Research on Bi-level Optimal Allocation of Emergency Materials Considering Material Competition and Game

Yubo Zhang, Changfeng Zhu, Bin Ma, Qingrong Wang, and Enhua Xu

***Abstract*—In order to improve the efficiency of emergency response, a bi-level programming model for Emergency Materials Allocation (EMA) was established by considering the psychological satisfaction of disaster victims for emergency materials. Considering the idea of time differential, an upper model was constructed to minimize the delivery time and cost of emergency materials. Considering the competition game of emergency materials, the improved relative demand ratio function was introduced to describe the demand of disaster victims for emergency materials. A lower model was established with the goal of maximizing the satisfaction of emergency materials. According to the characteristics of the model, a hierarchical hybrid algorithm with genetic algorithm at the upper level and improved particle swarm optimization algorithm at the lower level was designed to solve the model. A case was designed to verify the proposed model and algorithm in the paper. The case solution results show that the non-linear integer bi-level programming model with multiple allocation centers and multiple disaster-stricken points makes the allocation of emergency materials more efficient, and can more reasonably measure the fairness of disaster victims' needs for emergency materials. The results of the discussion and analysis show that the delivery time and cost of emergency materials are equally important factors in the middle of an emergency, which should be paid more attention by decision makers. The model will provide reference for rational allocation of emergency materials.**

***Index Terms*—Emergency Materials Allocation (EMA), Relative demand ratio function, Material competition game, Hierarchical hybrid algorithm**

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I. INTRODUCTION

The frequent occurrence of major natural disasters such as the 2008 Wenchuan earthquake in China, social security incidents such as the collapse of residential buildings in France in 2014, and public health events such as the COVID-19 pandemic in 2019 directly affect social stability and economic balance. Emergency rescue can be divided into three stages: the initial stage, the middle stage, and the recovery and reconstruction stage in [1]. This paper focuses on emergency materials allocation (EMA) in the middle stage of the emergency. Different stages of emergency response lead to different goals. Scientific and efficient allocation of emergency materials directly affects the efficiency of emergency rescue. Moreover, efficient and reasonable EMA is an essential part to reduce casualties and avoid a large number of economic losses.

At present, many scholars have studied the EMA problems in different stages of disaster. EMA single-objective optimization models were established with the goal of minimizing emergency materials delivery time (EMDT) by considering vehicle paths and integrating multi-commodity network traffic in [2][3][4]. However, they did not consider the total cost of the EMA. Fortunately, [4][5] considered factors such as utility and allocation costs of EMA, and took timeliness, economy, fairness and satisfaction as the goals to establish an optimal allocation model for emergency materials. The above research results provided a certain reference for further research on EMA, but only considered the shortest EMA time or the minimum total cost of EMA. Therefore, the multiplicity of factors affecting emergencies cannot be accurately reflected, and most studies mainly focus on the initial stage of emergencies.

In view of the limitations of the single-objective mentioned above, some scholars proposed the EMA multi-objective optimization model. A multi-objective EMA model of single disaster-stricken point for the linear continuous consumption emergency materials scheduling problem was established in [6]. However, the allocating model of a single disaster-stricken point is not suitable for large-scale EMA. Fortunately, an EMA nonlinear time evaluation model that included multiple disaster-stricken points, multiple allocation centers and a single resource was constructed by combining the two scheduling objectives, which are time and material satisfaction, into a timely functional goal in [7]. However, in large-scale emergencies, a single resource does not match the reality. [8] constructed the EMA model with multiple resources and multiple disaster-stricken points in view of the emergency scheduling problem of multiple resources in the disaster chain. Although this model can solve the multiple disaster-stricken points EMA problem to a certain extent, it still has the limitation of incomplete target consideration.

[9][10][11][12][13] established a multi-objective optimization model of EMA by considering EMDT and emergency materials delivery cost (EMDC). Among them, the impact of casualties and vague needs on EMA also was considered in [10]. But the above literatures ignored the fairness of the distribution of emergency materials. Fortunately, [14][15][16][17] constructed a multi-objective optimization model of EMA by considering the delivery time of emergency materials, satisfaction of disaster victims or equity of material distribution. Among them, [17] described the satisfaction of disaster victims by introducing prospect theory and injustice theory, so as to measure the equity of allocation of emergency materials. However, the influence of secondary and derived disasters and the risk attitude of decision-makers on EMA were not considered in the above literatures. By considering the bounded rationality of the disaster victims in the actual emergency rescue process and the impact of secondary disasters, the EMA multi-population evolutionary game model was constructed by introducing the prospect theory in [18]. The impact of decision-makers' risk attitude on EMA was studied by considering the three-layer emergency relief material distribution network and two-stage material dispatch composed of emergency rescue supply points, allocation centers and demand points in [19]. The above multi-objective optimization models have made a great contribution to the study of EMA, but there are still some deficiencies. In the actual emergency rescue problem, the EMA usually has a principal-subordinate relationship between decision makers and victims at the disaster points. Unfortunately, the above EMA multi-objective optimization model cannot reflect the principal-subordinate game relationship.

In view of the deficiencies of the above EMA multi-objective study, some scholars tried to study the bi-level programming model of EMA. There are relatively few studies on the application of bi-level programming in the post-disaster EMA. Among them, a bi-level programming model with the goal of minimizing the transportation time of materials at the upper level and minimizing the transportation cost of materials at the lower level was established by considering multiple allocation centers and multiple disaster-stricken points in [26][27][28][29][30]. It is worth mentioning that [30] established a bi-level EMA model aiming at minimizing total cost and earliest system response time by judging the relationship between the inventory of allocation center and its critical inventory based on the objective fact of nonlinear continuous supply and consumption. [31] considered the game of demand for rescue workers among multiple disaster locations with limited emergency rescue worker and the bounded rational behavior of victims in the game process, and a bi-level game scheduling model of emergency rescue workers under bounded rationality had been constructed. However, the fairness of material distribution was not considered in the above literatures.

Based on the consideration of the rescue time and the fairness of the distribution of emergency materials, a bi-level programming model was established to minimize the transportation time of the upper level and maximize the fairness of the distribution of the lower level or the satisfaction of the disaster victims in [32][33][34][35][36]. However, EMDC is ignored. In addition, most researches are based on bi-level programming models of complete or deterministic disaster information. A multi-cycle bi-level optimization model of EMA was constructed with the goal of minimizing the transportation time, cost and risk of materials by considering the influence of uncertain factors such as fuzzy random information and road network damage on EMA in [38]. However, none of the above literatures took into account the dynamics of material demand and did not classify emergency materials.

The above research aimed at the efficient allocation of emergency materials after the disaster, and two aspects of the urgency of the time or cost of emergency materials delivery and the satisfaction of the disaster victims with the emergency materials obtained were analyzed. However, the comprehensive factors of EMA in the middle stage of a disaster are not considered, and most studies do not considered the influence of secondary and derived disasters on the route selection of emergency materials dispatching. In actual emergencies, emergency materials are often in short supply. However, few studies have considered the competitive game under the shortage of emergency materials.

In view of the above shortcomings, a nonlinear integer bi-level programming model for multiple emergency material allocation centers, multiple disaster-stricken points, and multiple emergency materials based on the timeliness and economy of emergency material delivery will be constructed in this paper. Not only the efficiency of EMA but also the overall maximum satisfaction of the disaster victims of the disaster-stricken point to the EMA scheme will be guaranteed in this model. By considering the influence of secondary and derived disasters on the choice of emergency path and the competitive game when the supply of emergency materials is in short supply, the efficient allocation of emergency materials in the middle stage of disasters is studied. The emergency materials are divided into two types according to whether they are affected by secondary and derived disasters, and the dynamic demands of the two types of emergency materials are put forward.

