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Optimizing Temporary Rescue Facility Locations for Large-Scale Urban Environmental Emergencies to Improve Public Safety

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ABSTRACT. Emergency rescue facility is an important component of urban system and affects public safety. Due to the special characteristics and complex environment of large-scale environmental disasters in urban areas, locations of emergency rescue facilities should be optimized. This study proposed an innovative methodological framework to optimize the locations of emergency rescue facility in the case of large-scale urban environmental disasters. A decision optimization model which consists of three-objectives representing service capacity, global efficiency and equity was developed. An appropriate spatial representation and encoding strategy was designed and coupled with the NSGA-II algorithm for model solving. Based on a hypothetical disaster scenario, a case study of Chaoyang district in Beijing is presented to demonstrate the methodology and explore the conflicting objectives. The results provide evidence that the model is able to successfully generate the Pareto-optimal frontier for the multi-objective emergency facility location problem, and provide a pool of alternative solutions to the decision-makers. The findings show that the framework proposed in this study has the potential to be a useful decision support tool for urban planning with respect to public safety.

Keywords: environmental disaster, facility location, spatial optimization, multi-objective, dominance solution

1. Introduction

Natural disasters such as earthquakes, floods, or man-made accidents (terrorist attacks, chemical leakages, fire and explosion) can cause vast damage to a large-scale area in a short time, and leave many casualties behind (Jia et al., 2007a, 2007b; Rawls and Turnquist, 2010), especially in densely populated urban areas. In recent years, a number of severe environmental emergencies such as the explosion of H_2S in Chongqing in 2004, the water pollution incident of Songhua River in 2005, and the oil spill in Dalian in 2010 have occurred in China, causing enormous property damage and life-loss (Liao et al., 2012). Following the rapid urbanization, public safety and health in the highly populated urban areas has caught national attentions, due to disastrous events (Liao et al., 2011; Xiang et al., 2011), which raises tremendous demands of rescue supplies (e.g., shelters, food, water, medicine, etc.) to be quickly dispatched to the requesting areas (Caunhye et al., 2012). In this context, numbers of temporary emergency rescue facilities are oftentimes set up in the short-term post-disaster emergency logistics stage (FEMA, 2008). These temporary emergency rescue facilities are crucial for ensuring the efficiency of emergency relief distribution and casualty transportation (FEMA, 2008; Lee et al., 2009; Horner and Downs, 2010; Maliszewski and Horner, 2010; Caunhye et al., 2012; Maliszewski et al., 2012). One of the most prominent associated issues is: how should one properly locate these facilities? In other words, what are the optimal locations of the temporary emergency rescue facilities? Consequently, developing optimal strategies for effectively locating these temporary emergency rescue facilities is of great significance for disaster mitigation and public safety protection.

The essential issue of the temporary emergency rescue facility locations (TERFLs) problem is actually a facility location optimization problem (Church and ReVelle, 1974; Revelle and Hogan, 1989; Jia et al., 2007a; Church and Murray, 2009). Research on this problem is abundant and many decision models have been developed to solve various facility location problems, including the ones in the context of regular emergency services (e.g., fire stations, medical centres, etc.) (Chrissis, 1980; Revelle and Snyder, 1995; Liu et al., 2006; Alçada-Almeida et al., 2009; Indriasari et al., 2010; Maliszewski and Horner, 2010). However, disasters are extremely large-scale events, with the special characteristic of low frequency and sudden tremendous demand for supplies, distinguished from other regular emergency events (Jia et al., 2007a). Therefore, the strategy for locating regular emergency facilities may not be suitable for the special situations of

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large-scale disaster emergency services (Jia et al., 2007b; Huang et al., 2010). For example, the low frequency feature of large-scale emergencies means that maintaining an enormous relief materials reserve in peacetime is too expensive for any local government. Generally, the better strategy instead is concentration of a large amount of relief supplies in National Logistics Staging Areas (NLSAs) by the federal government in peacetime. Once the catastrophe occurs, these relief supplies will be first allocated to the Local Logistics Staging Areas (LLSAs) operated by the local government, and finally distributed to the victims through some temporary rescue facilities (e.g., PODs-points of distribution) that are selected and deployed by the Local Emergency Management Agencies (LEMAs) (FEMA, 2008; Lee et al., 2009; Horner and Downs, 2010). A general relief distribution framework in a large-scale disaster emergency situation is shown in Figure 1. Moreover, tremendous uncertainty of demand and insufficient supplies will exist in a large-scale emergency due to damage of the transportation infrastructure or existence of the worst weather conditions, implying that redundant and dispersed placement of temporary rescue facilities is necessary to improve the serviceability (Jia et al., 2007a). Furthermore, the role of temporary rescue facilities in large-scale emergency logistics is usually not solely for rescue, and these facilities may play the roles of both relief distribution and casualty transportation at the same time (Caunhye et al., 2012). Therefore, the criteria for evaluating the optimum locations of these facilities should be comprehensive, taking into account the special characteristics of large-scale disaster emergency situations.

In recent years, the TERFLs problem for large-scale disaster emergencies has received increasing attention from the emergency management and homeland security communities. Caunhye et al. (2012) reviewed the optimization models utilized in disaster emergency logistics, and several research gaps were identified as well as future research directions proposed; Jia et al. (2007a, 2007b) surveyed general models used to address a regular emergency, and proposed a general facility location modelling framework suitable for large-scale emergency situations; Horner and Downs (2010) proposed a spatial modelling framework for locating critical supply facilities in the context of a hurricane emergency. Maliszewski et al. (2012) compared four pairs of conflicting objectives and explored the trade-offs between pairs of them; Bell et al. (2011) performed sensitivity analysis in order to determine the impact of different objectives on the location model, but a systematic exploration of the effects of conflicting objectives simultaneously is still lacking in the literature. In summary, the decision models in present studies tend to involve solely single- or bi-objectives; to date, models embracing multi-objective features are sparse (Caunhye et al., 2012).

