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Research

Volunteer dispatch considering fatigue effect and satisfaction in emergency situation

Zongwei Ren[1] · **Qiuyu Zhang**[1]

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Abstract
Rescue organization scheduling is a hot issue in the field of emergency management, in which the participation of volunteer rescue organizations, a social force, is of great significance to improve the efficiency of emergency rescue. In the case of known rescue services required by the affected place and the information of rescue services provided by volunteer rescue organizations, the goal is to maximize the satisfaction of the victims and minimize the fatigue of the volunteer rescue organizations. The volunteer rescue organization scheduling problem is an NP-hard problem. To solve the studied problem model, two multi-objective optimization algorithms are applied in this article. With the goal of improving the overall rescue efficiency of volunteer rescue organizations implementing rescue at the disaster site during a single emergency, this study analyzes the practical problems related to emergency rescue, taking into account the effects of the time sensitivity of the disaster victims, the preference of the rescue services, the fatigue accumulation rate of the volunteer rescue organizations, and the matching of the rescue skills. Finally, this article distills some scheduling strategies applicable to emergency volunteer rescue organizations, hoping to provide theoretical basis and practical guidance for the Emergency Management Center and related emergency management departments to better configure and optimize emergency human resource scheduling problems.

Highlights

1. The degree of time sensitivity and matching of rescue service preferences influence disaster victims' satisfaction.
2. Accelerated rates of fatigue accumulation and growth in rescue service duration increase fatigue levels in volunteer rescue organizations.
3. The Multi-Objective Particle Swarm Algorithm (MOPSO) exhibits superior solution speed, while the Hybrid Gray Wolf-Particle Swarm Algorithm (HGWPSO) finds better solutions in global optimization for this case.

Keywords Dispatching · Fatigue effect · Satisfaction · Hybrid Gray Wolf Particle Swarm Optimization (HGWPSO) · Multi-objective Particle Swarm Optimization (MOPSO)

✉ Qiuyu Zhang, zqy@s.hrbcu.edu.cn | [1]School of Management, Harbin University of Commerce, Harbin 150028, China.

1 Introduction

In recent years, many countries and regions worldwide have faced various catastrophic natural disasters or serious infectious diseases. These events have caused significant economic losses and human casualties. Although there have been efforts to establish emergency rescue forces and plans, there are still challenges such as an incomplete rescue system, inadequate dispatch of personnel, and unsophisticated rescue methods. These obstacles can lead to additional hazards. Over the past 5 years, China's emergency management department has seen 177 sacrifices among its personnel, mainly among grassroots and frontline emergency management officials, firefighters, and rescuers [1]. Therefore, it is crucial to ensure the safety and smooth operation of disaster relief efforts, optimize the efficiency and quality of immediate post-disaster relief, and avoid secondary disasters.

Emergency personnel dispatch refers to the process of sending various types of emergency relief personnel to serve the victims in each affected area as quickly as possible. This includes providing emergency medical services, preventing secondary disasters, providing disaster information, and offering psychological counseling. In addition to professional emergency rescue teams such as fire and medical rescue teams, the Emergency Management Center also dispatches volunteer rescue organizations to assist with rescue support work. Volunteer organizations are typically formed by community members, including students and residents, who receive basic rescue training. However, there are challenges when sending volunteer rescue organizations to disaster areas. These include fatigue among individual volunteers, a mismatch between the skills of volunteers and the needs of the victims, and delays in providing rescue services. These problems lead to wasted resources, increased costs, and reduced efficiency in rescue operations. Additionally, they can worsen the impact of disasters and even potentially cause secondary disasters.

This article presents a model for dispatching emergency volunteer rescue organizations that aims to address the problems of redundant, wasteful, and inefficient configurations. The model takes into account factors such as volunteer fatigue and victim satisfaction to ensure accurate dispatching of personnel.

1.1 Problem statement

Assuming that there are a number of disaster-affected areas, there are a number of emergency volunteer rescue organizations participating in the rescue work, but there are differences in the rescue skills, work tolerance load, location, transportation time to the disaster-affected areas, and rescue costs of each emergency volunteer rescue organization, so the optimal dispatching scheme needs to be solved according to the specific situation.

The rescue dispatch schematic diagram of volunteer rescue organizations under emergency situations is shown in Fig. 1. The left side of the arrow indicates the input data, which consists of two parts. First, the information of the rescue service provider (volunteer rescue organization) includes its fatigue effect, the rescue skills it possesses, and the matching degree with the rescue skills of the disaster-affected areas; second, the information of the rescue service demander (the disaster victims in disaster-affected areas) includes the type of demand for the rescue service and the waiting time. Rescue dispatch decisions are made by the Emergency Response Center (EC). To the right of the arrow is the output dispatch scheme, indicating the distribution scheme between the affected sites and the volunteer rescue organizations. The problem considered in this article is: assuming that the rescue capacity of the emergency volunteer rescue organization and the status quo of the affected places are known, adjusting the constraints according to the actual situation, and solving the relative optimal dispatching scheme based on the different rescue needs of the affected places, so as to maximize the comprehensive rescue benefits.

The article is structured as follows:

- Section 2 discusses previous works and highlights the differences from this study.
- Section 3 develops a mathematical model for emergency volunteer rescue organizations dispatching.
- Section 4 utilizes two different multi-objective optimization algorithms to solve the model, explaining the principles and application process of these algorithms.
- Section 5 validates the algorithm and personnel dispatching through a simulation model of emergency volunteer rescue organizations in disaster areas.