The rest of this paper is summarized as follows: Section II constructs the EMA bi-level programming model. A hierarchical hybrid algorithm is designed to solve the model in Section III. A case is designed to verify the model and algorithm in Section IV, and the results of emergency materials distribution are obtained. Section V analyzes the influence of some parameter changes on the results. Finally, the conclusion of this paper is in Section VI.

II. Model Building

A. Problem Description

Assuming that there are m disaster-stricken points. The set of disaster-stricken points is J={1,2,…j…,m}. There are n allocation centers to supply all kinds of emergency materials.

The set of allocation centers is $I=\{1,2,\ldots i\ldots,n\}$, $I=I_1\cup I_2$. I_1 and I_2 indicate the government's emergency reserves and the emergency reserves prepared by society respectively. The configuration of the allocation centers is shown in Fig. 1.

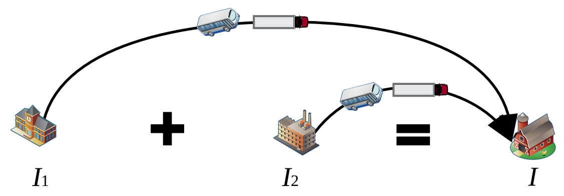

Fig. 1. Schematic diagram of the composition of the allocation centers

The disaster victims need to determine the dynamic demand $d_j(t)$ of emergency materials at the disaster-stricken point j according to the degree of the disaster and the impact of secondary and derivative disasters on the disaster, so as to compete with the emergency materials of the allocation centers. At the same time, emergency decision makers need to formulate EMA plan according to the specific demand and game situation of disaster-stricken point j and the 0-1 variable x_{ij} of path selection, so as to make reasonable and efficient allocation of emergency material supply s_i of allocation center i on the basis of fully considering the psychological satisfaction of disaster victims. If the route from the allocation center i to the disaster-stricken point j is selected to transport emergency materials, x_{ij} is 1; otherwise, it is 0.

It can be seen that the EMA has a principal-subordinate relationship between the decision-maker's choice of path and the executor's distribution of materials. Therefore, this study intends to construct a bi-level programming model of upper level path selection and lower level material distribution to solve the EMA problem in the middle of emergencies.

B. Model Assumptions

Hypothesis 1: Assume that the number and location of each allocation center and each disaster-stricken point are known.

Hypothesis 2: It is assumed that only one mode of transportation is used to transport emergency materials, that is, different transportation costs generated by different modes of transportation are not considered.

C. Upper Level Modeling

C.1. Upper Objective Function

Construct 0-1 variables as follows (1):

$$u_{ij} = \frac{n_{ij}}{\max\left\{n_{ij},\pi\right\}} \tag{1}$$

Where, u_{ij} represents whether emergency materials are transported on the path between the allocation center i to the disaster-stricken point j. n_{ij} indicates the number of emergency materials transferred from the allocation center i to the disaster-stricken point j. π represents the equilibrium constant, and $0<\pi<min\{n_{ij}\}$. π is a very small positive number selected according to actual problems.

According to the 0-1 variables constructed above, the differential idea is used to characterize EMDT. Each path from the allocation center i to the disaster-stricken point j is divided into several small segments, and t_z is assumed to represent the loading time of unit emergency materials. Let P_{ij}^n be the influence coefficient of secondary disasters on material transportation time on section n, $0 < P_{ij}^n \leqslant 1$. As shown in Fig. 2 below, the larger the value of P_{ij}^n, the smaller the impact of secondary disasters on this section, that is, the closer the actual transportation time of materials is to the normal transportation time.

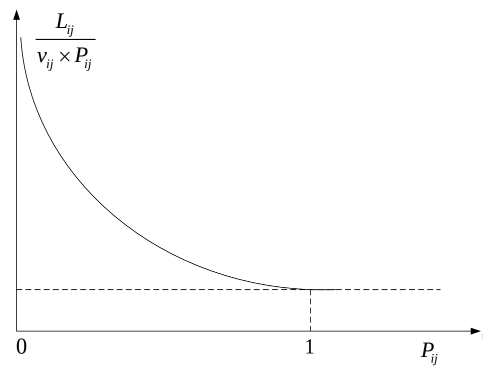

Fig. 2. The influence of secondary disaster influence coefficient on the transport time of emergency materials

In Fig. 2, L_{ij}^n is the length of section n, v_{ij}^n is the operation speed of transporting emergency materials in the absence of emergencies, then the actual EMDT of section n is $t_{ij}^n = L_{ij}^n/(v_{ij}^n\times P_{ij}^n)$, so the total time of transporting materials in this section is $T_{ij}=\sum_{n=1}^{n} t_{ij}$. Thus, the actual transport time function of emergency materials can be obtained, namely:

$$T = T_{ij}\times x_{ij}\times n_{ij} \tag{2}$$

According to the 0-1 variables constructed above and the road section differential idea, EMDC is described: Suppose r_{ij}^1 and r_{ij}^2 represent the unit transportation cost and unit risk cost of emergency materials from the allocation center i to the disaster-stricken point j respectively, then the unit transportation cost function and unit risk cost function are shown in (3) and (4) respectively.

$$R_{ij}^1 = r_{ij}^1\times n_{ij} \tag{3}$$

$$R_{ij}^2 = r_{ij}^2\times n_{ij}\times Q_{ij} \tag{4}$$

Where, Q_{ij} is the risk coefficient of materials transportation from the allocation center i to the disaster-stricken point j. The greater the value of Q_{ij}, the greater the risk of transportation, and $0< Q_{ij}\leqslant 1$. Then, the total transportation cost of emergency materials from the allocation center i to the disaster-stricken point j is $R=(R_{ij}^1+R_{ij}^2)\times x_{ij}$.

In the middle and late stages of an emergency, EMDT is not the only consideration for EMA issues, and EMDC should also be considered by decision makers. Therefore, with the minimum EMDT and the minimum EMDC as the goal, the upper model is constructed. (5) and (6) respectively represent the smallest EMDT and the smallest EMDC. The upper-level decision variable is the path selection variable x_{ij}.

$$\min f_T = T = T_{ij}\times x_{ij}\times n_{ij} \tag{5}$$

$$\min f_R = R = (R_{ijm}^1+R_{ijm}^2)\times x_{ij} \tag{6}$$

(7) and (8) are the dimensionless results.

$$f_1 = \frac{T-T_{\min}}{T_{\max}-T_{\min}} \tag{7}$$

$$f_2 = \frac{R - R_{\min}}{R_{\max} - R_{\min}} \tag{8}$$

Where, $T_{\min}$ and $T_{\max}$ are the minimum and maximum values of EMDT respectively. $R_{\min}$ and $R_{\max}$ are the minimum and maximum values of EMDC respectively. f_1 , $f_2 \in [0,1]$. Then the upper-level objective function can be obtained as shown in (9).

$$\min\ f = W \times (W_1 f_1 + W_2 f_2) \tag{9}$$

Where, W_1 and W_2 represent the decision preference coefficients of decision makers in the upper model for EMDT and EMDC respectively, and $W_1 + W_2 = 1$. In order to make the generalized cost of emergency materials transportation more explicit, the value conversion coefficient of generalized cost W is defined to measure the generalized cost of emergency materials transportation more accurately, and $W = \max\{T_{\max}, R_{\max}\}$.

C.2. Upper Constraints

The constraints of the upper model are as follows.

