Research on Emergency Personnel Scheduling Considering the Psychological Perception of both Disaster Victims and Emergency Personnel

Kangru Liu, Qingrong Wang, Changfeng Zhu, Zhiwei Zhang, and Wenjun Sun

***Abstract*—In large-scale emergencies under the background of multiple disaster areas, scientific and reasonable scheduling of emergency personnel can reduce the negative impact of the emergency. In this regard, this paper proposes a multi-objective emergency personnel scheduling (EPS) model with the goal of maximizing time satisfaction, scheduling fairness, and task competence. The model mainly considers the psychological perception of both disaster victims and emergency personnel. Through the use of cumulative prospect theory (CPT) and inequity aversion theory (IAT), the victims' subjective perceptions of the arrival time and the number of emergency personnel are portrayed separately. At the same time, on the basis of considering the subjective task preferences of emergency personnel, the competence of emergency personnel for emergency tasks is described, and a task assignment method for emergency personnel that prioritizes the importance of the task and takes into account the overall task is proposed. Based on the proposed model, the NSGA-II algorithm is designed, and the fuzzy logic method is adopted to select the ideal solution from the Pareto frontier solution set. The case study shows that the model in this paper can improve the satisfaction of victims and emergency personnel while ensuring the basic rescue effect. The consideration of the psychological perception of personnel can provide an effective reference for the actual EPS work.**

***Index Terms*—emergency personnel scheduling, multiple disaster areas, time satisfaction, inequity aversion, task preferences, NSGA-II**

I. INTRODUCTION

Natural disasters, such as the Great East Japan Earthquake and Wenchuan Earthquake, accident disasters, such as the Tianjin Port explosion, and public health events, such as the SARS epidemic and novel coronavirus pneumonia, have occurred frequently. These large-scale emergencies seriously threaten social stability, economic development, and the safety of people's lives and property [1][2]. Emergency personnel scheduling (EPS) is one of the most critical links in emergency resource scheduling (ERS) after emergencies. Scientific and reasonable EPS can improve the efficiency of actual emergency rescue work, thereby minimizing the negative impact of emergencies [3]. Therefore, how to dispatch emergency personnel scientifically and reasonably is a topic of great practical significance.

In the research related to ERS, most studies focus on emergency materials scheduling [4][5][6][7][8][9], the site selection of emergency facilities [10][11][12], and the selection of emergency routes [12][13][14][15][16]; by contrast, there are few studies on EPS. Existing research mainly solves the EPS problem by constructing single-objective or multi-objective programming models.

In the research of single-objective programming, a grouping model of emergency personnel aiming at the maximum comprehensive evaluation value of emergency personnel completing tasks is proposed in [17]. [18] describes EPS as a rescue unit assignment and scheduling problem and establishes a decision support model to minimize the sum of the completion time of the event. In [19], the authors consider the collaboration of rescue units to portray emergency personnel dispatch as a binary minimization problem and design a branch-price algorithm to solve it. A mixed-integer programming model based on the comprehensive optimal scheduling of repair personnel and rescue vehicles to minimize the last transportation time of all demand nodes is established in [20]. Due to the complexity of the EPS problem, in reality, single-objective programming models are limited. Therefore, some scholars solve the EPS problem by constructing a multi-objective programming model.

In the research of multi-objective programming, [21][22][23][24] establish an EPS optimization model with time satisfaction and task competency as goals by considering factors such as the uncertainty of rescue time, the survival probability of victims, and road reconstruction. However, the EPS problem in the context of large-scale emergencies often has the characteristics of multiple emergency points-multiple disaster areas-multiple emergency tasks (M-PDT), and the above studies ignore this point. [25][26] extend the EPS problem to the level of M-PDT. Further, [25] describes the task competency of

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emergency personnel by combining personnel willingness and objective ability evaluation, and [26] uses the NSGA-II algorithm to solve the multi-objective optimization model instead of converting the multi-objective problem into a single-objective problem.

The above research mainly studies the EPS problem from the perspective of time utility and rescue effect and does not consider the impact of the psychological factors of disaster victims and emergency personnel on emergency rescue. In terms of disaster victims, to prevent the occurrence of extreme events, it is necessary to consider the psychological perception of disaster victims on emergency rescue. [9][16][27][28][29] describe victims' perceived satisfaction with rescue time by introducing Prospect Theory (PT). Notably, [27][28][29] depicts the victims' perception of the fairness of resource scheduling based on the reality that emergency resources are in short supply in the early stages of emergencies. The fly in the ointment is that the above studies ignore the uncertainty of rescue time in the characterization of time satisfaction. In terms of emergency personnel, due to the differences in professional skills and experience, emergency personnel have different subjective preferences for different emergency tasks. However, most of the existing research only considers the objective ability evaluation of emergency personnel, which is not conducive to the full play of the ability of emergency personnel.

Based on the above analysis, this paper focuses on the EPS problem in the initial stage of large-scale emergencies with the characteristics of M-PDT, uncertain rescue time, and a shortage of emergency personnel. By considering the psychological perception of disaster victims and emergency personnel, a multi-objective programming model that aims to maximize time satisfaction, scheduling fairness, and task competency is established, and the corresponding NSGA-II algorithm is designed to solve it.

Compared with existing research, the main contributions of this paper are as follows: (1) The EPS problem studied in this paper has the characteristics of M-PDT and emergency personnel in short supply, which is more suitable for the EPS scenario in the early stages of a large-scale emergency. In the EPS, the process of dispatching emergency personnel to various disaster areas and assigning emergency tasks to emergency personnel who arrive at each disaster area is an indivisible whole. In other words, in the process of transferring emergency personnel to the disaster area, it is necessary to consider what tasks should be assigned to emergency personnel. However, most research has studied only one of the stages and assumed that the number of emergency personnel was not less than the number needed, a deviation from reality. (2) This paper considers the psychological perception of disaster victims and emergency personnel in emergency rescue. This enables the measurement of disaster victims' satisfaction and emergency personnel's competence to be more in line with the real situation and reflects the humanitarian principles of emergency rescue. In addition, this also helps to provide a reference for decision makers to formulate EPS schemes from the perspective of improving the satisfaction of disaster victims and emergency personnel.

The rest of this paper is summarized as follows: Section II presents the mathematical description of the problem. Based on Section II, the EPS multi-objective programming model considering the psychological perception of disaster victims and emergency personnel is established in Section III. Through an analysis of the model, Section IV designs the corresponding NSGA-II algorithm and ideal solution selection method. Section V verifies the rationality of the model through a case study and analyses the impact of parameter changes on the results. Finally, the conclusions of this paper and directions for future research are presented in Section VI.

II. Problem Statement

A large-scale emergency occurs in a certain place, a total of n disaster areas is formed, and there is a total of m emergency points that can dispatch emergency teams. The corresponding set of emergency points and disaster areas are $A=\{A_i|i=1,2,\cdots,m\}$ and $D=\{D_k|k=1,2,\cdots,n\}$ respectively. In terms of the disaster areas, the damage degree of the disaster area D_k is denoted as λ_k. The greater the λ_k value, the more severe the disaster at the disaster area D_k, $0<\lambda_k\leq 1$ and $\sum_{k=1}^{n}\lambda_k=1$. The number of emergency team requirements at the disaster area D_k is d_k. In terms of the emergency points, the number of emergency teams at emergency point A_i is a_i, and the *j-th* emergency team at emergency point A_i is P_{ij}.

Taking into account the influence of weather, road conditions, emergency team preparations and other factors on the rescue arrival time, the rescue arrival time is described as an interval $[ET_{ik}, LT_{ik}]$. The actual arrival time is denoted as t_{ik}, $ET_{ik}\leq t_{ik}\leq LT_{ik}$. ET_{ik} represents the ideal arrival time from the emergency point A_i to the disaster point D_k. LT_{ik} represents the latest arrival time. The latest arrival time LT_{ik} is calculated as (1).

$$LT_{ik}=ET_{ik}\cdot(1+\omega_{ik}^{1}+\omega_{ik}^{2})+T_i \tag{1}$$

Where ω_{ik}^{1} denotes the influence coefficient of road conditions, weather, and other factors on arrival time, $\omega_{ik}^{1}\geq 0$; ω_{ik}^{2} represents the influence coefficient of the emergency team on the arrival time due to rest on the way, $\omega_{ik}^{2}\in[0,1]$; T_i denotes the preparation time for the emergency team in A_i.