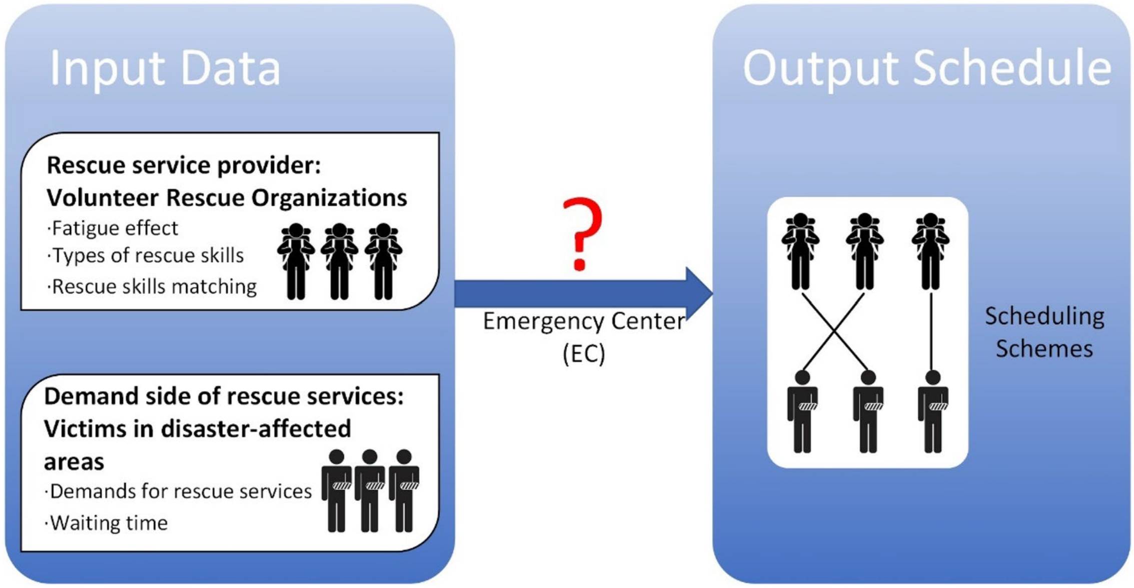

Fig. 1 Emergency Volunteer Rescue Organizations Scheduling

- Section 6 presents observations on emergency management based on the conclusions from the simulation analysis, and discusses the limitations of the study and future research directions for scheduling emergency rescue organizations.

2 Literature review

The key for emergency management to reasonably dispatch volunteers for disaster relief activities is to address whether the volunteer rescue services in the disaster area match the needs of the victims. Relevant scholars at home and abroad have conducted exploratory studies on the dispatch of emergency responders after disasters from different perspectives. As early as 2007, Gilberti et al. [2] conducted a study on the problem of assigning alert duties to emergency service providers by evenly distributing the workload in order to optimize the level of service measured in terms of intervention time. In the emergency rescue personnel dispatching problem, 2012, Yuan et al. [3] launched a detailed study on the emergency rescue team dispatching problem, and provided an optimization model of rescue team dispatching as well as a solution method for the problem of multi-node failure in the lifeline network system, which is the first batch of scholars in China to conduct research on the dispatching of emergency rescue personnel; in 2013, Yuan and other scholars [4] continued to conduct in-depth study on the emergency rescue time satisfaction of rescue personnel arriving at the rescue demand point for rescue tasks for different points of dispatch. In 2017, Zhang et al. [5] proposed a multi-stage allocation model for rescue organizations to dynamically respond to the disaster chain and formulated three priority dispatch strategies defined according to the principle of burden-benefit consistency. Song et al. [6] pointed out that an assignment scheme that considers both rescue time satisfaction and team competency is different from an assignment that considers only a single objective, which can ensure rescue capability and effectively improve rescue time satisfaction to achieve higher rescue efficiency. Li and his team [7] studied a problem of dispatching rescue personnel to multiple rescue points during an emergency. They calculated the matching degree between each rescue personnel and each rescue point based on their competency and satisfaction in rescue tasks and emergency response time. They then created an optimization model for dispatching emergency rescue personnel and demonstrated the practicality of the model using examples. In 2021, Cao and Li [8] discussed the current progress of the mathematical planning model for emergency organization allocation. They focused on the order of emergency rescue tasks and the number of objectives, reviewed the exact heuristic algorithm for solving the model, and suggested further research on topics like simulation and modeling of emergency organization allocation optimization. In the same year, Li et al. [9] proposed an optimal dispatch model and solution algorithm by taking maximizing the rescue benefit as the objective function from the perspective of the participation of social rescue forces in disaster relief. Fei and Wang [10] in 2022 studied to effectively dispatch rescuers to multiple disaster areas by combining Dempster-Shafer theory (DST) and linguistic term sets to evaluate and make decisions about rescue information in uncertain linguistic environments to maximize rescuer competence and satisfaction with rescue time. Cao et al. [11] proposed an emergency responder assignment model considering collaboration information. The model is based on the synergistic effect and synergistic ability among rescuers to calculate the degree of collaboration and derive the comprehensive ability of each rescuer, and then calculates the satisfaction of rescuers and obtains the task adaptation according to the subjective preference of rescuers, and constructs an emergency responder allocation model with the goal of maximizing the satisfaction of rescue time and task adaptation. The research subjects involved in the above literature are mostly professional emergency rescue organizations and individual rescue workers, while the research on emergency volunteer rescue organizations and individuals participating in rescue is still scarce. In addition, the above research did not take into account the fatigue phenomenon caused by the gradual loss of physical strength and the increase of rescue time after the emergency rescue workers continued to participate in rescue activities, as well as the gradual decline of rescue efficiency, which is of further significance.

Xu et al. [12] stated that fatigue is a widespread and serious problem for workers in all industries and the organizations that employ them, leading to decreased productivity, increased risk of negative safety consequences, increased probability of illness, and fatigued individuals are a strain on themselves, their families, employers, and society. Nayeri et al. [13], while studying the emergency management problem of natural disaster occurrence, argued that it is necessary to consider the different capabilities and fatigue effects of each rescue unit and stated that Natural Disaster Management (NDM) is not similar to the classical deterministic scheduling problem, where the processing times of events and operations are usually assumed to be constants without any dependence on their position in the sequence. It was observed that studies on the allocation and dispatch of rescue units in NDM problems account for only a small portion of the literature, while few studies have been conducted on the fatigue of rescue units. Previous studies have concluded that rescue time is fixed and that rescue units become fatigued after multiple rescues and rescue efficiency is subsequently reduced. The objective function previously studied by Wex et al. [14] minimized the weighted sum of the time to complete the rescue. Nayeri et al. [15] conducted an in-depth study based on this, considering the need for emergency operations to initiate rescue quickly, adding the weighted sum of the late time as an objective function.

Currently, there are many studies on emergency supply and rescue vehicle dispatch in academia. However, there is a lack of research on the involvement of social organizations in disaster relief, specifically the dispatch of volunteers in emergency situations. Compared to professional rescue organizations, volunteer organizations are more limited by their own rescue skills and dedicate more time and energy to rescue work. Therefore, studying the relationship between volunteer fatigue and rescue efficiency can optimize the involvement of social organizations in on-site emergency rescue. This, in turn, can improve China's overall level of emergency relief. To address this, it is necessary to establish a model for volunteer rescue dispatch in emergency situations. This model should consider volunteer fatigue and victim satisfaction. The multi-objective particle swarm optimization (MOPSO) algorithm and the hybrid gray wolf particle swarm optimization (HGWPSO) algorithm can be used to solve the model and develop an optimal dispatch strategy.

