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Multiple-resource and multiple-depot emergency response problem considering secondary disasters

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ABSTRACT

Optimal allocation of emergency resources is a crucial content of emergency management. It is a key step in emergency rescue and assistance. Multiple resources and potential secondary disasters are often neglected in the existing methods, which desperately need to be improved. In this paper, we formulate the emergency resource allocation problem with constraints of multiple resources and possible secondary disasters, and model the multiple resources and multiple emergency response depots problem considering multiple secondary disasters by an integer mathematical programming. For the complexity, a heuristic algorithm is designed to efficiently solve it based on linear programming and network optimization. The algorithm modifies the solutions of the linear programming by setting a priority of preference for each location where the secondary disasters will take place with certain possibilities. The numerical simulation provides evidence for its effectiveness and efficiency. Our method and algorithm can also be implemented in the practical applications with large-scale scenario.

1. Introduction

Emergency resources allocation is a key research content of emergency management of disasters. It is also a key step of emergency rescue and assistance. The various features of disasters, such as suddenness, uncertainty, environment hardness of rescue, and various properties of resources, determine the substantial differences between this task and the original resource planning problem. From 1970s, there are some methods have been proposed to solve the problem of disaster relief for its importance. Chaiken and Larson (1972) provided a description of emergency service systems and designed a strategy to solve the corresponding operational problems. Based on their model, several improvements have been achieved for specific requirements and conditions in the disasters or incidents. Considerable attentions have been devoted to determine the optimal facility location and the dispatching strategies in the decision support systems (Fiedrich, Gehbauer, & Rickers, 2000; Ozdamar & Ekinci, 2004). Most of the methodologies in the literatures are for detecting the minimum response time to the disasters so that they can be cleared at minimum cost.

Specifically, Fiedrich et al. (2000) provided a dynamic combinatorial optimization model to find the optimal resource schedule with the goal of minimizing the total number of fatalities during the search and rescue (SAR) period, which refers to the first few days after the disaster. In their model, the constraints of rescue time and the quantitative limits of rescue resources are reflected in the emergency resource allocation. Suppose the quantitative availability of resources is limit and the amount of resource requirement is predictable, Ozdamar and Ekinci (2004) proposed an effective model for the emergency response problem to optimally satisfy the demands of these emergency resources in natural disasters. They also assumed that the response commands of vehicles are contained in a series of breakpoints in process. Barbarosoglu and Arda (2004) proposed a two-stage stochastic programming model for the emergency resources allocation problem. They developed a multi-commodity, multi-modal network flow formulation to describe the flow of materials over an urban transportation network. Tzeng, Cheng, and Huang (2007) built a fuzzy multiple-objective mathematical programming model to formulate the emergency resources allocation problem. Their objective functions contain the minimum of the cost, the total arrival time, and the maximum satisfaction of the basic support of the disasters. (Sheu, 2007) presented a hybrid fuzzy clustering-optimization approach to the operation of emergency logistics co-distribution responding to the urgent relief demands in the crucial rescue period. Case study with a real large-scale earthquake disaster occurring in Taiwan was implemented. The corresponding results

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indicate the applicability of the proposed method and its potential advantages. Recently, Campbell, Vandenbussche, and Hermann (2008) proposed a model of the disaster relief problem based on the classic traveling salesman problem (TSP) and the vehicle routing problem (VRP). Two alternative objective functions in their models are to minimize the maximum arrival time and minimize the average arrival time, respectively. The models are solved by well-known insertion heuristics and local search techniques. Pal and Bose (2009) built a reliability-based mixed integer programming model to find the best locations of incidence response depots and assign the response vehicles to these depots. The objective function is to minimize the cost of incident relief. Sheu (2010) presented a dynamic relief-demand model for emergency logistics operations under imperfect information conditions in large-scale natural disasters. The proposed methodology consists of three steps: (1) data fusion to forecast relief demand in multiple areas, (2) fuzzy clustering to classify affected area into groups, and (3) multi-criteria decision making to rank the order of priority of groups. Vitoriano, Ortuno, Tirado, and Montero (2011) proposed a multi-criteria optimization model for the distribution problem of humanitarian aid, with operation conditions and without objective function, taking into account main criteria being involved in a disaster response operation (e.g. time, cost, reliability, security and equity). An illustrative case study based on the 2010 Haiti catastrophic earthquake was presented to show the model usefulness. Bozorgi-Amiri, Jabalameli, and Mirzapour Al-e-Hashem (2011) presented a multi-objective robust stochastic programming model for disaster relief logistics under uncertainty. Their model not only attempts to minimize the sum of the expected value and the variance of the total cost of relief chain while penalizing the solution's infeasibility due to parameter uncertainty, but also aims to maximize the affected satisfaction levels through minimizing the sum of the maximum shortages in the affected areas. The effectiveness and efficiency of their method are shown in a case study of earthquake disaster relief efforts.

