Research on Bi-level Game Scheduling for Emergency Rescue Workers under the Condition of Limited Rationality

Sinan Liu, Changfeng Zhu, Yanhui Zheng, and Qingrong Wang

***Abstract*—In the event of an emergency, the efficient and reasonable scheduling of emergency rescue workers in the initial stage of the emergency rescue process can considerably reduce the associated loss. In this regard, this paper proposes a bi-level game scheduling model for emergency rescue workers under the condition of limited rationality, primarily considering the demand game for limited emergency rescue workers in multiple disaster areas and the limited rational behavior of victims in the game process. Based on the proposed model, a Shuffled Frog Leaping Algorithm (SFLA) is designed to solve the problem. Finally, the rationality of the model is verified through a case study. The results indicate that the model of the emergency rescue workers scheduling (ERWS) proposed in this paper can take into account both the fairness of the scheduling while ensuring a satisfactory basic rescue effect, thereby considerably improving the satisfaction of the victims and reducing the loss resulting from the emergency. The findings can provide further emergency decision-making reference for decision-makers.**

***Index Terms*—emergency rescue workers scheduling, limited rationality, non-cooperative game, bi-level programming**

I.INTRODUCTION

Many uncertain disaster factors, such as the evolution of regional climate, the deterioration of environmental ecology, and the complexity of social system have shown extremely complex evolutionary trends, while emergencies triggered by these factors indicate a trend of spatial spread and intensification. Additionally, various natural disasters such as the Wenchuan Earthquake, the Southern Snowstorm, as well as other shocking emergencies such as the COVID-19 epidemic, SARS epidemic, and the Tianjin Port explosion, not only severely damaged social stability, hindered economic development, wounded people 's lives and property, but also seriously challenged the social carrying capacity and the emergency response capability. In the event of such emergencies occur, the government must take corresponding emergency measures to control the adverse influence caused by the emergency to the greatest extent. However, ERWS is inseparable from the implementation of emergency measures. The rescue effect will be greatly reduced if ERWS is unreasonable. Therefore, it is necessary to study how to schedule emergency rescue workers efficiently and reasonably to minimize the loss caused by emergencies.

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Sinan Liu and Yanhui Zheng are master degree candidates at School of Traffic and Transportation, Lanzhou Jiaotong University, Lanzhou 730070, China, e-mail: LiuSN1323@163. com (S. Liu), ZhengYH2015@163. com (Y. Zheng).

Changfeng Zhu is a Professor at School of Traffic and Transportation, Lanzhou Jiaotong University, Lanzhou 730070, China. (corresponding author, phone:+86 18919891566, e-mail:cfzhu003@ 163. com).

Qingrong Wang is a Professor at School of Electronic and Information Engineering, Lanzhou Jiaotong University, Lanzhou 730070, China. (e-mail: wangqr003@163. com).

At present, although some scholars have started to study emergency resource scheduling (ERS), almost no researches on ERWS have been carried out. The existing researches are mainly focused on the emergency materials scheduling (EMS), emergency vehicles scheduling (EVS) and the selection of emergency routes, etc. Most scholars mainly construct single-objective and multi-objective planning models to solve these problems, while a few scholars have provided some practical emergency resource scheduling schemes for the emergency rescue system by establishing a bi-level programming model. In terms of single-objective planning, an emergency warehouse location model with the goal of maximizing the coverage is proposed in [1]. The emergency resource scheduling schemes with single objective function have been studied in [2][3], and the goals of them are to minimize the time cost. Aiming at the resource allocation problem of elastic application in multi-path network, an optimal resource allocation scheme for multi-path networks based on Particle Swarm Optimization (PSO) is proposed in [4]. In terms of multi-objective planning, a multi-objective programming model with consideration of time satisfaction and demand satisfaction is constructed to obtain the optimal schemes of EMS [5][6]. The multi-objective programming model for multi-period dynamic ERS is proposed in [7][8], which is on the premise of the number of emergency resources is sufficient. [9] developed a heuristic resource allocation algorithm based on multi-objective programming to solve the resource allocation problem of heterogeneous services in peer-to-peer networks. [10] proposed an optimal model of vehicle routing for emergency cold chain logistics under the condition of minimum loss, and designed a heuristic algorithm to solve the model based on the idea of network optimization and Baidu Map API. In terms of bi-level programming, the bi-level model of EMS for multiple suppliers is proposed in [11][12], where the heuristic algorithm is used to solve the model. The two-layer emergency logistics system is developed to provide auxiliary decision-making for EMS [13][14]. [15] proposed a robust bi-level optimization model for the emergency rescue network (ERN) under uncertainty in demand and supply parameters.

In fact, emergency rescue workers play an important role in emergency rescue work. The efficient and reasonable ERWS is bound to make emergency rescue more effective. However, most of the existing researches are on the problem of EMS, and only a few scholars have conducted relevant researches on the ERWS. For example, Several rescue task assignment schemes for rescuers have been studied in [16][17]. Targeting at the volunteer assignment problem, [18] proposed a multi-objective programming model with consideration of two major factors for volunteer preference and demand matching to minimize the mismatched demand and maximize the volunteer preference. However, the above researches on emergency rescue workers scheduling are all on condition that the number of emergency rescue workers is sufficient, ignoring that the number of emergency rescue workers is usually limited in the initial stage of emergency rescue, and there must be a game of demand for limited emergency rescue workers in multiple disaster areas. Moreover, all the above studies assume that the decision-maker is completely rational, ignoring that the decision-maker is often limited rational in the actual decision-making. Therefore, this paper focuses on the ERWS in the initial stage of emergency rescue with the consideration of decision behavior of decision-maker under limited rationality and the game of demand for limited emergency resource workers in multiple disaster areas.