3 Mathematical modeling

The complexity of dispatching volunteer relief organizations requires comprehensive consideration of skills, location, time, equipment, manpower, and other factors, and detailed dispatch scheduling planning for volunteer organizations to maximize the efficiency of disaster relief.

3.1 Model assumptions

Integrating the complexity of the disaster site situation and the complexity of the multi-parameter optimization mathematical model, the following reasonable assumptions need to be set for the convenience of research and solution:

1. After the occurrence of the disaster, the emergency center can dispatch emergency volunteer rescue organizations to participate in the rescue after evaluation, and the number of rescue organizations is sufficient;
2. Emergency volunteer rescue organizations can participate in rescue only after evaluation of their rescue skills;
3. The arrival time of the emergency volunteer rescue organization at the disaster site and the rescue time can be estimated;

4. The degree of damage in the disaster-affected areas can be estimated, and the satisfaction of the victims with the volunteer rescue mission can be estimated;
5. The emergency rescue tasks required by the victims are independent of each other.

The basic setup of the proposed model is given for ease of description.

$D = \{D_1, D_2, ..., D_m\}$: is the set composed of the affected places within the emergency relief, where D_i denotes the ith affected place in D, $i \in M = \{1, 2, ..., m\}$, $m \geq 2$ and is a positive integer. The affected place is the demand side of the emergency relief service for emergencies, while the quantity of emergency relief service for emergencies is generally determined by the emergency response center.

$M = \{M_1, M_2, ..., M_n\}$: is the set composed of volunteer rescue organizations within the scope of emergency relief, where M_j denotes the jth volunteer rescue organization, $j \in N = \{1, 2, ..., n\}$,$n \geq 2$ and is a positive integer. Volunteer rescue organizations are providers of emergency rescue services in emergencies, with public welfare as the primary principle, and economic factors are not taken into account when rescuing.

$P = \{P_1, P_2, ..., P_d\}$: is a collection of the types of emergency response skills that make up the emergency response in a critical incident.

$Ur = \{Ur_{id} | i = 1, 2, 3 \ldots, m, d = 1, 2, 3 \ldots, k\}$: is the urgency Ur_{id} of the need for the rescue skill type P_d at the disaster site D_i, which is rated as low (I), medium (II), and high (III), respectively.

$A = \{a_{jd} | j = 1, 2, 3 \ldots, n, d = 1, 2, 3 \ldots, k\}$: is the level a_{jd} of rescue skills mastered by the volunteer rescue organization M_j, each of which is categorized as low (1), medium (2), or high (3).

$S = \{s_i | i = 1, 2, 3..., m\}$: is the maximum demand s_i for the services of the volunteer rescue organization M_j at the disaster site D_i.

3.2 Victim satisfaction

3.2.1 Victims' time-sensitive satisfaction

To mitigate further harm to individuals impacted by a disaster during its initial stages, it is imperative that relief services, including psychological counseling, basic medical attention, and distribution of necessary supplies, are expeditiously provided by volunteers. The prompt execution of these services is crucial in securing the cooperation of those affected and facilitating subsequent rescue operations. The quality of volunteer services provided significantly influences the satisfaction of the disaster-affected individuals, with waiting time and duration of service being critical factors to consider. Scholars such as Sung et al. [16], Li et al. [17], and Fan et al. [18] have employed a monotone decreasing time-sensitive evaluation function, specifically a sigmoid function, to describe the probability of survival among such individuals after a disaster. Proper calibration of parameters can simulate emergency rescue activities. This article utilizes the aforementioned concept of time perception satisfaction to describe the satisfaction of disaster victims. The function of the victim's satisfaction g_i with the volunteer emergency service acquisition time t_{ij} in the affected place D_i is Eq. (1):

$$g_i\left(t_{ij}\right) = \mathrm{e}^{-t_{ij}^2/\theta_i} \tag{1}$$

where θ_i is the time sensitivity coefficient, the smaller the value of θ_i indicates that the smaller the patience threshold of the victims waiting for the rescue service, the higher the sensitivity of the time-sensitive satisfaction function. Figure 2 shows the time-sensitivity satisfaction curve when θ_i in [5,10,15,20,30]. When θ_i=5, the time-sensitive satisfaction of the victims is higher in the first 10% of the time window, and the post-disaster survival rate is the highest when relief services are performed in this time period. As time passes the time-sensitive satisfaction gradually decreases, and when it reaches 20% of the rescue time, the victims' time-sensitive satisfaction shows an extremely sensitive state, and the rescue service in that time window should be accelerated and completed. And when the time sensitivity of the victims after 50% of the time window drops to extremely low, it is difficult to restore the time satisfaction of the victims by carrying out rescue activities at this time.

3.2.2 Victims' preference satisfaction

Individual disaster victims are heterogeneous due to the degree of disaster, so there is a difference in their preference for the type of disaster relief services. The preference information provided by the subject of the victims reflects the degree of

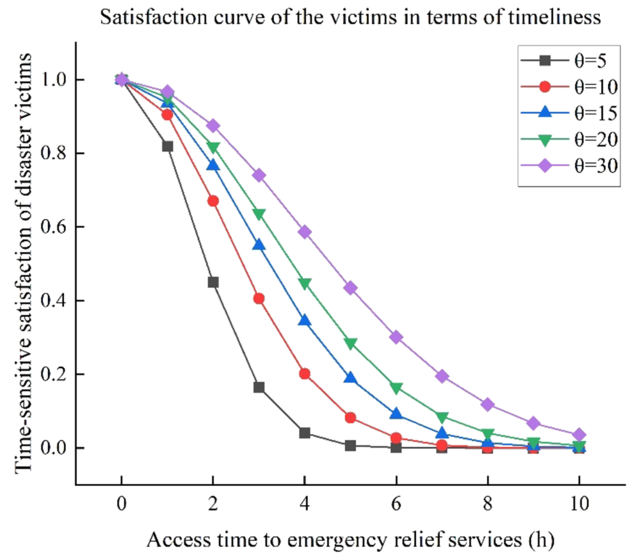

Fig. 2 Time-sensitive satisfaction curve for disaster victims

satisfaction with the scheduling subject to a certain extent, however, in the actual rescue process, the increase of the preference ordinal value does not fully reflect the decrease of their degree of satisfaction, and the two do not present a linear relationship, so in order to better describe the degree of satisfaction of the victims with the rescue services provided by the volunteer rescue organization, this article draws on the preference proposed by Guo et al. [19]. Matching task assignment model, the preference satisfaction of the victims and the matching satisfaction of volunteer rescue organizations are defined as follows:

