Multiobjective Site Selection Model for Emergency Shelter Facilities in Urban Areas

Kuo-Chi Yen (yenkuochi0706@gmail.com)  
National Defense University

Weid Chang  
National Defence University

Wu-Chiao Shih  
National Defense University

Research

Keywords: Sudden urban disaster, Location problem, Multiobjective programming

DOI: https://doi.org/10.21203/rs.3.rs-783428/v1

License: ☑️ This work is licensed under a Creative Commons Attribution 4.0 International License.  
Read Full License
Multiobjective site selection model for emergency shelter facilities in urban areas

Kuo-Chi Yen*, Weid Chang and Wu-Chiao Shih

Department of Logistics Management, National Defense University, Taipei City, 112, Taiwan, R.O.C.

* Correspondence: yenkuochi0706@gmail.com
Abstract

Industrial and economic development is primarily applied to densely populated urban areas. If a sudden disaster occurs in such areas, the consequences can be severe. Shelter facility location affects the implementation of postdisaster relief work. This study explored residents’ perceived utility of evacuation time, their risk utility for road blocking, and the cost factors associated with constructing shelter facilities in the context of governance. A location model for emergency shelter facilities in cities was established on the basis of the aforementioned factors. Because the resolution of the random-weighted genetic algorithm (RWGA) is susceptible to influence from random weights, a robustness random-weighted method (RRWM) was developed. The validity and feasibility of the location model were examined through numerical analysis. Finally, the convergence of the RRWM was analyzed and compared with that of the RWGA and a single-objective genetic algorithm. The results revealed that the proposed algorithm exhibited satisfactory performance and can assist in evaluation and decision-making related to the selection of urban shelter facility locations.

Keywords: Sudden urban disaster, Location problem, Multiobjective programming
1. Introduction

Climate change and social disruption may lead to natural or artificial disasters such as typhoons, earthquakes, and nuclear accidents, all of which can substantially affect urban economies [1]. After a sudden large-scale disaster or major accident, the affected population must immediately seek refuge in safe and shelter facilities. Therefore, the selection of shelter facility locations is crucial to urban disaster prevention and urban development, and the locations of such facilities should be based on pedestrian patterns.

Existing places of refuge should be selected as locations for facilities with short- and medium-term sheltering functions. Resources can then be allocated to improve and reconstruct these facilities and to stockpile supplies in order to meet safety standards. Therefore, numerous factors must be considered during the site selection process. Accordingly, the “Easy-to-Do” program of the National Science and Technology Center for Disaster Reduction (Taiwan) considers the physical environment, shelter-related facilities, and factors such as distance to a sheltered facility (https://easy2do.ncdr.nat.gov.tw/easy2do/). Several studies have suggested that the time required to seek refuge is a critical factor for site selection [2, 3].
However, unsuspecting city residents may be influenced by psychological factors such as panic and fear during a disaster because of the chaos caused by the interruption of urban traffic networks and the breakdown of communication. Lin et al. [4] have thus suggested that panic following a disaster hinders individual judgment. The public may not act entirely rationally when confronted by an unexpected disaster [5]. Consequently, according to prospect theory [6, 7], effective decision-making behavior is based on bounded rationality under an emergency. However, an increasing number of studies evaluating shelter facilities have focused on residents’ subjective feelings, including their satisfaction with evacuation time [8]. Shelter distance and evacuation time alone may not explain residents’ perspectives regarding shelter facilities following a disaster. Hence, residents’ perceived evacuation time must be considered to accurately determine their choice of shelter facilities following a disaster.

Because road networks may be blocked or destroyed following a disaster, the urban space undergoes drastic changes. When residents with bounded rationality are confronted by these changes, they may experience difficulty in making accurate risk assessments while on the road. The risk of road network blockage affects the safe
travel of residents to shelter facilities; therefore, this phenomenon should be considered during site selection [8]. Moreover, medium- and short-term shelter facilities should be constructed even if no urban disasters are expected. In the context of budgeting [1], resources should be allocated to reconstruction and the establishment of shelter environments that conform to disaster resistance standards.

The aforementioned factors directly affect the efficiency of shelter selection among people affected by a disaster. Accordingly, this study considered the effects of the aforementioned factors on postdisaster situations. Such factors include the perception of the time required to reach a shelter, the risk of using roads to reach the shelter, the cost of establishing shelter facilities, and the accommodation limitations of the shelter. The study developed a multiobjective model of site selection for urban shelter facilities. This model considers the aforementioned factors; therefore, when an unexpected disaster occurs, shelter facility information should be transmitted to mobile phones and other devices. This method for disseminating relevant information eliminates the need for the public to make decisions regarding where to find shelter.

A multiobjective problem involves a trade-off between various objectives. The optimal solution for this problem can be obtained using the random-weighted genetic
algorithm (RWGA; [9]). However, because the RWGA is easily affected by weight changes, the quality of its solutions is inconsistent. Therefore, we incorporated the elitism method into the RWGA to develop a robustness random-weight method (RRWM). In the RRWM, the coverage and distribution of the solution set are used to evaluate the solution and thus obtain improved solution performance. The rest of this paper is organized as follows. First, the research topic is analyzed and explained. Second, relevant studies are reviewed. Third, the proposed multiobjective site selection model for urban shelter facilities is described. Fourth, a robust stochastic weighting method is proposed for the developed model, and a method for evaluating the multiobjective solution set is presented. Fifth, an example network is described for Zhongzheng District in Taipei City. This network was used to test the accuracy and applicability of the proposed model. The results obtained using the proposed model were compared with those obtained using other algorithms in the aforementioned example; the comparison results indicated that the proposed model outperformed the other algorithms. Finally, the conclusions of this study, applications of the proposed model, and directions for future research are presented.

2. Problem analysis and literature review
2.1. Refuge location selection model

Current et al. [10] used a multiobjective approach to solve a site selection problem; since their study, such approaches have been extensively used to solve site selection problems in various fields. Fan [11] obtained the relative weights of various assessment factors by using an expert questionnaire and the analytic hierarchy process. On the basis of these weights, the researchers established four assessment items with subcriteria such as structural safety, location, traffic, living function, and service for flood refugees. These subcriteria can serve as a reference for the assessment of shelter facilities for flood victims.

Location problems are typically divided into four types: P-median, P-center, location coverage, and maximum coverage location. Farahani et al. [12] comprehensively examined the models, solutions, and applications of coverage problems for facility site selection. To solve a site selection problem for disaster emergencies, Li et al. [13] proposed a coverage location model and applied various algorithms. Hobeika [14] considered the travel time between residences and storm shelter facilities and proposed a site selection model to minimize the travel time.

Sherali et al. [15] studied evacuation facilities for flood disasters and proposed a
bilevel planning model: The upper-level problem is a site selection problem for evacuation facilities, and the aim is to minimize the time required to reach the shelter. The lower-level problem is related to the route between the residence and the shelter. They used a genetic algorithm (GA) to solve this two-level problem.

On the basis of a case study of the 2010 Chile earthquake, Pérez-Galarce et al. [16] considered the challenge of earthquake disasters in urban areas. They developed a flexible model for optimizing the service quality of shelter facilities after disasters. This model also enables the provision of appropriate shelter and medical assistance through improved shelter facilities. Boonmee et al. [17] discussed emergency models for facilities such as distribution centers, warehouses, shelters, and medical centers. They examined each type of facility, data model, and disaster. Accordingly, they proposed a model that can be used to select sites for shelter facilities according to the characteristics of the disaster, the needs of the victims, and the principle of equity.