The main contributions of this paper are as follows: (1) The ERWS in the initial stage of emergency rescue is divided into two stages: the first scheduling and the rescheduling. We can find that none of those bi-level scheduling models for emergency materials proposed in [11][12][13][14] have taken the perspective of phased scheduling into account. However, decision-makers' grasp of disaster information must go through a process from incomplete to gradually complete in the initial stage of emergency rescue. Therefore, the ERWS in the initial stage of emergency rescue is divided into two stages: the first scheduling and the rescheduling, which complement each other. (2) The game of demand for limited emergency rescue workers in multiple disaster areas is considered in this paper. The models of ERWS proposed in [16][17][18] takes sufficient emergency rescue workers as a prerequisite, which means those models ignore the universality of scarcity of emergency rescue workers in the initial stage of emergency rescue, and there must be a game of demand for limited emergency rescue workers in multiple disaster areas. Therefore, this competition is expressed as a non-cooperative game model under the condition of limited rationality, which depicts the participation mechanism of victims in the decision-making process of ERWS more vividly. (3) The prospect theory is introduced to portray the limited rational behavior of the victims in the game process. The models of ERWS proposed in [16][17][18] are on condition that decision-makers are completely rational, but disaster areas, as players in the game, usually show the behavior of limited rationality in decision-making. Therefore, this paper uses the value function of prospect theory to describe the perceived satisfaction of victims to the ERWS, which not only makes the measure of satisfaction more suitable for people's actual psychology but also reflects the influence of limited rationality of victims on emergency rescue decision-making.

The rest of this paper is summarized as follows: We describe the problems studied in this paper in Section II, and a bi-level game scheduling model for emergency rescue workers under the condition of limited rationality is formulated in this section. Based on the proposed model, the SFLA is designed to solve the problem in Section III. Then we verify the rationality of the model by a case study in Section IV, and the influence of parameter changes on the results is also analyzed in this section. Finally, the conclusion of this paper is in Section V.

II. MATHEMATICAL MODELING

In the event of large-scale emergencies, ERWS is one of the issues that decision-makers attach great importance to. The decision-maker's access to disaster information has to go through a process from incomplete to gradually complete in the initial stage of emergency rescue. Therefore, this paper divides ERWS in the initial stage of emergency rescue into two stages, namely scheduling and rescheduling. Scheduling and rescheduling complement each other, so the ERWS in the initial stage of the emergency rescue process is a typical bi-level programming problem [19]. Considering that disaster information is not comprehensive enough in the first scheduling stage, and victims are more sensitive to rescue time at this time, so the upper level is to maximize the basic rescue effect. However, as the decision-makers have a more comprehensive access to disaster information, they pay more attention to the subjective feelings of victims for ERWS in the rescheduling stage, so the lower-level is to maximize the perceived satisfaction of victims.

A. Upper Level Modeling

A.1 Upper Objective Function

The upper model is to maximize the basic rescue effect. The emergency rescue responding time, the emergency rescue competence, and the number of emergency rescue workers scheduled are the main factors influencing the emergency rescue effect, so the upper objective function can be expressed as

$$\max F = \sum_{i\in I}\sum_{j\in J}\sum_{k\in K} x_{ijk}^{1}\cdot\left(u_{ik}\cdot \beta_{ik}/1 - t_{ij}/1440\right) \tag{1}$$

Where x_{ijk}^{1} denotes the *k-th* rescue team from rescue point i is scheduled to disaster area j for emergency rescue in the first scheduling stage. u_{ik} is the competence of the *k-th* rescue team from rescue point i for rescue missions, $0 \le u_{ik} \le 1$ and $\sum_{k\in K} u_{ik} = 1\ i \in I, k \in K$. β_{ik} is the number of the *k-th* rescue team at rescue point i . t_{ij} is the emergency rescue responding time of rescue point i to disaster j .

In order to simplify the calculation, dimensionless method [20] is introduced to make the number of emergency rescue workers and emergency rescue responding time have the same dimension.

A.2 Upper Constraints

$$\sum_{j\in J}\sum_{k\in K} x_{ijk}^1 \cdot \beta_{ik} \le n_i, \forall i \in I, k \in K \quad (2)$$

$$\sum_{i\in I}\sum_{k\in K} x_{ijk}^1 \cdot \beta_{ik} = Q_j^0, \forall j \in J \quad (3)$$

$$t_{ij} \cdot x_{ijk}^1 \le \tau_j \quad (4)$$

$$\begin{cases} \beta_{ik} > 0, x_{ijk}^1 = 1 \\ \beta_{ik} = 0, x_{ijk}^1 = 0 \end{cases} \forall i \in I, j \in J, k \in K \quad (5)$$

Constraints (2) ensure that the total number of emergency rescue workers can be scheduled, for every rescue point, cannot exceed n_i (the total number of emergency rescue workers at rescue point i). Constraints (3) guarantee that the total number of emergency rescue workers scheduled from rescue points B to disaster area j must be equal to Q_j^0 (the minimum demand of disaster area j). Constraints (4) state the emergency rescue responding time satisfies the optimal rescue time of every disaster area. Constraints (5) state x_{ijk}^1 is a 0-1 variable. If rescue point i schedules rescue team k to disaster area j for emergency rescue, $x_{ijk}^1 = 1$, otherwise, $x_{ijk}^1 = 0$.

TABLE I
PARAMETERS INVOLVED IN THE PROPOSED MODEL

Symbol	Meaning
A	Set of disaster areas ($A=\{A_1, A_2, \cdots, A_j\}$ $j \in J$)
B	Set of rescue points ($B=\{B_1, B_2, \cdots, B_i\}$ $i \in I$)
K	Set of rescue teams ($K=\{1,2,3,\cdots,l\}$ $k \in K$)
P_{ik}	The *k-th* rescue team at rescue point i
w_j	The severity of the disaster situation for disaster area j
N'	The number of emergency rescue workers remaining for rescheduling after the first scheduling process.