So far, most of these available models either considered single resource allocation with multiple disaster points or multiple resources allocation with single disaster point. Some models for multiple-incident multiple-response or multiple-resource multiple-incident problem have also been proposed (Barbarosoglu & Arda, 2004; Ozdamar & Ekinci, 2004; Vitoriano et al., 2011). However, it is often that there are multiple resources and multiple disaster response depots as well as multiple disaster points in practical situations. Moreover, it is highly possible that the secondary disasters or a disaster chain would take place after the primary disaster's attacks. Strong earthquakes will cause followed mountain collapse, landslides, debris flows, flooding of breaking dam breach, fire and explosion of flammable materials. For instance, China's Sichuan earthquake in 2008 and the Great East Japan Earthquake in 2011 apparently brought disaster chains individually. The former earthquake resulted serious barrier lakes threatening and drowning many places and the later triggered a massive tsunami.

In the published studies, there are few methods to model the practical situations of multiple-resource, multiple-response and multiple-point, especially the disasters companying with secondary disasters. The experience shows that the damage caused by secondary disasters often even worse than that of the primary ones. The occurrence of secondary disasters often results in a chain reaction of the domino effects, which make the increasing complexity of disasters or incidents, enlarge the disaster scale and losses, and extend the disaster process. Therefore, the presence of secondary disasters in the emergency resource allocation is urgently needed to improve the scientific decision-making and accuracy. (Sherali & Subramanian, 1999) formulated a mixed integer programming (MIP) model for the multiple-incident multiple-response problem. In the objective function, they modeled the effect of loss in coverage to be reflected by including a new term related to an opportunity cost for serving future incidents that might occur probabilistically on the emergency service region. They presented an alternative model with a particular structure which can dramatically improve the computational performance. However, their method still does not satisfy the conditions that there are multiple potential incidents of secondary disasters in the road network.

In this paper, we build an integer mathematical programming approach to model the multiple-resource multiple-depot emergency response problem. There are multiple resources will be dispatched to multiple disaster places from multiple emergency depots. We also explore the effects of secondary disasters which will occur in disaster locations with certain probabilities individually. For simplicity, the follow-up disasters of these secondary disasters will not be considered simultaneously. We category the demands into the demand of primary disasters and that of secondary disasters, and assume that they are independent each other. Meanwhile, considering the multiplicity of necessary resources and the limitation of resource suppliers, we model the real-time multiple-incident multiple-response multiple-resource allocation problem. The objective function contains the minimization of the rescue costs of primary and secondary disasters, and the constraints are involved in these multiple limitations.

The reminder of this paper is organized as follows. Section 2 formulates the model of multiple-resource multiple-response emergency resource allocation problem with considering secondary disasters, and describes the equivalent form of the objective function. Section 3 proposes an effective heuristic algorithm to solve above model. Section 4 depicts a numerical case of an emergency allocation problem using the simulation data, and provides the corresponding results to demonstrate the feasibility and effectiveness of the proposed method. The conclusion and remarks about our research are summarized in Section 5.

2. Mathematical programming model

2.1. Notation and terminology

Given a road network $G = (V,E)$, let V be node set, E be arc set. Let $A_1, A_2, \ldots,$ and A_n be the n emergency response locations. The set of emergency response centers is L, $L \subset V$. Each emergency response unit contains w kinds of available resources. The resource type set is R. Let $B_1, B_2, \cdots B_m$ be the m primary disaster nodes having occurred at some node set F, $F \subset V$. Let $C_1, C_2, \ldots, C_k$ be the k nodes potentially occur at some node set M for the secondary disasters, $M \subset V$. For each potential secondary disaster point, the possibility of the incident occurrence is p_v ($v \in M$).