In addition, the approaches for model solution proposed in previous studies are generally exact approaches, such as linear or integer programming methods. Unfortunately, there are practical limitations associated with the use of these exact methods in the large-scale emergency facility location problem, because huge sets of geographical spatial data are usually involved and it is recognized as a typical NP-hard problem (Xiao et al., 2002). The computational effort often increases dramatically with extremely numerous and detailed spatial data, which means that medium- to large-sized solution space problems often exceed the capabilities of these exact approaches (Tong et al., 2009; Murray, 2010). In order to overcome the limitations of exact methods, researchers have resorted to some types of evolutionary algorithms (e.g., GA) in solving the large-scale facility location problem (Jia et al., 2007b; Indriasari et al., 2010). When GA is applied to solve multi-objective optimization problems, the scalar fitness information should be provided to combine the multiple objectives into a single objective by using some kinds of aggregating approaches such as weighted sum approach, goal programming, etc. (Coello, 1999). This strategy is simple in use, but its limitation is obvious. Firstly, some accurate scalar information on the range or behaviour of each objective function should be provided in order to avoid having one of them to dominate the others, which is normally a very expensive process in most real-world application cases (Coello, 1999). Moreover, this approach has a serious drawback in actual applications that it may miss concave portions of the trade-off curve, saying it does not guarantee to generate proper Pareto optimal solutions in the presence of non-convex search spaces (Brian et al., 1994; Xiao et al., 2002). Furthermore, in many applications, it is usually difficult for decision makers to determine the appropriate weights when some features of the problem are not fully understood during the early stages of decision-making (Miettinen, 1999; Xiao et al., 2007). Therefore, it is necessary to adopt a more appropriate approach to solve the multi-objective TERFLs problem in a large-scale emergency situation.

In the last decades, several novel algorithms have emerged in the evolutionary computation community for solving multi-objective optimization problems, called multi-objective evolutionary algorithms (MOEA) (Zitzler and Thiele, 1999; Deb et al., 2002; Knowles, 2008). MOEA are essentially heuristic methods that are often more efficient than exact approaches, and they are less susceptible to the shape or continuity of the Pareto optimal frontiers (Coello, 1999). They are derived from evolutionary algorithms (EAs) and have been successfully demonstrated as efficient posterior approaches in solving various multi-objective spatial optimization problems (Xiao et al., 2002, 2007; Farhana and Murray, 2008; Huang et al., 2008; Lee and Xiao, 2009; Cao et al., 2011; Wu et al., 2011; Algirdas and Julius, 2013). The main advantage of MOEA is their ability to deal simultaneously with a set of possible solutions and allow one to find multiple Pareto optimal solutions in a single simulation run (Deb et al., 2002), instead of having to perform a series of separate runs as in the case of traditional mathematical programming methods (Georgiadou et al., 2010). The strategy in MOEA is called posterior articulation of preferences, which does not require the intensive participation of decision makers before or during the process of generating alternatives. A diverse set of non-dominated solutions can be generated and distributed on the Pareto optimal frontier. These solutions are subsequently presented to the de-

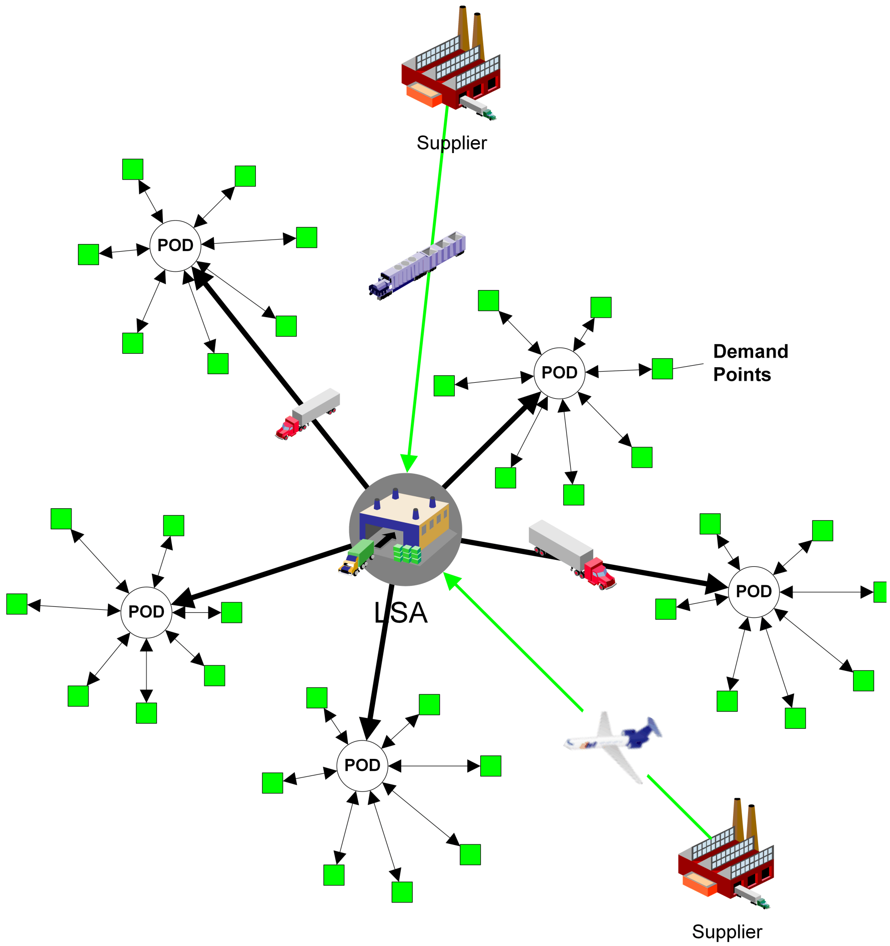

Figure 1. Framework for emergency rescue operations in large-scale disaster situation associated with the facilities and flows (FEMA, 2008).

cision makers, who make a final decision about the problem by examining and negotiating about the merits of alternatives. These advantages of MOEA suggest a promising future for solving the multi-objective TERFLs problem in large-scale emergency situations, as well as the model's incorporation into a decision support system.

This research proposes an innovative methodology for solving TERFLs problem in the context of large-scale environmental disaster in urban areas. Both the framework of decision model construction and the model solution strategy are presented. The key features that distinguish this research from previous works consist in: (1) a three-objective decision optimization model is constructed, which includes a variant of max-cover model, the p-median model and p-center, representing service capacity, global efficiency and equity, respectively; (2) an appropriate spatial presentation and encoding strategy is designed and coupled with the NSGA-II algorithm for model solution. The case study of the Chaoyang district in Beijing is presented to demonstrate the capabilities and potentials of the methodology.

2. Multi-Objective Optimization Model for TERFLs Problem

The essence of TERFLs is a spatial optimization problem that involves multiple conflicting objectives (Birkin, 1996). This study developed an innovative methodological framework for solving multi-objective TERFLs problems, as shown in Figure 2. The following presents the general characteristics of multi-objective optimization problems, and then the multi-objective decision optimization model for TERFLs in a large-scale emergency.