Constraint ①: Rescue constraints of the allocation centers: The emergency materials in the middle after the emergencies are relatively scarce, so each virtual allocation center should be involved in the process of EMA, and the following constraint (10) is established.

$$\sum_{j \in J} x_{ij} \geq 1, i \in I \tag{10}$$

Constraint ②: The disaster-stricken points are constrained by rescue: Considering the fairness and balance of material distribution, each disaster-stricken point is provided with emergency materials, and the following constraint (11) is established.

$$\sum_{i \in I} x_{ij} \geq 1, j \in J \tag{11}$$

Constraint ③: Due to the short supply of emergency materials and their scarcity, all materials of each allocation center should be involved in the distribution, and the following constraint (12) should be established.

$$\sum_{j \in J} x_{ij} \times d_j(t) \geq s_i, i \in I \tag{12}$$

The types of emergencies and the seasons in which they occur directly affect the types of emergency materials and the demand for each type of materials. [37] only proposed a description of the dynamic demand for emergency materials, and did not classify emergency materials. In this paper, emergency materials are divided into two categories according to whether they are affected by secondary and derived disasters, and the dynamic demand of emergency materials is described according to these categories.

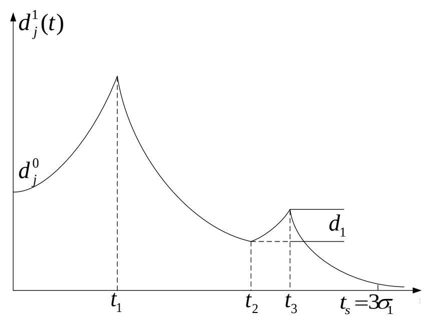

Fig. 3. Changes in the demand for emergency materials of the first category

The dynamics of $d_j(t)$ are shown in Fig. 3 and Fig. 4. The sudden drop in the emergency materials demand at t_2 is the emergency materials allocated to the disaster-stricken points in the second stage in Fig. 4.

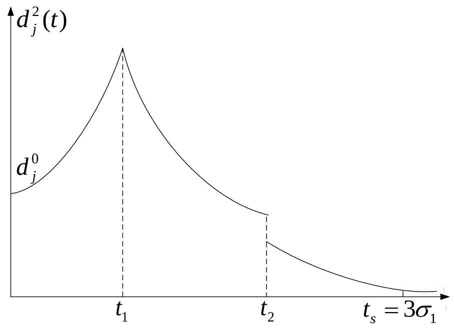

Fig. 4. Changes in the demand for the second type of emergency materials

$d_j(t)$ can be thought of in two phases. The dynamic requirements for the two types of emergency materials are the same in the first phase (the initial distribution phase) because secondary and derived disasters will occur in the second phase. In the first stage, the demand for emergency materials at the disaster-stricken points will increase with the occurrence of the disaster, so the dynamic demand for emergency materials at this time is expressed in (13) below.

$$d_j(\mathrm{t}) = N_j \times a_1 \times b_1^t + d_j^0 \tag{13}$$

Where, N_j represents the number of people affected by the disaster-stricken point j, and d_j^0 represents the amount of emergency materials that existed before the disaster-stricken point j. Both a_1 and b_1 are constants. Before the emergency materials of the second stage are delivered, the amount of emergency materials at each disaster-stricken point can maintain the demand of the disaster victims, so the demand at this time is in a process of non-linear decline. The right half of the normal distribution curve corresponds to this change. Therefore, the dynamic changes of materials demand can be described as follows.

$$d_j(t) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{t^2}{2\sigma}} \tag{14}$$

In the second phase, the unmet requirements phase of the initial distribution, the dynamic requirements for the two types of emergency materials will be different due to secondary and derived disasters.

For the first type of emergency materials affected by secondary and derivative disasters, the demand changes are as follows (15).

$$d_j(t) = \frac{N_j \times a_2 \times b_2^t}{\min\{P_{ij}\}} \tag{15}$$

Where, a_2 and b_2 are constants. When the time is relatively large, the demand for materials at the disaster-stricken point j shows a downward trend, so the following (16) represents the demand change at this time.

$$d_j(t) = \frac{\frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{t^2}{2\sigma}}}{\min\{P_{ij}\}} + d_1 \tag{16}$$

Where d_1 represents the demand for new emergency materials after the second stage.

For the second type of emergency materials that are not affected by secondary and derivative disasters, the change in demand is shown in the following formula (17):

$$d_j(t) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{t^2}{2\sigma}} \tag{17}$$

Constraint ④: The transportation volume of emergency materials should not exceed the storage amount of the allocation centers, so the storage limit of emergency materials in each allocation center should be considered, and the following constraint (18) should be established.

$$\sum_{i \in I} x_{ij} \times s_i \le S_i, j \in J \tag{18}$$

Where S_i represents the maximum storage capacity of emergency materials in the allocation center *i*.

Constraint⑤: Limitation of inadequate supply: The materials actually delivered to the disaster-stricken points do not exceed its demand, which reflects the actual situation of insufficient supply of emergency materials in the middle of an emergency. The following mathematical expression (19) is established.

$$\sum_{i \in I} x_{ij} \times y_{ij} \le d_j(\mathrm{t}), j \in J \tag{19}$$

Where y_{ij} is the decision variable of the lower model, that is, the quantity of emergency materials actually obtained by the disaster-stricken point *j* in the competition of the allocation center *i*.

D. Lower Level Modeling

D.1. Lower Objective Function

The competition of the disaster-stricken points for emergency materials constitutes a game between them. Relative demand satisfaction can better reflect the rational allocation of emergency materials by decision makers, so it is completely reasonable to use it to describe the game. The specific non-cooperative game elements are as follows.

The player: The disaster-stricken points that have a competitive relationship with emergency materials.

Pure strategy: The number of emergency materials obtained by actual competition between the player *j* in the allocation center *i*;

Pure strategy set: The strategy selection set of player *j* is $u_j=\{y_{1j}, y_{2j}, \ldots, y_{r(j)j}\}$, where $r(j)$ is the number of strategies that player *j* can choose.

Satisfaction function: The improved relative demand ratio function is used to measure the disaster victims' perceived satisfaction at the level of the quantity of emergency materials in [15], and (20) is used to represent the ratio between the actual quantity of materials satisfied and the demand at the disaster-stricken point *j*.

$$Y_j = \frac{\sum_{i \in I} y_{ij} \times x_{ij}}{d_j(t)}, j \in J \tag{20}$$

The satisfaction function of the player *j* when he adopts strategy u_j is shown in (21).

$$g_{u_j}(j) = \frac{Y_j - 1}{\sum_{j=1}^{n_s} Y_j} \tag{21}$$

Where n_s represents the number of the players in the game.

Suppose that $u_j \mid u'_j$ represents the situation when the strategy of the player *j* changes from u_j to u'_j, and the other players' strategies remain unchanged.

The satisfaction function of the disaster-stricken point *j* to emergency materials is constructed as follows.

$$\max\ f_3 = \sum_{i \in I} g_{u_i \mid u'_i}(j), j \in J \tag{22}$$

D.2. Lower Constraints

The constraints of the lower model are as follows.

Constraint ①: Limitation of emergency materials: The actual total amount of emergency materials transported from the allocation center *i* to each disaster-stricken point should be equal to the supply of the allocation center *i*, as shown in (23).

$$\sum_{i \in I} y_{ij} = s_i, i \in I \tag{23}$$

Constraint ②: The connection function between upper and lower levels: When the path selection variable of the allocation center *i* to the disaster-stricken point *j* is 1, this path is used to transport emergency materials, otherwise, this path is not used for the deployment of emergency materials as shown in (24).

$$y_{ij} \le x_{ij} \times s_i, i \in I, j \in J \tag{24}$$

Constraint ③: The non-zero constraint of the emergency materials delivery volume is as follows (25).

$$y_{ij} \in N, y_{ij} \ge 0, i \in I, j \in J \tag{25}$$

Constraint ④: The emergency materials transportation time window is restricted, as shown in (26).

$$t_{\min} \le t \times x_{ij} \le t_{\max} \tag{26}$$

Where, t_{max} represents the maximum constraint time and t_{min} represents the minimum constraint time.

