function value | Constraint violation | Penalty function value | The number of evaluation functions |
|---|---|---|---|---|
| A1 | 14 | 0.00048 | – | 20,000 |
| A2 | 12 | 0.24746 | – | 40,000 |
| B1 | 14 | 0.00878 | 15.31759 | 30,000 |
| B2 | 15 | 0.00286 | 15.00286 | 20,000 |
| C1 | 15 | 0.00000 | – | 20,000 |
| C2 | 13 | 0.00000 | – | 20,000 |
| D | 12 | 0.00000 | – | 20,000 |

Table 5. The parameter setting of the competing algorithms.

| The hybrid algorithms | Maximum number of generation | Population of swam | Initial temperature | Annealing rate | Minimum temperature |
|---|---|---|---|---|---|
| A1 | 500 | 40 | 100,000 | 0.25 | 0.01 |
| B1 | 750 | 40 | 10,000 | 0.65 | 0.01 |
| B2 | 500 | 40 | 10,000 | 0.95 | 0.01 |
| C1 | 500 | 40 | – | – | – |
| C2 | 500 | 40 | 100,000 | 0.75 | 0.01 |
| D | 500 | 40 | 100,000 | 0.96 | 0.01 |
| The hybrid algorithm | Maximum number of generation | Population of swarm | Crossover probability | Mutation probability | Selection strategy |
| A2 | 500 | 40 | 0.95 | 0.01 | Tournament selection |

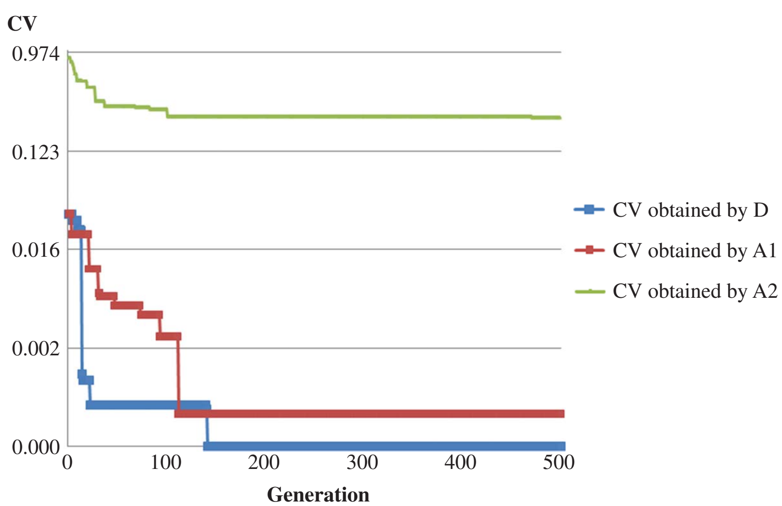


Figure 5. Changes of constraint violation (CV) of A1, A2, and D.

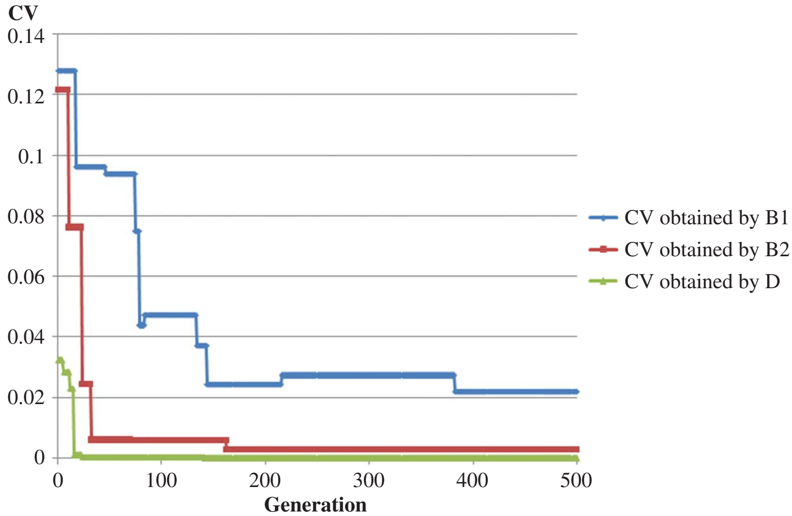


Figure 6. Changes of constraint violation (CV) of B1, B2, and D.

standstill when the CV becomes very small, because the difference of their orders of magnitude leads to difficulty in finding the optimal solution. In D, OFVs and CVs are considered separately. The feasibility-based rule prefers the solution with smaller CV; therefore, it guides the particles to find the feasible solution quickly. Figure 6 indicates that the optimal solution found by D is feasible and is better than that of B1 and B2.