The explanation of the other variables and parameters is listed in the following.

r_i^j: The amount of jth resource available in the emergency response unit i, $i \in L, j \in R$;
n_f^j: The demand of jth resource at the disaster node f, $f \in F$ or $f \in M$, $j \in R$;
t_{iv}: The minimum arrival time from the emergency response unit i to the disaster node v, $i \in L$, $v \in V$;
t_v: The minimum in $t_{iv}, t_v = \min_{i \in L}\{t_{iv}\} \quad \forall v \in V$;
x_{if}^j: The amount of jth resource assigned from the response unit i to the primary disaster node f;
y_{iv}^j: The amount of jth resource assigned from the response unit i to the secondary disaster node v;
s_i^j: The rest of amount of jth resource in the response unit i after assigning the resources to the primary disaster nodes, $i \in L$, $j \in R$.

2.2. Establishment of model

The multiple-resource multiple-response emergency resource allocation problem considering secondary disasters can be formulated as the following mixed integer programming model:

$$\text{Min} \quad \sum_{i\in L}\sum_{f\in F}\sum_{j\in R} t_{if}x_{if}^j + \sum_{i\in L}\sum_{v\in N}\sum_{j\in R} p_v(t_{iv}-t_v)y_{iv}^j \tag{1}$$

$$s.t. \quad \sum_{f\in F} x_{if}^j + s_i^j = r_i^j \quad \forall i\in L, \quad \forall j\in R \tag{2}$$

$$\sum_{i\in L} x_{if}^j = n_f^j \quad \forall f\in F, \quad \forall j\in R \tag{3}$$

$$\sum_{i\in L} y_{iv}^j = n_v^j \quad \forall v\in M, \quad \forall j\in R \tag{4}$$

$$y_{iv}^j \leqslant s_i^j \quad \forall i\in L \quad \forall, v\in M \quad \forall j,\in R \tag{5}$$

$$x, y \geqslant 0(\text{integers}), s \geqslant 0 \tag{6}$$

The objective function (1) is the cost of the total time of dispatching emergency resources, which mainly contains two parts. First, $\sum_{i\in L}\sum_{f\in F}\sum_{j\in R} t_{if}x_{if}^j$ is the cost of emergency resource allocation generated by the primary disasters, Second, $\sum_{i\in L}\sum_{v\in N}\sum_{j\in R} p_v (t_{iv}-t_v)y_{iv}^j$ is the opportunity cost of assigning these emergency resources to the possible secondary disaster points. The constraint (2) refers to the demands of the resource assumption for the primary disasters. The constraint (3) refers to the equilibrium of supply and demand of these emergency resources response to the primary disasters. Similarly, the constraint (4) presents the equilibrium of supply and demand of the emergency resources for these potential secondary disasters. The constraint (5) refers to the amount of various resources available for the secondary disasters. The constraint (6) is the nonnegative and integer constraints of the decision variables. x, y, s are the corresponding vector with the element of x_{if}^j, y_{iv}^j, s_i^j individually.

2.3. Transformation of objective function

For every strategy $\varphi = \{\alpha_1, \alpha_2, \ldots, \alpha_{|F|}, \beta_1, \beta_2, \ldots, \beta_{|M|}\}^T$, where

$$\alpha_f = \begin{bmatrix} x_{1f}^1 & x_{2f}^1 & \cdots & x_{|L|f}^1 \\ x_{1f}^2 & x_{2f}^2 & \cdots & x_{|L|f}^2 \\ \vdots & \vdots & \ldots & \vdots \\ x_{1f}^w & x_{2f}^w & \cdots & x_{|L|f}^w \end{bmatrix}, \quad \beta_v = \begin{bmatrix} y_{1v}^1 & y_{2v}^1 & \cdots & y_{|L|v}^1 \\ y_{1v}^2 & y_{2v}^2 & \cdots & y_{|l|v}^2 \\ \vdots & \vdots & \ldots & \vdots \\ y_{1v}^w & y_{2v}^w & \cdots & y_{|L|v}^w \end{bmatrix}.$$

where α_f is the emergency resource allocation strategy for the primary disaster node B_f, $f \in F$, β_v is the resource allocation strategy for the secondary disaster node C_v. In the matrix, $\forall j \in R$, the jth row represents the vector of the jth resource assigned from these emergency response units to the disaster point B_f (or C_v). The ith column of the matrix represents the resource vector from the response unit A_i to the disaster point B_f (or C_v). Column vector *0* means that the response unit does not provide any emergency rescue service.