B. Lower Level Modeling

B.1 Game Theory and Prospect Theory

The lower model is to maximize perceived satisfaction of the victims in every disaster area, and the competition for limited emergency rescue workers among multiple disaster areas is expressed as a non-cooperative game model under limited rationality [21]. The standard form of this model is defined as follows:

$$G=\left(A, \{S_j\}, \{U_j\}\right) \quad (6)$$

Strategy set: disaster areas are regarded as players in a game, where $A=\{A_1, A_2, A_3, \cdots, A_j\}, j \in J$ is the set of j players. $S_j = \{S_1^{(j)}, S_2^{(j)}, S_3^{(j)}, \cdots, S_{mj}^{(j)}\}, j \in J$ denotes a set of limited strategies for disaster area A_j, and in order to highlight the strategies of the *j-th* player, we define it as $S=\{S_j, S_{-j}\}$, where S_{-j} denotes the strategies taken by all players in the game except player j, U_j denotes the payment function of the disaster area A_j.

Payment function: The value function of prospect theory [22] is introduced to describe the perceived satisfaction of victims to ERWS in this paper. We take the weighted utility of time reference point and demand reference point as the reference point of the value function. Then we assume that the value of the reference points for all disaster areas is the same, which is defined as V_0, and $V_O > 0$, so the value function of the reference point for disaster area A_j is

$$V\left(\rho_j^0\right) = V_0 \quad (7)$$

According to the literature [23], the curve of value function of the disaster area A_j about the scheme of ERWS is shown in Fig. 1, and the calculation formula is

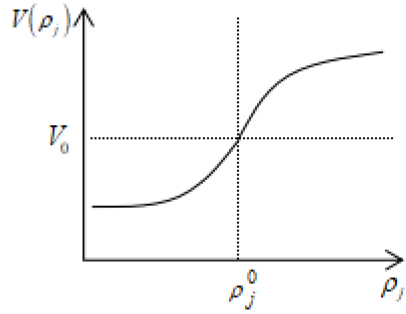

Fig. 1. Value function curve of disaster area j

$$V\left(\rho_j\right) = \begin{cases} \left(\rho_j - \rho_j^0\right)^\alpha + V_0, & \rho_j \ge \rho_j^0 \\ -\lambda\left(\rho_j^0 - \rho_j\right)^\beta + V_0, & \rho_j < \rho_j^0 \end{cases} \quad (8)$$

where α is the parameter of risk aversion, β is the parameter of risk seeking, and λ is the parameter of sensitivity of decision-maker to loss. Usually, α=β=0.88, λ=2.25, $V_0 = 0.5$.

The utility function of the disaster area j is given as follows:

$$\rho_j = \eta f\left(T_j\right) + (1-\eta) f\left(R_j\right) \quad (9)$$

where η is the weight of time perceived satisfaction, $0 \le \eta \le 1$.

$f\left(T_j\right)$ is the satisfactory degree function for time, which is defined as:

$$f\left(T_j\right) = \begin{cases} 0, & T_j = 0 \\ 1, & 0<T_j \le \tau_j \\ e^{-0.5\left[\left(T_j-\tau_j\right)/\tau_j\right]_2}, & T_j > \tau_j \end{cases} \quad (10)$$

where τ_j is the optimal rescue time of disaster area j. T_j denotes the time when all rescue teams arrive at the disaster area j.

$$T_j = \max_{i\in I, k\in K} \left\{x_{ijk}^2 \cdot t_{ij}\right\}, \forall j \in J \quad (12)$$

where x_{ijk}^2 denotes the *k-th* rescue team from rescue point i is scheduled to disaster area j for emergency rescue in the rescheduling stage.

$f\left(R_j\right)$ is the satisfactory degree function for demand, which is defined as:

$$f\left(R_j\right)=R_j/d_j \tag{12}$$

where R_j denotes the actual number of emergency rescue workers scheduled to disaster area j in the rescheduling stage, $R_j=\sum_{i\in I}\sum_{k\in K}x_{ijk}^2\cdot\beta_{ik}$. d_j is the number of emergency rescue workers needed by disaster area j.

The utility function of the reference point is given as follows:

$$\rho_j^0=\eta f\left(T_j^0\right)+(1-\eta)f\left(R_j^0\right) \tag{13}$$

where T_j^0 is time reference point, R_j^0 is demand reference point.

$$T_j^0=\sum_{i\in I}t_{ij}/m \tag{14}$$

$$R_j^0=d_j\cdot\left(\sum_{i\in I}n_i\Big/\sum_{j\in J}d_j\right) \tag{15}$$

The payment function of every disaster area not only depends on the benefits generated by the number of emergency rescue workers it obtained in the game, but also depends on the losses of other disaster areas that lose these rescue workers in the game. Therefore, we use U_j^1 to indicate that the benefits obtained by player A_j for obtaining emergency rescue workers scheduled from the rescue point B_i, and use U_j^2 to indicate the losses other players suffered for abandoning these emergency rescue workers.

$$U_j^1=\sum_{k\in K}x_{ijk}^2\cdot\beta_{ik}\cdot\Delta f_j\cdot V\left(\rho_j\right) \tag{16}$$

$$U_j^2=\sum_{q\neq j}\sum_{k\in K}\left(N'-x_{iqk}^2\cdot\beta_{ik}\right)\cdot\Delta f_j\cdot V\left(\rho_q\right) \tag{17}$$

In (16) and (17), Δf_j represents the potential loss caused by rescuing the disaster area j with the emergency rescue workers of different rescue points, the more potential loss is, the greater severity of the disaster situation will be, therefore, Δf_j can be replaced by w_j.