2.1. Multi-Objective Optimization Problem

The pioneering study on optimality in multi-objective problems is attributed to Pareto (Coello, 1999); therefore, a multi-objective problem is usually called "Pareto Optimal". Based on his analytical work, without loss of generality, the mathematical form of multi-objective optimization problems can be formulated as follows:

$$Minimize \ \left\{ f_1(x), f_2(x), \cdots, f_m(x) \right\}; \qquad x \in S \tag{1}$$

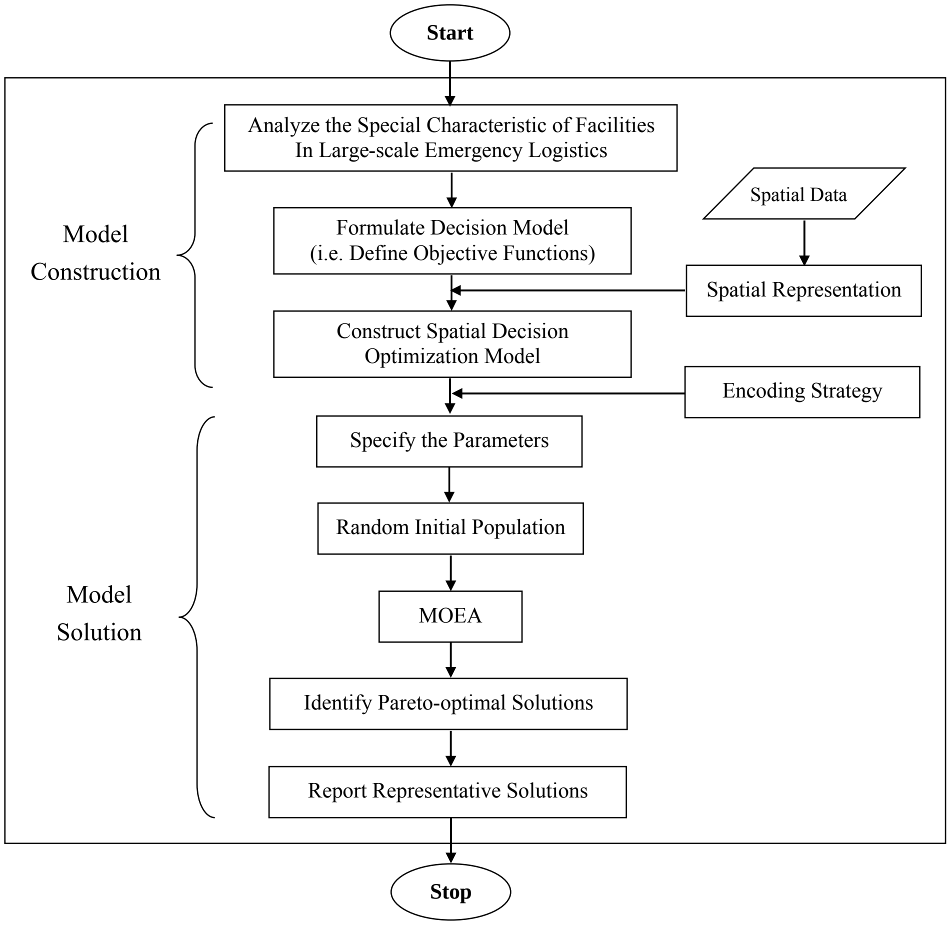

Figure 2. Flowchart of the methodology for solving multi-objective TERFLs problem.

where S corresponds to the decision variable set (all feasible solutions), f is a vector of m objective functions (f_1, f_2,⋯, f_m) that are to be minimized, and x is a vector of decision variables.

In order to avoid the use of value trade-offs involving subjective judgments, an alternative approach can be followed by using the concept of "dominance". The concept of "dominance" enables solutions to be compared and ranked without imposing any a priori measure as to the relative importance of individual objectives, neither in the form of subjective weights or arbitrary constraints (Marseguerra et al., 2004). Specifically, a decision vector $x' \in S$ is said to dominate a decision vector $x'' \in S$ if and only if:

$$\forall i \in \{1, 2, \cdots, m\}: f_i(x') \le f_i(x'') \wedge \exists i \in \{1, 2, \cdots, m\}: f_i(x') < f_i(x'') \tag{2}$$

That is, if no objective function value of x' is higher (worse) than that of x'', and there is at least one objective function value of x' that is lower (better) than that of x'', then the solution x' dominates solution x'', i.e. $x' \prec x''$. A subset of all feasible solutions is called non-dominated (or efficient) if its members are not dominated by any other solutions, and if solutions outside this subset are dominated by at least one solution in this subset. The subset of non-dominated solutions is called the "Pareto optimal set" or "Pareto optimal frontier" (Miettinen, 1999).

2.2. Optimization Model Construction for TERFLs

Generally, optimization models for facility location problems aim to achieve certain decision objectives (e.g., maximizing benefit or minimizing costs, etc.), and they are usually constructed with three major components: decision variables, objective function(s), and constraints. Specifically, decision variables represent location and service options; objective functions explicitly establish goals to be achieved and mathematical formulations for the quality of the decision; constraints dictate the limitations or requirements of the optimization problem. In this section, the multi-objective decision optimization model for the TERFLs problem is constructed based on the special characteristics of large-scale disaster emergencies.

2.2.1. Assumptions

In order to formulate the TERFLs problem, the following assumptions are made: (1) the entire study area is deemed the demand region, i.e. the region of interest is represented by a two-dimensional continuous space, and the extent of damage caused by the disaster to the entire region is almost the same; (2) the service capacity limitation of each temporary emergency rescue facility is not taken into consideration, in other words, the resources and service abilities of each facility (e.g., the amount of supplies, medical staff, vehicles etc.) are sufficient to support the demand units it services; (3) the service distance of each facility is not constrained, as individual facility may be destroyed by the disaster and resource allocation among different facilities is usually carried out in emergency rescue (FEMA, 2008).

2.2.2. Objectives of Decision

Based on the special characteristics of large-scale disaster emergencies, the prioritized objectives of decision are delineated before the model formulation as follows:

(1) Service capacity: the amount of demand covered by a specified number of facilities should be maximized, i.e., the global rescue capacity should be maximized.

(2) Global efficiency: the sum of total weighted distances or travel time from any demand unit to its closest facility should be minimized, i.e., the global rescue efficiency should be maximized, because a facility that is close to a demand unit provides a better quality of emergency rescue service than the facilities located far from that demand unit (Jia et al., 2007b).

(3) Equity: similar to the objective of global efficiency, given a specified number of facilities, the maximum distance or response time from any demand point to its closest facility should be minimized; in other words, the equity of locating the temporary emergency rescue facilities within the region should be maximized.