### 5.3.3. *Local search effectiveness of SA*

Three algorithms (NDPSO hybridized with feasibility-based rule only (C1), NDPSO hybridized with feasibility-based rule and SA for global best update (C2), and D) were compared in order to evaluate the local search effectiveness of SA. Changes of OFV and CV in the generation process of these three algorithms are illustrated in Figures 7 and 8.

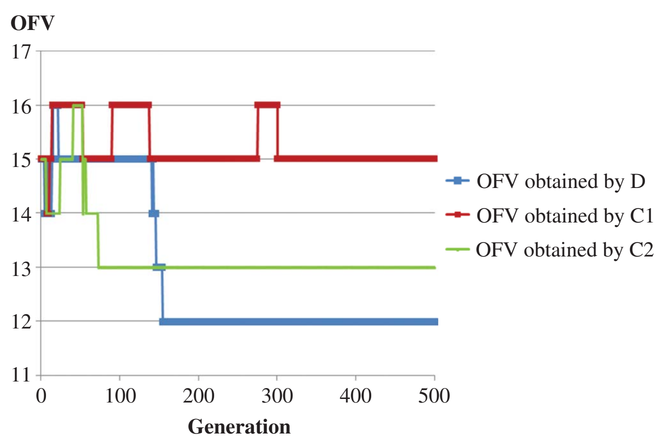


Figure 7. Changes of objective function value (OFV) of C1, C2, and D.

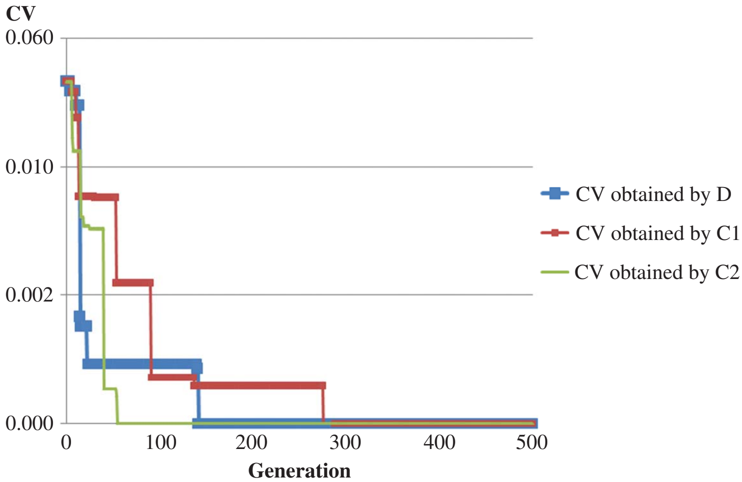


Figure 8. Changes of constraint violation (CV) of C1, C2, and D.

Figure 7 clearly indicates that the effectiveness of C2 and D is better than C1 due to the incorporation of the SA mechanism. C1 eventually finds good feasible solutions by strictly complying with the feasibility-based rule. Although C1 can ensure to find feasible solutions, it can easily be trapped into a certain feasible solution that is only a local optimum. By combining with SA, the search scopes of C2 and D become larger, bringing the hope of finding the most promising solutions. Figure 8 shows that C2 and D find the feasible solutions faster than C1. In Figure 7, the OFVs of optimal solutions found by C2 and D are also better than that of C1. D has better search ability than C2 because SA is employed as a local search for each particle's local optimum and enlarges more information throughput in D. In Figure 8, C2 finds the feasible solutions faster than D. With the increase of generation, Figure 7 shows that the OFVs of solutions obtained by D are better than that of C2.

### *5.3.4. Parametric study of SA*

The local search effectiveness of SA depends on setting appropriate initial temperature ($T_0$), annealing rate ($K$), and minimum temperature ($T_{\min}$). We used the trial and error method in a parametric study.