2.2. Objective and limiting factors for shelter site selection

After an urban disaster, the external environment changes dramatically. Because the public’s perception of these environmental changes influences their behavior, such changes should be considered in shelter site selection processes. Moreover, panic after
a disaster reduces the ability of victims to make sound judgments, which leads to imperfect rationality [5] or bounded rationality [6, 7]. Therefore, site selection for shelter facilities may consider the bounded rationality of disaster victims according to their perceptions of the external environment. If a shelter location is selected solely according to its distance from the disaster area [18] and without consideration of public perception, then the selection policy may not match the behavior of the affected individuals. The suitability of a shelter facility location is reflected in the victims’ levels of perception at different sites [19]. For a given shelter facility, people in different affected areas have different levels of satisfaction. The linear time satisfaction function is the simplest method for converting evacuation time or distance into time satisfaction [8, 20]. Therefore, maximizing the public perception of the time required to reach a shelter after an urban disaster was the primary model objective in the present study.

Urban road networks may be interrupted by urban disasters, which can lead to building collapses or the destruction of underground chemical pipelines. Therefore, the risk of urban road network blockage should be considered when selecting shelter facility sites, and the impact of this risk should be minimized. To identify the factors
influencing shelter site selection, Zhu and Wang [21] have improved the conventional spatial location selection problem by establishing a road emergency evacuation index and a road risk coefficient to quantify road network risks. In addition, Hsu and Lu [22] determined the risk of earthquake-induced road blockages. They created a joint utility function by combining this risk with the influence of traffic load on traffic congestion to obtain the path of least risk for earthquake relief. By combining a geographic information system with a traffic assignment function, they established an application model for disaster relief path selection. Shen et al. [8] considered human vulnerability to toxic chemical gases, road accessibility probability, and satisfaction with evacuation time as influencing factors for the selection of shelter sites in a chemical industry zone. They established a site selection model according to the maximum road accessibility probability.

After an appropriate urban shelter site is selected from various alternatives (excluding potentially dangerous sites), resources are invested to construct facilities according to the required medium- or short-term functions of the site. Therefore, the cost of construction and the distance from the affected area are factors that warrant consideration in shelter site selection processes for construction. Karatas [23] have
argued that the cost of facility construction affects site selection. Chen et al. [24] considered construction cost and asylum setup benefits as target factors in the selection of an emergency shelter site. They proposed two site selection objectives—namely minimizing total distance and minimizing construction cost—and established three hierarchical site selection models for emergency shelters.

The capacity limitation of a shelter facility is a crucial modeling constraint. Current and Storbeck [25] established location coverage and maximum coverage models for selecting locations with capacity constraints. Wu et al. [26] proposed a coverage model for site selection under capacity and construction cost constraints. To evaluate emergency evacuation strategies for major urban emergencies, Li et al. [19] comprehensively considered shelter capacity and the uneven distribution of the urban population; they suggested that effective strategies should ensure that shelter capacity is not exceeded and that the distance between residences and shelters is minimized.

Their results indicated that the model with capacity constraints was superior to that without such constraints because it could more accurately reflect the real-life situation of the problem.

2.3. Multiobjective programming models and related algorithms
Multiobjective programming is a mathematical method for solving decision problems with multiple objectives through linear programming. The aim of this approach is to identify the optimal solution within the constraints of limited resources and conflicting objectives. Kuhn and Tucker [27] deduced the optimality conditions for the existence of effective solutions, which laid the foundation for multiobjective theory. Multiobjective programming includes multiple quantifiable objective functions with well-defined constraints. The mathematical programming component evaluates trade-offs between the objectives and obtains a set of noninferior solutions or nondominated solutions. Multiobjective optimization has been extensively studied and applied in numerous fields. Shukla and Deb [28] divided methods for solving multiobjective optimization problems into two categories: traditional and nontraditional methods, among which the non-traditional methods developed evolutionary multiobjective optimization (EMO) is based on the concept of natural selection. EMO identifies multiple Pareto optimal solution sets in the space of feasible solutions. The graph surface formed by all nondominant solutions is called the Pareto front.

Alçada-Almeida et al. [29] verified evacuation plan safety by using a
multiobjective planning approach; this approach involves the use of a geographic
information system and a multiobjective programming model in the design of a
decision support system. Zhou et al. [30] proposed a multiobjective model for
selecting the sites of urban shelter facilities. The model incorporates the maximum
weighted minimum distance as well as the weighted and maximum coverage areas for
shelter facilities. Coutinho-Rodrigues et al. [31] developed a multiobjective planning
model for evacuation path and shelter facility locations by using six objectives,
including risks associated with path and shelter locations, evacuation path length, and
the final evacuation time from residences to shelters. Because of the complex
environments people must traverse during urban disasters, researchers have
considered various attributes, characteristics, and objectives in the development of
disaster models. Therefore, the locations of shelter facilities have often been
interpreted and expressed within the context of multiobjective planning.

Most relevant algorithms are based on evolutionary algorithms (EAs). Because of
their suitability for solving complex problems, search algorithms have also been
applied to various optimization problems [32]. In EAs, adaptive individuals with
diverse genetic characteristics can be selected from a population according to their
environmental fitness. EAs can be categorized according to three design choices, namely individual representation, parent selection, and operating mode. Evolutionary programming, evolutionary strategies, and GAs are examples of EAs, with GAs being the most common EAs.

Multiobjective GAs (MOGAs) focus on the development of adaptive functions. Numerous MOGAs have been developed to solve multiobjective problems with different characteristics on the basis of the evaluation of adaptive functions. Konak et al. [33] categorized MOGAs according to their adaptive functions and algorithm programs and compared the advantages and disadvantages of these algorithms. Among these methods, the aggregation function was the first to be developed and is the most direct approach for solving multiobjective optimization problems. In this method, a single-objective solution is obtained for the multiobjective problem by adjusting the weight coefficient through combination or aggregation. The RWGA proposed by Murata and Ishibuchi [9] are based on weight summation. Murata and Ishibuchi [9] compared the RWGA with the vector-evaluated GA (VEGA). Their results revealed that the RWGA yielded more optimal solutions than did the VEGA.

2.4. Comprehensive evaluation and analysis
In the present study, the public perception of evacuation time, road availability, and facility construction cost in the context of urban disasters were considered as factors affecting site selection. The aim of a site selection strategy should be the maximization of the utility of perceived evacuation time, maximization of road accessibility, and minimization of the construction cost of facilities. On the basis of the aforementioned literature review, this study conducted a comprehensive evaluation, which is described as follows:

1. After an urban disaster, victims typically move to shelter facilities by walking quickly. The distance from residences is typically the main factor considered when planning facility locations. Accordingly, the current study considered the $P$-median problem for site selection. Service time satisfaction [8, 20] and the utility function proposed by Fiedrich et al. [34] were combined to transform the simple distance factor into the perceived utility of evacuation time.

2. The three objectives established for the proposed model were to maximize the perceived utility of evacuation time, maximize the utility of network access risk, and minimize the cost of shelter construction. We considered these three objectives to maintain the functions necessary for the postdisaster life of asylum
seekers within the capacity of shelter facilities. Therefore, a multiobjective model was established for selecting emergency shelter facility sites for urban disasters.