In summary, the payment function that player A_j selects strategy S_j is

$$\begin{aligned}U_{jr(j)m(j)}&=\sum_{k\in K}x_{ijk}^2\cdot\beta_{ik}\cdot w_j\cdot V\left(\rho_j\right)\\&+\sum_{q\neq j}\sum_{k\in K}\left(N'-x_{iqk}^2\cdot\beta_{ik}\right)\cdot w_j\cdot V\left(\rho_q\right)\end{aligned} \tag{18}$$

B.2 Lower objective function

Def 1 Strategy combination X^* is a Nash equilibrium solution of *J-player* non-cooperative game, if X^* satisfies the following formula:

$$U_j\left(X^*\left\|s_m^{(j)}\right.\right)\le U_j\left(X*\right),\ j=1,2,\cdots,J \tag{19}$$

where $X^*\left\|s_m^{(j)}\right.$ indicates that player A_j in the game replaces his own strategy in strategy combination X^* with $s_m^{(j)}$, and the strategies of other players remain unchanged.

In the lower model, there must be a demand game for limited emergency rescue workers among multiple disaster areas, player A_j, at this time, selects a strategy from his own strategy set S_j to form a strategy combination X of the *J-player* game.

According to the definition of Nash equilibrium [24], the lower objective function is defined as:

$$\min f=\sum_{j\in J}\max\left\{U_j\left(X\left\|s_m^{(j)}\right.\right)-U_j\left(X\right),0\middle|m=1,2,\cdots,l\right\} \tag{20}$$

When strategy combination X^* is a Nash equilibrium solution, for each player A_j, no more benefits can be obtained if the strategy is changed to $s_m^{(j)}\left(m=1,2,\cdots,l\right)$ separately. At this time, the objective function takes the minimum value 0.

B.3 Lower constraints

$$\sum_{i\in I}\sum_{j\in J}\sum_{k\in K}x_{ijk}^1+\sum_{i\in I}\sum_{j\in J}\sum_{k\in K}x_{ijk}^2=0 \tag{21}$$

$$\begin{cases}\beta_{ik}>0,x_{ijk}^2=1\\\beta_{ik}=0,x_{ijk}^2=0\end{cases}\forall i\in I,j\in J,k\in K \tag{22}$$

Constraints (21) guarantee that each rescue team can be scheduled only once. Constraints (22) state x_{ijk}^2 is a 0-1 variable. If rescue point i schedules rescue team k to disaster area j for emergency rescue, $x_{ijk}^2=1$, otherwise, $x_{ijk}^2=0$.

III. MODEL SOLUTION

A. Shuffled Frog Leaping Algorithm

SFLA is a heuristic algorithm proposed by Eusuff and Lansey [25], which has been used in the field of resource scheduling by many domestic and foreign scholars, such as the problem of workshop job scheduling [26], the problem of water resources scheduling [27], etc. Therefore, this paper uses the idea of SFLA to solve the problem of ERWS.

The flow chart of algorithm used to solve the model of ERWS is shown in Fig. 2.

The core of SFLA is the process that updates the local worst solution constantly by doing local search, and the detailed update methods are shown in Fig. 3 and Fig. 4.

The first update method is shown in Fig. 3. First, we get a new plan according to the method in Fig. 3, and then check whether this new plan satisfies the upper constraints, if not, we repeat the operation in Fig. 3 until finding a new plan that satisfies the upper constraints. Then, it is judged whether the benefits obtained by this new plan are better than the benefits corresponding to the group worst. If the benefits of new plan are not better than the group worst, we will use global best and group worst to generate a new plan, which is shown in Fig. 4.

If the benefits of new plan obtained by the second update method are still not better than the group worst corresponding to, then a new plan is generated randomly, which is used to replace the group worst. As mentioned above, we only have finished an update within the group.

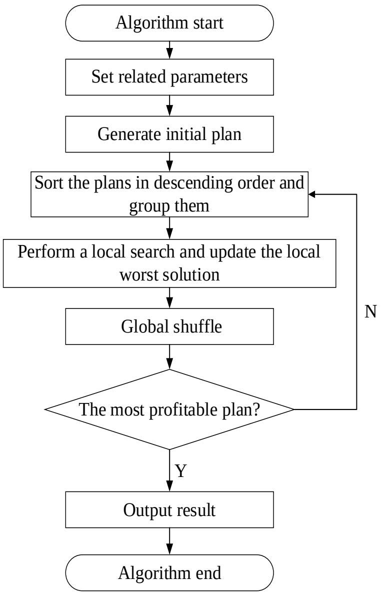

Fig. 2. Flow chart of algorithm

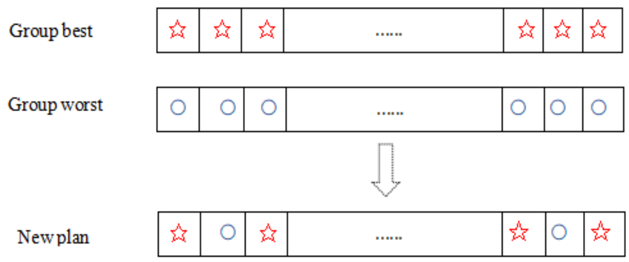

Fig. 3. First update method

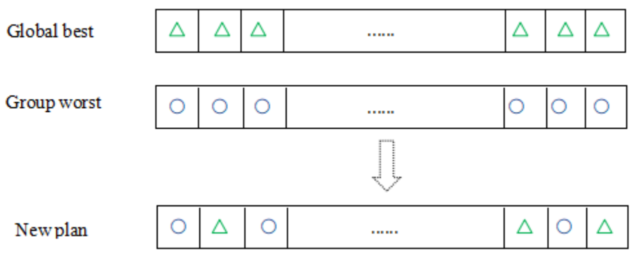

Fig. 4. Second update method

B.Fitness function building

The maximum value of objective function in the model is converted into the minimum value of the fitness function with consideration of the stability of the solution for SFLA [29]. The converted fitness function is