III. ALOGRITHM DESIGN

Bi-level programming belongs to NP-Hard problem. At present, there have been rich results in the research of bi-level programming. A bi-level programming model was established to solve problems in water, electricity, transportation, enterprise service, agriculture and other aspects respectively in [20][21][22][23][24][25]. Combined with the characteristics of the model established in this paper, since this model is the path choice problem of 0-1 variables in the upper level and the non-cooperative game model about material competition in the lower level, a hierarchical hybrid algorithm with genetic algorithm in the upper layer and improved particle optimization algorithm in the lower layer is designed to solve the bi-level programming model in this paper.

A. Algorithm Description

The upper genetic algorithm uses roulette to select operators, as shown in Fig 5. Where, x_c represents the upper path selection chromosome, and c=1,2,3,4. c_p_c represents the fitness ratio and selection probability of x_c, and $c\_p_c = fs_c / \sum_1^4 fs_c$. *rand* represents a random number between 0 and 1, and the x_c chromosome is selected when it falls within the cumulative probability region of x_c.

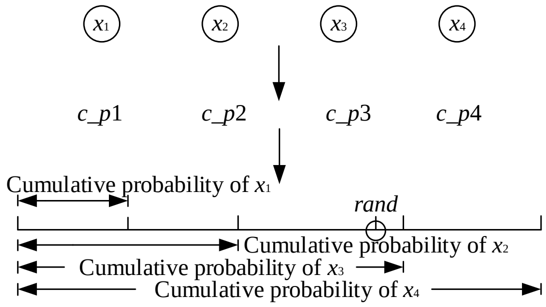

Fig. 5. Roulette selection operator

Considering that the single-point crossover operator has little damage to individual, the single-point crossover operator is adopted to carry out crossover operation on individuals. Based on the demarcation point of x_{ij1} and x_{ij2} gene sequences (path selection variable 0-1), the x_{ij2} gene sequence of two chromosomes is crossed at a single point. There is also a variation in a gene in x_{ij2}. The crossover variation process of the upper genetic algorithm is shown in Fig. 6.

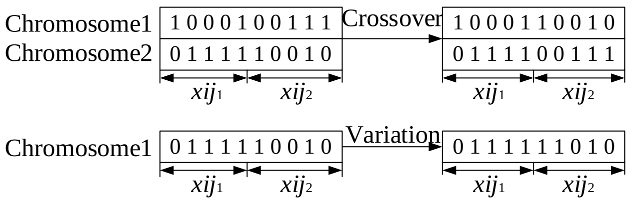

Fig. 6. Schematic diagram of crossover variation

In order to improve the convergence performance of the elementary particle swarm optimization (PSO) algorithm, this paper makes the following improvements.

The first improvement: In order to achieve the optimal balance between the global search ability and the local search ability of the algorithm, the value of inertia weight is dynamically adjusted in the iterative process of the algorithm. This paper introduces the following adaptive nonlinear decreasing inertia weights, as shown in (27).

$$\omega=(\omega Max-\omega Min)\times e^{-\frac{1}{1+\frac{iterMax-iter}{iterMax}}}+\omega \tag{27}$$

Where, ωMax and ωMin are the maximum weight coefficient and the minimum weight coefficient respectively. *iter* is the current iteration number of the algorithm. *iterMax* is the upper limit of the iteration number of the algorithm.

The second improvement: Random disturbance was added to *gBest*, that is, variation operation was performed on *gBest*. Assuming that the random variable η obeys the standard normal distribution, the value of *gBest* can be changed by the following formula (28).

$$gBest=gBest\times(1+\eta\times 0.5) \tag{28}$$

The standard particle swarm optimization algorithm is improved based on the above two points. The optimization iteration is performed according to the particle swarm iteration rules shown in (29) and (30).

$$\begin{aligned} v_l(t+1) &= \omega\times v_l(t)+ \\ & c_1\times r_1\times[pBest-x_l(t)] \\ & +c_2\times r_2\times[gBest-x_l(t)] \end{aligned} \tag{29}$$

$$x_l(t+1)=x_l(t)+v_l(t+1) \tag{30}$$

Where, $x_l(t)$ and $v_l(t)$ are the position and velocity of particle l respectively. r_1 and r_2 are random numbers between 0 and 1. *pBest* and *gBest* are respectively the best position experienced by particle l and the global best position experienced by the whole population. ω is the inertia weight, which can be determined according to the specific optimization problem.

Since the distribution amount of the lower-level materials needs to be an integer, it is necessary to prevent each particle from overflowing into a decimal, as shown in Fig. 7. Where, The amount of emergency materials in y'_{ij} is the updated value under the basic particle swarm update rule, and its value is a decimal and greater than the amount of emergency materials in y_{ij}. The volume of emergency materials in y''_{ij} is the updated value under the speed update rounding up update rule, and its value is an integer and less than or equal to the volume of emergency materials in y_{ij}.

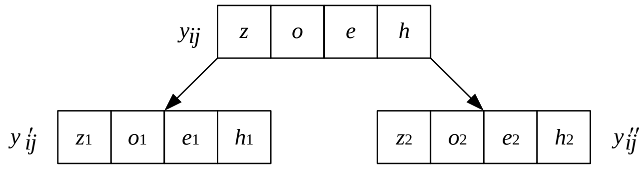

Fig. 7. Schematic diagram of preventing particle overflow

B. Fitness Function and Algorithm Steps

The fitness function of the upper-level mainly considers the comprehensive generalized cost of EMDT and EMDC for decision makers, so the objective function of the upper model is the fitness evaluation function. The upper-level fitness evaluation function f_s is determined as follows in (31). The lower-level fitness function mainly considers the satisfaction of the disaster victims for the needs of emergency materials, so the negative value of the objective function at the lower model is the fitness evaluation function. The fitness evaluation function f_x of the lower-level is shown in (32).

$$f_s = f \tag{31}$$

$$f_x = -f_3 \tag{32}$$

The population N is initialized according to the value range of 0-1 variables (choice of transportation path of emergency materials) of the upper model decision variables. The length of chromosome is the product of the number of the allocation centers and the number of the disaster-stricken points, and the value of gene position is 0 or 1. When the value of gene position is 1, it means the delivery of emergency materials.

The population N_1 is set according to the lower model decision variable y_{ij} (the strategy combination of the players in the game). Y is the lower-level population composed of the optimal solution of the lower model corresponding to each emergency material transportation route selection of the upper-level population.

Based on the above analysis, the design of hierarchical hybrid algorithm flow chart is shown in Fig. 8.