2.2.3. Model Formulations

Based on the objectives above, the decision optimization model is formulated as follows.

Objective functions:

$$\textit{Maximize} \quad F_1 = \sum_{i \in n} g_i Y_i \sum_{j \in m} e^{-kd_{ij}} \tag{3}$$

$$\textit{Minimize} \quad F_2 = \sum_{i \in n} \sum_{j \in m} g_i d_{ij} Z_{ij} \tag{4}$$

$$\textit{Minimize} \quad F_3 = L_{\max} \tag{5}$$

subject to:

$$\sum_{j \in m} X_j = p \tag{6}$$

$$\sum_{j \in m} a_{ij} X_j \geq Y_i, \quad \forall i \in n \tag{7}$$

$$Z_{ij} \leq X_j, \quad \forall i \in n, \quad j \in m \tag{8}$$

$$\sum_{j \in m} d_{ij} Z_{ij} - L_{\max} \leq 0, \quad \forall i \in n \tag{9}$$

$$\sum_{j \in m} Z_{ij} = 1, \quad \forall i \in n \tag{10}$$

where

n: set of demand units;

m: set of potential facility sites;

i: index of demand units, $i \in n$;

j: index of potential facility sites, $j \in m$;

g_i: amount of demand in unit i;

d_{ij}: the distance or travel time between any demand unit i and each potential facility site j. In this study, the Euclidian distance is used and calculated based upon their coordinates:

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{11}$$

where

k & $e^{-kd_{ij}}$: attenuation coefficient and attenuation factor, respectively, indicating that the service capacity will decrease with increasing spatial distance between the facilities and demand units;

L_{max}: the maximum distance between any demand unit and its closest facility;

p: number of facilities to be located;

$$a_{ij} = \begin{cases} 1, \text{ if facility located at site } j \text{ covers demand at unit } i \\ 0, \text{ if otherwise} \end{cases}$$

$$Z_{ij} = \begin{cases} 1, \text{ if demand at unit is served by a facility located at site } j \\ 0, \text{ if otherwise} \end{cases}$$

$\forall i \in n, \quad j \in m$;

$$X_j = \begin{cases} 1, \text{ if a facility is located at potential site } j \\ 0, \text{ if otherwise} \end{cases}$$

$\forall j \in m$;

$$Y_i = \begin{cases} 1, \text{ if demand at unit } i \text{ is covered by at least one facility} \\ 0, \text{ if otherwise} \end{cases}$$

$\forall i \in n$;

$$Z_{ij} = \begin{cases} 1, \text{ if demand at unit is served by a facility located at site } j \\ 0, \text{ if otherwise} \end{cases}$$

$\forall i \in n, \quad j \in m$.

According to the formulation, the actual decision variables are Y_i, Z_{ij} and L_{max}.

2.2.4. Model Specifications

The model has three objectives, where objective 1 (Equation 3) maximizes the amount of demand covered by a specified number of facilities, representing global rescue capacity (Church and ReVelle, 1974). Its primary purpose is to provide the high demand areas with more facilities. Objective 2 (Equation 4) minimizes the sum of total weighted distances between any demand unit and its closest facility (i.e., p-median model) (Daskin, 1995). It represents the global rescue efficiency of the rescue facilities, as a facility that is closest to a demand unit provides more efficient rescue service than the others (Jia et al., 2007b). Objective 3 (Equation 5) minimizes the maximum distance L_{max} from any demand unit to its closest facility (i.e., p-centre model), representing the rescue equity of the rescue facilities (Daskin, 1995).

Constraint 1 (Equation 6) stipulates that p facilities are to be located in the area. Constraint 2 (Equation 7) states that demand at unit i cannot be covered unless at least one of the facility that cover unit i is selected. Constraint 3 (Equation 8) states that demands at unit i can only be assigned to a facility at location j ($Z_{ij} = 1$) if the facility is located ($X_j = 1$). Constraint 4 (Equation 9) states that L_{max} must be greater than the distance between any demand unit i and open facility j to which it is assigned. Constraint 5 (Equation 10) states that each unit i must be assigned to a facility at some node j.

The combination of these objective functions and constraints constitute a multi-objective decision optimization model for the TERFLs problem, which is:

$$Minimize \quad [obj_1, obj_2, obj_3] \tag{12}$$

where

$$obj_1 = \frac{1}{F_1}, \quad obj_2 = F_2, \quad obj_3 = F_3 \tag{13}$$

3. Solution

The multi-objective evolutionary algorithm (MOEA) has proved to be an efficient approach to solve various multi-objective optimization problems. However, using MOEA directly in solving multi-objective TERFLs optimization problem is intractable, because it unavoidably involves spatial issues. Therefore, it is necessary to design an appropriate spatial representation and encoding strategy in order to make MOEA match with the decision model.

3.1. Spatial Representation

In this study, a grid-based spatial representation strategy is adopted for the convenience of genetic coding and improving the accuracy of search results, similar to the "land-block" representation for multi-objective land-use planning optimization (Dilip Datta, 2007; Georgiadou et al., 2010; Cao et al., 2011). Specifically, the entire study region is divided into a number of fine spatial grids, shown in Figure 3, where each grid represents a demand unit and the total number of grids in the area is equal to $M \times N$, where M is the total numbers of rows and N is the total numbers of columns. Subsequently, each grid is transformed into a point, and a value is assigned to the point to represent the amount of demand, corresponding to the weight value g_i of objective functions (1) and (2). Consequently, the spatial location of each demand unit can be represented by its coordinates.

3.2. Encoding Strategy

The strategy for genetic encoding is directly related to the search efficiency and accuracy of model solution. At present, some kinds of genetic encoding strategies have been used in solving various spatial optimization problems (Xiao et al., 2002; Li Figure et al., 2009; Wu et al., 2011). In these works, traditional binary coding or a real number coding strategy are usually adopted. However, these kinds of encoding strategies may only be suitable for virtual or small-scale data; they are incapable of solving large-scale TERFLs problems, because of the massive spatial data involved and huge solution space (Xiao et al., 2007; Tong et al., 2009).

In this study, based on the grid-form spatial representation strategy, an appropriate genetic encoding method was designed and used for model solution, as shown in Figure 3. Specifically, the decision space was the same as the entire set of grids, i.e., the locations of candidate facilities were selected from the grids in the region. According to the basic principles of evolutionary algorithms, the chromosome is composed of "genes", which take specific values, and an "individual" (i.e. a potential solution of the problem) encodes the corresponding decision vector into a "chromosome" based on an appropriate structure (Veldhuizen, 1999). The coordinates of each candidate facility $P_m(X_m, Y_m)$ were defined as a "gene"; the "chromosome" G was encoded sequentially by the coordinates of each candidate facility $P_p(X_p, Y_p)$ in the following form:

$$G(P_1, P_2, ..., P_P) \tag{14}$$

where P is the number of facilities that will be placed in the region, which is the same as the variable P of the optimization model.