3. The proposed programming model for solving the multiobjective problem is based on trade-off solutions. On the basis of the aforementioned studies, the RWGA, which is based on the MOGA, was adopted for the programming model. Moreover, this algorithm was improved to facilitate the resolution of the relevant multiobjective problem.

3. **Research model construction**

In the conventional maximum coverage problem, the aim is to minimize the average travel distance between the demand and service nodes. Therefore, demand nodes that are located outside the maximum service distance from a given service node must be covered by other service nodes. However, in the context of traveling to shelter facilities after disasters, the service level of shelter facility $j$ is not limited to its spatial distance from disaster site $i$. The evacuation time $t_{ij}$ between disaster site $i$ and shelter facility $j$ should be the main basis for assessment. Therefore, $t_{ij} \leq L_i$ indicates that victims at disaster node $i$ feel safe traveling to shelter node $j$. The term $L_i$ denotes the longest time that people at disaster node $i$ are willing to accept when evacuating to
Disaster victims decide to leave the affected area to seek shelter according to their expectations of the facility and environmental factors. In this case, distance is the main consideration in shelter site selection processes, and the travel time between the disaster site and the shelter facility is ignored. However, in practice, urban spaces change substantially after disasters, and the members of the public are in a state of bounded rationality. Therefore, an accurate perception of the distance to shelter facilities may be difficult for the public to obtain.

Herein, $U(t_{ij})$ is defined as the perceived utility of evacuation time between disaster node $i$ and evacuation facility $j$, and $L_{i,\text{desired}}$ is defined as the maximum evacuation time that victims at disaster node $i$ can accept for traveling to shelter facility $j$. In an emergency, victims are expected to travel to shelter facilities in the shortest possible time because they are likely to be highly anxious; in addition, evacuation time is influenced by the disaster situation. According to the evacuation time defined by Ren et al. [35] and the graded mean integration representation method proposed by Chou et al. [36], the maximum acceptable evacuation time can be defined as follows:
\[ L_{i,\text{desired}} = \frac{t_{ij,\text{optimistic}} + 4t_{ij} + t_{ij,\text{longest}}}{k}, \quad k = 6 \]  

(1)

where \( t_{ij,\text{optimistic}} \) is the most optimistic time from disaster node \( i \) to shelter facility \( j \) (e.g., the shortest possible time to complete an evacuation activity), \( t_{ij} \) is the actual evacuation time from disaster node \( i \) to shelter facility \( j \), and \( t_{ij,\text{longest}} \) is the longest evacuation time from disaster node \( i \) to shelter facility \( j \). Therefore, the psychological factors of the affected people are modeled as a trade-off between \( t_{ij} \) and \( t_{ij,\text{longest}} \) (i.e., \( L_{i,\text{desired}} \)), which is used to evaluate their perceived evacuation time. To normalize perceived evacuation time, this factor is transformed into a utility value between 0 and 1. The utility function for perceived evacuation time is presented in Eq. (2) [7, 19].

\[
U_{a}(t_{ij}) = \begin{cases} 
1 & \text{if } t_{ij} \leq L_{i,\text{desired}} \\
1 - \left( \frac{t_{ij} - L_{i}}{\max_{ij} t_{ij} - L_{i}} \right)^{k_{i}} & \text{if } L_{i} < t_{ij} \leq t_{ij,\text{longest}} \\
0 & \text{if } t_{ij} > t_{ij,\text{longest}}
\end{cases} 
\]  

(2)

We can assume that the utility function of perceived evacuation time is nonlinear. The value of \( k_{i} \) can be considered the sensitivity coefficient for evacuation time. This parameter represents the sensitivity of people in different regions (e.g., cities and rural areas) to the evacuation time. The higher the value of \( k_{i} \) is, the higher the gradient of
the utility function of perceived evacuation time is, which indicates greater time
sensitivity. Ma et al. [20] suggested that \( k_i \) should be between 0.5 and 1.5. The effect
of sensitivity coefficient \( k_i \) is illustrated in Figure 1. Individual perceptions of
evacuation time can vary even in the same area. However, the aim of the present
study was not to estimate individual heterogeneity. Therefore, the utility function of
perceived evacuation time is defined according to the assumption of homogeneous
sensitivity coefficients.

On the basis of the suggestions provided by Shen et al. [7] and Hsu and Lu [21],
the utility of the risk of a roadblock for a road section after a disaster can be defined
as follows. The risk of a roadblock is defined as the probability of a roadblock due to
the collapse of buildings and to other factors influencing the road section. For a
known roadblock risk, a utility function is used to convert the risk value into a utility
value. Herein, the utility function for roadblock risk is a decreasing exponential utility
function. If the roadblock probability is 0, the road section is unaffected, and the
utility value is 1. If the roadblock probability is 1, the road section has been severely
damaged, and its safety and reliability are extremely low; thus, the utility value is 0.
The utility function of roadblock risk for road section \( a \) is defined as follows:
where $R_a$ is the roadblock probability for road section $a$. The utility value of the roadblock risk for a section reflects the safety and reliability of the road. It can also be considered to be the probability of being able to pass through a road section. The higher the utility of the roadblock risk is for a road section, the higher is the probability of disaster victims being able to use this section to reach shelter facilities.

Therefore, on the basis of the discussion on road passability by Shen et al. [7], the utility of the roadblock risk of road section $a$ is defined as the passability of road section $a$, as presented in Eq. (4). Moreover, $u_{ij}^k$ is defined as the utility value of roadblock risk for path $k$ from disaster node $i$ to shelter node $j$. Similarly, $p_{ij}^k$ is defined as the probability that path $k$ can be used to travel from disaster node $i$ to shelter node $j$. Therefore, the risk of a roadblock in a road section and the utility value of the risk of a roadblock are defined as follows:

\[
U_a = P_a \quad \forall a \in A \tag{4}
\]

\[
p_{ij}^k = \prod_{a=1} P_a S_{a}^{ij} \quad \forall i \in I, j \in J, k \in K \tag{5}
\]

\[
u_{ij}^k = p_{ij}^k \quad \forall i \in I, j \in J \tag{6}
\]
where \( \delta_{ik}^a \) indicates whether road section \( a \) is included in path \( k \) from disaster node \( i \) to shelter node \( j \). If road section \( a \) is included in path \( k \), then \( \delta_{ik}^a = 1 \); otherwise, \( \delta_{ik}^a = 0 \). To simplify operations, Eq. (5) can be rewritten as follows by taking logarithms on both sides:

\[
\log p_k^i = \log P_1^i \delta_{i_1k}^1 + \log P_2^i \delta_{i_2k}^2 + \ldots + \log P_a^i \delta_{i_ak}^a \quad \forall i \in I, j \in J, k \in K \quad (7)
\]

Eqs. (6) and (7) can then be combined as follows:

\[
u_k^i = \sum_a \log P_a \delta_{i_ak}^a \quad \forall i \in I, j \in J, k \in K \quad (8)
\]

Finally, the cost of constructing shelter facilities is based on the investment of resources at sites that meet a set of conditions. If the number of shelter facilities is unknown, the number of facilities should be determined in terms of their construction costs. At least one facility should be constructed. The number of shelter facilities to be constructed depends on their construction costs, and this number cannot exceed the maximum number of alternative sites \( N \).

On the basis of the problem description, the multiobjective model for the selection of urban shelter sites comprises three objectives, as presented in Eqs. (9)–(11):

maximizing the utility of perceived evacuation time (Objective 1), maximizing the utility of roadblock risk (Objective 2), and minimizing the construction cost of shelter
facilities (Objective 3). These objectives are subject to various restrictions, which are presented in Eqs. (12)–(23).