The competence of the emergency team to emergency tasks is the combination of subjective satisfaction and objective ability [25]. There are a total of C emergency tasks, and the set of emergency tasks is $TA=\{TA_c|c=1,2,\cdots,C\}$. The number of emergency tasks in the disaster area D_k is L_k, $1\leq L_k\leq C$. In practice, due to the difference in the disaster situation of different disaster areas, the importance of emergency tasks in each disaster area will also be different. In this regard, the assessment of the importance of the disaster area D_k to the emergency task TA_c is denoted as DTA_c^k, $DTA_c^k=0,1,\cdots,L_k$. The smaller the DTA_c^k, the higher the assessment of the importance of the disaster area D_k to the emergency task TA_c. In particular, $DTA_c^k=0$ means that the disaster area D_k has no task TA_c. In terms of the subjective satisfaction of the emergency team, the number of tasks that the emergency team P_{ij} is willing to complete is S_{ij}. The preference order of the emergency team P_{ij} to the emergency task TA_c is r_{ij}^c, $r_{ij}^c=0,1,\cdots,S_{ij}$. The smaller the r_{ij}^c, the stronger the willingness of the emergency team P_{ij} for emergency task TA_c. Particularly,

r_{ij}^{c}=0 means that P_{ij} has no intention to complete the task TA_c. In terms of objective ability evaluation of the emergency team, there is a total of Q capability evaluation indicators. The emergency task TA_c index weight set is $U_c=\{U_c^q \mid q=1,2,\cdots,Q\}$, $U_c^q \in [0,1]$ and $\sum_{q=1}^{Q} U_c^q = 1$. The emergency team capability evaluation index matrix in the emergency point A_i is $E_i = [E_{ij}^q]_{a_i \times Q}$.

Whether the emergency team P_{ij} is assigned to D_k is expressed as 0-1 variable x_{ijk}. If P_{ij} is assigned to D_k, then x_{ijk}= 1, otherwise x_{ijk}= 0.

To more clearly illustrate the EPS problem with the M-PDT characteristics studied in this paper, a schematic diagram of an EPS problem with three emergency points, three disaster areas, and three emergency tasks is shown in Fig. 1.

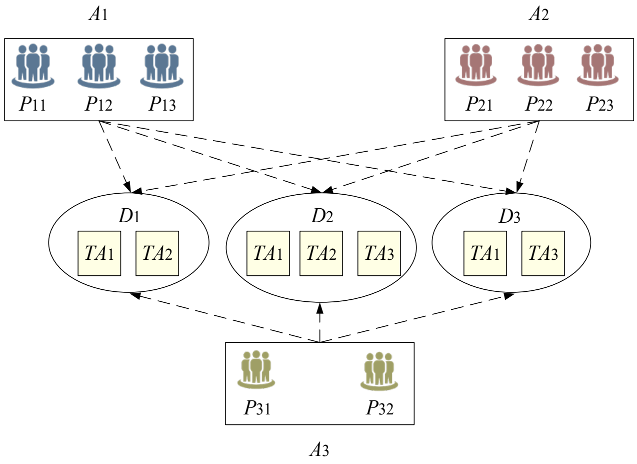


Fig. 1. EPS problem with M-PDT characteristics.

III. Mathematical Modelling

A. Time Satisfaction

For uncertain rescue arrival times with arbitrarily many outcomes, cumulative prospect theory (CPT) compensates for the inadequacy of PT for risk prospects with arbitrarily many outcomes by introducing cumulative rather than separate decision weights [30]. In addition, CPT truly depicts people's limited rational psychological perception behavior by considering the characteristics of people's reference dependence and risk attitude. Therefore, this paper adopts the CPT to describe the perceived satisfaction of the victims with the rescue time.

CPT uses the value function and weight function to determine the prospect value of a certain risk result. The value function reflects that the victims' perception of time value is based on the reference point, they will avoid risks in the face of gain, pursue risks in the face of loss, and are more sensitive to losses. The weight function reflects the psychology of disaster victims who will be infatuated with small probability events.

Disaster victims' perceived satisfaction with rescue time has the characteristics of reference dependence. The time reference point T_k^0 of the disaster victims is shown in (2).

$$T_k^0 = \frac{\sum_{i=1}^{m} ET_{ik}}{m} \tag{2}$$

Based on the time reference point, the value function of time satisfaction is shown in (3). From (3), we can see that when the emergency team arrives earlier than the time reference point, the victims perceive gains, and when the emergency team arrives later than the time reference point, the victims perceive losses.

$$v(t_{ik}) = \begin{cases} (T_k^0 - t_{ik})^{\alpha} & , \quad t_{ik} \le T_k^0 \\ -\lambda (t_{ik} - T_k^0)^{\beta} & , \quad T_k^0 < t_{ik} \end{cases} \tag{3}$$

Where α is the parameter of risk aversion, β is the parameter of risk-seeking, 0<α, β≤1; λ is the loss aversion coefficient, λ≥1. Usually, α=β=0.88, λ=2.25 [30][31][32]. The time value function curve is shown in Fig. 2.

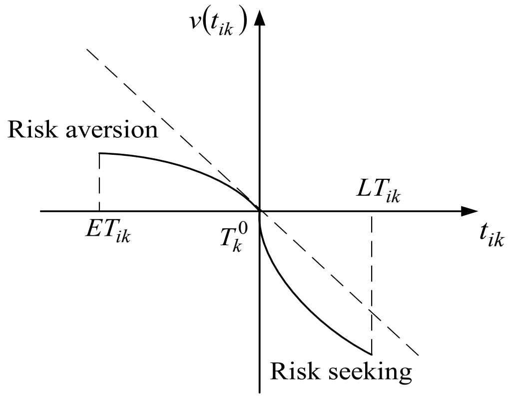


Fig. 2. Time value function curve.

The probability corresponding to the actual arrival time t_{ik} is p_{ik}. The probability weights when the victims perceive gains and losses are shown in (4). The weight function curve is shown in Fig. 3.

$$\begin{cases} w^+(p_{ik}) = \dfrac{p_{ik}^{\gamma}}{[p_{ik}^{\gamma} + (1-p_{ik})^{\gamma}]^{1/\gamma}} \\ w^-(p_{ik}) = \dfrac{p_{ik}^{\delta}}{[p_{ik}^{\delta} + (1-p_{ik})^{\delta}]^{1/\delta}} \end{cases} \tag{4}$$

Where $w^+(p)$ and $w^-(p)$ respectively represent the probability weight of gain and loss; γ represents the perceived probability parameter of gain, 0<γ<1; δ represents the perceived probability parameter of loss, 0<δ<1. Usually, γ= 0.61, δ= 0.69 [30][31][32].

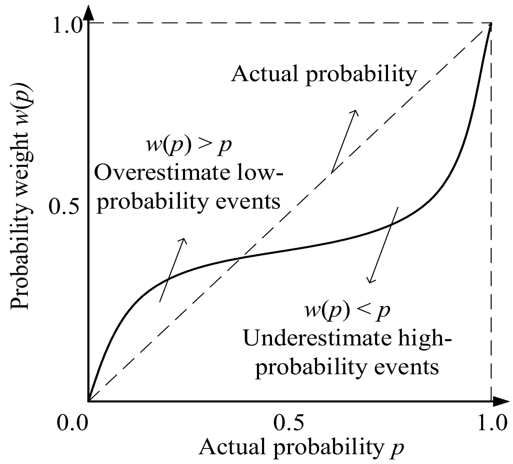


Fig. 3. Weight function curve.

A large body of empirical evidence suggests that people's ability to distinguish small differences within time intervals is so limited that it is unnecessary to describe arrival times as continuous [33]. Given this, assuming that there are M+N+1 actual possible arrival times from A_i to D_k, $t_{ik}^{-M} < \cdots < t_{ik}^{0} < \cdots < t_{ik}^{N}$, the corresponding probability is $p_{ik}^{-M}, \cdots, p_{ik}^{N}$. Then, the cumulative probability weight when victims perceive gains and losses can be expressed as (5).

$$\begin{cases} \pi^{+}(p_{ik}^{g}) = w^{+}(p_{ik}^{g} + \cdots + p_{ik}^{N}) \\ -w^{+}(p_{ik}^{g+1} + \cdots + p_{ik}^{N}), 0 \le g \le N \\ \pi^{-}(p_{ik}^{g}) = w^{-}(p_{ik}^{-M} + \cdots + p_{ik}^{g}) \\ -w^{-}(p_{ik}^{-M} + \cdots + p_{ik}^{g-1}), -M \le g < 0 \end{cases} \tag{5}$$

The arrival time interval is discretized into K segments, where t_{ik}^{g} is the median value of the *g-th* segment and p_{ik}^{g} is the probability corresponding to t_{ik}^{g} [31][32]. Then, the time satisfaction of the victims of disaster area D_k for dispatching emergency team P_{ij} to disaster area D_k is (6).

$$v_{ijk} = \sum_{g=0}^{N} \pi^{+}(p_{ik}^{g}) v(t_{ik}^{g}) + \sum_{g=-M}^{-1} \pi^{-}(p_{ik}^{g}) v(t_{ik}^{g}) \tag{6}$$

The time satisfaction of the victims in the disaster area D_k can be expressed as (7).