We set $T_{\min} = 0.01$ and $T_0 = 10{,}000$, 100,000, 1,000,000, and 10,000,000, and changed $K$ from 0.01 to 0.99 by an increment of 0.01. Changes of OFVs of the modified PSO algorithm are shown in Figure 9 (only the feasible solutions are included in the figure). From Figure 9, it is easy to see that the algorithm obtains the best solution when $T_0 = 10{,}000$, $K = 0.94$; $T_0 = 100{,}000$, $K = 0.92$, 0.96, 0.97; and $T_0 = 1{,}000{,}000$, $K = 0.92$.

In addition, we set $T_0 = 100{,}000$ and $T_{\min} = 0.1$, 0.01, 0.001, and 0.0001, and changed $K$ from 0.01 to 0.99 by an increment of 0.01. Changes of the OFVs of the modified PSO algorithm are shown in Figure 10 (only the feasible solutions are included in the figure). From Figure 10, it is also easy to see that the algorithm obtains the best solution when $T_{\min} = 0.1$, $K = 0.96$; $T_{\min} = 0.01$, $K = 0.92$, 0.96, 0.97; $T_{\min} = 0.001$, $K = 0.62 \sim 0.76$; and $T_{\min} = 0.001$, $K = 0.92$, 0.93, 0.95, 0.96.

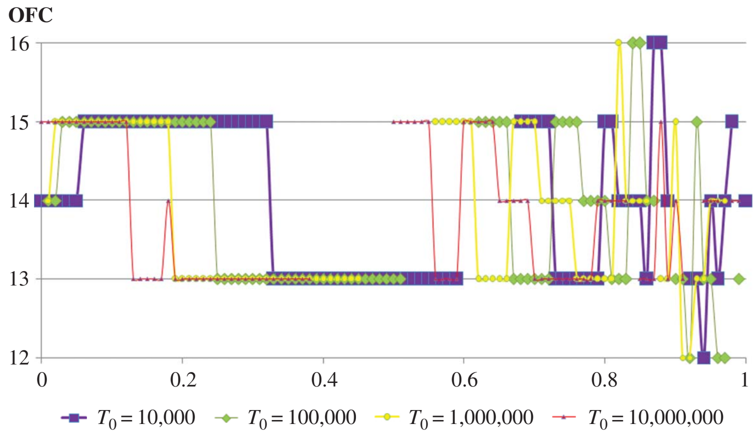


Figure 9. Changes of the objective function values (OFVs) of the proposed modified PSO algorithm with the annealing rate from 0.01 to 0.99 by a 0.01 increment, when the minimum temperature is 0.01 and initial temperature is 10,000, 100,000, 1,000,000, and 10,000,000.

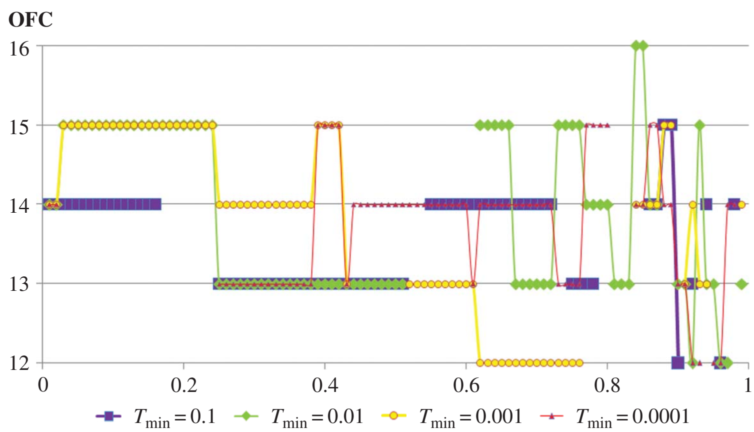


Figure 10. Changes of the objective function values (OFVs) of the proposed modified PSO algorithm with the annealing rate from 0.01 to 0.99 by a 0.01 increment, when initial temperature is 100,000 and minimum temperature is 0.1, 0.01, 0.001, and 0.0001.

### *5.3.5. The optimal allocation solution obtained by the proposed modified PSO algorithm*

Table 6 shows the result of earthquake emergency shelter allocation in the Zhuguang Block based on the modified PSO algorithm. The shelters whose original serial numbers are 2, 4, 6, 7, 9, 10, 12, 14, 15, 17, 19, and 20 were selected and the evacuation assignment scheme was simultaneously identified. For example, the 1st community and the 14th community are assigned to the 2nd shelter and the 2nd community is assigned to the 7th shelter.