Max \( Z_1 = \sum_{i \in I} \sum_{j \in J} h_{ij} f(t_{ij}) y_{ij} \) \hspace{1cm} (9)

Max \( Z_2 = \sum_{i \in I} \sum_{j \in J} u_{ij} y_{ij} \) \hspace{1cm} (10)

Min \( Z_3 = \sum_{j \in J} C_j x_j \) \hspace{1cm} (11)

Subject to \( \sum_{j \in J} y_{ij} \geq 1 \hspace{0.5mm} \forall i \in I \) \hspace{1cm} (12)

\( \sum_{i \in I} y_{ij} \leq nx_j \hspace{0.5mm} \forall i \in I, j \in J \) \hspace{1cm} (13)

\( 1 \leq \sum_{j \in J} x_j \leq N \hspace{0.5mm} \forall j \in J \) \hspace{1cm} (14)

\( \sum_{i \in I} h_{ij} y_{ij} \leq cap_j x_j \hspace{0.5mm} \forall j \in J \) \hspace{1cm} (15)

\( \sum_{j \in J} h_{ij} y_{ij} = \bar{h}_i \hspace{0.5mm} \forall i \in I \) \hspace{1cm} (16)

\( \sum_{i \in I} h_{ij} y_{ij} = \hat{h}_j \hspace{0.5mm} \forall j \in J \) \hspace{1cm} (17)

\( p_k^{ij} = \prod_{a=1}^{\delta_{ak}} P_a^{ij} \hspace{0.5mm} \forall i \in I, j \in J, k \in K \) \hspace{1cm} (18)

\( u_k^{ij} = \sum_{a=1}^{\delta_{ak}} \log P_a^{ij} \hspace{0.5mm} \forall i \in I, j \in J, k \in K \) \hspace{1cm} (19)

\( h_{ij} \geq 0 \hspace{0.5mm} \forall i \in I, j \in J \) \hspace{1cm} (20)

\( x_j = \{0, 1\} \hspace{0.5mm} \forall j \in J \) \hspace{1cm} (21)

\( y_{ij} = \{0, 1\} \hspace{0.5mm} \forall i \in I, j \in J \) \hspace{1cm} (22)

\( \delta_{ak} = \{0, 1\} \hspace{0.5mm} \forall i \in I, j \in J, a \in A \) \hspace{1cm} (23)
According to Eq. (12), at least one shelter facility $j$ must be provided for each disaster node $i$. Eq. (13) indicates that multiple disaster nodes $i$ can be simultaneously assigned to a single shelter facility $j$. Eq. (14) indicates that a site must be selected for at least one shelter facility $j$. In this equation, the maximum number of alternative locations is represented by $N$. According to Eq. (15), the total capacity of the shelter facility must be greater than or equal to the total number of disaster victims. Eqs. (16) and (17) are conservation constraints for the number of disaster victims. Eq. (18) represents the probability of using path $k$ from disaster node $i$ to shelter facility $j$. Eq. (19) defines the utility of the risk of following path $k$ from disaster node $i$ to shelter facility $j$. Eq. (20) indicates that the number of victims traveling from disaster node $i$ to shelter facility $j$ is nonnegative. As indicated by Eq. (21), if shelter facility $j$ has been opened, then $x_j = 1$; otherwise, $x_j = 0$. According to Eq. (22), if disaster victims travel from disaster node $i$ to shelter facility $j$, then $y_{ij} = 1$; otherwise, $y_{ij} = 0$. As indicated by Eq. (23), if road section $a$ is part of path $k$, then $\delta^k_{ai} = 1$; otherwise, $\delta^k_{ai} = 0$.

3. Solution algorithm

3.1. Algorithm steps

In the RWGA, random weights are initialized, and an optimal solution is searched.
for through the evolution of each weight [8]. However, because this method is susceptible to random values, the quality and efficiency of its solutions can be inconsistent. Therefore, we developed the RRWM, which is based on the RWGA. The RRWM has two components.

In the first component of the RRWM, a fitness function is calculated through a compromise programming method (CPM; \[37\]), and the adaptive weight approach (AWA; \[38\]) is used to normalize the values of each objective function. Because the objectives may be in conflict, an approximation of the ideal solution is obtained using the CPM to calculate the distance between the individual solutions and the ideal solution. This approach can be considered an objective search method based on the \(L^1\) distance function \[37, 26\]. Moreover, all solutions in the current solution set are used to readjust the weights of each objective by using the AWA. The multiobjective EA is designed to tend toward the global solution. Therefore, the fitness function for a multiobjective problem can be redefined as follows to determine the closest ideal solution based on the CPM and AWA:

\[
Z_i^k = \sum_{i=1}^{q} \left( \frac{z_i^{max} - z_i^k}{z_i^{max} - z_i^{min}} \right) \quad \forall \ k \in SOL, \ i \in 1 \sim q
\]  

(24)
where $SOL$ is the solution set for the multiobjective problem, $q$ is the number of objectives, and $z^k_i$ is the value of the $i$th objective function of the $k$th solution in $SOL$. If objective $i$ is fixed (e.g., $i = 1$), $z^k_i$ can be considered the result of the standardization of the $k$th solution in the solution set for objective $i$. Therefore, we can standardize each objective function as follows:

\[
z_i^{norm}(x) = \begin{cases} 
  \frac{z_i(x) - z_i^{min}}{z_i^{max} - z_i^{min}}, & \text{if } z_i^{max} > z_i^{min} \\
  0, & \text{if } z_i(x) = z_i^{min}
\end{cases} \quad \forall \ i = 1 \sim k, \ x \in P \tag{25}
\]

\[
z_i^{norm}(x) = \begin{cases} 
  \frac{z_i^{max} - z_i(x)}{z_i^{max} - z_i^{min}}, & \text{if } z_i^{max} > z_i^{min} \\
  0, & \text{if } z_i(x) = z_i^{max}
\end{cases} \quad \forall \ i = 1 \sim k, \ x \in P \tag{26}
\]

\[F(x) = \sum_{i=1}^{k} w_i \cdot z_i^{norm}(x), \ i = 1 \sim k, \ x \in P \tag{27}\]

Eqs. (25)–(27) represent the method for normalizing the values of objective function $i$ for a given solution $x$. In these equations, $z_i(x)$ and $z_i^{norm}(x)$ denote the values of the $i$th objective function before and after normalization, respectively, and $z_i^{min}$ and $z_i^{max}$ denote the minimum and maximum values of the $i$th objective function for solution $x$ before normalization, respectively. After normalization, the values of the objective functions are between 0 and 1. Next, the values of the normalized objective functions are multiplied by their respective weights, and the
results are summed to obtain the fitness value for solution $x$. The fitness function of
the multiobjective problem is presented in Eq. (27).

In the second component of the RRWM, the set of Pareto optimal solutions
produced in each generation is adjusted according to the weights randomly generated
in the current generation. This effect is reflected in the quality of the current
generation’s solution and that of the overall multiobjective solution. Therefore, the
elitist strategy is adopted to select the superior solution from the set of Pareto optimal
solutions in each generation. Finally, the elite Pareto optimal solution set is obtained
to normalize the quality of the Pareto optimal solutions. The steps of the RRWM are
described as follows:

**Step 1:** Initiate the algorithm.

**Step 2:** Calculate the network values.

Based on given postdisaster information, the optimistic evacuation time ($t_{ij,optimistic}$),
the actual evacuation time ($t_{ij}$), and the longest evacuation time ($t_{ij,longest}$) between
disaster node $i$ and shelter node $j$ is obtained using the shortest path algorithm, and the
utility function of perceived evacuation time is derived according to Eq. (4).