Through this genetic encoding method, the spatial representation strategy is coupled with MOEA, and the final goal corresponds to achieving the optimum solutions that minimize all the three decision objectives.

3.3. Non-Dominated Sorting Genetic Algorithm

Compared to traditional methods for solving multi-objective optimization problems, MOEAs can avoid subjective judgments until the final step of the decision analysis, and it has

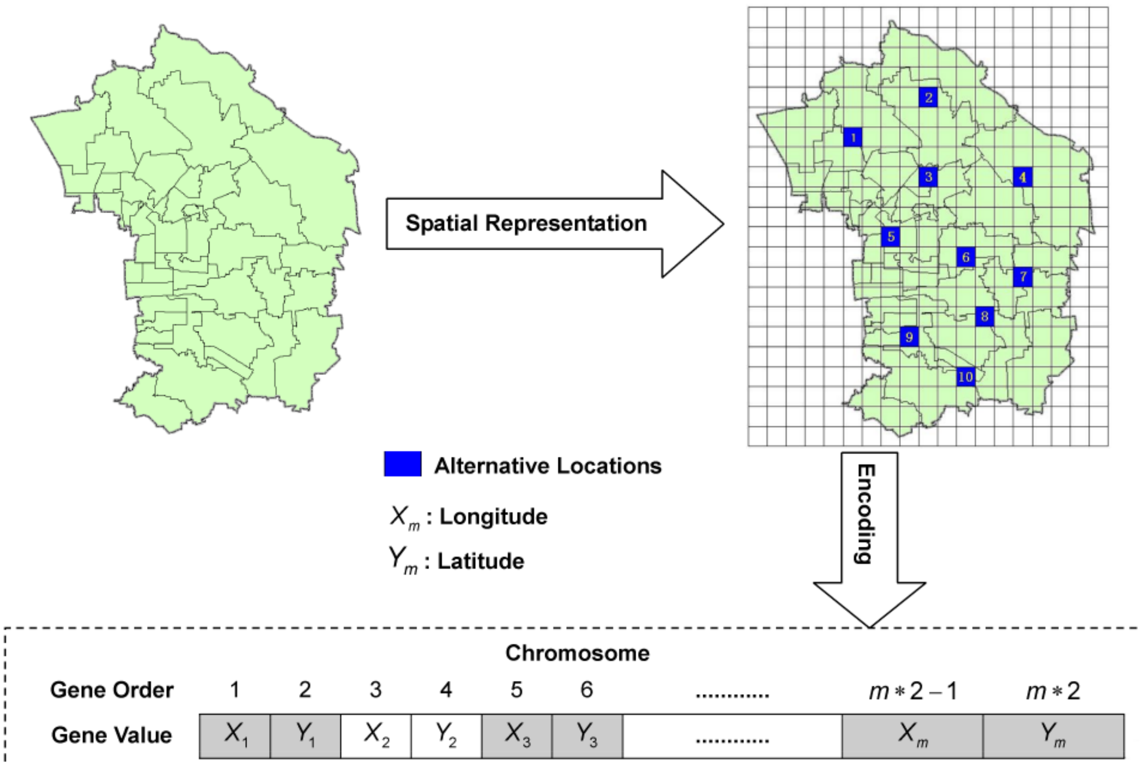

Figure 3. Spatial representation and encoding strategy for model solution.

the ability to find multiple Pareto-optimal solutions in a single run. Therefore, in this study, a well-known and efficient MOEA, the non-dominated sorting genetic algorithm-II (NSGA-II) (Deb et al., 2002), was used for solving the multi-objective TERFLs problem.

NSGA-II involves an elitist-preserving approach to speed up the performance of the algorithm and help prevent the loss of elitist solutions once they are found. Moreover, a fast non-dominated sorting approach is applied to reduce the computational complexity, and a crowding distance evaluation mechanism is used to preserve the diversification of Pareto optimal solutions. For more details of the algorithm, please refer to the literature (Deb et al., 2002).

4. Case Study

A case study is presented to demonstrate the methodology developed in this study for the multi-objective TERFLs optimization problem in the case of a hypothetical disaster.

4.1. Study Area

The Chaoyang district (Figure 4) of Beijing lies in the east of the city, with a total area of 470.8 km^2. It is composed of 42 sub-districts and has a population of around 3.6 million. As a typical urban district, Chaoyang is a densely populated district including many residential, commercial, and industrial zones. Therefore, it is susceptible to heavy damage (e.g., terrorist attacks, chemical leakages, etc.) and the tremendous demand for rescue supplies should be distributed by means of temporary emergency rescue facilities.

The Chaoyang district has a plain terrain, and the terrain tilts slowly from the northwest to southeast; the elevation is between 20 and 46 meters, the average elevation is 34 meters, and the slope is generally between 1/1000 and 1/2500. Therefore, the effect of terrain on the model's performance could be negligible.

4.2. Data Collection and Model Configuration

Spatial geographic data and census data of the study area were collected from the local authorities and processed using standard GIS software. The grid-based population density map was exported and shown in Figure 4. Following the spatial representation method presented in section 3.1, this raster format data layer was then converted into a point format vector layer, which represents the searching space of the optimization model.

In a large-scale emergency situation, the number of temporary facilities that could be set up would be limited due to the resource or financial limitations. Therefore, in this study, the number of candidate emergency rescue facilities in the region was set to 10, i.e. $p = 10$. Based on the strategy presented in section 3.2, the chromosome was encoded to represent the optimal locations of the 10 candidate facilities.