Definition 1. $\phi = \{\alpha_1, \alpha_2, \cdots, \alpha_{|F|}, \beta_1, \beta_2, \cdots, \beta_{|M|}\}^T$ is a resource allocation strategy. If the jth columns of matrix α_f and matrix β_v satisfy the constraints (2)–(6) in the model, then φ is *feasible* for jth resource. If $\forall j \in R$, the strategy φ is feasible for jth resource, then φ is named a *feasible strategy*.

The former objective function in the model can be written as:

$$\text{Min} \quad \sum_{i\in L}\sum_{f\in F}\sum_{j\in R} t_{if}x_{if}^j + \sum_{i\in L}\sum_{v\in N}\sum_{j\in R} p_v t_{iv} y_{iv}^j - \sum_{i\in L}\sum_{v\in N}\sum_{j\in R} p_v t_v y_{iv}^j. \tag{7}$$

From the constraint (4), i.e. $\sum_{i\in L} y_{iv}^j = n_v^j$, then

$$\sum_{i\in L}\sum_{v\in N}\sum_{j\in R} p_v t_v y_{iv}^j = \sum_{v\in N}\sum_{j\in R} p_v t_v n_v^j. \tag{8}$$

For p_v, t_v, n_v^j is the given parameters, $\sum_{v\in N}\sum_{j\in R} p_v t_v n_v^j$ is a constant. Set $\sum_{v\in N}\sum_{j\in R} p_v t_v n_v^j = C$, then (8) can be rewritten as

$$\sum_{i\in L}\sum_{f\in F}\sum_{j\in R} t_{if}x_{if}^j + \sum_{i\in L}\sum_{v\in N}\sum_{j\in R} p_v t_{iv} y_{iv}^j - C. \tag{9}$$

The constant has no effects to the solutions, so the objective function (1) is equivalent to

$$\text{Min} \quad \sum_{i\in L}\sum_{f\in F}\sum_{j\in R} t_{if}x_{if}^j + \sum_{i\in L}\sum_{v\in N}\sum_{j\in R} p_v t_{iv} y_{iv}^j \tag{10}$$

In the multiple-incident multiple-response emergency resource allocation problem with the consideration of secondary disasters, formulation (10) indicates the summation of the cost of assigning the resources for primary disasters and the expectation cost of secondary disasters. Fortunately, the expectation cost of the secondary disasters can be straightforwardly calculated for the particular structure of this problem.

Let Ω be the set of feasible strategy, from Definition 1 and (10), the objective function (1) of the problem can be transformed to:

$$\text{Min}_{\substack{\phi\in\Omega \\ \Omega\neq\Phi}} \sum_{i\in L}\sum_{f\in F}\sum_{j\in R} t_{if}x_{if}^j + \sum_{i\in L}\sum_{v\in N}\sum_{j\in R} p_v t_{iv} y_{iv}^j. \tag{11}$$

3. Algorithm

Definition 2. We asendantly sorted the distances between the response unit set L and the possible secondary disaster point $v (v \in M)$. Suppose $\lambda_{\rho v}$ is the ρ*th shortest distance* to the disaster point v, that is, λ_{1v} is the shortest distance to disaster point v, λ_{2v} is the second shortest distance to $v, \ldots$, and $\lambda_{|L|v}$ is the longest distance to v. Then, we constructed a *sorted distance matrix* $SP_{|L|\times|M|}$ from one response unit to possible secondary disaster points, i.e.

$$SP_{|L|\times|M|} = \begin{bmatrix} (i_{11}, \lambda_{11}) & (i_{12}, \lambda_{12}) & \cdots & (i_{1|M|}, \lambda_{1|M|}) \\ (i_{21}, \lambda_{21}) & (i_{22}, \lambda_{22}) & \cdots & (i_{2|M|}, \lambda_{2|M|}) \\ \vdots & \vdots & \ldots & \vdots \\ (i_{|L|1}, \lambda_{|L|1}) & (i_{|L|2}, \lambda_{|L|2}) & \cdots & (i_{|L||M|}, \lambda_{|L||M|}) \end{bmatrix}.$$

Where each element in matrix $SP_{|L|\times|M|}$ is a couple $SP_{(\rho,v)} = (i_{\rho v}, \lambda_{\rho v})$, $i_{\rho v}$ is the response unit to the disaster point v with ρth shortest distance ($i_{\rho v} \in L$) and $\lambda_{\rho v}$ is the corresponding shortest distance to the disaster point v.