Moreover, the value of the utility for roadblock risk $U_a$ is obtained according to the
roadblock risk value $R_a$ for each road section $a$.

**Step 3:** Encode the network nodes.

Binary gene encoding [0,1] is applied with the decision variable $y_{ij}$ under the assumption that chromosome length is equal to the total number of shelter and disaster nodes, where 0 represents a disaster node and 1 represents a shelter node. Each chromosome represents a feasible solution—a configuration of shelter nodes.

**Step 4:** Randomly generate an initial population of chromosomes and place the initial population in $N_{pop}$, and then set the total number of generations $T$.

**Step 5:** Evolve the chromosomes.

Confirm whether the chromosomes conform to the model constraints. Next, calculate the values of the objective functions for the chromosomes in $N_{pop}$ that meet these constraints. Normalize these values by using Eqs. (25) and (26). The current Pareto solution set is updated according to these normalized values.

**Step 6:** Calculate the fitness value.

Eq. (28) is used to obtain the random weights, which are then substituted into Eq. (27) to calculate the fitness value for each chromosome. Subsequently, a linear proportional transformation function [presented in Eq. (29)] is used to calculate $p_i$. 
Next, $N_{pop}/2$ pairs of chromosomes are selected from $N_{pop}$ for mating and mutation.

\[ w_i = \frac{\text{random}_i(g)}{\sum_{j=1}^{n} \text{random}_j(g)}, \quad i = 1, 2, ..., n \]  

\[ p_i = \frac{z_i - z_{\text{min}}}{\sum_{j=1}^{n} (z_j - z_{\text{min}})} \]

**Step 7:** Select the elite chromosomes ($N_{\text{elite}}$) from the Pareto optimal solution set.

The chromosomes with the highest fitness values in the Pareto optimal solution set are selected as the elite chromosomes ($N_{\text{elite}}$).

**Step 8:** Perform mating.

The single-point mating method is applied to the selected chromosomes with a mating rate $R_C$ of 0.8 and randomly selected mating sites. Two new chromosomes are produced, with the mating site serving as the baseline. This mating mechanism yields new chromosomes for the population $N_{pop}$.

**Step 9:** Perform mutation.

A certain number of genes in the chromosome are mutated at a mutation rate $R_m$ of 0.06. The selected genes are mutated from 0 to 1 or from 1 to 0.

**Step 10:** Apply the elitist strategy.

A certain number of $N_{\text{elite}}$ chromosomes are randomly removed from the population.
Next, $N_{\text{elite}}$ additional chromosomes are randomly selected from the current Pareto optimal solution set and added to $N_{\text{pop}}$ to replace the chromosomes that were randomly removed.

**Step 11:** Terminate the algorithm according to the condition test.

The condition for termination in this model is reaching the maximum number of generations $T$. If this condition is satisfied, the algorithm is terminated. If the condition is not satisfied, set $t = t + 1$ and return to Step 4.

This algorithm yields a set of elite Pareto optimal solutions, and the most suitable compromise solution can be selected from this set.

### 3.2. Evaluation of solution sets for the multiobjective problem

In the MOGA, solutions are obtained by approaching the Pareto optimal front through continuous evolution. The present study adopted the assessment of solution sets for the multiobjective problem methods proposed by Zitzler et al. [39]. The solution sets can be evaluated in terms of diversity and convergence. These evaluation methods are described as follows:

1. **Convergence of solution sets:** Zitzler et al. [39] proposed an evaluation method based on the convergence of solution sets. Assuming that $P'$, $P'' \subseteq P'$ are two
solution sets in the multiobjective space, a mapping from \((P', P'')\) to the interval [0,1] can be used to obtain the coverage rate \((CS)\) of \(P'\) and \(P''\). The parameter \(CS (P', P'')\) is defined as follows:

\[
CS (P', P'') \triangleq \frac{|\{x'' \in P'' | \exists x' \in P', x' \succ x'' \text{ or } x' = x''\}|}{|P''|}
\]  

(30)

According to Eq. (30), if all solutions \(x'\) in \(P'\) are dominant or equal to all solutions \(x''\) in \(P''\), then the coverage rate is equal to 1. Thus, the coverage rate is between 0 and 1.

2. Spatial distribution of the solution set: In the present study, three objectives were optimized simultaneously. After being normalized, the objective function values were plotted in a three-dimensional space. The method proposed by Zitzler et al. [39] was used to calculate the spatial distribution of the solution set in the space defined by the normalized objective function values, as presented in Eq. (31). The lower the standard deviation is, the lower the average and minimum distances between members of the solution set are and the more uniform the distribution of the solution set is in the space defined by the normalized objective function values.

\[
d_{trb} = \sqrt{\frac{1}{k-1} \sum_{i=1}^{k} (\bar{d} - d_i)^2}
\]

(31)

4. Numerical analysis
4.1. Test network data

This study used Zhongzheng District, Taipei City, as a test network. Figure 2 shows that this network contains 31 villages, 153 nodes, and 481 road links. The green nodes represent the 18 existing shelters, such as Zhong-Yi Primary School. The population’s temporary shelter requirements due to disaster-induced damage were estimated using the Taiwan Earthquake Loss Estimation System. If a disaster results in 21,452 equivalent number of victims, most people would not have access to shelter. Therefore, 14 alternative shelter sites, such as Chiang Kai-Shek Memorial Hall, were determined, as indicated by the yellow nodes in the figure. The network information is listed in Tables 1 and 2.

4.2. Testing and analysis

In this study, the RRWM was used to solve the multiobjective problem of selecting urban shelter facility sites. The number of selected shelter facilities should not exceed the total number of available sites (i.e., 32). The total number of chromosomes in $N_{pop}$ was set to 500, the number of generations was set to 500, the mating rate $R_c$ was set to 0.8, and the mutation rate $R_m$ was set to 0.06. Key information from the test results is presented subsequently.
With 500 generations, the RRWM was able to search the entire solution space. The total computation time was 249 s, and 500 optimal solution sets were obtained. The minimum adaptive value was 0.58 and was obtained after solution set 340; thus, this set was the superior compromise solution set. The node numbers of the refuge facilities corresponding to the optimal compromise solution included 122, 123, 126, 129, 130, 131, 132, 133, 134, 135, 136, 137, 138, 139, 140, 143, 144, 147, 148, 149, 150, 152, and 153. According to Eqs. (9)–(11), the total utility of perceived evacuation time was derived as 19257.55 (Objective 1), the total utility of roadblock risk was 67.92 (Objective 2), and the total construction cost was NT$77 million (Objective 3).

Table 3 presents the assignment of victims from disaster to shelter facilities. For example, the equivalent number of victims at node 8 was 235. Because of capacity constraints, 144 equivalent number of victims were assigned to node 132 for shelter. On the basis of the developed allocation mechanism, the remaining 91 equivalent number of victims were assigned to node 140, which exhibited the second-greatest utility of perceived evacuation time. Moreover, node 140 was located near node 132. Overall, the sum of the equivalent number of victims assigned to the different shelter
nodes was equal to the equivalent number of victims at the disaster nodes. Thus, the solution satisfied the constraint for the multiobjective model presented in Eq. (18).