Use α_{ij} to denote the preference satisfaction of the disaster-affected areas D_i to the volunteer rescue organization M_j, and β_{ij} is the match satisfaction of the volunteer rescue organization M_j to the disaster area D_i, α_{ij} and β_{ij} are denoted as respectively:

$$\alpha_{ij} = \begin{cases} \frac{l(x)}{c_i}, & j \in W(i) \\ 0, & j \notin W(i) \end{cases} \tag{2}$$

$$\beta_{ij} = \begin{cases} \frac{g(x)}{b_j}, & i \in T(j) \\ 0 & i \notin T(j) \end{cases} \tag{3}$$

where c_i is the number of volunteer rescue organizations needed at the disaster site D_i, and b_j is the number of rescue tasks acceptable to the volunteer rescue organization M_j. In this article, we use sequence preference and set $l(x)$ and $g(x)$ as the expression of the preference of the subjects on both sides of the scheduling, and the higher the value of the bit sequence is the smaller the subject's satisfaction, so we set $l(x)$ and $g(x)$ as monotonically decreasing functions, and $l(x) \geq 0, g(x) \leq 1$, and expressed as follows:

$$l(x) = \frac{p_i + 1 - x}{p_i} \tag{4}$$

$$g(x) = \frac{q_j + 1 - x}{q_j} \tag{5}$$

Then the two-party preference satisfaction is transformed:

$$\alpha_{ij} = \begin{cases} \frac{p_i + 1 - r_i(j)}{c_i p_i}, & j \in W(i) \\ 0, & j \notin W(i) \end{cases} \tag{6}$$

$$\beta_{ij} = \begin{cases} \frac{q_j+1-h_j(i)}{b_j q_j}, & i \in T(j) \\ 0, & i \notin T(j) \end{cases} \tag{7}$$

where p_i denotes the length of the preference sequence of the disaster-affected areas D_i, q_j denotes the length of the preference sequence of the volunteer rescue organization M_j, and $r_i(j)$ is the number of bits of the volunteer rescue organization M_j in the preference list of the disaster-affected areas D_i. When the rescue service provided by the volunteer rescue organization is not in the preference sequence of the disaster victims, the satisfaction level of the current disaster victims with the volunteer rescue organization is 0. The satisfaction level of all the disaster victims with the volunteer rescue organization in the current time period is represented by the matrix $Sat_T = [\alpha_{ij}]_{p \times q}$, and the satisfaction matrix is obtained as follows according to the above rules for calculating the satisfaction level:

Satisfaction matrix of preferences of victims-volunteer rescue organizations

Disaster area	c_i	Volunteer rescue organizations		
		M_1	...	M_j
D_1	c_1	$\alpha_{11} = \begin{cases} \frac{p_1+1-r_1(1)}{c_1 p_1}, i \in T(j) \\ 0, i \notin T(j) \end{cases}$		$\alpha_{1j} = \begin{cases} \frac{p_1+1-r_1(j)}{c_1 p_1}, i \in T(j) \\ 0, i \notin T(j) \end{cases}$
...	...	...	...	...
D_i	c_i	$\alpha_{i1} = \begin{cases} \frac{p_i+1-r_i(1)}{c_i p_i}, i \in T(j) \\ 0, i \notin T(j) \end{cases}$		$\alpha_{ij} = \begin{cases} \frac{p_i+1-r_i(j)}{c_i p_i}, i \in T(j) \\ 0, i \notin T(j) \end{cases}$

In order to ensure that there is a suitable matching relationship between the demand for rescue services in the disaster-affected areas and volunteer rescue organizations, combined with the allocation model of stable matching [20], the following definition of stable matching will be given:

1. $\exists D_i, D_b \in T, \exists M_j, M_a \in W, \langle D_i, M_a \rangle \in TW, \langle D_b, M_j \rangle \in TW$, satisfying $r_i(j) < r_i(a)$ and $h_j(i) < h_j(b)$;
2. $\exists D_i \in T, \exists M_j, M_a \in W, \langle D_i, M_a \rangle \in TW, \left| [M_j]_M \right| = 0$, satisfying $r_i(j) < r_i(a)$;
3. $\exists D_i, D_b \in T, \exists M_j \in W, \langle D_b, M_j \rangle \in TW, \left| [D_i]_M \right| = 0$ or $0 < \left| [D_i]_M \right| < c_i$, satisfying $h_j(i) < h_j(b)$;
4. $\exists D_i \in T, \exists M_j \in W, \left| [D_i]_M \right| = 0, \left| [M_j]_M \right| = 0$, satisfying $i \in T(j)$ and $j \in W(i)$.

where (1) denotes that rescue demands D_i,D_b are assigned to volunteer rescue organizations M_j,M_a, respectively, and rescue demand D_i has a higher preference for volunteer rescue organization M_j over existing assigned object M_a, and volunteer rescue organization M_j has a higher preference for D_i over existing assigned object D_b; (2) denotes that rescue demand D_i is assigned to volunteer rescue organization M_a, the volunteer rescue organization M_j is unassigned, and rescue demand D_i has a higher mutual preference for M_j but is not paired; (3) indicates that volunteer rescue organization M_j is assigned to rescue demand D_b, rescue demand D_i is unassigned, and rescue demand D_i has a higher mutual preference for rescue organization M_j but is not paired; and (4) indicates that rescue demand D and rescue organization M_j are not assigned to each other, but have a willingness to assign to each other. When any one or more of the above situations occur, then D_i,M_j is said to be an unstable matching pair.

3.3 The fatigue effect of volunteer rescue organizations

Fatigue is a common experience that can greatly impact our quality of life and overall well-being. In work settings, factors like work intensity, speed, psychology, environment, and timing can all contribute to the level of fatigue experienced by employees. For rescue missions specifically, volunteers may experience a decline in performance due to accumulated fatigue, leading to an increased risk of accidents and errors. By implementing a scientifically-designed rescue program, we can help reduce the level of fatigue experienced by volunteer organizations and achieve efficient and effective rescue efforts.