3.1. Framework of algorithm

It is a mixed integer programming model of the multiple-disaster multiple-response emergency resource allocation problem. Traditional methods including branch-and-bound method and cutting-plane method can find the accurate solutions (Hillier & Lieberman, 1990), while the mix integer programming problem is an NP-complete problem (Lin & Hwang, 2004). It is only applicable to use the traditional methods to solve small-size problems to achieve optimal solution. In practical emergencies, it needs a real-time algorithm to solve the large-scale problems for promptness and efficiency. In this work, we designed a linear programming (LP) based algorithm by local search techniques with high-possibility high-priority rule.

The algorithm is designed to efficiently satisfy the constraints and objective function in the mathematical programming model. Due to the effective algorithms of LP, the algorithm will begin from the relaxed LP problem. For avoiding iteratively solve many LP problems in the branch-and-bound algorithm of handling the non-integer solutions, we modified the relaxed-LP solutions to lower the complexity and shorten the computing time.

The basic idea of our algorithm is firstly to relax the LP solutions, and then modify the fractional parts of optimal relaxed solutions to find the allocation strategy for the primary disaster points. Based on the primary solutions, we set allocation priorities for the secondary disaster points according to their probabilities of occurrence. By the priorities, we employed the local search technique to assign the emergency resources to these points with potential secondary disasters. Reasonable solutions will be achieved after we dispatch the resource to each secondary disaster point.

3.2. Details of algorithm

Based on the framework of algorithm, we built a heuristic algorithm as follows:

Step 1: Initialization. Let the response unit set is L, the primary disaster point set is F, the potential secondary disaster points set is M, and the occurrence probability in the secondary disaster point is p_v. The shortest distance from the response unit i to the disaster point v is calculated by Dijkstra algorithm. Denote the shortest distance (time) to be t_{iv}. We built the matrix $SP_{|L|\times|M|}]$ of sorted distances from all response units to these possible secondary disaster points.

Step 2: Getting the solutions of emergency response problem by relaxing the mixed integer programming model. If we find the integer solutions, the optimal strategy of emergency resource allocation has been achieved. The algorithm will be terminated, otherwise go to **Step 3**.

Step 3: Suppose that $\bar{x}$ is the solution of relaxed MIP with fractional part. Then $x = \lfloor\bar{x}\rfloor + \xi$, where $\lfloor\bar{x}\rfloor$ is the ground integer of $\bar{x}$, $0 \leqslant \xi \leqslant e$, where e is the unit vector. We modified ξ by solving the following TP:

$$\mathbf{TP}: \mathrm{Min}\sum_{i\in L}\sum_{f\in F}\sum_{j\in R} t_{if}\xi_{if}^{j} \tag{12}$$

$$s.t.\sum_{f\in F}\xi_{if}^{j} \leqslant r_i^j - \sum_{f\in F}\lfloor\bar{x}_{if}^{j}\rfloor \quad \forall i \in L, \quad \forall j \in R \tag{13}$$

$$\sum_{i\in L}\xi_{if}^{j} = n_f^j - \sum_{i\in L}\lfloor\bar{x}_{if}^{j}\rfloor \forall f \in F, \quad \forall j \in R \tag{14}$$

$$0 \leqslant \xi \leqslant e \tag{15}$$

TP has an optimal 0-1 solution vector ξ^* (Bazaraa, Jarvis, & Sherai, 1990). Obviously, TP is solved based on the constraints of the original MIP model. Therefore, we can find the emergency response strategy for the primary disasters, i.e. $x^* = \lfloor\bar{x}\rfloor + \xi^*$.

Step 4: For possible secondary disasters and emergency resources $\forall j \in R$:

4.1. According to the occurrence probabilities of these secondary disasters, we set various priorities of assigning resources for each potential secondary disaster point $\forall v \in M$. The disaster points with high possibility of secondary disaster will be assigned emergency resources with high priority.