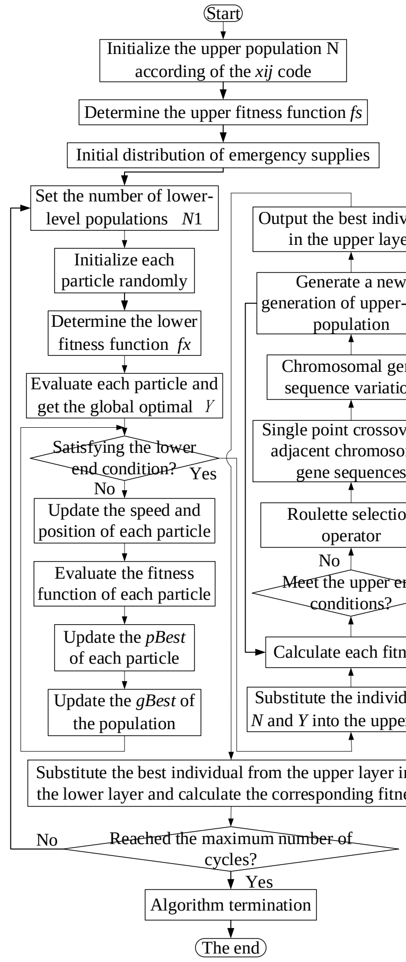

Fig. 8. Flow chart of hybrid algorithm

IV. CASE STUDY

A. Case Background

Suppose a major natural disaster occurs in *A* area. The number of disaster-stricken points is 10, which numbered from 1 to 10. There are 5 allocation centers that can provide materials, numbered from 1 to 5. The emergency materials of the allocation center are shown in Table I. See Table II for the disaster level of the disaster-stricken point *j*. The impact coefficients of secondary and derivative disasters for each path are shown in Table III. The emergency materials requirements of the disaster-stricken points are shown in Table IV. The transportation time of materials from the allocation center *i* to the disaster-stricken point *j* without considering secondary and derivative disasters is shown in Table V. The response time between each node is shown in Table VI. Table VII shows the unit transportation cost of emergency materials.

TABLE I
SUPPLY OF EMERGENCY MATERIALS IN THE ALLOCATION CENTERS

	Disaster-stricken point number				
	1	2	3	4	5
Supply (100 pieces)	1000	440	1050	1400	1000

TABLE II
THE EXTENT OF THE DISASTERS

	Disaster-stricken point number									
	1	2	3	4	5	6	7	8	9	10
Damage level	II	IV	IV	I	III	III	II	IV	III	III

Note: I represents the most severe disaster.

TABLE III
IMPACT COEFFICIENT P_{ij} OF SECONDARY AND DERIVATIVE DISASTERS

		Allocation Center Number				
		1	2	3	4	5
Disaster-stricken point number	1	0.6	0.8	0.85	0.6	0.75
	2	0.75	0.7	0.8	0.5	0.7
	3	0.9	0.9	0.65	0.9	0.95
	4	0.6	0.85	0.65	0.8	0.99
	5	0.65	0.95	0.7	0.99	0.6
	6	0.5	0.6	0.8	0.7	0.75
	7	0.9	0.75	0.65	0.7	0.8
	8	0.95	0.9	0.75	0.8	0.4
	9	0.9	0.6	0.8	0.45	0.1
	10	0.9	0.3	0.65	0.8	0.75

TABLE IV
DEMAND FOR EMERGENCY MATERIALS AT DISASTER-STRICKEN POINTS

	Disaster-stricken point number				
	1	2	3	4	5
Demand (100 pieces)	600	342	565	800	400
	Disaster-stricken point number				
	6	7	8	9	10
Demand (100 pieces)	400	600	449	400	400

TABLE V
MATERIAL TRANSPORTATION TIME WITHOUT CONSIDERING THE IMPACT OF SECONDARY AND DERIVATIVE DISASTERS

		Allocation Center Number				
		1	2	3	4	5
Disaster-stricken point number	1	9.378	8.36	9.163	5	10
	2	9.938	5.25	7.6	7.5	14
	3	6.192	8.1	3.757	3.6	2.85
	4	6.6	7.14	7.618	6.4	4.95
	5	4.063	6.08	8.4	4.95	10.8
	6	11.5	10.8	12.8	7	15
	7	7.2	9	13	10.5	14
	8	4.75	9	13.5	9.6	10
	9	9	14.4	12	9	1.6
	10	19.8	2.4	7.8	19.2	7.5

TABLE VI
MATERIAL TRANSPORTATION TIME $t_{ij}(h)$ CONSIDERING THE IMPACT OF SECONDARY AND DERIVATIVE DISASTERS

		Allocation Center Number				
		1	2	3	4	5
Disaster-stricken point number	1	15.63	10.45	10.78	8.33	13.33
	2	13.25	7.5	9.5	15	20
	3	6.89	9	5.78	4	3
	4	11	8.4	11.72	8	5
	5	6.25	6.4	12	5	18
	6	23	18	16	10	20
	7	8	12	20	15	18
	8	5	10	18	12	25
	9	10	24	15	20	16
	10	22	8	12	24	10

The unit transportation cost of emergency materials is shown in Table VI. Set t_{min}=0(h), t_{max}=100(h).

TABLE VII
ACTUAL TRANSPORTATION COST OF EMERGENCY MATERIAL r_{ijm}

		Allocation Center Number				
		1	2	3	4	5
Disaster-stricken point number	1	4.5	5.3	4.6	9.3	4.1
	2	6.2	6.6	5.4	3.9	5.6
	3	8.9	3.9	5.5	4.5	8.2
	4	6.3	4.8	6.6	5.2	4.2
	5	5.6	6.2	6.4	3.8	4.2
	6	6.1	2.9	4.7	5.6	5.3
	7	5.4	3.8	8.5	5.6	4.2
	8	7.8	3.5	3.5	5.6	5.6
	9	6.5	5.6	3.9	7.8	2.8
	10	3.2	6.7	6.3	3.6	5.4

B. *Case Solving*

Set the population size of the upper genetic algorithm C_1=50, the selection probability *Choice_P*=0.2, the crossover probability *Cross_P*=0.9, the mutation probability *Var_P*=0.02, and the upper-level iteration number *Generation*=500. Set the population size of the lower-level improved particle swarm optimization algorithm C_2=30, the maximum value $\omega\max = 0.9$ and minimum value $\omega\min = 0.1$ of nonlinear decreasing inertia weight, the constraint factor *r*=1.0, the weight "self-cognition" coefficient c_1=0.05, the weight "social cognition" coefficient c_2=0.05, and the iteration times of the lower layer *generation*=500. Let the value of the generalized cost conversion coefficient *W* be 1800, and the decision preference coefficients W_1 and W_2 of decision makers for the transportation time and cost of emergency materials are both 0.5.

The algorithm of this paper is implemented based on VisualStudio2019 software and C# programming language.

The iterative process of the algorithm is shown in Fig. 9 below.

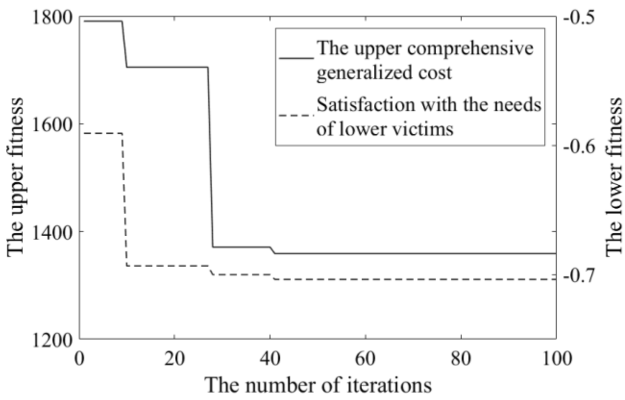

Fig. 9. Algorithm iteration diagram

As it can be seen from Fig. 9, the comprehensive fitness of EMDT and EMDC of the upper model is stable at 1359, and the satisfaction of the lower model disaster victims with demand is stable at -0.704. However, the upper and lower models converge tend to be stable quickly in about 40 generations, which is caused by the particularity of the problem. The distribution of emergency materials in the lower model should be an integer, so the speed update formula of particle swarm optimization algorithm is solved by rounding up to an integer. Therefore, this problem has a strong purpose of iteration and a fast convergence speed.

See Table VIII for the solution results of the upper model path selection.