Upper fitness function

$$\Theta_1 = \frac{1}{\sum_{i\in I}\sum_{j\in J}\sum_{k\in K} x_{ijk}^1 \cdot \left(u_{ik} \cdot \beta_{ik}/1 - t_{ij}/1440 \right)} \quad (23)$$

Lower fitness function

$$\Theta_2 = -\sum_{j\in J} \max\left\{ U_j\left(X \| s_m^{(j)}\right) - U_j(X), 0 \middle| m = 1,2,\cdots,l \right\} \quad (24)$$

C.Model solving steps

The specific steps are as follows:

Step 1 Define relevant parameters and assign the initial schemes. Ψ scheduling schemes are randomly generated in the upper search space, and every scheduling scheme consists of a ψ -dimensional decision vector, which is denoted by $X_\psi = \left(X_\psi^1,\ X_\psi^2\right), \psi = 1,2,\cdots,\Psi$, thereinto, X_ψ^1 represents the upper decision vector, which consists of the upper decision variable x_{ijk}^1 , and X_ψ^2 represents the lower decision vector, which consists of the lower decision variable x_{ijk}^2 .

Step 2 The SFLA is used to solve the non-cooperative game model in the lower level.

Step 2.1 The upper decision vector X_ψ^1 is taken as the parameter, and G scheduling schemes are randomly generated in the lower search space. Further, the scheduling schemes are expressed as $X_{\psi g} = \left(X_\psi^1, X_\psi^2\right), g = 1,2,\cdots,G$.

Step 2.2 According to the fitness function (24), the fitness value of every frog's position, namely the benefits of every strategy combination, is calculated. Then the frogs are grouped in order from the largest to the smallest.

Step2.3 G frogs search repeatedly in the lower constrained domain and the updated strategy of SFLA is executed in a loop.

Step 2.4 Judge whether the scheme obtained at this time has the highest perceived satisfaction, if so, output the Nash equilibrium solution X_ψ^{2*} of the non-cooperative game model in the lower level, otherwise, return to step 2.2.

Step 3 The upper objective function uses SFLA again to solve the global optimal solution.

Step 3.1 Take $\left(X_\psi^1, X_\psi^{2*}\right)$ as the parameter, repeat step 2.2 according to the fitness function (23).

Step 3.2 A deep search is executed in the upper constrained domain, then do the same as step 2.2.

Step 3.3 Judge whether the scheme obtained at this time has the largest basic rescue effect. If so, output the global optimal solution, namely the optimal scheme of ERWS, otherwise, return to step 3.1.

IV.CASE STUDY

A.Case background

Based on the background of the emergency rescue in large public events, the rationality of the model proposed in this paper is verified by a case study. Suppose that a major public health emergency occurred in an area, which led 6 places to become major disaster areas. The number of medical rescue workers required by every disaster area is shown in Table II. The government sent 4 rescue points to provide medical assistance to these 6 disaster areas, the number of rescue teams that every rescue point can provide and the competence of every rescue team for this rescue task are shown in Table III. The emergency rescue responding time for different disaster areas is shown in Table IV. The disaster severity and the optimal rescue time of every disaster area are shown in Table V and Table VI.

B.Case solving

Through many tests, we find that the solving efficiency of the model and the stability of the solution are the best when the initial swarm is set to 100, both the frequency of evolution within a group and global iterations in the first scheduling stage are 15, the frequency of evolution within a group and global iterations in the rescheduling stage are 13, and the maximum adjustment step size for both scheduling and rescheduling is 2. Therefore, the above parameters in this case are introduced to the model, and MATLAB is used to solve this case. The iterative graph of the algorithm is shown in Fig. 5, and the optimal solution, namely the optimal scheme of ERWS is shown in Fig. 6.

TABLE II
DEMAND OF DIFFERENT DISASTER AREAS FOR EMERGENCY RESCUE WORKERS

A_j	d_j	Q_j^0
A_1	46	10
A_2	57	13
A_3	60	15
A_4	53	12
A_5	57	13
A_6	41	10

TABLE III
THE NUMBER OF EMERGENCY RESCUE WORKERS CAN BE SCHEDULED AND COMPETENCIES OF RESCUE TEAMS

B_i	P_{ik}	β_{ik}	u_{ik}
B_1	P_{11}	12	0. 223
	P_{12}	20	0. 335
	P_{13}	10	0. 214
	P_{14}	15	0. 228
B_2	P_{21}	14	0. 431
	P_{22}	13	0. 344
	P_{23}	18	0. 225
B_3	P_{31}	15	0. 118
	P_{32}	15	0. 104
	P_{33}	12	0. 189
	P_{34}	10	0. 305
	P_{35}	20	0. 284
B_4	P_{41}	13	0. 134
	P_{42}	10	0. 275
	P_{43}	16	0. 296
	P_{44}	15	0. 102
	P_{45}	11	0. 193

TABLE IV
EMERGENCY RESPONDING TIME FOR DIFFERENT DISASTER AREAS

B_i	t_{ij}					
	A_1	A_2	A_3	A_4	A_5	A_6
B_1	17	14	19	17	11	20
B_2	12	13	10	17	18	11
B_3	20	14	13	14	19	13
B_4	17	19	12	20	13	18