$$V_k^1 = \lambda_k \sum_{i=1}^{m} \sum_{j=1}^{a_i} x_{ijk} v_{ijk} \tag{7}$$

B. Scheduling Fairness

Considering the fairness of EPS is necessary in view of the reality that emergency personnel is in short supply in the early stages of large-scale emergencies. The inequity aversion theory (IAT) reflects the psychological characteristic that people want to minimize the inequity of benefits when making decisions [28][34]. We adopt the IAT to characterize the fair perception of the disaster victims on the distribution of the number of emergency teams. The scheduling fairness function of disaster area D_k can be expressed as (8).

$$\begin{aligned} V_k^2 = \lambda_k [E_k - \eta_k \frac{1}{n-1} \sum_{h=1}^{n} \max(E_h - E_k, 0) \\ - \rho_k \frac{1}{n-1} \sum_{h=1}^{n} \max(E_k - E_h, 0)] \end{aligned} \tag{8}$$

There are three parts in the square brackets on the right side of the equal sign in (8). E_k in Part 1 represents the satisfaction rate of the disaster victims with the number of emergency teams, and E_k is calculated as (9). Part 2 represents the fair loss of disaster victims in the disadvantage inequality, and η_k denotes the disadvantage inequality parameter, $\eta_k \geq 0$. Part 3 represents the fair loss of disaster victims in the advantage inequality, and ρ_k denotes the advantage inequality parameter, $0 \leq \rho_k \leq 1$ and $\eta_k \geq \rho_k$. $\eta_k \geq \rho_k$ reflects the fact that the disadvantage inequality will cause more loss of fairness than the advantage inequality.

$$E_k = \frac{\sum_{i=1}^{m} \sum_{j=1}^{a_i} x_{ijk}}{d_k} \tag{9}$$

C. Task Competency

Task competency is a combination of subjective satisfaction and objective ability of emergency personnel. The subjective preference function in [25] is linear and cannot fully reflect the changes in the emergency team's satisfaction with different emergency tasks. Thus, the willingness perception parameter ε(ε>0) is introduced to modify the subjective preference function. For 0<ε<1, the subjective satisfaction function is a downwards concave function, and the satisfaction first decreases slowly with an increase in r_{ij}^{c} and then decreases rapidly. ε=1 indicates that the subjective satisfaction function is linear, and the satisfaction decreases linearly with an increase in r_{ij}^{c}. For ε>1, the subjective satisfaction function is a downwards convex function, and the satisfaction first decreases rapidly with an increase in r_{ij}^{c} and then decreases slowly. In addition, the unwilling sensitivity parameter θ is introduced to describe the sensitivity of the emergency team to complete unintentional tasks, $\theta \in [0,1)$. The revised subjective satisfaction function is shown in (10). The image of the subjective satisfaction function when ε takes different values is shown in Fig. 4.

$$W_{ij}^{c} = \begin{cases} \left(\dfrac{S_{ij} - (r_{ij}^{c} - 1)}{S_{ij}} \right)^{\varepsilon} & , \ r_{ij}^{c} \neq 0 \\ \left(\dfrac{\theta}{S_{ij}} \right)^{\varepsilon} & , \ r_{ij}^{c} = 0 \end{cases} \tag{10}$$

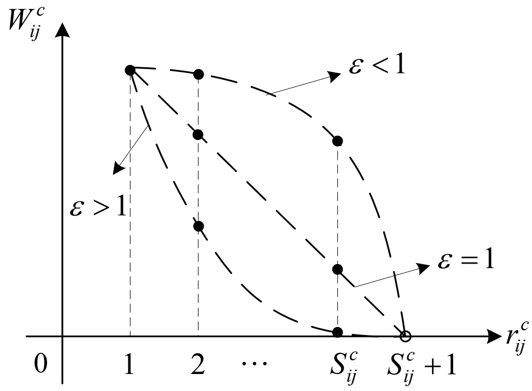


Fig. 4. Image of subjective satisfaction function when ε takes different values ($r_{ij}^{c} \neq 0$).

According to the emergency team capability index evaluation matrix and the emergency task index weight, we can obtain an objective evaluation of the emergency team's ability to complete the emergency task. First, the normalized ability index evaluation matrix can be expressed as $e_i = [e_{ij}^{q}]_{a_i \times Q}$, and the calculation of e_{ij}^{q} is shown in (11).

$$e_{ij}^{q} = \frac{E_{ij}^{q} - E_{q}^{\min}}{E_{q}^{\max} - E_{q}^{\min}} \tag{11}$$

Where $E_{q}^{\max} = \max\{E_{ij}^{q} \mid i = 1, 2, \cdots, m, j = 1, 2, \cdots, a_i\}$, $E_{q}^{\min} = \min\{E_{ij}^{q} \mid i = 1, 2, \cdots, m, j = 1, 2, \cdots, a_i\}$. Then, the objective evaluation value EV_{ij}^{c} of emergency team P_{ij} to complete emergency task TA_c is calculated according to (12).

$$EV_{ij}^{c} = \sum_{q=1}^{Q}\left(e_{ij}^{q} \cdot U_{c}^{q}\right) \tag{12}$$

The task competence of emergency team P_{ij} to complete the emergency task TA_c is calculated by the geometric average operator via (13).

$$v_{ij}^{c} = \sqrt{W_{ij}^{c} \cdot EV_{ij}^{c}} \tag{13}$$

Given the M-PDT characteristics of EPS, a task assignment method for emergency teams is proposed to assign tasks to emergency teams at each disaster area and calculate the task competency. The cumulative formula for the task competency of the disaster area D_k is shown in (14).

$$V_{k}^{3} = V_{k}^{3} + v_{ij}^{c} \tag{14}$$

To ensure the overall rescue effect, we assume that the difference in the number of emergency teams for any two emergency tasks should not exceed one. Based on this, a task allocation method of the emergency team with the priority of task importance and consideration of the overall task is shown in Fig. 5.

D. Construction of the EPS Model

The EPS model considering the psychological perception of disaster victims and emergency personnel is constructed as (15)-(23).

$$\max Z_1 = \sum_{k=1}^{n}\lambda_k \cdot \left(\sum_{i=1}^{m}\sum_{j=1}^{a_i} x_{ijk} \cdot v_{ijk}\right) \tag{15}$$

$$\begin{aligned}\max Z_2 = \sum_{k=1}^{n}\lambda_k [E_k - \eta_k \frac{1}{n-1}\sum_{r=1}^{n}\max(E_r - E_k, 0) \\ - \rho_k \frac{1}{n-1}\sum_{r=1}^{n}\max(E_k - E_r, 0)]\end{aligned} \tag{16}$$

$$\max Z_3 = \sum_{k=1}^{n} V_k^3 \tag{17}$$

s.t.

$$\sum_{k=1}^{n} x_{ijk} = 1,\ i = 1,2,\cdots,m,\ j = 1,2,\cdots,a_i \tag{18}$$

$$\sum_{j=1}^{a_i} x_{ijk} \le a_i,\ \ i = 1,2,\cdots,m,\ k = 1,2,\cdots n \tag{19}$$

$$\sum_{i=1}^{m} a_i < \sum_{k=1}^{n} d_k \tag{20}$$

$$\sum_{i=1}^{m}\sum_{j=1}^{a_i} x_{ijk} \le d_k \tag{21}$$

$$\sum_{i=1}^{m}\sum_{j=1}^{a_i} x_{ijk} \ge L_k \tag{22}$$

$$x_{ijk} \in \{0,1\}, i = 1,2,\cdots m, j = 1,2,\cdots a_i, k = 1,2,\cdots n \tag{23}$$

Where (15)-(17) are the objective functions of time satisfaction, scheduling fairness, and task competence respectively; Constraint (18) ensures that a team can only go to one disaster area; Constraint (19) guarantees that the number of emergency teams dispatched by each emergency point cannot exceed its reserve; Constraint (20) indicates that the number of emergency teams is in short supply; Constraint (21) states that the number of emergency teams assigned to the disaster area cannot exceed the number of emergency teams required by the disaster area; Constraint (22) guarantees that each emergency task in each disaster area must be completed by at least one team; Constraint (23) is the value constraint of the decision variable x_{ijk}.

IV. MODEL SOLUTION

The determination of EPS scheme has obvious parallelism, and the characteristics of group fitness evaluation and random search of NSGA-II algorithm make it have the advantage of global parallel search [35]. At the same time, the NSGA-II algorithm improves the convergence speed, uniformity, and accuracy of the Pareto front by proposing a fast non-dominated sorting operator, a crowding degree comparison operator, and an elite strategy [36]. We use the NSGA-II algorithm to solve the established model. The NSGA-II algorithm flow is shown in Fig. 6.