3.3.1 Cumulative fatigue effects of operational loads

The fatigue effect is the deterioration effect resulting from the phenomenon of fatigue, and this deterioration effect was initially applied to the problem of workpiece machining, i.e., as a function of the time at which the workpiece starts to be machined in relation to the position in which it is located [21]. Scholars such as Jaber [22], concerned with the correlation between fatigue and production results, and in order to solve possible problems related to the worker's abilities and limitations in manufacturing environments, proposed the "Learning-Forgetting-Fatigue-Recovery Model" (LFFRM) mathematical model on fatigue effects, considering the repetitive nature of the actions of the volunteers in disaster relief, and therefore combining with the characteristics of the human muscle fatigue [23], fatigue is considered to increase exponentially with time, and in this article the cumulative fatigue effects of the volunteer organization are expressed in the following Eq. (8) Expressed:

$$F(t) = 1 - e^{-\lambda t} \tag{8}$$

where $F(t)$ is the fatigue accumulated at rescue time $t \leq MET$, MET (Maximum Endurance Time Maximum Endurance Time) is the time at which the operator reaches the maximum level of fatigue (i.e., 100%), and when the maximum fatigue level is exceeded, the operator can no longer work. λ is the fatigue exponent, specifying fatigue rate. Where, the fatigue exponent is set to three levels: slow, medium and fast, corresponding to λ=0.01,λ=0.03, λ=0.05 respectively. Setting fatigue curves with different values of λ allows for comparison of the difficulty levels of different rescue missions.

Interrupting the operational process by resting can trigger a recovery state as a link to fatigue [24], so a recovery time function of exponential form is set. Assuming that a volunteer has accumulated a fatigue level of $F(t^{\tau})$ at time $t^{\tau} < MET$, if at this time the volunteer is given a rest time of $t^{\tau+1} - t^{\tau}$, the updated residual fatigue level at $t^{\tau+1}$ is as follows:

$$F\left(t^{\tau+1}\right) = F(t^{\tau})e^{-\mu\left(t^{\tau+1}-t^{\tau}\right)} \tag{9}$$

where μ denotes the fatigue recovery rate, i.e., the rate at which recovery occurs. Formula (9) indicates that the degree of fatigue of a volunteer at each time t depends on the previous task sequence and previous operational performance. And $F(t) \in [0, F_{max}]$, where F_{max} is the maximum fatigue level. Set λ_{ij} as the fatigue accumulation rate of volunteer rescue organization j performing task type i, and μ_j denotes its fatigue recovery rate. Therefore, the fatigue level when volunteer rescue organization j performs task type i in time t^{τ} is shown in the following equation:

$$F_j\left(t^{\tau+1}\right) = min\left(F_j(t^{\tau}) + \left(1 - F_j(t^{\tau})\right)\left(1 - e^{-\lambda_{ij}\left(t^{\tau+1}-t^{\tau}\right)}\right), F_{j,max}\right) \tag{10}$$

The fatigue level at rest when the time window goes from $t^{\tau+1}$ to $t^{\tau+2}$ is then:

$$F_j\left(t^{\tau+2}\right) = max\left(0, F_j\left(t^{\tau+1}\right)e^{-\mu_j\left(t^{\tau+2}-t^{\tau+1}\right)}\right) \tag{11}$$

3.3.2 Rescue skills matching fatigue effect

In addition, emergency volunteer rescue organizations have different rescue skills, and their skill level grades are also differentiated between high and low, and the intensity of rescue operations directly affects the accumulation of individual fatigue, so the matching degree calculation of the skill level mastered by the volunteer rescue organizations and the rescue skills demanded by the victims can reflect the fatigue level caused by the intensity of rescue operations, and the smaller the degree of the match indicates that the greater the intensity of rescue operations, the greater the cumulative value of the fatigue effect. The smaller the matching degree is, the greater the intensity of rescue operation and the greater the cumulative value of fatigue effect. Therefore, the problem of minimizing the cumulative value of fatigue effect is transformed into the problem of minimizing the intensity of rescue operation, which is expressed by the following formula (12):

$$z_{ij} = 1 - \sum_{d=1}^{k} \left(Ur_{id} - a_{jd}\right)^2 / \sum_{d=1}^{k} Ur_{id}^2 \tag{12}$$

where z_{ij} is the matching degree of the volunteer rescue organization M_j to the disaster-affected areas D_i,$z_{ij} \in [0, 1]$, the closer z_{ij} is to 1 means the higher the matching degree, and the closer z_{ij} is to 0 means the lower the matching degree.

3.3.3 Fatigue effect of work timing

Wang and other scholars [25] considered the fatigue level of workers from the perspective of their operating moments and were inspired by the FAID (Fatigue Audit InterDyne) model, which optimized the linear component (the length of the work cycle) and the sinusoidal component (the circadian timing of the work cycle) in the FAID model as a function of the time variation, and through the actual result It is observed that the fatigue increments of workers are different in different work periods, reflecting the differences in workloads in different periods. Therefore, this article combines the above first-order time-varying system to describe the fatigue state of volunteer rescue organizations:

$$\begin{aligned} b_{im} &= b_{i(m-1)} exp\left(Tg_{im}\right) \\ &= b_{i(m-2)} exp\left(Tg_{i(m-1)}\right) exp\left(Tg_{im}\right) \\ &= b_{i0} exp\left(T \sum_{j=1}^{m} g_{ij}\right) \end{aligned} \tag{13}$$

where g_{ij} is the coefficient that represents the fatigue increment or decrement of volunteer rescue organization i during the j rescue mission period, b_{im} is the fatigue state of volunteer rescue organization i at the moment of mT, and T is the sampling period of the fatigue state. In the following, g_{ij} is referred to as the workload coefficient of volunteer rescue organization i during the jth rescue mission period.

Although the fatigue model (13) was able to show that fatigue accumulates faster when volunteer rescue organizations are in a higher state of fatigue under the same workload and was able to reflect changes in the workload of each rescue task, the model was not able to track the changes in fatigue of volunteer rescue organizations under varying workloads, and was therefore based on a fatigue dynamics with conditional weights modified as shown below:

$$b_{im} = b_{i0} exp\left(T \sum_{j=1}^{m} \tilde{g}_{ij}\right) \tag{14}$$

$$\tilde{g}_{ij} = \begin{cases} g_{ij}\phi_u, & if\ b_{ij} > b_u, g_{ij} > 0 \\ g_{ij}\phi_l, & if\ b_{ij} > b_u, g_{ij} < 0 \\ g_{ij}, & otherwise \end{cases} \tag{15}$$