Table 4 shows the sum of the equivalent number of victims from each disaster-affected node to the shelter node, which meets the shelter facilities' limitations for victims. Take Central Culture Park (shelter node 140) as an example, victims from 16 different distasting-affected nodes go to shelter at shelter node 140. the equivalent number of victims was 2,495. It can be seen that all the site selection conditions obtained under multiple objectives meet the capacity constraints of asylum facilities.

4.3. Convergence to the pareto optimal front

This section discusses the coverage rate and spatial distribution of the optimal solution sets. The adaptive values and normalized target values of two elite Pareto optimal solution sets were input into Eq. (30), and a coverage rate of 94% was derived. This result indicates that the new solution was improved relative to the previous solution set. Next, the normalized objective function values \((Z'_1, Z'_2, Z'_3)\) of the Pareto optimal solution set were input into Eq. (31), and a spatial distribution of 0.018972 was obtained. This value indicates the degree to which the nondominated
solutions are uniformly distributed in the three-dimensional space defined by the normalized objective values. We used STATISTICA 6.1 software to plot the spatial distribution of the solution set (Figure 3). The distribution of the solution set near the origin was similar to that of the Pareto optimal front, demonstrating the suitability of the RRWM.

Table 5 presents a comparison of the results of the RRWM, RWGA, and single-objective GA (SOGA). The performance of the optimal solution set obtained using the RRWM was further evaluated. Eight weight values from the SOGA were tested. The number of solution sets \(N_{\text{pop}}\) and the number of generations were 500 for the RRWM, RWGA, and SOGA. Table 5 lists the adaptation values, spatial distributions, and coverage rates of the aforementioned algorithms. First, Eqs. (25) and (26) were used to derive the RRWM fitness value of 0.58, which was superior (lower) to those obtained using the other algorithms. Second, the coverage rate of the RRWM reached 94%, and its spatial distribution was 0.018972. In contrast to the RWGA and SOGA, the RRWM achieved robust convergence in terms of solution performance and coverage rate.

Furthermore, on the basis of the state of the scatter diagram. In Figure 4, the
distribution of the solution set obtained by RWGA does not form a Pareto front. As for The spatial distribution of the SOGA was optimized with weights of 0.92, 0.04, and 0.04 (as shown in Figure 5). However, this solution set was not forming a Pareto frontier either. By contrast, the spatial distribution value of the RRWM was suboptimal; however, the solution set was close to a Pareto optimal front when plotted in the space defined by the normalized objective function values. Moreover, the solution set of the RWGA was oriented in the direction of the $Z'_2$-axis with a suboptimal spatial distribution. For other weighting strategies, the solution sets were oriented in the direction of the axis with the highest enactment value (i.e., aligned according to the specific weight ratio).

5. Conclusions and recommendations for future work

This study presents a model for site selection for shelter facilities after large-scale urban disasters. A trade-off exists among the utility of perceived evacuation time, the utility of roadblock risk, and the cost of shelter construction. Accordingly, the relationships between these parameters were modeled using a multiobjective model. The locations selected for shelter facilities should be the optimal compromise between the aforementioned parameters. The number of people required to move from disaster nodes to shelter nodes and the capacities of the shelter facilities are also included in
the developed model.

In contrast to the RWGA, the proposed RRWM includes an elitist mechanism and is designed to evolve an evenly distributed trade-off frontier defined by nonconvex functions. The RRWM yields a nondominated solution set with satisfactory distribution; hence, it may provide valuable assistance to decision-makers. This finding demonstrates the flexibility of the proposed method for practical planning problems and its effectiveness for evaluating decision schemes.

This study was limited to a single category of displaced people. In the future, different identities can be included to solve problems caused by multiple identities. Information on the utility of perceived evacuation time and the utility of roadblock risk can be collected during regular household surveys and urban environmental audits. The main focus of the present study was on modeling and algorithm design. In future studies, the proposed model can be applied and evaluated by adding parameters after calibration to ensure that the results are more suited to practical requirements.

Declarations

Availability of data and materials
All data generated or analysed during this study are included in this published article.

**Competing interests**

To the best of our knowledge, the named authors have no conflict of interest, financial or otherwise.

**Funding**

This research was supported by Ministry of Science and Technology/108-2410-H-606-007-

**Authors' contributions**

Conception and design: KCY, Provision of study materials: KCY; WC; WCS,

Collection and assembly of data: WC; WCS, Data analysis and interpretation: KCY;

WC, Manuscript writing: All authors.

**Acknowledgements**

The authors thank anonymous referees for their helpful and constructive comments for improving the paper. In addition, the study was supported by the Ministry of Science and Technology (Project No. 108-2410-H-606-007-). Finally, this manuscript was edited by Wallace Academic Editing.

**Authors' information (optional)**
Kuo-Chi Yen. Ph.D. Associate professor.

Weid Chang. Master of Business Administration.

Wu-Chiao Shih. Ph.D. Assistant professor.

References

1. Bashawri A, Garrity S, Moodley K. An overview of the design of disaster relief shelters. Proc Econ Finance. 2014;18:924–31.

2. Kongsomsaksakul S, Yang C, Chen A. Shelter location-allocation model for flood evacuation planning. J East Asia Soc Transp Stud 2005;6:4237–52.

3. Bayram V, Tansel BÇ, Yaman H. Compromising system and user interests in shelter location and evacuation planning. Transp Res Part B Methodol. 2015;72:146–63.

4. Lin YY, Ding CU, Wu CG, Ma T, Jiang X. Study on emergency evacuation behavior of residents in urban high-density residential areas. Planners. 2013;7:105–9.

5. Chopra S, Lovejoy W, Yano C. Five decades of operations management and the prospects ahead. Manage Sci. 2004;50:8–14.
6. Kahneman D, Tversky A. Prospect theory: an analysis of decision under risk. Econometrica. 1979;47:263–2291.

7. Kahneman D, Tversky A. Choices, values, and frames. In: MacLean LC, Ziemba WT, editors, Handbook of the fundamentals of financial decision making. Cambridge, UK: Cambridge UP; 2000. p. 269-278.

8. Shen Y, Wang Q, Yan W, Wang J. A transportation-location problem model for pedestrian evacuation in chemical industrial parks disasters. J Loss Prev Proc Ind. 2015;33:29–38.

9. Murata T, Ishibuchi H. MOGA: multi-objective genetic algorithms. In: IEEE International Conference on Evolutionary Computation. Perth, Australia; 1995 Nov.

10. Current JR, Min H, Schilling D. Multiobjective analysis of facility location decisions. Eur J Operat Res 1990;49:295–307.

11. Fan CA. A study on assessing rules of flood refuge [Master's thesis]. Hsinchu, Taiwan, Republic of China: National Chiao Tung Univ; 2014.

12. Farahani RZ, Asgari N, Heidari N, Hosseininia M, Goh M. Covering problems in facility location: a review. Comput Ind Eng. 2012;62:368–407.
13. Li X, Zhao Z, Zhu X, Wyatt T. Covering models and optimization techniques for emergency response facility location and planning: a review. Math Methods Operat Res 2011;74:281–310.

14. Hobeika AG. Optimal diversion strategies for a congested urban network: final project report. Phase1 (No. MAUTC/VPI01-0189); 1991.

15. Sherali HD, Carter TB, Hobeika AG. A location-allocation model and algorithm for evacuation planning under hurricane/flood conditions. Transp Res Part B Methodol. 1991;25:439–52.