TABLE VIII
SOLUTION RESULTS OF UPPER LAYER PATH SELECTION

		Allocation Center Number				
		1	2	3	4	5
Disaster-stricken point number	1	0	1	0	0	1
	2	0	0	0	1	1
	3	1	0	0	1	1
	4	0	1	1	0	0
	5	1	1	0	0	1
	6	1	0	1	0	1
	7	1	1	0	1	0
	8	1	0	0	1	0
	9	1	0	1	1	0
	10	1	1	1	1	1

According to Table IV, Table VII and Table VIII, the initial distribution of the lower model emergency materials can be obtained as shown in Table IX.

TABLE IX
INITIAL DISTRIBUTION TABLE OF EMERGENCY MATERIALS

		Allocation Center Number				
		1	2	3	4	5
Disaster-stricken point number	1	0	0	0	0	600
	2	0	0	0	0	0
	3	0	0	0	0	0
	4	0	440	360	0	0
	5	400	0	0	0	0
	6	0	0	400	0	0
	7	600	0	0	0	0
	8	0	0	0	0	0
	9	0	0	290	110	0
	10	0	0	0	0	400

According to Table VIII and Table IX, the disaster-stricken point 1 is taken as an example to illustrate the principle of initial allocation. Both the allocation centers 2 and 5 can deliver emergency materials to the disaster-stricken point 1. However, considering the urgency of time, the allocation center 5 is selected to supply emergency materials. Therefore, there is the material transportation situation in Table IX, which also reflects the relationship between the upper and lower models. The "decision makers" at the lower level obey the "decision makers" at the upper level, but do not completely obey the "decision makers" at the upper level, and have full decision-making power within a certain range.

Thus, the emergency material distribution route is shown in Fig. 10.

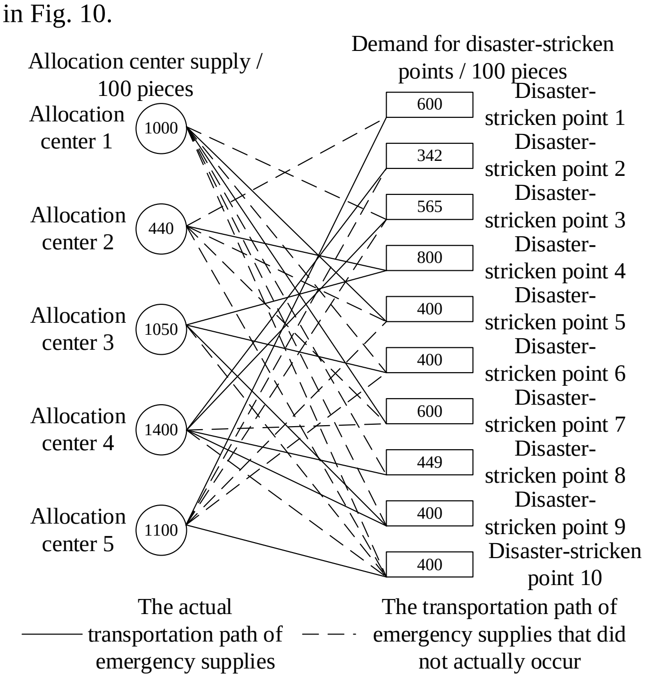

Fig. 10. Schematic diagram of emergency materials distribution route

It can be seen from Fig. 10 that the solid line represents the actual emergency materials transportation path, and the dashed line represents the emergency materials transportation path that does not occur. The disaster-stricken point 4 has no unoccupied transportation routes, which embodies the principle of distribution of emergency materials that prioritizes the most severely affected needs.

As it can be seen from Table IX and Fig. 10, the emergency materials in the allocation center 4 are surplus, but the disaster-stricken points 2, 3 and 8 do not receive emergency materials, because the initial distribution of emergency materials makes the surplus of emergency materials in allocation center 4 unable to meet the demand for emergency materials in the disaster-stricken points 2, 3 and 8. Therefore, the disaster-stricken points 2, 3, and 8 compete for the remaining emergency materials in the allocation center. If the disaster-stricken points 2, 3 and 8 are regarded as the players 1, 2 and 3 in the non-cooperative game, then the pure strategy sets of the three players are respectively: {1, 2, ..., 382}, {1,2, ..., 565}, {1,2, ..., 449}. According to the hierarchical hybrid algorithm, the optimal solution of the lower model is -0.694, and the corresponding pure policy combination is (342,565,383). The amount of emergency materials delivered by the allocation center 4 to the disaster-stricken points 2, 3 and 8 is 34200, 56500 and 38300 respectively. Therefore, the actual transportation amount of emergency materials is shown in Fig. 11.

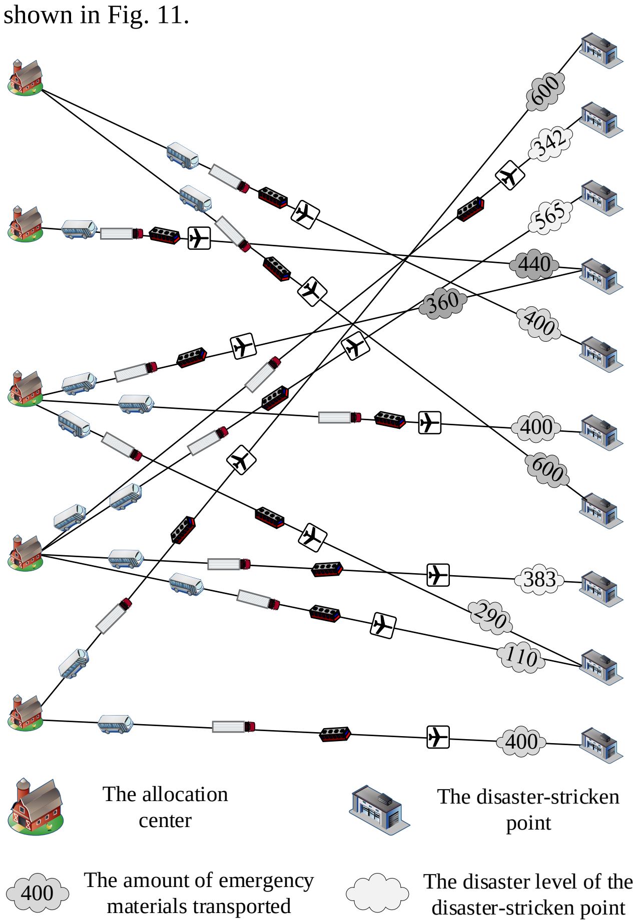

Fig. 11. Schematic diagram of the actual amount of emergency materials

V. Discuss and Analyze

In actual emergencies, the change of decision preference coefficients W_1 and W_2 for EMDT and EMDC will affect EMA plan, and then affect EMA's comprehensive generalized cost. Secondary and derived disasters can affect the comprehensive generalized cost of EMA. This section mainly introduces the influence of W_1, W_2, P_{ij} and Q_{ij} changes on EMA's generalized cost.

A. The Influence of W_1 and W_2 on the Generalized Cost of EMA

The influence of decision preference coefficients W_1 and W_2 on the comprehensive generalized cost of EMA is shown in Fig. 12.