A. Coding Description

The decision variable x_{ijk} is a 0-1 variable, so the chromosomes are coded in binary. The entire chromosome can be divided into $\sum_{i=1}^{m} a_i$ gene segments, and the number of genes in each segment is equal to the number of disaster areas n. Specifically, the *k-th* locus of a certain gene segment indicates whether the emergency team referred to by the gene segment is sent to the disaster area D_k. If the emergency team is sent to D_k, the value of the locus is 1, otherwise, it is 0. Chromosome length is $\sum_{i=1}^{m} a_i \cdot n$. The binary coding chromosome is shown in Fig. 7.

B. Fitness Function

Before determining the fitness function, the constraints need to be processed first. We embed constraints (18)-(21) directly into the generation of new individuals. Such as individual initialization, crossover, and mutation operations. In addition, the penalty function method is used to deal with constraint (22), and the penalty function is shown in (24).

$$\Delta = R \cdot \max{}^{\zeta} \{0, \sum_{k=1}^{n}(L_k - \sum_{i=1}^{m}\sum_{j=1}^{a_i} x_{ijk})\} \tag{24}$$

Where R denotes the penalty coefficient, $R = s^{\sigma}$. s, σ, ζ are constants, and the values depend on the function on which the penalty function acts.

Then, the fitness function is shown in (25).

$$\begin{cases} f_1 = Z_1 \\ f_2 = Z_2 - \Delta \\ f_3 = Z_3 \end{cases} \tag{25}$$

C. Crossover and Mutation Operators

This paper adopts single-point crossover and single-point mutation. Specifically, the crossover position of the crossover operator points to the junction of two adjacent gene segments. The mutation position of the mutation operator points to any gene segment. Suppose there are three disaster areas and three emergency points, and each emergency point has an emergency team. The crossover and mutation operators are shown in Fig. 8 and Fig. 9, respectively.

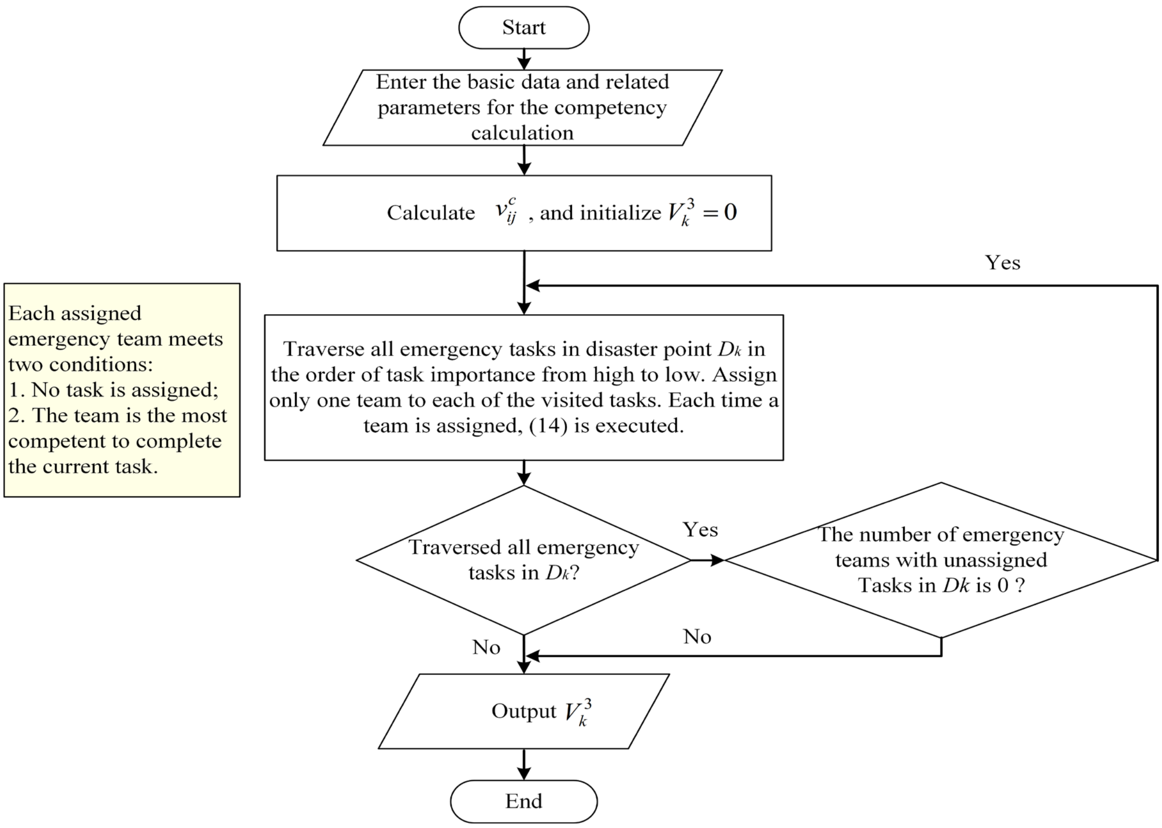


Fig. 5. Team task allocation method.

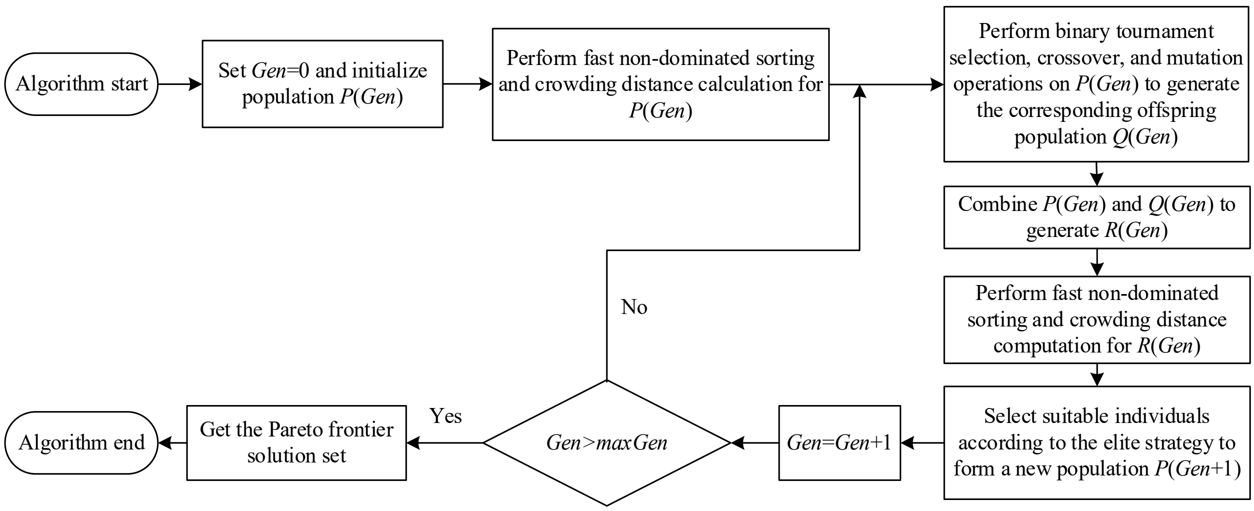


Fig. 6. NSGA-II algorithm flow.

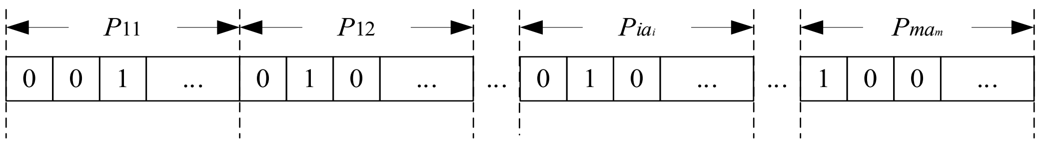


Fig. 7. Binary coding chromosome.

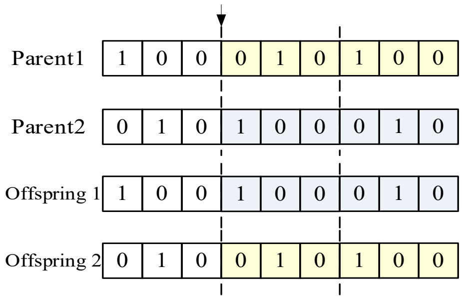


Fig. 8. Crossover operator.

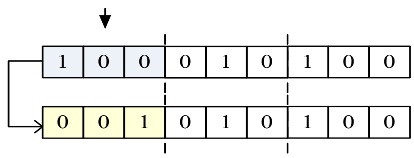


Fig. 9. Mutation operator.

D. Selecting the Ideal Solution

While the Pareto solution set provides multiple alternatives, it also brings difficulties for decision maker to make the final decision. When the decision maker has no obvious preference and the emergency decision-making time is tight, it is necessary to give an ideal solution selection method. Given this, we adopt the fuzzy logic method in [26] to screen ideal solutions.