According to the methodology presented in the previous

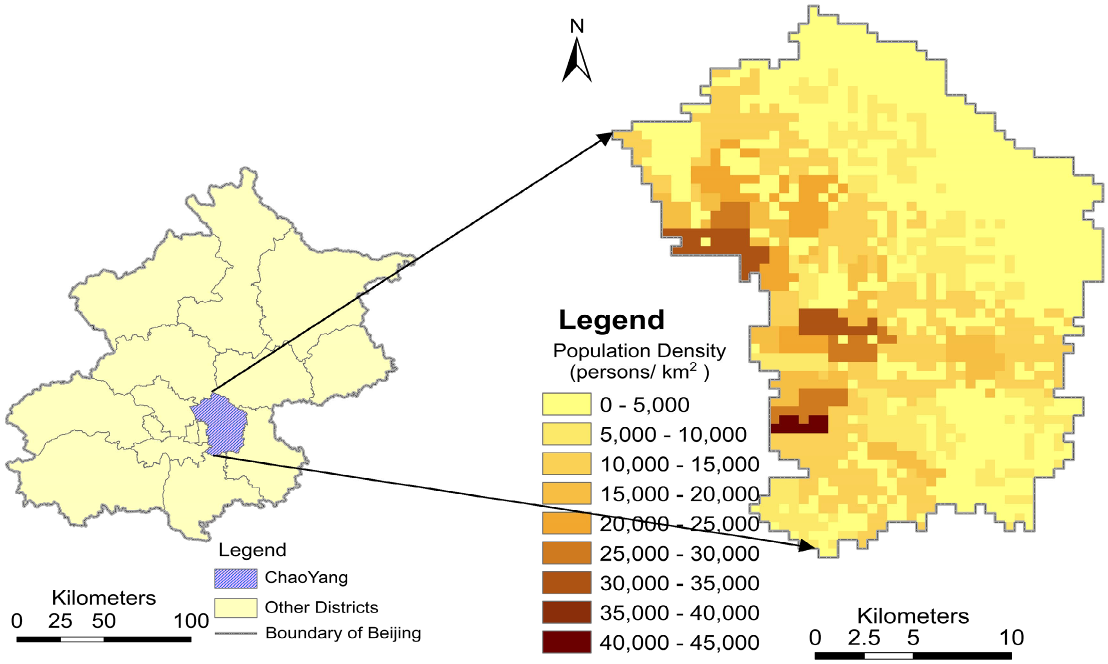

Figure 4. The location of Chaoyang district and the population density distribution.

sections, the multi-objective TERFLs optimization model was constructed. The parameters of NSGA-II algorithm were specified as follows: the maximum number of evolutionary generations was 100; the size of initial population was limited to 100; the crossover probability was 0.8 and mutation probability was 0.05. The optimization model and the algorithm were coded and run on a mobile workstation with Pentium 4 CPU 3.4 GHz processor and 2.0 GB RAM.

Due to the stochastic nature of evolutionary algorithms, it is necessary to perform several parallel runs to evaluate its performance (Coello, 2005). Furthermore, it is interesting to have a robust algorithm that approximates the global Pareto-optimal frontier of a problem consistently, rather than converging to the global Pareto-optimal frontier only occasionally. Therefore, 10 independent runs were conducted by using fixed parameter values but with different random seed generators. Hence, the final solutions obtained by non-dominated sorting among all 10000 iterations or function evaluations are the global Pareto-optimal solutions of each independent run.

4.3. Results

The statistical analyses on the final Pareto-optimal solutions of each run are presented in Table A1 of Appendix A. This table shows the numbers of final Pareto-optimal solutions obtained from each run, the maximum and minimum value of each objective function, and the mean value of each objective function before and after normalization for each run. Without loss of generality, the results from experimental run 2 (bold font in Table A1) were considered the best non-dominated solutions, as the "sum" was smaller and the number of non-dominated solutions (380) were larger than the other experimental runs. Therefore, the nondominated solutions obtained from experimental run 2 were taken to draw the final Pareto-optimal frontier, as shown in Figure 5.

In Figure 5, the progress of iterations is also shown: the green-cube points represent the initialized population by the random seed generator; the red-ball and blue-pyramid points represent the local Pareto-optimal frontier after the 10th and 50th generation, respectively; the yellow-ball points are the final Pareto-optimal frontier after the 100th generation.

Furthermore, in order to evaluate the capabilities for maintaining diversity and converging progressively to the global Pareto-optimal frontier, the behaviour of the algorithm during the evolutionary process was analysed. From generation to generation, a number of non-dominated solutions emerged, of which some evolved into the final Pareto-optimal frontier at the end of 10000 iterations. The number of the non-dominated solutions emerging during every 10 generations increased sharply, as shown in Figure 6. This indicated that the diversity of non-dominated solutions increased along with the evolutionary process.

Moreover, the convergence property of the algorithm was analysed based on the metric of convergence. In the study, the final Pareto-optimal frontier of the 100th generation was set as the reference, and then the Pareto-optimal frontiers of the 5th and every 10th generation were compared to the reference. The results of convergence comparison are shown in Figure 7.

After the verification of the model, the 380 non-dominated solutions on the final Pareto-optimal frontier of the experimental run 2 constitute a candidate pool for decision makers, and they can then be used to derive suitable trade-off solutions according to the subjective preference of different dec-

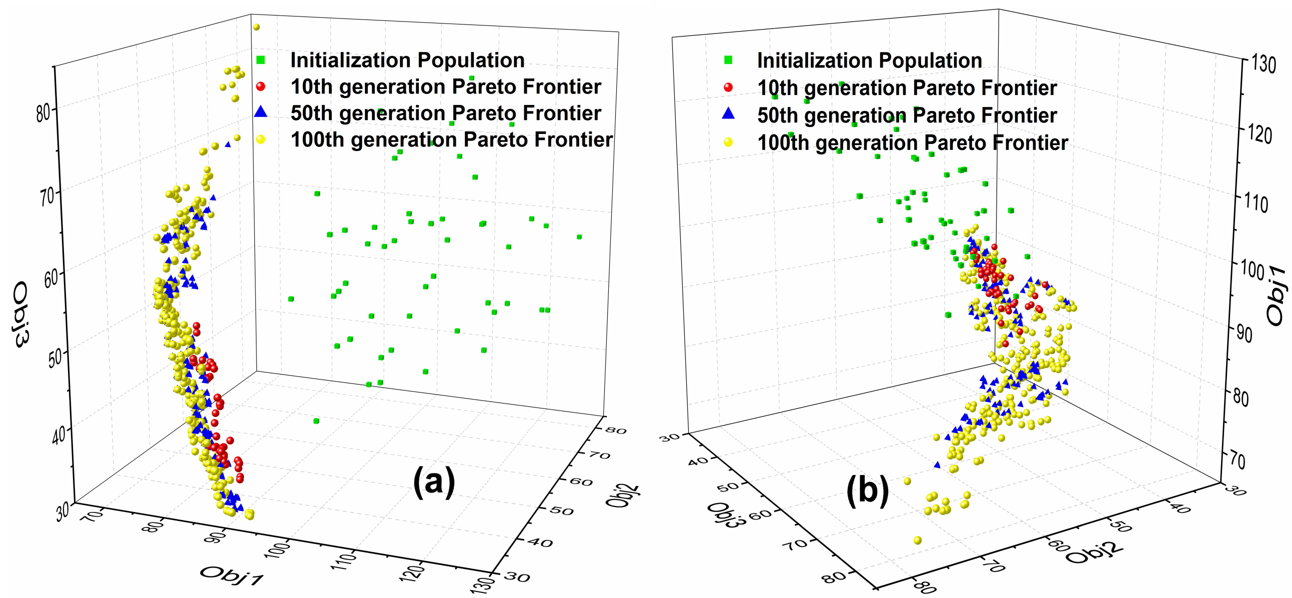

Figure 5. Pareto-optimal frontiers of different evolutionary generations (Initialization, 10th, 50th, and 100th) representing the performance of convergence (a) and diversity (b) of non-dominated solutions during the process of iterations.