4.2. Utilizing the priority information of resources, for every possible secondary disaster points v, we find the sorted distance vector from it to the other response units, i.e. $\{(i_{1v}, \lambda_{1v}), (i_{2v}, \lambda_{2v}), \cdots, (i_{|L|v}, \lambda_{|L|v})\}^T$ in $SP_{|L|\times|M|}$.

4.3. Based on the strategy x^* of emergency resource allocation to the primary disaster points, we calculated the rest amount of emergency resource in each response unit by $s_i^{*j} = r_i^j - \sum_{f\in F} x_{if}^{*j}, \quad \forall i \in L$.

4.4. Utilizing the local search techniques, we identified the resource allocation strategy for the secondary disaster point $v: \beta_v^j = \{(i_{1v}, s_{i_{1v}}^{*j}), (i_{2v}, s_{i_{2v}}^{*j}), \cdots, (i_{v_{\max}-1v}, s_{i_{v_{\max}-1v}}^{*j}), (i_{v_{\max}v}, n_v^j - \sum_{k=1}^{v_{\max}-1} s_{i_{kv}}^{*j}), (i_{v_{\max}+1v}, 0), \cdots, (i_{|L|v}, 0)\}$. Where each element of β_v^j is a couple. The first is for the emergency response unit, and the second is the amount of supplying resource of the corresponding response. $\sum_{k=1}^{v_{\max}-1} s_k^{*j} < n_v^j \leqslant \sum_{k=1}^{v_{\max}} s_k^{*j}$, where $v_{\max}$ is the maximum indexed point in these sorted response units which can satisfy the demand of resources.

Step 5: $\forall j \in R$, for $\forall v \in M$, check if the demands of emergency resources have been satisfied. If yes, each disaster point has been well dispatched by these emergency resources and we achieved the corresponding objective function value Z. The algorithm is terminated. Otherwise go to Step 4.

4. Case study

The following simulation case will provide evidence for the effectiveness and efficiency of the proposed algorithm. For instance, suppose there is an earthquake in some place, where contains 50 nodes when we model its road network and locates 10 depots which can provide emergency responses. Our goal is to provide an optimal strategy for dispatching the emergency resources of these depots to the disaster points. For simplicity, assume there are 5 places require the emergency rescues for the primary disasters of collapse, and in which 3 places will have secondary disasters with the possibilities of $p_1 = 0.2$, $p_2 = 0.5$, $p_3 = 0.8$. The emergency resources store in the response units contains three supplies, i.e., relief persons, emergency vehicles and commonly used drugs. We

Table 1
The amount of emergency resource available from response unit.

Response unit	A_1		A_2			A_3		A_4			A_5		A_6			A_7		A_8		A_9			A_{10}	
Available resource	1	2	1	2	3	1	1	2	3	1	2	1	2	3	1	3	1	2	3	2	3	1	2	3
Amount	10	15	10	8	15	14	15	9	12	9	10	8	10	16	10	14	12	8	13	10	9	15	12	7

Table 2
The amount of demand of emergency resource in disaster point.

Disaster point	B_1	B_2		B_3			B_4	B_5		C_1		C_2		C_3		
Available resource	1	1	2	1	2	3	3	2	3	1	3	1	2	1	2	3
Amount	18	20	15	25	16	26	21	22	12	6	13	7	10	18	15	9

Note: For simplicity, the amounts of emergency resource available and in demands are scalar variables. In practical situation, they mean the different dimensions of person, vehicle, and drug individually.

Table 3
Distance matrix from response unit to incident point.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}
B_1	8.5	2	10	6.8	7.1	18	20	10.3	8	4
B_2	23	7.3	11.2	9.5	10	8.8	13.2	3	15	5
B_3	12	14.2	7.8	17	8.2	11	7.4	16.5	18	10
B_4	6.8	9.5	8.1	12.3	16	18.2	10	8.7	13.4	9.7
B_5	3	14.2	12	10	14	6	7	8	20	2
C_1	5.2	2	1.3	9	15	8	3	6	12	21
C_2	6	8	10	4	11	23	7	3	1	13
C_3	3	2	9	7	15	10.5	20	4.6	6	8

denote them as 1, 2 and 3 resources individually. The simulation data includes the amount of emergency resources in these response units, the demands of emergency resources in these incident places, and the distance matrix from the response units to the incident places. They are shown in Tables 1–3, respectively.