In Table 6, the capacity satisfaction index (CSI) for shelters is a measure of the satisfaction level of resident demands for shelters, calculated by Formula (19):

$$\mathrm{CSI}_i = \frac{AS_i}{\mathrm{PCS}_i \times L} \quad \forall i = 1, 2, \ldots, N \tag{19}$$

Table 6. The location planning result of earthquake emergency shelters in the Zhuguang Block.

| Community | Population | Shelter | Valid refuge area (m$^2$) | Capacity satisfaction index for shelter (%) |
|---|---|---|---|---|
| 1 | 3637 | 2 | 7858 | 100 |
| 14 | 3593 | | | |
| 2 | 3408 | 7 | 3897 | 100 |
| 3 | 3310 | 14 | 6920 | 100 |
| 18 | 3135 | | | |
| 4 | 3031 | 9 | 9441 | 100 |
| 8 | 3918 | | | |
| 9 | 2406 | | | |
| 5 | 4290 | 20 | 9167 | 100 |
| 17 | 4834 | | | |
| 6 | 5709 | 17 | 6869 | 100 |
| 7 | 3812 | 12 | 7478 | 100 |
| 16 | 3334 | | | |
| 10 | 4205 | 15 | 4242 | 100 |
| 11 | 3624 | 4 | 3859 | 100 |
| 12 | 5775 | 10 | 6013 | 100 |
| 13 | 4595 | 6 | 5884 | 100 |
| 15 | 5058 | 19 | 5323 | 100 |

where $\mathrm{CSI}_i$ *denotes CSI for the* $i$th shelter; $\mathrm{AS}_i$ *denotes the area of the* $i$th shelter; $\mathrm{PCS}_i$ *denotes the total population of communities served by the* $i$th shelter; and $L$ denotes the least refuge area per capita.

The CSIs of all selected shelters reached 100%, which confirms that the optimal allocation solution has satisfied the capacity constraint. By applying procedures presented in Section 4.1.1, all the candidate shelters have also satisfied the distance constraint. Therefore, the result of shelter allocation in the Zhuguang Block is valid. The experiment also shows that the modified PSO algorithm can identify the number and locations of emergency shelters through finding the optimal evacuation assignment scheme.

## 6. Conclusion

The main merit of this research is the introduction of the PSO algorithm into the field of geographic optimization. We effectively solved the complicated OAEES problem using the modified PSO algorithm. Three important methods have been hybridized: (1) An NDPSO algorithm was employed for solving the integer programming problem, (2) the feasibility-based rule was used to handle the constraint problem, and (3) an SA algorithm had been hybridized to enhance search capability.

This study has demonstrated that the modified PSO algorithm that hybridized NDPSO, the feasibility-based rule, and the SA outperforms other hybrid algorithms reviewed in this article. Compared with the rounding-based DPSO, the NDPSO lets all particles fly in a rational integer value domain and the particles' diversity was maintained by the mutation and crossover operators. In comparison with GA, with the NDPSO each particle has search directions toward its personal best and global best, making the algorithm converge to the optimal solution fast. Penalty function approach is sensitive to the penalty parameter and penalty parameter-less approach easily leads the particles to a standstill when CV becomes very small. Comparatively, the feasibility-based rule prefers the solution with smaller CV, guiding particles to find feasible solutions quickly. So the NDPSO and the feasibility-based rule are suitable methods for handling the discrete and constrained optimization problems. Hybridizing with SA leads to the improvement of search ability by avoiding jumping into local optima. Additionally, SA as a local search for global optimum and SA as a local search for each particle's local optimum have been compared. The latter converges to better feasible solution due to the increase of information throughput.

The model for the OAEES problem not only takes distance and capacity constraints into consideration but also emphasizes cost saving of shelters. The result in the case study is feasible, in which all selected shelters complied with the two constraints. Therefore, the modified PSO algorithm is viable for solving the OAEES problem.

Our modified PSO algorithm can be applied to other complex geographic optimization problems, such as allocation of emergency supplies and other emergency facility site selection. The model is also useful for other types of disaster shelter allocation such as hurricane shelters and typhoon shelters.

In our model, a number of complicated factors have been simplified. For example, population of a community is assumed to be concentrated at its central point and the impact of collapsed houses on evacuation paths is ignored. These issues will be the target of our future research. However, PSO, with its strong adaptability and computational capability, has the potential to be further developed to fit more complex geographic optimization problems.

## Acknowledgments

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## Notes

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