TABLE V
SEVERITY OF DISASTER SITUATION IN DIFFERENT DISASTER AREAS

item	A_1	A_2	A_3	A_4	A_5	A_6
ω_j	0. 151	0. 109	0. 233	0. 167	0. 147	0. 193

TABLE VI
OPTIMAL RESCUE TIME FOR DIFFERENT DISASTER AREAS

item	A_1	A_2	A_3	A_4	A_5	A_6
τ_j	15	19	13	14	18	13

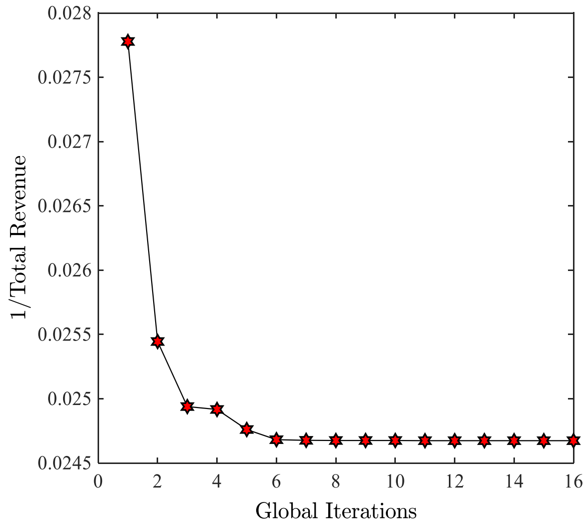

Fig. 5. Algorithm iteration diagram

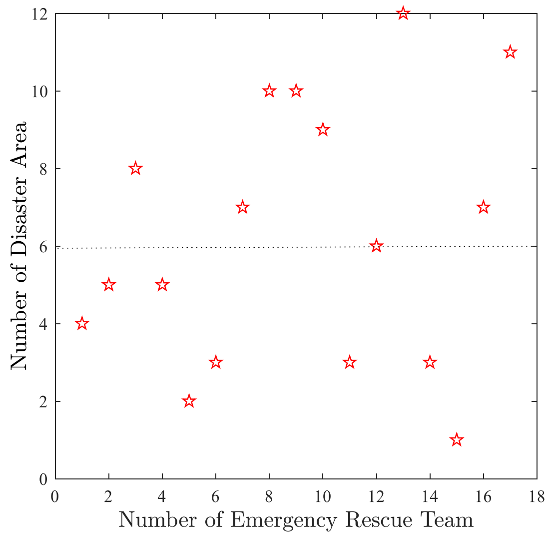

Fig. 6. Scheduling scheme of emergency rescue team

During the period of emergency rescue, decision-makers have high requirements for efficiency on obtaining optimal scheme of ERWS. It can be seen from Fig. 5 that the convergence rate of SFLA is very fast, and the results have basically converged at the completion of 6th iteration. Therefore, SFLA is more suitable for the solution of scheme for ERWS.

The number 6 on the Y-axis of Fig. 6 divides the scheduling of the emergency rescue team into two stages. 1-6 denotes the first scheduling scheme of the emergency rescue team with incomplete disaster information, and 7-12 denotes the rescheduling scheme of the emergency rescue team in the case of more complete disaster information. It should be noted that the rescue objects in the rescheduling are the same as that in the first scheduling.

The scheduling scheme of the emergency rescue team on the upper level (scheduling) is shown in Table VII, and the scheduling scheme of the emergency rescue team on the lower level (rescheduling) is shown in Table VIII.

TABLE VII
UPPER-LEVEL SCHEDULING SCHEME

A_j	P_{ik}	R_j
A_1	P_{43}	16
A_2	P_{21}	14
A_3	$P_{22}+P_{34}+P_{42}$	45
A_4	P_{11}	12
A_5	$P_{12}+P_{14}$	35
A_6	P_{35}	20

TABLE VIII
LOWER-LEVEL SCHEDULING SCHEME

A_j	P_{ik}	Z_j
A_1	$P_{23}+P_{44}$	33
A_2	P_{13}	10
A_3	P_{33}	12
A_4	$P_{31}+P_{32}$	30
A_5	P_{45}	11
A_6	P_{41}	13

From Table V and Table VI, we can find that there is a negative correlation between the optimal rescue time of the disaster area and the severity of the disaster situation. For example, the worst-hit disaster area A_3 has the shortest optimal rescue time. In addition, we can find that the disaster area A_3 has the greatest demand for emergency rescue workers from Table II. Therefore, the number of emergency rescue workers obtained by disaster area A_3 is the most in the first scheduling stage. Although the information of the disaster situation is more comprehensive in the rescheduling stage, the number of emergency rescue workers is still in shortage. Therefore, there must be a competition for limited emergency rescue workers among the 6 disaster areas, which can be seen from Table VII and Table VIII. Finally, we can find that the number of emergency rescue workers obtained by every disaster area is still lower than their needs. Obviously, such a scheme of ERWS is more realistic.

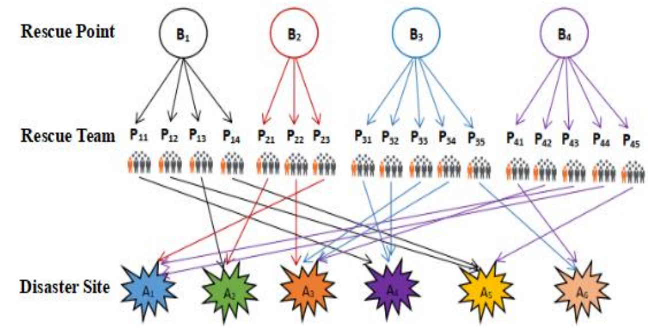

Fig. 10. Optimal scheduling scheme

Through the simulation analysis, we find that the benefits of the scheme are the greatest when $\alpha=\beta=0.88, \quad \eta=0.5$. The optimal scheme of ERWS is shown in Fig. 10, and the total benefits corresponding to the optimal scheme is $F_{total}=1/0.0247=40.486$, thereinto, the upper benefits is $F=168.998$, the lower benefits is $f=53.314$.