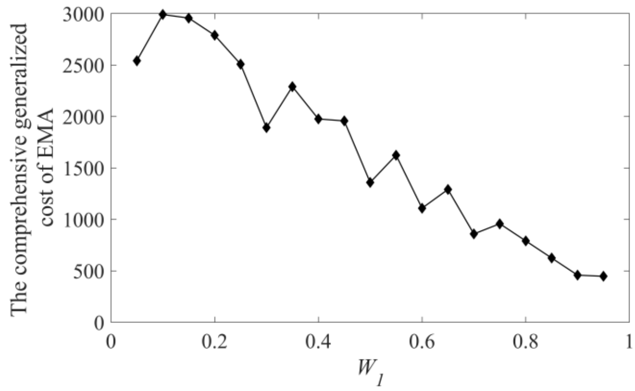

Fig. 12. Influence of EMDT preference coefficient

It can be seen from Fig. 12 that with the increase of W_1, the cost of EMA decreases generally. In other words, when decision makers pay more attention to EMDT, the generalized cost of EMA is smaller. In the medium term after an emergency, although EMDT and EMDC are assumed to be equally important factors in this case, it is clear that in practical situations EMDT is the primary concern of decision makers. W_1 will fluctuate between 0.3 and 0.75, which reflects the uncertainty of decision makers in the medium term after an emergency to prefer EMDT or EMDC.

B. The Impact of Each Disaster-stricken Point P_{ij} and Q_{ij} on the Generalized Cost of EMA

The impact of each disaster-stricken point P_{ij} and Q_{ij} on the generalized cost of EMA is shown in Fig. 13-18 below.

The impact diagram of the disaster-stricken point 7 P_{17} and Q_{17} on the generalized cost of EMA is shown in Fig. 13.

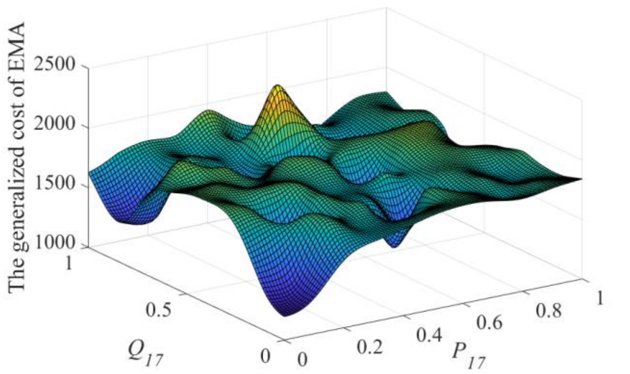

Fig. 13. The impact diagram of disaster-stricken point 7 P_{17} and Q_{17} on the generalized cost of EMA

With the change of P_{ij} and Q_{ij}, the EMA generalized cost of the disaster-stricken point 4 and the disaster-stricken point 7 have the same trend of change. It can be seen from Fig. 13 that for the disaster-stricken point 7, with the change of P_{17} and Q_{17}, the generalized cost of EMA fluctuates, but there is no obvious trend. When P_{17} and Q_{17} tend to 0, the generalized cost of EMA is small, indicating that for the disaster point 7 and 4, the EMDC from each allocation center to the disaster-stricken point 7 and 4 has a greater impact on the generalized cost of EMA, while the EMDT from each allocation center to the disaster-stricken point 7 and 4 has a smaller impact on the generalized cost of EMA.

The impact diagram of the disaster-stricken point 1 P_{51} and Q_{51} on the generalized cost of EMA is shown in Fig. 14. The impact diagram of the disaster-stricken point 5 P_{15} and Q_{15} on the generalized cost of EMA is shown in Fig. 15.

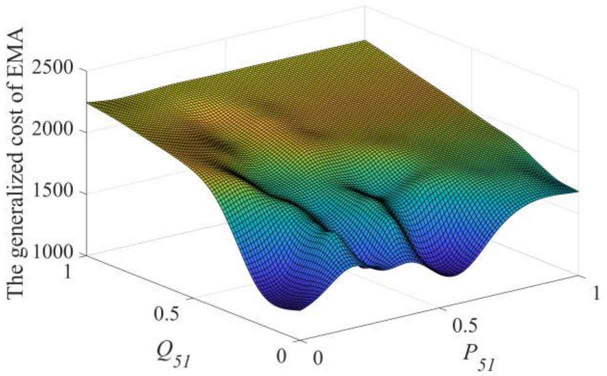

Fig. 14. The impact diagram of the disaster-stricken point 1 P_{51} and Q_{51} on the generalized cost of EMA

As can be seen from Fig. 14, when the value of Q_{51} is constant, with the increase of P_{51}, the generalized cost of EMA also increases. However, when the value of P_{51} is constant, the change of the value of Q_{51} has no significant effect on the generalized cost of EMA. It is shown that EMDT plays a decisive role in the EMA generalized cost of the disaster-stricken point 1. EMDT is mainly taken into account in the EMA of the disaster-stricken point 1. Since the damage degree of the disaster-stricken point 1 is not the slightest, it is necessary to deliver emergency materials as quickly as possible. When the value of Q_{51} is between 0.3 and 0.8, the variation of EMA's generalized cost will be fluctuant, reflecting the comprehensive consideration of EMDT and EMDC by decision makers.

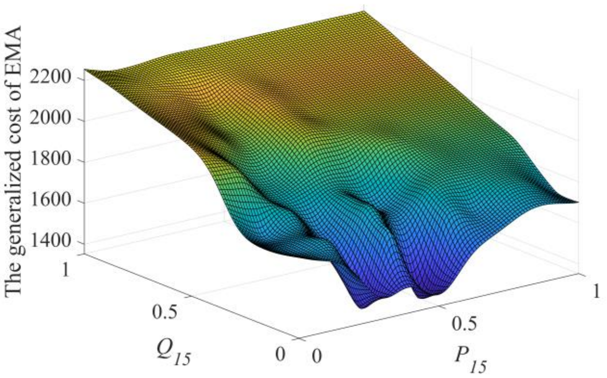

Fig. 15. The impact diagram of the disaster-stricken point 5 P_{15} and Q_{15} on the generalized cost of EMA

As can be seen from Fig. 14 and Fig. 15, with the change of P_{ij} and Q_{ij}, the EMA generalized cost of the disaster-stricken point 1 and the disaster-stricken point 5 have the same trend of change. It is shown that EMDT plays a decisive role in the EMA generalized cost of the disaster-stricken point 5. EMDT is mainly taken into account in the EMA of the disaster-stricken point 5. Since the damage degree of the disaster-stricken point 5 is not the slightest, it is necessary to deliver emergency materials as quickly as possible.

The impact diagram of the disaster-stricken point 6 P_{36} and Q_{36} on the generalized cost of EMA is shown in Fig. 16.

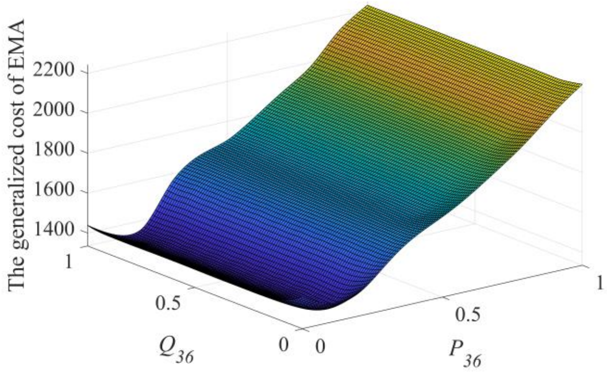

Fig. 16. The impact diagram of the disaster-stricken point 6 P_{36} and Q_{36} on the generalized cost of EMA

It can be found from Fig. 16 that for the disaster-stricken point 6, when the value of P_{36} is constant, with the increase of Q_{36}, the generalized cost of EMA also increases. When the value of Q_{36} is constant, the change of P_{36} value has no significant impact on the generalized cost of EMA. It indicates that EMDC plays a decisive role in the generalized cost of EMA at the disaster-stricken point 6. The EMA at the disaster-stricken point 6 mainly considers EMDC, which is caused by the larger EMDC of the allocation centers that can supply emergency materials to the disaster-stricken point 6.