In the modified fatigue dynamic model, the fatigue increment/decrement rate can be adjusted when the fatigue state is higher than the set fatigue state b_u. Since the dynamic model shown in Formula (15) is not linear with respect to the workload coefficients, a logarithm is taken for b_{im}:

$$\ln b_{im} = \ln b_{i0} + T \sum_{j=1}^{m} \tilde{g}_{ij} \tag{16}$$

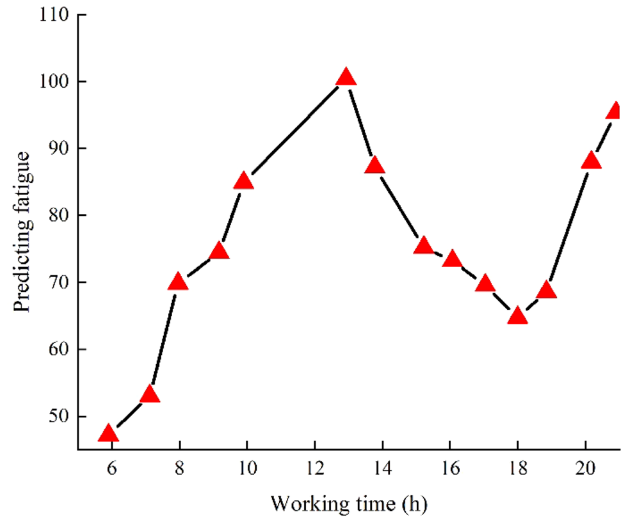

Fig. 3 Simulation of predicted fatigue level

Since this article only considers a single day rescue task for emergency rescue, the rescue service carrying out time is set to be from 07:00 to 20:00 on the same day without considering the rest and recovery process between the same day and the second day, so the workload coefficients of the volunteer rescue organization i in the period of jth rescue task, g_{ij}, are all positive, and the fatigue level simulation diagram is obtained as in Fig. 3:

3.4 Models and constraints

The optimization criterion is defined as the maximum value of the rescue benefit. This entails a comprehensive consideration of both the minimum fatigue effect value of volunteer rescue organizations and the maximum satisfaction of disaster-affected individuals, as depicted in the formula below:

$$max\ E_1 = \sum_{i=1}^{m}\sum_{j=1}^{n}(\xi_1 e^{-t_{ij}^2/\theta_i} + \xi_2\alpha_{ij} + \xi_3 z_{ij}) \cdot x_{ij} \tag{17}$$

$$max\ E_2 = \sum_{i=1}^{m}\sum_{j=1}^{n}\left\{\psi_1 F_j(t^\tau) + \psi_2 Y_e\right\} \cdot (-x_{ij}) \tag{18}$$

$$s.t.\quad x_{ij} + \sum_{k:p_{ik}<p_{ij}} x_{ik} + \sum_{l:q_{lj}<q_{ij}} x_{lj} \geq 1 \tag{19}$$

$$\sum_{j=1}^{n} t_{ij}x_{ij} \leq u_i \tag{20}$$

$$\sum_{i=1}^{m} z_{ij}x_{ij} > 0.5 \tag{21}$$

$$\sum_{i=1}^{m} x_{ij} = 1 \tag{22}$$

$$\sum_{j=1}^{n} x_{ij} \leq s_i \tag{23}$$

$$\ln b_{i0} + T\sum_{j=1}^{m} \tilde{g}_{ij} \leq Y_e \tag{24}$$

$$\sum_{j \notin W(i)} x_{ij} = 0 \tag{25}$$

$$x_{ij} \geq 0, x_{ij} = \{0, 1\} \tag{26}$$

$$0 < t_{ij} \leq 10 \tag{27}$$

$$\theta_i > 0 \tag{28}$$

where ξ_1, ξ_2, ξ_3 are the weighting coefficients of the sub-problems in the satisfaction of the victims E_1, ψ_1, ψ_2 are the weighting coefficients of the sub-problems in the fatigue effect of the volunteer rescue organizations E_2, and $\xi_1 + \xi_2 + \xi_3 = 1$, $\psi_1 + \psi_2 = 1$.

Formula (17) represents the goal of maximizing the satisfaction of the victims; Formula (18) represents the goal of minimizing the fatigue effect of the volunteer organizations, and the negative sign of the equation is transformed into the maximum value for the convenience of calculation; Formula (19) is the quantitative constraint of the bilateral matching between the supply and demand of the emergency relief services; Formula (20) represents the constraint of the time limit of the disaster relief; Formula (21) represents that the volunteer organizations' level of the rescue skills should meet the requirement of 0.5 or above to go to the relief [9]; Formula (22) indicates that each volunteer rescue organization can only go to one disaster-affected areas to carry out rescue services; Formula (23) indicates that the number of volunteer rescue organizations dispatched to a certain disaster-affected areas can not exceed the maximum number of organizations of the disaster-affected areas, and the maximum demand for rescue services is determined by the specific disaster-affected factors; Formula (24) indicates that the fatigue effect of all the volunteer rescue organizations (24) represents the minimum upper bound constraint on the natural logarithm of all volunteer rescue organizations; Formula (25) is that if the disaster-affected place D_i has no preference for the volunteer rescue organization M_j, i.e., the volunteer rescue organization M_j is not in the preference list of the disaster-affected place D_i, the allocation between the disaster-affected place D_i and the volunteer rescue organization M_j cannot be carried out; Formula (26) is the non-negative constraint and 0–1 constraint on the limiting variables; Formula (27) is the time limit of the arrival of the volunteer rescue organization to the disaster-affected place; Formula (28) is the positive constraint on the time sensitivity coefficient.

4 The principle of multi-objective particle swarm optimization algorithm and hybrid gray Wolf particle swarm optimization algorithm

The mathematical model constructed in this article contains two nonlinear objective functions, which are the satisfaction maximization function of the victims and the fatigue minimization function of the volunteer rescue organizations. And the model has quite a number of constraints, mixing integer constraints and non-integer constraints, and is a non-deterministic polynomial time hardness (NP-Hard) model, so conventional exact algorithms and algorithms for single-objective optimization problems cannot be used to solve the above model. NP-hard problems are those that are difficult to solve in polynomial time, and their solution time grows exponentially with the size of the problem, so they