First, the evaluation value of each candidate solution under the corresponding target is μ_i:

$$\mu_i = \begin{cases} 1 , & F_i^{\max} \le F_i ; \\ \dfrac{F_i - F_i^{\min}}{F_i^{\max} - F_i^{\min}} , & F_i^{\min} \le F_i < F_i^{\max} ; \\ 0 , & F_i \le F_i^{\min} . \end{cases} \quad (26)$$

Where $F_i^{\max}$ and $F_i^{\min}$ respectively represent the maximum and minimum values of the *i-th* objective function value of the candidate solution in the Pareto solution set.

Then the evaluation value of the *k-th* candidate solution in the Pareto solution set is $\mu[k]$, and the calculation of $\mu[k]$ is as (27). The higher the evaluation value, the more ideal the corresponding candidate solution is.

$$\mu[k] = \sum_{i=1}^{M} \mu_i[k] / \sum_{j=1}^{N_{Pareto}} \sum_{i=1}^{M} \mu_i[j] \quad (27)$$

Where M represents the number of targets; N_{Pareto} represents the number of solutions in the Pareto solution set, and $\mu_i[k]$ represents the evaluation value of the *k-th* candidate solution under the *i-th* target.

V. Case Study

A. Case Background

Suppose an earthquake occurs in a certain location, and the earthquake causes four major disaster areas: D_1, D_2, D_3, and D_4. The disaster areas need emergency teams composed of professional medical personnel to complete four types of emergency tasks: frontline rescue tasks (TA_1), medical tasks in temporary settlements (TA_2), health and epidemic prevention tasks (TA_3), and medical assistance tasks (TA_4). The capability evaluation indicators of emergency teams are first aid experience, communication and coordination ability, psychological stress tolerance, clinical experience, medical instrument operation level, work tolerance, and epidemic prevention level. There are 5 emergency points A_1, A_2, A_3, A_4, and A_5 that can dispatch emergency teams. The number of emergency teams in each emergency area is a_1=2, a_2=3, a_3=4, a_4=4, and a_5=3. The number of emergency teams required in each disaster area is d_1=8, d_2=3, d_3=4, and d_4=5. The disaster severity of each disaster area is λ_1=0.35, λ_2=0.2, λ_3=0.2, and λ_4=0.25. The number of tasks in each disaster area is L_1=4, L_2=2, L_3=3, and L_4=3. The response time of each emergency point is T_1=1, T_2=1.5, T_3=2, T_4=1.5, and T_5=1.5. The ideal arrival time of each disaster area is shown in Table I. The influence coefficients of road conditions and other factors on arrival time are shown in Table II. The importance of tasks in each disaster area is shown in Table III. The weights of emergency task indicators are shown in Table IV. The task preference order of the emergency team is shown in Table V. The evaluation values of the team indicators are shown in Table VI.

TABLE I
THE IDEAL ARRIVAL TIME

A_i	ET_{ik}			
	D_1	D_2	D_3	D_4
A_1	13	9	6	3
A_2	11	10	3	4
A_3	4	13	7	10
A_4	2	5	9	14
A_5	5	8	13	1

TABLE II
THE INFLUENCE PARAMETERS OF ROAD CONDITIONS AND OTHER FACTORS ON ARRIVAL TIME

A_i	ω_{ik}^1			
	D_1	D_2	D_3	D_4
A_1	0.2	0.2	0.2	0.3
A_2	0.2	0.3	0.3	0.2
A_3	0.3	0.2	0.3	0.2
A_4	8	0.3	0.2	0.2
A_5	0.3	0.2	0.2	18

TABLE III
THE IMPORTANCE OF TASKS IN EACH DISASTER AREA

D_k	DTA_c^k			
	TA_1	TA_2	TA_3	TA_4
D_1	1	2	4	3
D_2	0	1	0	2
D_3	0	2	3	1
D_4	2	3	1	0

TABLE IV
THE WEIGHTS OF EMERGENCY TASK INDICATORS

TA_c	U_c^q						
	1	2	3	4	5	6	7
TA_1	0.4	0.3	0.2	0.1	0	0	0
TA_2	0.1	0.1	0.2	0.3	0.3	0	0
TA_3	0	0.3	0	0	0	0.2	0.5
TA_4	0	0.2	0	0	0.2	0.5	0.1

TABLE V
TASK PREFERENCE ORDER OF THE EMERGENCY TEAM

P_{ij}	r_{ij}^c			
	TA_1	TA_2	TA_3	TA_4
P_{11}	3	1	2	4
P_{12}	3	4	1	2
P_{21}	1	3	2	4
P_{22}	2	1	3	4
P_{23}	0	3	1	2
P_{31}	4	1	3	2
P_{32}	3	0	2	1
P_{33}	1	2	4	3
P_{34}	1	4	2	3
P_{41}	2	1	3	0
P_{42}	0	1	2	3
P_{43}	1	2	3	4
P_{44}	3	0	1	2
P_{51}	3	4	2	1
P_{52}	1	2	3	4
P_{53}	1	3	2	4

TABLE VI
EVALUATION VALUE OF TEAM INDICATORS

P_{ij}	E_{ij}^q						
	1	2	3	4	5	6	7
P_{11}	4	3	5	7	5	1	2
P_{12}	3	5	2	1	2	4	6
P_{21}	8	4	3	2	1	1	5
P_{22}	7	3	4	6	1	2	3
P_{23}	0	6	2	3	2	5	9
P_{31}	1	2	2	3	2	5	9
P_{32}	2	2	3	0	1	8	4
P_{33}	6	4	2	9	3	4	1
P_{34}	9	4	3	1	2	7	2
P_{41}	7	2	2	6	3	1	3
P_{42}	0	2	3	7	2	3	5
P_{43}	7	4	3	5	2	3	4
P_{44}	3	7	2	0	2	6	7
P_{51}	4	4	2	1	2	9	3
P_{52}	8	3	2	6	4	2	3
P_{53}	6	4	4	1	2	2	4

B. Case Solving

Based on the VisualStudio2017 development environment, this paper uses the C++ programming language to implement algorithms and solve the case.

In terms of model parameters, let the disadvantage inequality parameter η_k be 0.5; the advantage inequality parameter ρ_k be 0.5, k=1,2,⋯,n; the unwilling sensitivity parameter θ is 0.1; the willingness perception parameter ε is 2. In terms of algorithm parameters, let the population size *popsize* is 100; the number of iterations *maxGen* is 500; the crossover probability *pc* is 0.9; the mutation probability *pm* is 0.02. Set the parameters in the penalty function to s=0.5, σ=2, and ζ=2.

The iterative curve of the number of Pareto frontier solutions is shown in Fig. 10.

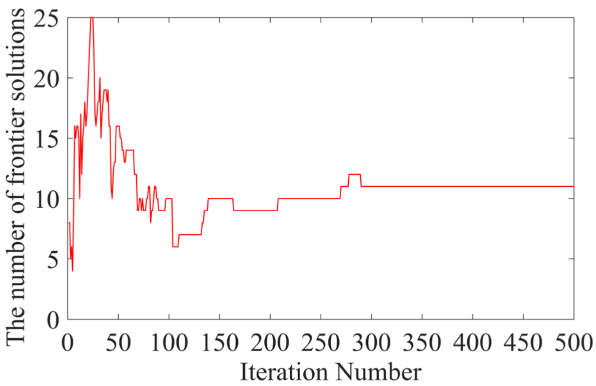


Fig. 10. The iterative curve of the number of Pareto frontier solutions.

From Fig. 10, we can see that the number of Pareto frontier solutions converges to 11 when the algorithm iterates to approximately 300 generations. Fig. 11 compares the Pareto frontier at generation 300 and generation 500 to verify that the algorithm converges at generation 300.