The impact diagram of the disaster-stricken point 9 P_{39} and Q_{39} on the generalized cost of EMA is shown in Fig. 17.

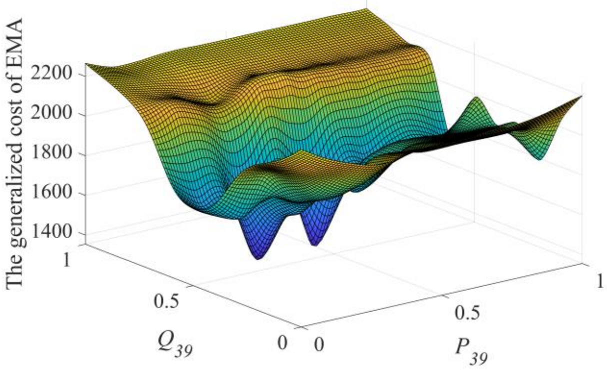

Fig. 17. The impact diagram of the disaster-stricken point 9 P_{39} and Q_{39} on the generalized cost of EMA

As the change of P_{ij} and Q_{ij}, the EMA generalized cost of the disaster-stricken point 9 and the disaster-stricken point 10 have the same trend of change. It can be seen from Fig. 17 that for disaster-stricken point 9, when the value of Q_{39} is constant, with the increase of P_{39}, the generalized cost of EMA first decreases and then increases. When P_{39} is 0.5, EMDC reflects the most significant influence on EMA's generalized cost, and the integration of EMDC and EMDT minimizes EMA's generalized cost. However, when the value of P_{39} is constant, the change of the value of Q_{39} has no significant effect on the generalized cost of EMA. It shows that EMDT plays a decisive role in the EMA generalized cost of the disaster-stricken point 9 and 10, and the EMA of the disaster-stricken point 9 and 10 mainly takes EMDT into account.

The impact diagram of the disaster-stricken point 2 P_{22} and Q_{22} on the generalized cost of EMA is shown in Fig. 18.

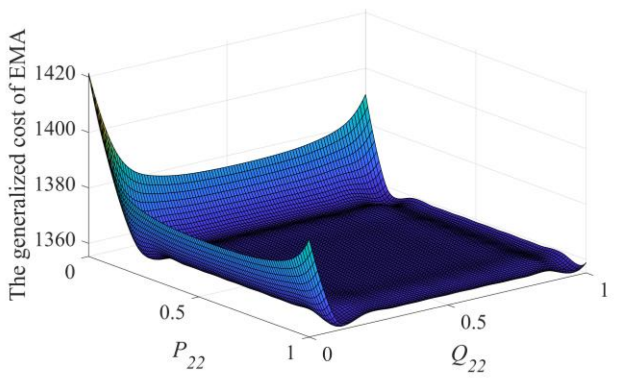

Fig. 18. The impact diagram of the disaster-stricken point 2 P_{22} and Q_{22} on the generalized cost of EMA

As can be seen from Fig. 18, for the disaster-stricken point 2, 3 and 8, the change of P_{22} and Q_{22} has no significant impact on the generalized cost of EMA. Because in this case, the demand for emergency materials at the disaster-stricken point 2, 3 and 8 has not been met in the initial distribution. In this case, the demand for emergency materials at the disaster-stricken point 2, 3 and 8 is not met in the initial distribution, so the final material distribution result of the players in the lower game is a certain value. Therefore, the changes of P_{ij} and Q_{ij} of the disaster-stricken point 2, 3 and 8 will not have a significant impact on the generalized cost of EMA.

When P_{ij} and Q_{ij} of each disaster-stricken point change, the minimum and maximum value of EMA's generalized cost are shown in Fig. 19.

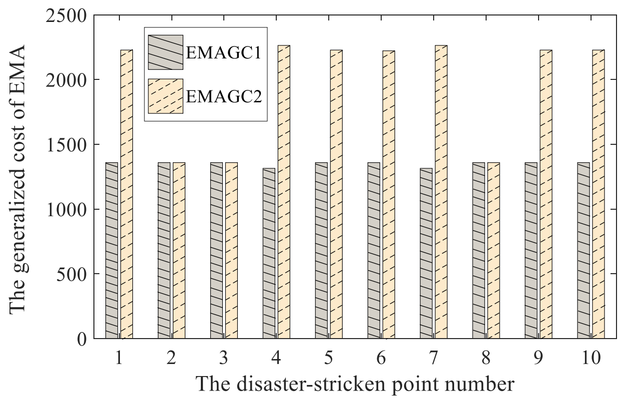

Fig. 19. Minimum and maximum comparison of EMA's generalized cost

As shown in Fig. 19, EMAGC1 represents the minimum value of the generalized cost of EMA when P_{ij} and Q_{ij} of each disaster-stricken point change. EMAGC1 represents the maximum value of the generalized cost of EMA when P_{ij} and Q_{ij} of each disaster-stricken point change. It can be seen from Fig. 19 that each disaster-stricken point has basically no effect on the minimum value of the EMA generalized cost, which proves the correctness of the solution results in this paper. When P_{ij} and Q_{ij} of the disaster-affected points 2, 3 and 8 change, the minimum and maximum of EMA generalized cost are the same, because the demand for emergency materials at the disaster-affected points 2, 3 and 8 is not met and they have competition after the initial allocation of emergency materials. Other disaster-stricken points have basically no effect on the maximum generalized cost of EMA.

VI. Conclusion

This paper mainly studies the EMA problem in the middle of actual emergencies, and considers the time urgency and cost economy of emergency materials transportation, so as to analyze the competition game phenomenon of emergency materials among disaster victims in the situation of emergency materials shortage. In order to reduce the generalized cost of EMA and satisfy the demand of disaster victims for emergency materials to the greatest extent, a bi-level programming model of emergency materials is established by introducing the time differential idea and the improved relative demand ratio function under the condition of considering the material competition game.

The case simulation results show that the bi-level programming model can effectively measure the different impacts of secondary and derivative disasters on the transportation path of emergency materials. In addition, the model also considers the competition of emergency materials among disaster victims in the case of shortages of different kinds of emergency materials, which can more effectively explain the non-cooperative game phenomenon in the actual EMA, so that the decision-making results are more realistic. This model can be applied to the EMA problem of some emergencies. The EMA scheme obtained by solving the model also takes into account the perceived satisfaction of the material needs of the disaster victims at the disaster-stricken point and the generalized cost of the decision-maker.

After discussion and analysis of the results, the following conclusions can be found. First of all, EMDT is the primary factor that decision makers pay attention to when carrying out emergency materials. It shows that in practical problems, it is necessary to rescue the disaster-stricken points as quickly as possible. But for some disaster-stricken points, it is necessary to fully consider EMDC on the basis of considering EMDT as much as possible. For example, for the disaster-stricken point 6, because EMDC has a greater impact on the generalized cost of EMA, EMDC is the first consideration for decision makers, and EMDT is the second most important factor. Secondly, changes in the influence coefficient P_{ij} of the secondary disasters of each disaster-stricken point on the transportation time of materials and the risk coefficient Q_{ij} of the transportation of materials from the allocation center to the disaster-stricken point will cause changes in the total cost of EMA. However, changes in P_{ij} and Q_{ij} will not change the total cost of EMA for the disaster-stricken points whose initial allocation fails to meet the needs of emergency materials, which reflects the particularity of the material competition game among disaster victims in the lower model.

In the actual EMA problem, there are many different modes of transport for emergency materials. Therefore, for the following research, the impact of the cost of transporting emergency materials in different modes of transportation on the EMA scheme will be considered.

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