C.Parametric analysis in prospect theory

To quantify the psychological changes that victims undergo in the process of ERWS, the prospect theory is introduced to the lower level model. As players in the game, the subjective reactions of decision-makers are mainly influenced by the parameter in the value function. This section focuses on the influence of the subjective reactions of decision-makers based on the total revenue that caused by the parameter values in the prospect theory. The influences of α and β on the total revenue are shown in Fig. 7.

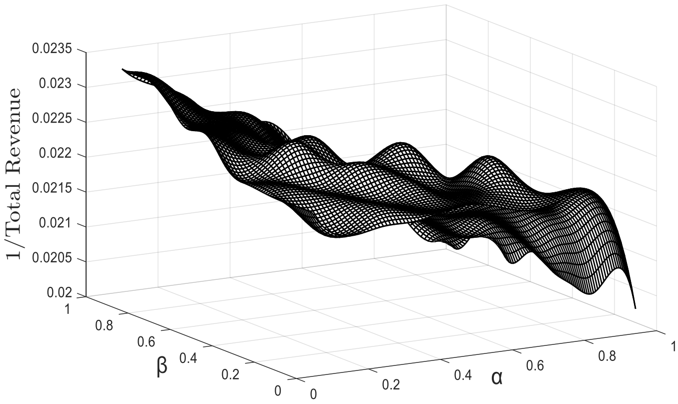

Fig. 7. Influences of α and β on total revenue

From Fig. 7, we can find that the larger the value of α, the higher the total revenue. In other words, the decision-maker is more inclined to risk seeking as α and β increase. The influences of α and η on the total revenue are shown in Fig. 8.

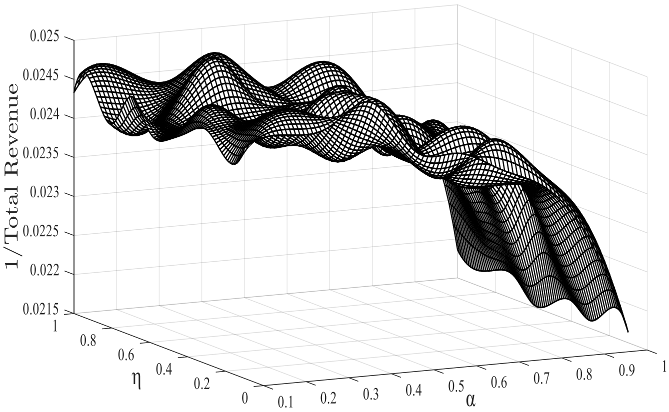

Fig. 8. Influences of α and η on total revenue

From Fig. 8, we can find that α more considerably influences the total revenue than η. When $\alpha>0.88$, the decision-maker is more inclined to risk seeking. To the contrary, when $\eta>0.88$, the tendency is more on risk aversion, and the inclination shifts to the opposite tendency only when $\eta\in[0.4,0.6]$. The influences of β and η on the total revenue are shown in Fig. 9.

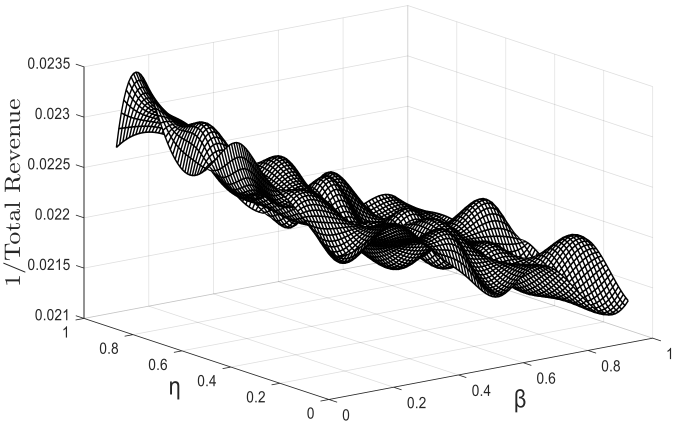

Fig. 9. Influence of β and η on total revenue

From Fig. 9, we can find that β influences the total revenue more considerably than η. The risk aversion is evident when $\beta < 0.88$, whereas the inclination to risk seeking is evident when $\eta \in [0.4, 0.6]$. By analyzing Figs. 8 and 9, it can be concluded that α and β have greater influences on the total revenue than η. In other words, the subjective reaction of the decision-maker is more sensitive to the changes in the values of α and β than η.

Based on the aforementioned analysis, it is obvious that the decision-maker is more inclined to risk seeking when confronted with a scheme with less expected benefits and more actual advantages. On the contrary, the decision-maker is more inclined to risk aversion when confronted with a scheme with more expected advantages and few actual benefits.

D.Convergence performance analysis

According to the discussion of the local search and global search based on the SFLA in Section III, it is noted that convergence performance of the scheme is mainly influenced by algorithm parameters, such as swarm size. This section presents 10 simulation experiments performed for different swarm sizes to analyze the influence of swarm size on the convergence performance of the scheme for ERWS. The simulation results are summarized in Table IX.

By comparing the convergence rates of schemes with different swarm sizes listed in Table IX, it is concluded that the convergence rate of the scheme slightly increases with the increase in swarm size. However, the swarm size cannot increase indefinitely with the limitation of program running time. In other words, the swarm size can be increased to improve the convergence rate of the scheme when the program running time can accommodate it.