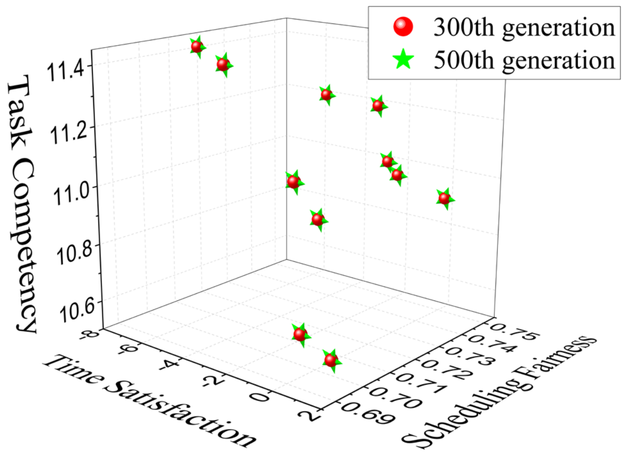
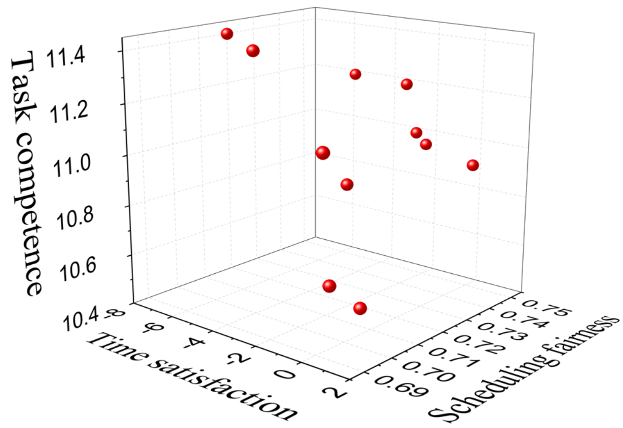
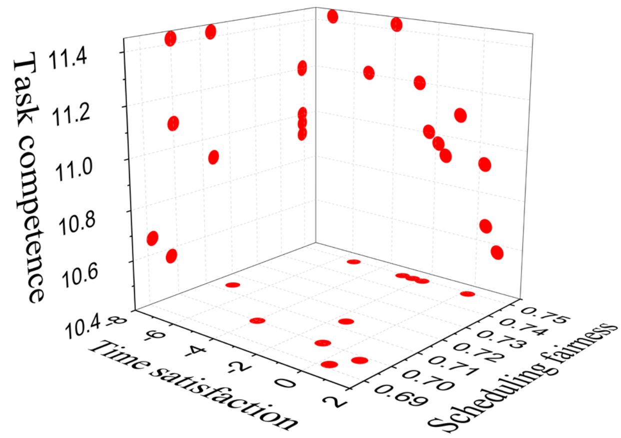


Fig. 11. The Pareto frontier at generation 300 and generation 500.

Fig. 11 shows that the Pareto frontiers of the 300th generation and the 500th generation are basically the same. Therefore, the Pareto frontier solution set of the 300th generation has converged. This shows that for the EPS problem studied in this paper, the designed NSGA-II algorithm can quickly and accurately obtain the frontier solution set. We take the Pareto frontier of the 300th generation for further analysis. The Pareto frontier of the EPS model is shown in Fig. 12.



(a)



(b)

Fig. 12. Pareto frontier. (a) The scatter diagram of Pareto frontier. (b) The projection figure corresponding to Fig. 12a.

As shown in Fig. 12, the correlation between scheduling fairness and the other two objective functions is not obvious. In contrast, there is a negative correlation between time satisfaction and task competency: as time satisfaction decreases, task competency gradually increases.

Considering the obvious conflict between time satisfaction and task competence, we focus on analyzing the optimal solution of time satisfaction (Scheme I), the ideal solution (Scheme II), and the optimal solution of task competence (Scheme III). The objective function values of the three solutions are shown in Table VII, and the specific scheduling schemes corresponding to the three solutions are shown in Tables VIII, IX, and X, respectively.

TABLE VII
THE OBJECTIVE FUNCTION VALUES CORRESPONDING TO THE THREE SCHEMES

	Z_1	Z_2	Z_3
Scheme I	0.9163	0.6979	10.5673
Scheme II	0.2229	0.7492	10.9153
Scheme III	-7.1213	0.7139	11.4202
Maximum value in Pareto solution set	0.9163	0.7492	11.4202

TABLE VIII
SCHEME I

D_k	TA_1	TA_2	TA_3	TA_4
D_1	P_{34} P_{52}	P_{31} P_{33}	P_{53} P_{32}	P_{51}
D_2	-	P_{41} P_{43}	-	P_{42}
D_3	-	P_{22}	P_{23}	P_{44}
D_4	P_{21}	P_{11}	P_{12}	-

TABLE IX
SCHEME II

D_k	TA_1	TA_2	TA_3	TA_4
D_1	P_{34} P_{52}	P_{31} P_{33}	P_{53}	P_{51}
D_2	-	P_{41} P_{43}	-	P_{42}
D_3	-	P_{22}	P_{44}	P_{32}
D_4	P_{21}	P_{11}	P_{23} P_{12}	-

TABLE X
SCHEME III

D_k	TA_1	TA_2	TA_3	TA_4
D_1	P_{34} P_{43}	P_{33} P_{42}	P_{53}	P_{32}
D_2	-	P_{41}	-	P_{51}
D_3	-	P_{31}	P_{22}	P_{44}
D_4	P_{21} P_{52}	P_{11}	P_{23} P_{12}	-

From Table VII, we can see that in terms of time satisfaction, Scheme II is close to Scheme I and far superior to Scheme III. However, the time satisfaction level of the three schemes is not high, which is caused by the suddenness of the earthquake and the uncertainty of rescue arrival time. In addition, in terms of scheduling fairness, Scheme II> Scheme III> Scheme I, and the scheduling fairness of Scheme II reaches the maximum value under the conditions of this case. Finally, from the perspective of task competence, Scheme II is a compromise.

Combining Tables I, II, and X, it can be seen that in Scheme III, emergency teams are dispatched to disaster areas with short ideal arrival times but are seriously affected by road conditions and other factors. This is caused by the conflict between goals. At the same time, this shows that the path with a short ideal arrival time that is seriously affected by road conditions has become a bottleneck restricting the improvement of the rescue effect, and decision makers must pay attention to this factor.

In the early stage of emergency rescue, to ensure the overall rescue effect, EPS will pay more attention to timeliness and fairness. Clearly, Scheme II is more in line with the EPS requirements in the early stage of emergencies. Therefore, we choose Scheme II (ideal solution) as the optimal scheme for the designed case.

C. EPS under Different Decision-making Scenarios

To further verify the rationality of the model developed in this paper, the EPS model under two different decision-making scenarios are compared and analyzed. The first considers the psychological perception of the victims and the emergency personnel. The second does not consider the psychological perception of the victims and the emergency personnel. The EPS model in the first decision scenario is (15)-(23). The time satisfaction, scheduling fairness, and task competency functions in the second decision scenario are (28), (29), and (17), respectively. In (17), the willingness perception parameter ε is set to 1, and the unwillingness sensitivity coefficient θ is set to 0. The EPS model constraints in the second decision scenario are (18)-(23).

$$\max Z_1^{'} = \frac{1}{\sum_{k=1}^{n} \lambda_k \cdot \left(\sum_{i=1}^{m} \sum_{j=1}^{a_i} x_{ijk} t_{ik}^{'} \right)} \tag{28}$$

$$\max Z_2^{'} = \sum_{k=1}^{n} \lambda_k E_k \tag{29}$$

where $t_{ik}^{'}$ takes the midpoint value of the time interval from emergency point A_i to disaster area D_k.

The average value of the three objectives in the EPS scheme set is selected as the comparison index, and the average values of the three objectives in the scheme set are represented by $\overline{Z}_1$, $\overline{Z}_2$, and $\overline{Z}_3$. The comparison of rescue effects considering the satisfaction of victims and emergency personnel is shown in Table XI, and the basic rescue effect comparison is shown in Table XII.

TABLE XI
COMPARISON OF RESCUE EFFECTS CONSIDERING THE SATISFACTION OF VICTIMS AND EMERGENCY PERSONNEL

	$\overline{Z}_1$	$\overline{Z}_2$	$\overline{Z}_3$
Model in Scenario 1	-3.4206	0.7243	11.1272
Model in Scenario 2	-4.1097	0.6967	11.0094
Growth rate (%)	16.77	3.96	1.07

TABLE XII
COMPARISON OF BASIC RESCUE EFFECTS

	$\overline{Z}_1$	$\overline{Z}_2$	$\overline{Z}_3$
Model in Scenario 1	0.0342	0.8091	11.2381
Model in Scenario 2	0.0344	0.8202	11.3661
Reduction rate (%)	0.62	1.37	1.14

Table XI shows that the EPS model under the first decision scenario has a slight decrease in the basic rescue effect: the average reduction is 1.04%. However, compared with the reduction of the basic rescue effect, Table XII indicates that the EPS model under the first decision-making scenario has more obvious advantages in the rescue effect considering satisfaction. The average growth rate of the rescue effect considering satisfaction is 7.27%. Based on the above analysis, the EPS model constructed in this paper can effectively improve the satisfaction of victims and emergency personnel while ensuring a certain basic rescue effect.

D. Parametric Analysis

To study the impact of the psychological perception of disaster victims and emergency personnel on EPS, we discussed and analyzed the key parameters in time satisfaction, scheduling fairness, and task competency.

D.1 Parametric Analysis of Time Satisfaction

Time satisfaction is affected mainly by risk attitude parameters α and β and perceived probability parameters γ and δ. We take the time satisfaction of Scheme I, Scheme II, and Scheme III as the research object to study the influence of the above parameters. The influence of the risk attitude parameter on the time satisfaction of the three schemes is shown in Fig. 13, 14, and 15, respectively.