16. Pérez-Galarce F, Canales LJ, Vergara C, Candia-Véjar A. An optimization model for the location of disaster refuges. Socio-Econ Plan Sci. 2017;59:56–66.

17. Boonmee C, Arimura M, Asada T. Facility location optimization model for emergency humanitarian logistics. Int J Disast Risk Red. 2017;24:485–98.

18. Berman O, Krass D. Flow intercepting spatial interaction model: a new approach to optimal location of competitive facilities. Locat Sci. 1998;6:41–65.

19. Li JG, Tang XM, Liu ZG, Wang HB. A refuge allocation algorithm based on optimal travel distance and limited capacity is studied. J Geodesy Geoinform Sci. 2011;40:489–94.
20. Ma Y, Wu H. Definitions and curve fitting of time satisfaction functions in facility location problems. In: 2006 International Conference on Management Science and Engineering Piscataway, NJ, USA; 2006.

21. Zhu T, Wang YM. Study on site selection of emergency logistics facilities considering road risks. Logist Eng Manage. 2014;8:102–5.

22. Hsu TP, Lu GH. Development of the minimal risk routing model for post-earthquake traffic management. Bull Coll Eng Natl Taiwan Univ. 2002;85:33-48.

23. Karatas M. A multi-objective facility location problem in the presence of variable gradual coverage performance and cooperative cover. Eur J Operat Res. 2017;262:1040–51.

24. Chen ZF, Chen J, Li Q. Study on hierarchical location of urban emergency shelters (II)- three-level location selection model. J Nat Disast. 2010;19:13–19.

25. Current JR, Storbeck JE. Capacitated covering models. Environ Plan B Plan Des. 1988;15:153–63.

26. Wu LY, Zhang XS, Zhang JL. Capacitated facility location problem with general setup cost. Comput Operat Res. 2006;33:1226–41.
27. Kuhn HW, Tucker AW. Nonlinear programming. In Proceedings of the 2nd Berkeley Symposium on Mathematical Statistics and Probability. Berkeley; 1951.

28. Shukla PK, Deb K. On finding multiple Pareto-optimal solutions using classical and evolutionary generating methods. Eur J Operat Res. 2007;181:1630–52.

29. Alçada-Almeida L, Tralhao L, Santos L, Coutinho · Rodrigues J. A multiobjective approach to locate emergency shelters and identify evacuation routes in urban areas. Geogr Anal. 2009;41(1):9–29.

30. Zhou YF, Liu M, Wang L. Study on the site selection of urban refuge based on multi-objective planning. J Safety Environ. 2010;20:205–9.

31. Coutinho-Rodrigues J, Tralhão L, Alçada-Almeida L. Solving a location-routing problem with a multi-objective approach: the design of urban evacuation plans. J Transp Geogr. 2012;22:206–18.

32. Deb K. Multi-objective optimization using evolutionary algorithms: an introduction. Multi-objective evolutionary optimisation for product design and manufacturing. London: Springer; 2011. p. 3-34.

33. Konak A, Coit DW, Smith AE. Multi-objective optimization using genetic algorithms: a tutorial. Reliabil Eng Syst Safety 2006;91:992–1007.
34. Fiedrich F, Gehbauer F, Rickers U. Optimized resource allocation for emergency response after earthquake disasters. Saf Sci. 2000;35:41–57.

35. Ren QL, Zeng K, Wang K. Model of evacuation route choice in emergency traffic based on prospect theory. J Chongqing Jiaotong Univ (Nat Sci). 2016;35:100–4.

36. Chou TY, Hsu CL, Chen MC. A fuzzy multi-criteria decision model for international tourist hotels location selection. Int J Hosp Manage. 2008;27:293–301.

37. Israeli Y, Ceder A. Transit route design using scheduling and multiobjective programming techniques. In: Daduna JR, Branco I, Piaxão J, editors. Computer-aided transit scheduling. Lecture notes in economics and mathematical systems. Berlin, Heidelberg: Springer; 1995. p. 56-75.

38. Gen M, Cheng R, Lin L. Network models and optimization: multi-objective genetic algorithm approach. London, UK: Springer; 2008.

39. Zitzler E, Deb K, Thiele L. Comparison of multiobjective evolutionary algorithms: empirical results. Evolut Comput. 2000;8:173–95.

Table 1 Network details for Zhongzheng district, Taipei City.

| Node | Facilities | Capacity | Setting cost | Node | Facilities | Capacity | Setting |
|------|------------|----------|--------------|------|------------|----------|---------|
| Number | (Equivalent population) | Number | (Equivalent population) | Number | (Equivalent population) |
|--------|--------------------------|--------|--------------------------|--------|--------------------------|
|        | (NT$ million)            |        |                          |        | (NT$ ten thousand)       |
| Zhongyi Elem. Sch. | 330 | 200 | 138 | 269 | 100 |
| Yingqiao Junior High School | 282 | 100 | 139 | 303 | 100 |
| Affiliated Experimenta Elementary School | 387 | 200 | 140 | 3355 | 1000 |
| Hongdao Junior High | 317 | 100 | 141 | Qidong Park | 360 | 300 |
| #  | School                      | Building | Level | Year | Ceiling | Area |
|----|----------------------------|----------|-------|------|---------|------|
| 126| Zhongxiao Park             | 142      |       |      | 380     | 300  |
| 127| Zhongzheng Sports Center   | 143      |       |      | 390     | 300  |
| 128| Zhongzheng Junior High School | 144      |       |      | 5109    | 1000 |
| 129| Taipei First Girls High School | 145      |       |      | 470     | 400  |
| 130| Guting Junior High School  | 146      |       |      | 390     | 300  |
| No. | Name                  | Grade Level | Students | Teachers | Ratio |
|-----|-----------------------|-------------|----------|----------|-------|
| 131 | Chenggong High School |             | 280      | 100      | 147   |
| 132 | Zhongxiao Elementary  | Elementary  | 280      | 100      | 148   |
| 133 | Dongmen Elementary    | Elementary  | 330      | 200      | 149   |
| 134 | He-Ti Elementary      | Elementary  | 320      | 100      | 150   |
| 135 | Nanmen Elementary     | Elementary  | 320      | 100      | 151   |
| 136 | Nanmen Junior High    | Junior High | 371      | 200      | 152   |
|     | Yongchang Park        |             | 380      | 300      |       |
|     | Yingqiao Park         |             | 290      | 200      |       |
|     | Nanchang Park         |             | 760      | 600      |       |
|     | Guling Park           |             | 510      | 400      |       |
|     | Wensheng Park         |             | 320      | 200      |       |
|     | Treasure Hill Temple  |             | 5109     | 1000     |       |
| Node numb | Equivalent number | of victims |
|------------|-------------------|-----------|
| 1          | 125               | 25        |
| 2          | 225               | 26        |
| 3          | 115               | 27        |
| 4          | 195               | 28        |
| 5          | 251               | 29        |
| 6          | 232               | 30        |
| 7          | 132               | 31        |
| 8          | 235               | 32        |
| 9          | 136               | 33        |
|   | 10 | 135 | 34 | 113 | 58 | 277 | 82 | 182 | 106 | 21 |
|---|----|-----|----|-----|----|-----|----|-----|-----|----|
| 11 | 225 | 35 | 161 | 59 | 177 | 83 | 184 | 107 | 175 |
| 12 | 125 | 36 | 205 | 60 | 146 | 84 | 182 | 108 | 230 |
| 13 | 225 | 37 | 105 | 61 | 140 | 85 | 182 | 109 | 132 |
| 14 | 154 | 38 | 205 | 62 | 179 | 86 | 182 | 110 | 132 |
| 15 | 254 | 39 | 244 | 63 | 273 | 87 | 222 | 111 | 165 |
| 16 | 195 | 40 | 144 | 64 | 147 | 88 | 139 | 112 | 165 |
| 17 | 177 | 41 | 191 | 65 | 182 | 89 | 105 | 113 | 54  |
| 18 | 277 | 42 | 118 | 66 | 182 | 90 | 205 | 114 | 53  |
| 19 | 177 | 43 | 197 | 67 | 162 | 91 | 154 | 115 | 51  |
| 20 | 136 | 44 | 198 | 68 | 122 | 92 | 197 | 116 | 52  |
| 21 | 225 | 45 | 164 | 69 | 222 | 93 | 198 | 117 | 165 |
| 22 | 125 | 46 | 264 | 70 | 179 | 94 | 239 | 118 | 94  |
| 23 | 254 | 47 | 164 | 71 | 125 | 95 | 122 | 119 | 93  |
| 24 | 161 | 48 | 164 | 72 | 225 | 96 | 222 | 120 | 93  |
|    |    |    |    |    |    |    |    |    | 121 | 93 |