ision makers. However, there appears to be no best among these non-dominated solutions, because they cannot dominate each other by definition. In order to make a decision among them, decision makers may have their own subjective preferences or determinant criteria. In this study, an equally weighted solution and three extreme preferred solutions were selected from the 380 non-dominated solutions. The four kinds of solutions are respectively labelled as "A", "B", "C" and "TradeOff", shown in Figure 8. They are compared as a demonstration of the model's effectiveness.

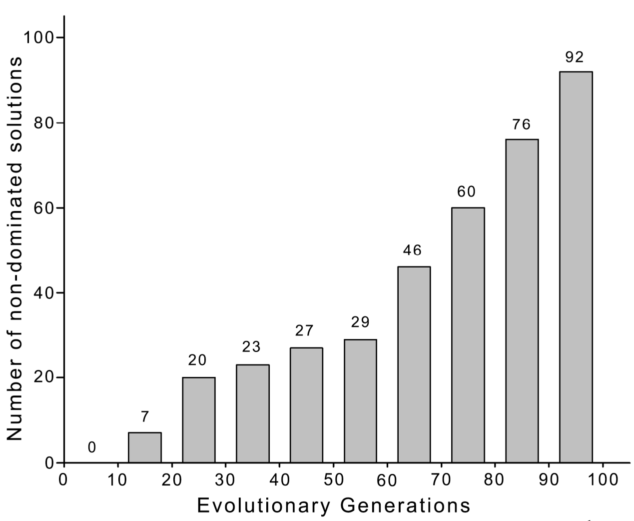

Figure 6. Non-dominated solutions emerging in every 10th generation that form the final Pareto-optimal frontier.

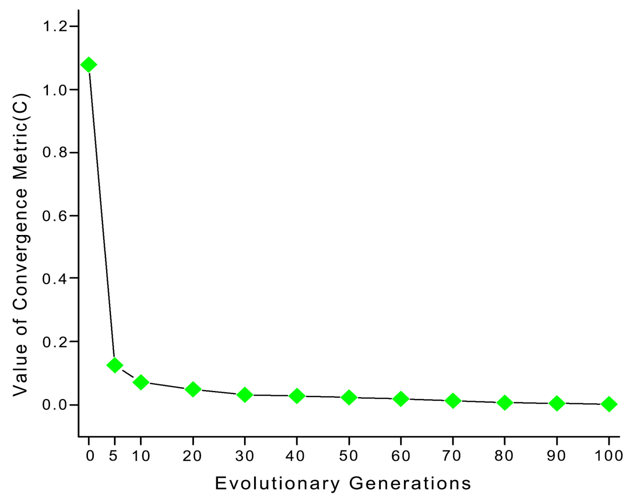

Figure 7. The values of convergence metric of initial population, 5th and every 10th generation.

The location maps of the four solutions are shown in Figure 9. It is seen that the locations of the 10 candidate facilities of solution "A" which is preferred by Obj1, are obviously concentrated around the centre of gravity of the population density map. The locations of the 10 candidate facilities of solution "C" which is preferred by Obj3, tend to be quite dispersed comparing to solution "A". The locations of the 10 candidate facilities of solution "B" which is preferred by Obj-2, are less dispersed than solution "C", but they cover the highly populated region in order to maximize the global efficiency. The result of the equally weighted solution, which is labelled "Trade-off", has the most balanced or best compromise of service capacity, total global efficiency, and equity among all the 380 non-dominated solutions.

Besides the scenario results shown as a map in Figure 9, the attribute information associated with the four kinds of solutions is presented in Table 1. The lowest value means the most preferred solution, e.g. Obj1 prefers the solution “A”.

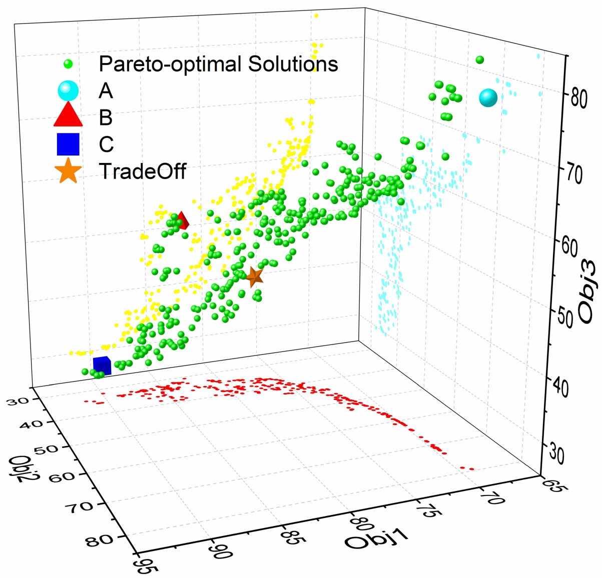

Figure 8. Four kinds of non-dominated solutions representing extreme and trade-off solutions.

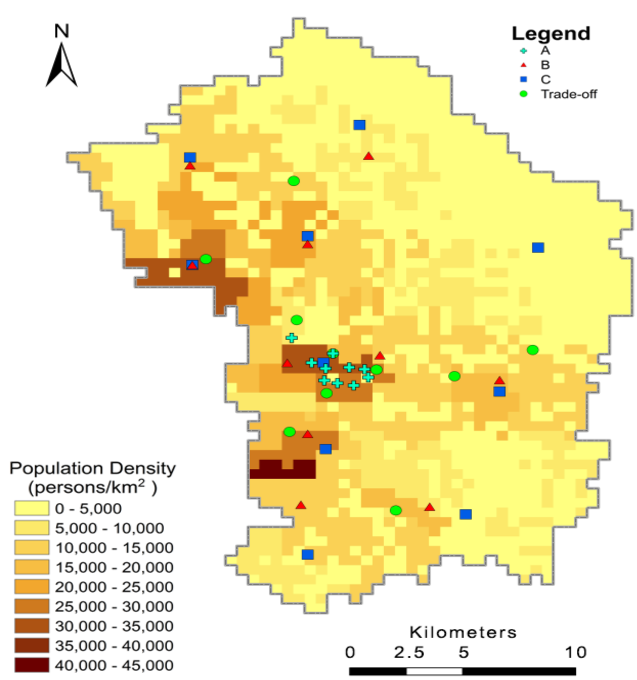

Figure 9. Facility location map of the three extreme and the trade-off solutions.