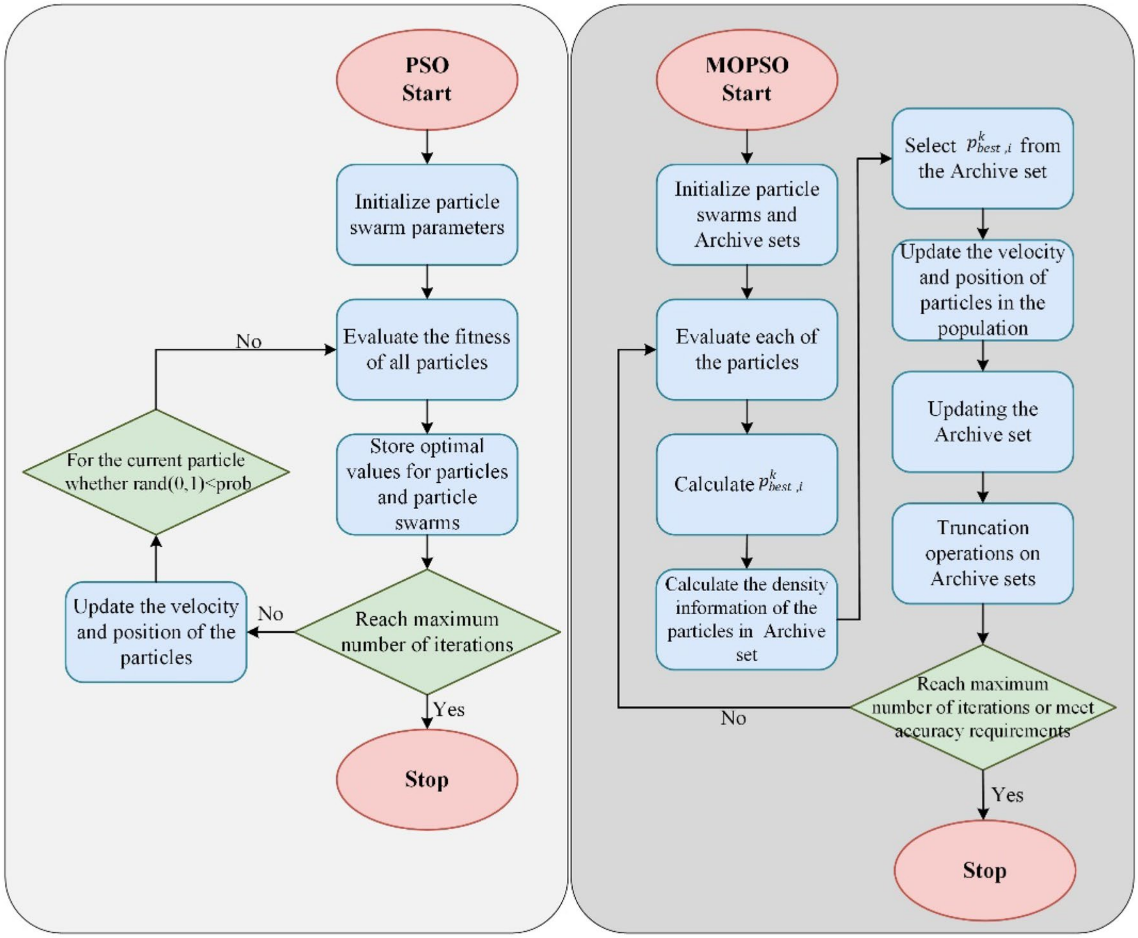

Fig. 4 Flowchart of PSO algorithm (left) and MOPSO algorithm (right)

usually need to be solved using heuristics or approximation algorithms. Therefore, in this article, two multi-objective optimization algorithms, namely multi-objective particle swarm (MOPSO) algorithm and hybrid grey wolf-particle swarm (HGWPSO) algorithm, are used to solve and optimize this problem in order to obtain an excellent scheduling solution from the solved pareto solution. The MOPSO algorithm used in this article evolved from the Particle Swarm Algorithm (PSO), while the HGWPSO algorithm evolved from a mixture of the Gray Wolf Algorithm and the PSO algorithm, which both belong to a kind of meta-heuristic algorithm based on group intelligence. Meta-heuristic algorithms have the advantages of generality, robustness, parallelism, global optimization capability, and ease of extension. They are widely used in various fields due to their ability to solve problems with complex and high-dimensional optimization spaces.

4.1 Multi-objective particle swarm optimization algorithm

Particle Swarm Optimization (PSO) algorithm is a swarm intelligence optimization algorithm inspired by the social cooperation and individual competitive behavior of biological communities such as fish and birds, which solves a single-objective problem by searching for the individual particles' historical optimal positions and the global optimal positions for numerical comparison [26]. However, real-world problems are often optimizations involving multiple objectives, so two scholars, Coello and Lechuga [27], proposed the MOPSO algorithm in 2002.

In the multi-objective optimization problem, there are two doubts that are contrary to the single-objective optimization problem, i.e., how to judge the superiority or inferiority of two particles' $p^k_{best,i}$ in the multi-objective problem and the leadership choice of multiple optimal particle individuals. For the former, the solution of MOPSO algorithm is to randomly