Table 3 Assignment of victims from disaster nodes to shelter facilities.
| Affected node | Victims of equivalent | Shelter facility | Equivalent victims of shelter |
|---------------|-----------------------|------------------|------------------------------|
| 8             | 235                   | 132              | 144                          |
| 25            | 261                   | 153              | 119                          |
| 27            | 205                   | 140              | 102                          |
| 50            | 146                   | 140              | 2                            |
| 51            | 279                   | 144              | 187                          |
| 57            | 177                   | 144              | 111                          |
| 64            | 147                   | 135              | 47                           |
| 66            | 182                   | 126              | 19                           |
|   |     |     |
|---|-----|-----|
|   | 144 | 163 |
| 70 | 136 | 67  |
| 72 | 144 | 112 |
| 74 | 148 | 185 |
| 74 | 144 | 40  |
| 74 | 122 | 205 |
| 80 | 149 | 7   |
| 80 | 138 | 152 |
| 82 | 149 | 47  |
| 82 | 149 | 4   |
| 82 | 144 | 178 |
| 88 | 137 | 117 |
| 88 | 150 | 22  |
| 92 | 150 | 63  |
| 92 | 144 | 134 |
| 93 | 147 | 183 |
| 93 | 144 | 15  |

50
### Table 4

Relationship between the holding status and capacity limits of shelter facilities.

| Affected node | Refuge node | Total equivalent number of displaced victims | Capacity of shelter facility |
|---------------|-------------|---------------------------------------------|-----------------------------|
| 3             | 140         | 139 (115)                                   | 64                          |
| 4             | 140         | 144 (195)                                   | 58                          |
| 5             | 140         | 134 (251)                                   | 44                          |
| 101           | 175         | 152                                          | 131                         |
| 104           | 239         | 130                                          | 99                          |
| 111           | 165         | 144                                          | 140                         |
|               |             | 123                                          | 150                         |
|               |             | 152                                          | 15                          |
| Affected node → Refuge node | Total equivalent number of displaced victims | Capacity of shelter facility |
|-----------------------------|--------------------------------------------|----------------------------|
| 8 → 140                     | 91                                        | 510                        |
| 9 → 140                     | 136                                       | 510                        |
| 10 → 140                    | 135                                       | 510                        |
| 16 → 140                    | 195                                       | 510                        |
| 18 → 140                    | 277                                       | 510                        |
| 27 → 140                    | 102                                       | 510                        |
| 28 → 140                    | 105                                       | 510                        |
| 29 → 140                    | 145                                       | 510                        |
| 38 → 140                    | 205                                       | 510                        |
| 50 → 140                    | 2                                         | 510                        |
| 19 → 140                    | 177                                       | 510                        |
| 84 → 150                    | 182                                       | 510                        |
| 88 → 150                    | 22                                        | 510                        |
| 92 → 150                    | 63                                        | 510                        |
| 96 → 150                    | 222                                       | 510                        |
Affected node $\rightarrow$ Refuge node

Total equivalent number of displaced victims | Capacity of shelter facility
--- | ---
106 $\rightarrow$ 150 (21)

Equivalent information on the number of disaster victims is presented in parentheses

**Table 5** Comparison of the convergence of different algorithms.

| Applied algorithms | Weights of $w_1$, $w_2$, $w_3$ | Fitness value | Distribution of space value | Cover value | CPU time (s) |
|--------------------|-------------------------------|---------------|-----------------------------|-------------|-------------|
| RRWM               | Random weights                | 0.58          | 0.018972                    | 0.94        | 248.82      |
| RWGA               | Random weights                | 1.01          | 0.045126                    | 0.97        | 248.82      |
| SOGA               | 0.92 : 0.04 : 0.04            | 0.91          | 0.011198                    | 0.90        | 319.02      |
|                    | 0.92 : 0.04 : 0.04            | 0.91          | 0.011198                    | 0.90        | 319.02      |
|                    | 0.04 : 0.92 : 0.04            | 0.81          | 0.036868                    | 0.97        | 270.66      |
|                    | 0.04 : 0.92 : 0.04            | 0.81          | 0.036868                    | 0.97        | 270.66      |
|                    | 0.04 : 0.04 : 0.77            | 0.77          | 0.043224                    | 0.81        | 296.52      |
|                    | 0.04 : 0.04 : 0.77            | 0.77          | 0.043224                    | 0.81        | 296.52      |
|                    | 0.04 : 0.04 : 0.77            | 0.77          | 0.043224                    | 0.81        | 296.52      |
| Applied algorithms | Weights of $w_1$, $w_2$, $w_3$ | Fitness value | Distribution of space | Cover value | CPU time (s) |
|--------------------|--------------------------------|---------------|----------------------|-------------|-------------|
|                    | 0.92                          |               |                      |             |             |
|                    | 0.96 : 0.02 :                 | 0.59          | 0.047214             | 0.93        | 271.38      |
|                    | 0.02                          |               |                      |             |             |
|                    | 0.02 : 0.96 :                 | 0.61          | 0.038667             | 0.97        | 269.04      |
|                    | 0.02                          |               |                      |             |             |
|                    | 0.02 : 0.02 :                 | 0.79          | 0.038329             | 0.81        | 256.80      |
|                    | 0.96                          |               |                      |             |             |
|                    | 0.98 : 0.01 :                 | 0.62          | 0.043297             | 0.95        | 271.02      |
|                    | 0.01                          |               |                      |             |             |
|                    | 0.01: 0.01: 0.98              | 0.79          | 0.037097             | 0.63        | 252.54      |

**Figure captions**

- **Fig. 1** Perceived utility function of evacuation time
- **Fig. 2** Network for Zhongzheng District, Taipei City
- **Fig. 3** Spatial distribution of the RRWM solution set
Fig. 4 Spatial distribution of the RWGA solution set

Fig. 5 Spatial distribution of the SOGA solution set under different target weights
Figures

Figure 1

Perceived utility function of evacuation time
Figure 2

Network for Zhongzheng District, Taipei City
Figure 3
Spatial distribution of the RRWM solution set

Figure 4
Spatial distribution of the RWGA solution set
Figure 5

Spatial distribution of the SOGA solution set under different target weights