We apply the above algorithm to solve the problem. Firstly, we initialize the emergency response unit set $L = \{A_1, A_2, \ldots, A_{10}\}$, the primary disaster point set $F = \{B_1, B_2, \ldots, B_5\}$, the potential secondary disaster point set $M = \{C_1, C_2, C_3\}$, the occurrence probabilities of the secondary disasters are $p_1 = 0.2$, $p_2 = 0.5$, $p_3 = 0.8$, individually. We employ the Dijkstra algorithm to calculate the shortest paths from the response units to the incident points respectively. Assume the shortest distance is t_{iv} and their details are shown in Table 3. We also construct the sorted distance matrix $SP_{|L|\times|M|}$ from these emergency response units to these possible secondary disaster points, i.e.,

$$SP_{|L|\times|M|} = \begin{bmatrix} (A_3, 1.3) & (A_9, 1) & (A_2, 2) \\ (A_2, 2) & (A_8, 3) & (A_1, 3) \\ (A_7, 3) & (A_4, 4) & (A_8, 4.6) \\ (A_1, 5.2) & (A_1, 6) & (A_9, 6) \\ (A_8, 6) & (A_7, 7) & (A_4, 7) \\ (A_6, 8) & (A_2, 8) & (A_{10}, 8) \\ (A_4, 9) & (A_3, 10) & (A_3, 9) \\ (A_9, 12) & (A_5, 11) & (A_6, 10.5) \\ (A_5, 15) & (A_{10}, 13) & (A_5, 15) \\ (A_{10}, 21) & (A_6, 23) & (A_7, 20) \end{bmatrix}$$

Then, the relaxed solutions of the LP can be achieved:

$$x_{21}^1 = 10,\ x_{41}^1 = 1,\ x_{101}^1 = 7,\ x_{82}^1 = 12,\ x_{102}^1 = 8,\ x_{33}^1 = 8.2,\ x_{53}^1 = 7,\ x_{73}^1 = 9.8;$$

$$x_{62}^2 = 3,\ x_{82}^2 = 8,\ x_{102}^2 = 4,\ x_{53}^2 = 10,\ x_{63}^2 = 6,\ x_{15}^2 = 14.4,\ x_{105}^2 = 7.6;$$

$$x_{63}^3 = 12,\ x_{73}^3 = 14,\ x_{24}^3 = 6,\ x_{44}^3 = 2,\ x_{84}^3 = 13,\ x_{45}^3 = 1,\ x_{65}^3 = 4,\ x_{105}^3 = 7, \quad \text{and the other} \quad x = 0.$$

For each solution with fractional part, we set $x_{33}^1 = 8 + \xi_{33}^1$, $x_{73}^1 = 9 + \xi_{73}^1$, $x_{15}^2 = 14 + \xi_{15}^2$, $x_{105}^2 = 7 + \xi_{105}^2$, $0 \leqslant \xi \leqslant e$. We solved the TP and got $\xi_{33}^{*1} = 0$, $\xi_{73}^{*1} = 1$, $\xi_{15}^{*2} = 0$, $\xi_{105}^{*2} = 1$, and the other $\xi^* = 0$. Apparently, we find the emergency resource allocation solutions for the primary disaster are $x_{33}^{*1} = 8$, $x_{73}^{*1} = 10$, $x_{15}^{*2} = 14$, $x_{105}^{*2} = 8$, and the others are the same to that of the relaxed solutions of the LP.

Fourthly, according the probability of the three secondary disasters, for each possible secondary disaster place $\forall v \in M$, we set the resource assignment priorities, i.e. $C_3 > C_2 > C_1$. Then we calculate the rest amount of each resource in each response unit. The rest amount of each resource of each response unit is listed in Table 4. For each resource $\forall j \in R$, we implement the local search technique to identify the assignment scheme for each secondary disaster point $\forall v \in M$. The results are presented in Table 5.

Last but not least, the demands of emergency resources of all disaster points have been responded successfully. The solutions of the multiple-resource multiple-depot emergency resource allocation problem are listed in Table 6. The objective function value is $Z = 1249.4$ by the heuristic algorithm. The algorithm is finally terminated.