E.Simulation analysis under different decision modes

To verify the rationality of the proposed model in this paper, we compare the results under three different decision modes, but considering the same situation. The first mode considers the ERWS from leader's perspective, involving maximizing the basic rescue effect without taking into account the subjective feelings of victims. The leader's perspective model is defined by Eqs. (1)–(5). The second mode considers the ERWS from follower's perspective, involving maximizing the perceived satisfaction of victims. The follower's perspective model considers the objective function defined by Eq. (20) subject to the constraints imposed by Eqs. (2)–(4) and (21)–(22). Notice that Eqs. (6)–(19) are the formation processes of the objective function. The first two modes consider the ERWS from the perspectives of different decision-makers and ignoring the extreme situations that can occur in a single-perspective situation. The third mode considers the ERWS from leader–follower perspective, which is defined as a bi-level model. Both decision-makers (leader and follower) are taken into account to identify the optimal schemes in the proposed bi-level model, thereby avoiding the occurrence of extreme cases in a single perspective.

The simulation results considering certain factors under the three different perspectives are summarized in Table X. The objective function of the upper and lower models are denoted by $F(x, y)$ and $f(x, y)$, respectively, and the running time of the program is represented by T.

TABLE IX
CONVERGENCE PERFORMANCE OF SCHEME WITH DIFFERENT SWARM SIZES

No.	Swarm size-50		Swarm size-100		Swarm size-150	
	Iterations	T/s	Iterations	T/s	Iterations	T/s
1	9	4.813	7	33.271	4	96.589
2	11	5.121	8	33.349	3	88.364
3	8	3.279	6	28.358	4	92.175
4	9	3.826	6	27.736	4	91.434
5	10	4.797	7	29.121	4	91.106
6	9	4.115	5	24.790	5	94.897
7	9	3.782	6	27.556	3	92.316
8	7	3.011	4	24.293	4	92.721
9	10	4.052	6	26.861	6	94.899
10	9	3.997	5	26.319	4	92.394
AVG	9	4.793	6	28.165	4	92.689

TABLE X
RESULTS CONSIDERING CERTAIN FACTORS UNDER THREE DIFFERENT PERSPECTIVES

	F(x, y)	*f(x, y)*	T/s
Leader's perspective	184.843	50.122	0.227
Follower's perspective	149.873	59.027	0.491
Leader–follower perspective	168.998	53.314	27.556

The simulation results listed in Table X are obtained according to the initial parameter values. As seen from Table X, $F_{leader} > F_{bi-level} > F_{follower}$, $f_{follower} > f_{bi-level} > f_{leader}$, and $T_{bi-level} > T_{follower} > T_{leader}$. The results indicate that (1) the single-level model from leader's perspective obtains the ERWS scheme with the largest basic rescue effects in least time, however, the perceived satisfaction of the victims is the lowest among the three perspectives. (2) The ERWS scheme obtained by the single-model from follower's perspective has higher perceived victim satisfaction than others, however, the basic rescue effect is the worst. Moreover, the solution speed is slightly lower than that of the leader. Evidently, both of these solutions are extremes. (3) The solution derived by the bi-level model from the leader–follower perspective, which takes into account the goals of both decision-makers, is evidently neutral. Therefore, the scheme from this perspective can afford further emergency decision-making reference for decision-makers.

To show the advantages of the proposed model in this paper, the growth rate formula proposed in [31] is introduced to calculate the percentage of decrease in the three schemes with different perspectives against the optimal scheme and the percentage of increase yielded by the bi-level model, the results are summarized in Tables XI and XII, respectively.

The growth rate formula is given as follows:

$$\%\ increase = \frac{(Current\ value) - (Best\ value)}{(Best\ value)} \tag{25}$$

Two comparisons are listed in Table XI. First, the basic rescue effects from the other two perspectives are compared with that from the leader's perspective. Second, by considering the perceived satisfaction of victims from the follower's perspective as the highest, the perceived satisfaction of the victims from other perspectives is compared with that from the follower's perspective.

As Table XII shows, the basic rescue effect increases by 68.548% by selecting the bi-level model instead of the single-level model from the leader's perspective. Further, by selecting the bi-level model instead of the single-level model from the follower's perspective, the perceived satisfaction of the victims also increases by 10.716%. Compared with the percentage of decrease in Table XI, the increase is clearly more significant than the decrease. Based on the foregoing analysis, the scheduling scheme for emergency rescue workers obtained in this study, takes into account the perceived satisfaction of the victims while ensuring a satisfactory basic rescue effect.

Considering the organization of the table layout, "basic rescue effect" is replaced by "E", and "perceived satisfaction of the victims" by "S".

TABLE XI
PERCENTAGE OF DECREASE IN SCHEMES WITH DIFFERENT PERSPECTIVES VERSUS OPTIMAL SCHEME

	Decrease in E (%)	Decrease in S (%)
Leader's perspective	−	15.086
Follower's perspective	18.919	−
Leader–follower perspective	8.572	9.679

TABLE XII
PERCENTAGE OF INCREASE PROVIDED BY BI-LEVEL MODEL

	Increase in E (%)	Increase in S (%)
Leader's perspective	68.548	−5.987
Follower's perspective	−11.317	10.716
Leader–follower perspective	–	–

V. CONCLUSIONS

This study focuses on the problem of the ERWS in the initial stage of the emergency rescue process. A bi-level game scheduling model is formulated for emergency rescue workers under the condition of limited rationality to maximize the basic rescue effect and the perceived satisfaction of the victims. The simulation results show that the scheme proposed for the ERWS in this paper takes into account both the perceived satisfaction of the victims and satisfactory basic rescue effect, which is superior to the schemes in the other two decision modes. The proposed scheme also has satisfactory convergence performance and may be applied to the problem of the ERWS at different scales. For future work, we will consider the influence of dynamic changes in requirements on the ERWS for further investigation.

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Sinan Liu was born in Ningxia, China, in 1997. She obtained her Bachelor degree in Traffic and Transportation from East China Jiaotong University, Nanchang, China, in the year 2019.
She is currently pursuing her master degree in Traffic and Transportation (the Planning and Management of Traffic and Transportation) in Lanzhou Jiaotong University. Her research interests include the optimization of emergency logistics network and the planning and management of traffic and transportation.