From Fig. 13, Fig. 14, and Fig. 15, we can see that (1) time satisfaction is positively correlated with α and negatively correlated with β. (2) The time satisfaction of Scheme I and Scheme II is more sensitive to α but also affected by β, and the time satisfaction of Scheme III is almost only affected by β. Under the three schemes, the victims' perception of rescue time is mixed low gain, mixed low gain, and high loss. Therefore, the phenomenon in Fig. 13 and Fig. 14 shows that when the rescue time is slightly earlier than expected by the victims, while the victims have the psychology of avoiding risks to retain the current gain, they will also have the psychology of pursuing risks to pursue greater gains. The phenomenon in Fig. 15 shows that disaster victims in a state of high loss are more inclined to pursue risk for gain. Further, overall, time satisfaction is more sensitive to β, which reflects the reality that disaster victims with limited access to information are more sensitive to losses and have high expectations for rescue. The influence of the perceived probability parameters on the time satisfaction of the three schemes is shown in Fig. 16, Fig. 17, and Fig. 18, respectively.

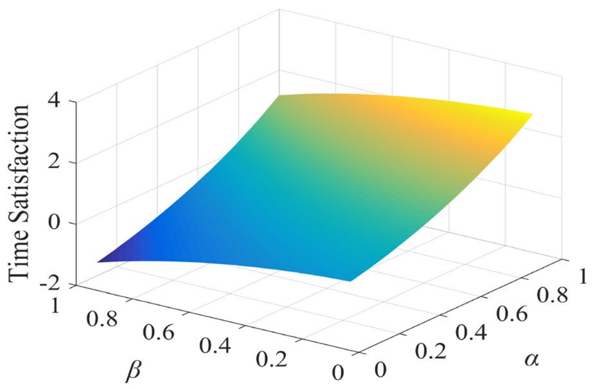


Fig. 13. Influence of parameters α and β on time satisfaction of Scheme I.

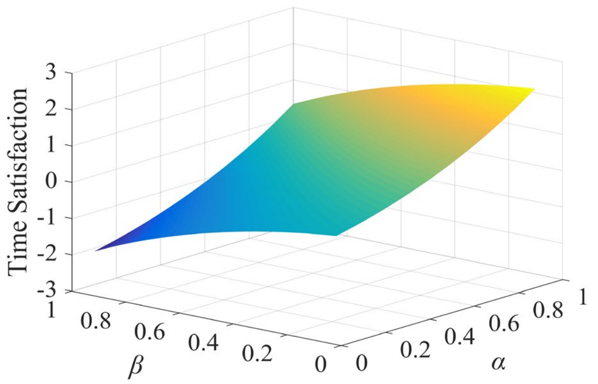


Fig. 14. Influence of parameters α and β on time satisfaction of Scheme II.

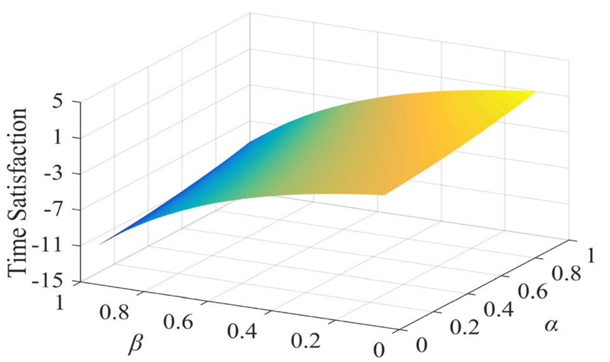


Fig. 15. Influence of parameters α and β on time satisfaction of Scheme III.

It can be seen from Fig. 16, Fig. 17, and Fig. 18 that (1) time satisfaction is positively correlated with γ and negatively correlated with δ. (2) The time satisfaction of Scheme I and Scheme II is more sensitive to δ but also affected by γ, and the time satisfaction of Scheme III is almost only affected by δ. The larger the δ, the more inclined the victims are to perceive that the scheme is invalid, so the time satisfaction of the three schemes is smaller. The analysis of γ is the same. Further, overall, time satisfaction is more sensitive to δ, which is in line with the reality that disaster victims will be more sensitive to the ineffectiveness of the scheme.

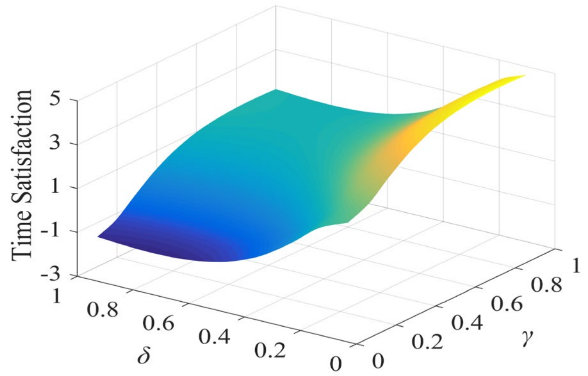


Fig. 16. Influence of parameters γ and δ on time satisfaction of Scheme I.

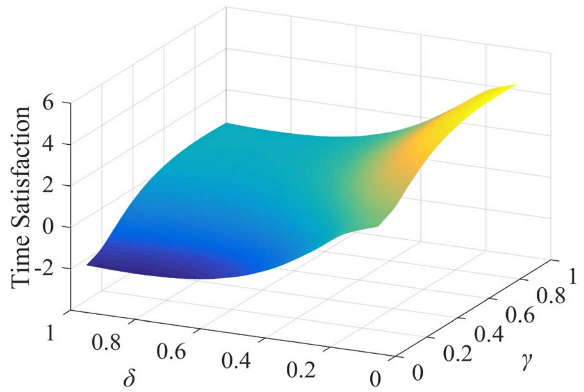


Fig. 17. Influence of parameters γ and δ on time satisfaction of Scheme II.

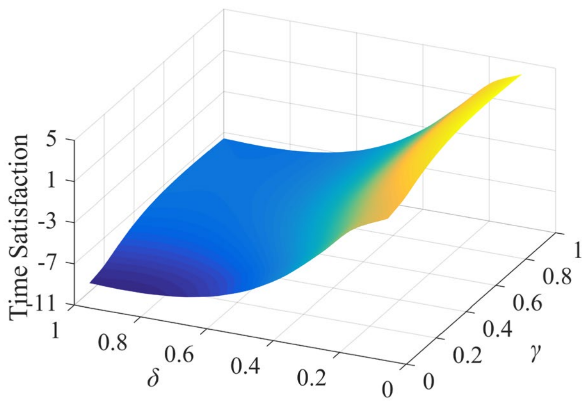


Fig. 18. Influence of parameters γ and δ on time satisfaction of Scheme III.

Based on the above analysis, we can find that compared with parameters α and γ, time satisfaction is more sensitive to β and δ, which reflects the reality that disaster victims are more sensitive to losses and ineffective schemes. In addition, the completeness of information acquisition will affect the psychological expectations of disaster victims for rescue. Disaster victims with limited access to information will have high expectations for rescue. In this regard, decision makers should first clarify the psychological expectations of the victims, and then select the corresponding reference points to better promote the optimization and adjustment of the scheme.

D.2 Parametric Analysis of Scheduling Fairness

The inequality parameter reflects the sensitivity of the disaster victims to the inequality of advantages and disadvantages. We take the scheduling fairness of the three schemes as the research object, and analyze the influence of the disadvantage inequality parameter η and the advantage inequality parameter ρ on it, as shown in Fig. 19 and Fig. 20.

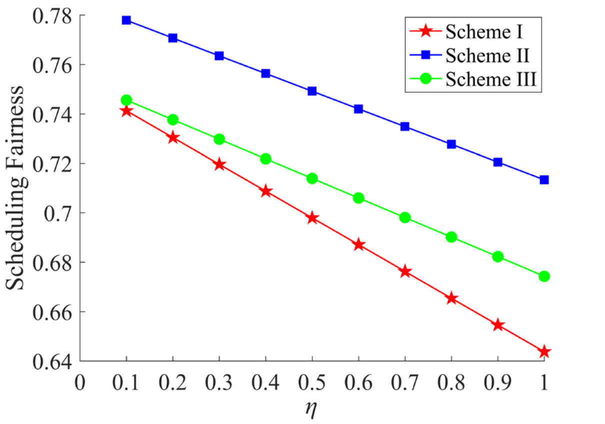


Fig. 19. Influence of parameter η on scheduling fairness.