In a Lenovo PC (1.60 GHz CPU, 1 GB memory, WinXP OS), we implement our algorithm by ILOG CPLEX 11.0. The results of our algorithm and that of the branch-and-bound method are compared in Table 7. We find that our method is better than the optimization based method in the computing time. Our algorithm needs to solve two LP problems and one of them is the simple TP. However, if we employ the branch-and-bound algorithm to solve the model, we need solve many LP problems. According the growing scale of practical application, it is a hard task to get the optimal solutions because the branch-and-bound algorithm requires the effort that grows exponentially with problem size. Our heuristic algorithm will perform much better and have more advantages. In the simulation study, the relative error ratio is only 0.65% between the objective

Table 4
The rest amount of emergency resource of response unit.

Response unit	A_1	A_2				A_3		A_4		A_5		A_6			A_7		A_8			A_9		A_{10}		
Rest resource	1	2	1	2	3	1	1	2	3	1	2	1	2	3	1	3	1	2	3	2	3	1	2	3
Amount	10	1	0	8	9	6	14	9	9	2	0	8	1	0	0	0	0	0	0	10	9	0	0	0

Table 5
The emergency resource allocation scheme for secondary disaster.

Secondary disaster point	Priority	Resource demand n_v^j			Sorted vector in $SP_{\|L\|\times\|M\|}$	**Allocation solution**		
		1	2	3		β_v^1	β_v^2	β_v^3
C_1	3	6	0	13	$A_3A_2A_7A_1A_8$ $A_6A_4A_9A_5A_{10}$	{(A_3,5), (A_6,1)}		{(A_4,9), (A_9,4)}
C_2	2	7	10	0	$A_9A_8A_4A_1A_7$ $A_2A_3A_5A_{10}A_6$	{(A_4,6), (A_3,1)}	{(A_4,6), (A_3,1)}	
C_3	1	18	15	9	$A_2A_1A_8A_9A_4$ $A_{10}A_3A_6A_5A_7$	{(A_1,10), (A_4,8)}	{(A_2,8), (A_1,1), (A_9,6)}	{(A_2,9)}

Table 6
The emergency response strategy of dispatching resource considering secondary disaster.

	A_1		A_2		A_3	A_4		A_5		A_6		A_7		A_8		A_9	A_{10}	
B_1			10^1				1^1										7^1	
B_2										3^2				12^1	8^2		8^1	4^2
B_3					8^1			7^1	10^2	6^2	12^3	10^1	14^3					
B_4			6^3				2^3							13^3				
B_5	14^2						1^3			4^3							8^2	7^3
C_1					5^1		9^3			1^1						4^3		
C_2					1^1	6^1	6^2									4^2		
C_3	10^1	1^2	8^2	9^3			8^1									6^2		

Note: The upper sign refers to the kind of resource.

Table 7
Comparison results of the heuristic algorithm and the optimization based method.

Algorithm	Objective value	**CPU computing time (second)**
Optimization	1241.3	1.125
Our algorithm	1249.4	0.828

function value of our algorithm and the minimum cost, while the computing time is saved about 26.4%. The simulation study shows the effectiveness and efficiency of our proposed algorithm. It is a real-time algorithm and can be used to solve large-scale practical problem. The government as well as other public service centers will benefit to make the reasonable disaster response decisions.

5. Conclusion

Optimal emergency response planning will provide prompt and effective guidance for scientific decision making and support in disaster management. The emergency resource allocation is an effective way to minimize the cost and loss of disasters. There are many kinds and amounts of demands of emergency resource in a short-period time during disaster response. Moreover, many demands of the secondary disaster points which are triggered by the primary incidents provide more challenges in the emergency rescue. In the former studies, there are few studies have considered the multiple-resource multiple-depot emergency response problem with considering the effects of possible secondary disasters. The available algorithms are often based on the optimal solutions and they are very hard to provide the real-time response to emergencies. The decision need be improved to fit the practical situations and provide more effective and flexible strategies for incident response. In this paper, we studied the multiple-resource multiple-depot emergency resource allocation problem. We introduced the opportunity cost of the secondary disasters in the objective function to build a mixed integer programming model for dispatching the multiple emergency resources. An effective heuristic algorithm has been proposed based on LP and network optimization. The algorithm modifies the relaxed LP solutions and assigns the proprieties for these resources based on the local search techniques. The results of the example provide more evidence for the effectiveness and efficiency of our proposed method. It is a real-time algorithm and can be implemented to solve large-size practical problems comprehensively.

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