5. Discussion and Conclusions

It can be seen that the improvement of non-dominated solutions becomes less and less until a convergence is reached (Figure 5a). Meanwhile, the NSGA-II was able to maintain a better diversity of non-dominated solutions across the three objectives during the iterations (Figure 5b).

Figure 7 exhibits a similar trend as Figure 5 regarding the improvement of non-dominated solutions, indicating the performance of convergence during the iterations. In Figure 7, the convergence metric quickly moves to nearly zero, implying that the non-dominated solutions starting from a random set quickly approached the final Pareto-optimal frontier. After about 30 generations, the solutions come very close to the final Pareto-optimal frontier, clearly demonstrating the global optimal searching ability of the model. From the 30th generation to the 100th generation, changes in the convergence metric are not obvious, which indicates that the values of objective functions are not significantly changed. However, in the meantime, the diversity of non-dominated solutions increases exponentially from generation to generation, which can be validated by the 3D plot of the evolutionary process shown in Figure 5.

All the results presented from Figure 5 to Figure 7 provide evidence that the Pareto-optimal frontier for the multi-objective TERFLs optimization problem is able to be successfully generated by the NSGA-II algorithm coupled with the spatial representation and encoding strategy designed in this study.

The candidate locations of solution “A” concentrated around the centre of gravity of the population density map, because redundancy coverage is incorporated into the objective function Obj1, and such locations can cover the maximum amount of people. The spatial pattern of solution “B” arises because of the weight value g_i involved in the objective function of Obj2. The spatial pattern of solution “C” comes about because of the emphasis of minimizing the maximum distance between any demand unit and its closest facility in order to achieve equity.

According to Table 1, each objective-preferred solution tends to be extreme, but they definitely reach the best scores with respect to the preferential single-objective. Moreover, the “Trade-off” scenario has the most balanced values of all the three objectives.

Table 1. Attribute Information Associated with the Four Kinds of Solutions

Category	Obj1	Obj2	Obj3
A	**69.02**	79.46	79.01
B	82.67	**30.69**	52.21
C	89.90	31.90	**29.75**
Trade-off	77.55	37.04	43.63

The locations of rescue facility are of utmost importance for disaster mitigation and public safety. This study presents a

Appendix A: Table 1A Statistic Analysis of the Final Pareto-Optimal Solutions in Each Run

No. of Run	Num.	Objectives	Max	Min	Average	Average (Normalization)
1	348	Obj1	92.60	69.93	79.26	0.41
		Obj2	64.80	32.14	41.68	0.29
		Obj3	68.84	29.04	48.24	0.48
		sum				1.19
2	**380**	Obj1	91.62	69.53	77.77	0.37
		Obj2	78.57	31.78	43.09	0.24
		Obj3	84.04	29.73	51.45	0.40
		sum				**1.01**
3	377	Obj1	88.71	69.68	78.03	0.44
		Obj2	63.22	32.42	40.86	0.27
		Obj3	69.67	29.36	47.71	0.46
		sum				1.17
4	366	Obj1	88.26	69.68	77.17	0.40
		Obj2	69.65	31.91	42.70	0.29
		Obj3	74.73	30.71	50.21	0.44
		sum				1.13
5	376	Obj1	96.29	70.25	79.23	0.35
		Obj2	59.27	32.03	41.70	0.35
		Obj3	68.85	28.75	47.88	0.48
		sum				1.18
6	329	Obj1	93.11	73.30	79.70	0.32
		Obj2	54.87	31.75	40.70	0.39
		Obj3	64.36	30.56	46.65	0.48
		sum				1.19
7	306	Obj1	91.11	72.91	78.87	0.33
		Obj2	62.74	32.24	42.25	0.33
		Obj3	66.65	29.26	49.29	0.54
		sum				1.19
8	306	Obj1	91.39	70.90	78.61	0.38
		Obj2	59.59	31.10	40.97	0.35
		Obj3	70.08	28.74	48.86	0.49
		sum				1.21
9	337	Obj1	87.65	70.34	76.50	0.36
		Obj2	56.40	32.07	40.63	0.35
		Obj3	67.31	31.04	51.43	0.56
		sum				1.27
10	333	Obj1	96.77	69.44	77.75	0.30
		Obj2	77.62	31.27	45.11	0.30
		Obj3	81.30	28.03	51.73	0.44
		sum				1.05

Num.: total number of final Pareto-optimal solutions in each run.
Max/Min: maximum/ minimum value of each objective function in each run.
Average/Average (Normalization): average value of each objective function before/after being normalized in each run.
Sum: sum of the average normalized values of the three objective functions in each run.

methodology for solving the TERFLs problem by taking into account the conflicting objectives of service capacity, global efficiency and equity. Moreover, an appropriate spatial representation and encoding strategy was designed since the TERFLs problem unavoidably involves spatial issues, and a well-known multi-objective evolutionary algorithm, NSGA-II, was coupled with the encoding strategy for model solution.

A case study of the Chaoyang district in Beijing was conducted to demonstrate the proposed methodology. The results show that the model can quickly and successfully capture a pool of alternative non-dominated solutions and generate the Pareto-optimal frontier for the TERFLs problem. The findings show that the methodology proposed in this study has the potential to be a useful decision support tool for urban planning with respect to public safety and health.

The locations map and the attributes information table demonstrate the effectiveness of the multi-objective spatial optimization model as well as the model solution method proposed in this study in solving the TERFLs problem. The optimized locations map could enhance environmental emergency management capability and improve public safety.

Although only three objectives were involved in the current model, it has the potential for involving more objectives and constraints into the methodology framework according to different disaster scenarios. In this study, the effect of a disaster on the study region was assumed to be uniform; however, the effect on different parts of the region may be different in reality. Therefore, it is necessary to incorporate spatial risk analysis into the model so as to present the potential risks of the disaster. Moreover, urban area is usually not continuous space, but rather is discrete space. Therefore, the Euclidean distance used in the model assumption may not be feasible in real applications; improvement in the calculation of spatial distance by replacing Euclidean distance with the actual transport network distance is necessary in the future research.

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