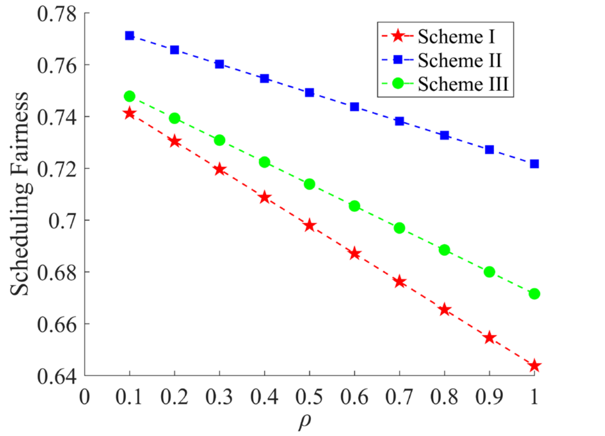


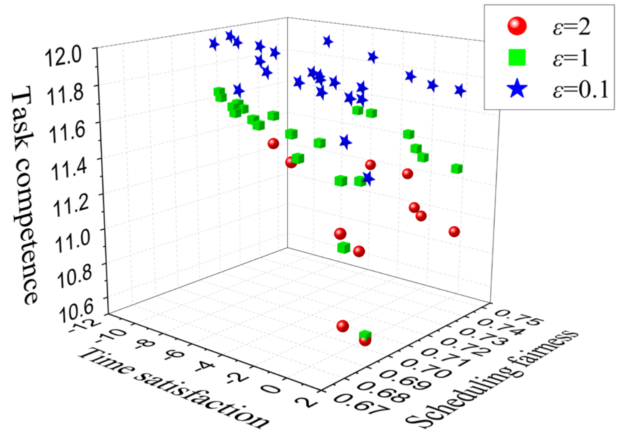
Fig. 20. Influence of parameter ρ on scheduling fairness.

From Fig. 19 and Fig. 20, we can see that (1) with the increase of η and ρ, the scheduling fairness gradually decreases. (2) The scheduling fairness of Schemes I and II are more sensitive to η and ρ, respectively, and the scheduling fairness of Scheme III is equally sensitive to η and ρ. (3) In terms of sensitivity to inequality parameters: Scheme II < Scheme III < Scheme I. Combining the demand satisfaction rate of each disaster area under the three schemes and the above analysis, we can draw the following conclusions. When the demand satisfaction rate of a few disaster areas is too low or too high, the sensitivity of scheduling fairness to η and ρ will increase accordingly, and the scheduling fairness will decrease. This shows that considering the people's aversion to unfairness, it can effectively prevent the extreme situation of the demand satisfaction rate in a few disaster areas, and make the obtained scheduling scheme fairer.

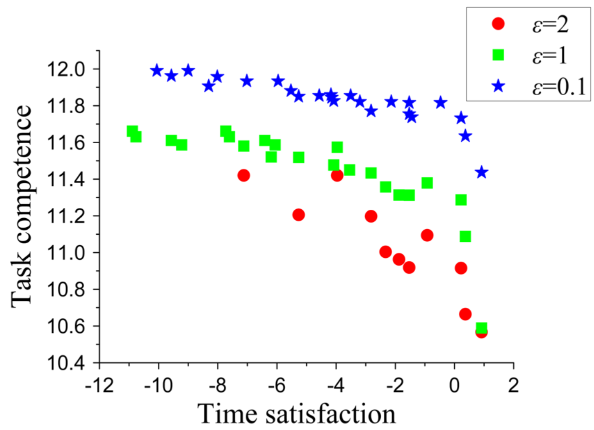
D.3 Parametric Analysis of Task Competency

This study describes the psychological perception of the emergency team by introducing the willingness perception parameter ε. The following is a discussion and analysis of the willingness perception parameter ε.

The willingness perception parameter ε reflects the change in satisfaction of the emergency team when completing tasks with different preference orders. The larger ε is, the more inclined the emergency team is to complete the first task in its preference order. The smaller ε is, the more inclined the emergency team is to complete the tasks of the middle and upper layers of its preference order. The Pareto solution set when the willingness perception parameter ε takes different values is shown in Fig. 21.



(a)



(b)

Fig. 21. Frontier solution when ε takes different values. (a) Frontier solution under three objective functions. (b) Frontier solution under two objective functions.

Fig. 21 shows that the frontier solution sets obtained by different willingness perception parameters differ in the number and layout of solutions. As the willingness perception parameter decreases, the number of frontier solutions gradually increases, and the overall competency value also increases. Furthermore, as time satisfaction decreases, the trend of gradually increasing task competency remains unchanged. To thoroughly study the effect of the willingness perception parameter ε on EPS, we compared the ideal solutions with different values of ε. When the willingness perception parameter ε is 0.1, the ideal solution changes, and the new ideal solution is shown in Table XIII. When ε takes different values, the distribution of the number of emergency teams completing tasks of different competence levels is shown in Fig. 22.

TABLE XIII
IDEAL SOLUTION WHEN ε=0.1

D_k	TA_1	TA_2	TA_3	TA_4
D_1	P_{34} P_{52}	P_{31} P_{33}	P_{53}	P_{51}
D_2	-	P_{41} P_{43}	-	P_{44}
D_3	-	P_{22}	P_{42}	P_{32}
D_4	P_{21}	P_{11}	P_{23} P_{12}	-

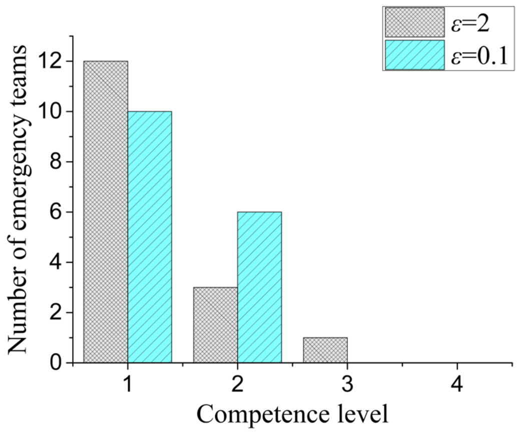


Fig. 22. Distribution of the number of emergency teams completing tasks at each competency level, when ε is different.

Fig. 22 shows that when the willingness perception parameter ε is 0.1, the number of emergency teams is more concentrated, and all emergency teams are assigned to the top two tasks in their ranking of competence. When the willingness parameter ε is 2, the distribution of the number of emergency teams is relatively scattered. At this time, more emergency teams are assigned to tasks that are ranked first in their competency rankings, but there are also instances where emergency teams complete their less competent tasks. This is in line with the reality that emergency teams do not correspond one-to-one with emergency tasks in practice. Notably, in the two ideal solutions, the tasks with high importance in each disaster area are matched with emergency teams with corresponding high competence. This shows that the task allocation method proposed in this paper can be adapted to the different disaster conditions of each disaster area, and is conducive to the orderly development of rescue work.

Based on the above analysis, it can be seen that different perceptions of willingness correspond to different task scheduling effects. The larger the willingness perception parameter ε is, the more the scheduling effect tends to maximize the matching degree between the emergency team and the emergency task while ignoring a few cases with low matching degrees. The smaller the willingness perception parameter ε is, the more the scheduling effect tends to achieve a balanced match between the emergency team and the emergency task. Combining with the task allocation method proposed in this paper, we can find that the first scheduling effect is more suitable for situations where the importance of emergency tasks in disaster areas varies greatly. The second scheduling effect is more suitable for situations where the importance of emergency tasks in the disaster area is more balanced. When the number of dispatchable emergency teams is sufficient, decision makers can screen emergency teams with corresponding willingness perception characteristics based on specific disaster conditions to improve rescue efficiency.

VI. CONCLUSIONS

This research focuses on realistic EPS problems with the characteristics of M-PDT, a shortage of emergency personnel, and an uncertain rescue time, and constructs a multi-objective EPS decision-making optimization model. To make the EPS scheme more suitable for the actual emergency rescue, the psychological perception factors of disaster victims and emergency personnel are considered in the model. In terms of disaster victims, CPT and IAT are introduced to describe the victims' perceived satisfaction with rescue time and fairness. In terms of emergency personnel, based on the subjective satisfaction and objective ability evaluation of emergency personnel on emergency tasks, the corresponding task competence is described.

The case solution results show that, based on the developed model, the ideal solution obtained by the NSGA-II algorithm and fuzzy logic method can better meet the requirements of EPS for timeliness, fairness, and efficiency. In addition, the designed NSGA-II algorithm can converge quickly and accurately, which is an effective means to solve the EPS problem in this paper. The comparison results of EPS models under different decision scenarios show that the EPS model that considers the psychological perception of personnel is better than the EPS model that only considers the basic rescue effect. The model in this paper can effectively improve the perceived satisfaction of disaster victims and emergency personnel while ensuring the basic rescue effect. Parameter analysis shows that the EPS model considering the psychological perception of victims and emergency personnel truly reflects the impact of the psychological factors of disaster victims and emergency personnel on EPS, which makes up for the lack of existing research. The resulting EPS scheme is beneficial to preventing the extreme behavior of disaster victims in emergencies, and to giving full play to the capabilities of emergency personnel, thereby improving rescue efficiency.

In future research, we will consider the dynamics of disaster situations and the synergistic effect of emergency personnel to further improve the efficiency of emergency rescue.

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