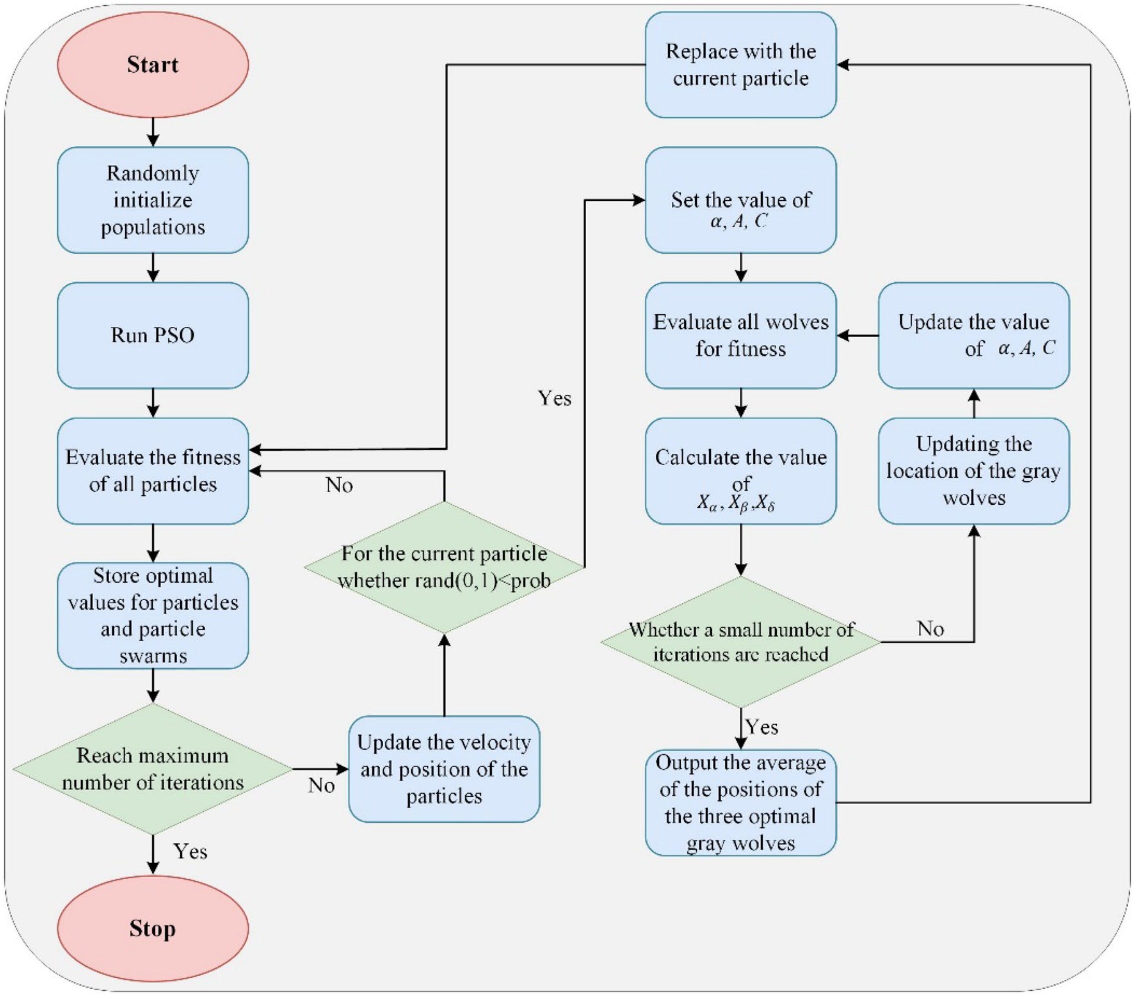

Fig. 5 Flowchart of HGWPSO algorithm

select one of the particles and judge it as the historical optimum when it is impossible to compare which particle is better under strict conditions; for the latter, MOPSO algorithm selects the particle with lower crowding as the leader based on the adaptive lattice method [28] for the optimal set in the Pareto temporary optimal section. The output of the multi-objective optimization problem is a set of non-inferior solutions, and in the iterative process of the population, there are constantly non-dominated solution individuals being stored into the Archive, and when the Archive inventory is full, the problem of retaining the old and new individuals can be judged by using the adaptive lattice method. In summary, the flow chart of PSO algorithm and MOPSO algorithm is shown in Fig. 4 below:

Therefore, this article applies the MOPSO algorithm to solve the bi-objective problem for the volunteer dispatch model, which encodes the volunteers' organization to the disaster-affected areas as position_code bytes, position_pre is the sorting result of the encoded values, position matrix is the specific dispatching method, and cost is the value of the two objective functions, and utilizes the external population archive to Archive to store all the non-dominated solutions, and consider the individuals in the external archive as elite individuals, control the direction of population evolution through the elite individuals, guide the population to approach the real Pareto frontier, and ultimately obtain the set of optimal solutions for volunteer dispatch output by the algorithm.

4.2 Hybrid GRAY Wolf particle Swarm Optimization Algorithm

Although the Gray Wolf Algorithm (GWO) has advantages in terms of search capability, parameter tuning, and tractability, it is obvious that GWO is difficult to cope with multivariate and escape from falling into local optimal solutions when solving high-dimensional optimization problems, therefore, Şenel and other scholars [29] developed a hybrid PSO-GWO optimization algorithm without changing the basic principles of PSO and GWO in order to solve the above mentioned problem. In solving practical optimization problems, PSO algorithms are almost always successful in finding the optimal value, but PSO tends to fall into local minima, while the exploration capability of GWO algorithms is used to direct some particles to the partially improved positions of GWO algorithms instead of directing them to the random positions, and thus avoiding deviation from the global minimum. However, the utilization of the above two heuristics by the HGWPSO algorithm is simple and straightforward, thus leading to longer running time. The flowchart of the HGWPSO algorithm is shown in Fig. 5. The pseudo-code of the HGWPSO algorithm is given below:

```
1: Initialize the population POP
2: Initialize a, A, C and w; %w=0.5+rand()/2
3: Calculate the fitness value of each search grey wolf
4: X_α = the best search grey wolf
5: X_β = the second best search grey wolf
6: X_δ = the third best search grey wolf
7: while (t < Max number of iterations)
8:     for each grey wolf
9:         Update the position and velocity of the current search grey wolf
10:    end for
11:    Update α, A, C and w
12:    Calculate the fitness values of all search grey wolf
13:    Update X_α, X_β and X_δ
14:    t=t+1
15: end while
16: return X_α
17: end
```

Therefore, in this article, we apply the HGWPSO algorithm to solve the volunteer dispatch problem by encoding the volunteers' organization to the disaster site as position_code bytes, position_pre as the sorting result of the encoded values, position matrix as the specific dispatching method, cost as the value of the two objective functions, and Archive as the pareto-optimal solution archive, where bytes are consistent with those in greywolves.

5 Simulation analysis

5.1 Parameterization

This article is based on the 6.8 magnitude earthquake disaster that occurred in Luding County, Ganzi Prefecture, Sichuan Province, China, on September 5, 2022, with the following parameters: five disaster-affected places and seven volunteer rescue organizations. The emergency service requirements of the disaster-affected places are shown in Table 1, and the types of rescue skills of the volunteer rescue organizations are shown in Table 2. Among them, P_1 is the secondary disaster prevention skills, P_2 is the professional rescue guide skills, P_3 is the auxiliary skills for earthquake emergency response, P_4 is the skills for disaster information collection, and P_5 is the skills for evacuation and

Table 1 Demand for emergency services in disaster-affected areas (Ur_{id})

Disaster area	Types of rescue skills				
	P_1	P_2	P_3	P_4	P_5
D_1	III	I	III	II	I
D_2	III	II	III	I	I
D_3	II	III	I	III	II
D_4	I	III	III	II	II
D_5	II	I	III	II	III

Table 2 Types of rescue skills of volunteer rescue organizations (a_{jd})

Volunteer rescue organizations	Types of rescue skills				
	P_1	P_2	P_3	P_4	P_5
M_1	2	3	2	1	1
M_2	2	3	2	2	2
M_3	3	3	1	2	3
M_4	3	2	3	3	3
M	1	2	3	3	3
M_6	2	1	1	1	2
M_7	3	1	2	2	2

Table 3 Time spent by volunteer rescue organizations to arrive (t_{ij})

Disaster area	Volunteer rescue organizations						
	M_1	M_2	M_3	M_4	M_5	M_6	M_7
D_1	2.20	3.21	2.49	1.48	2.43	1.28	2.56
D_2	1.95	1.28	1.80	2.02	3.04	3.07	1.52
D_3	3.14	1.88	2.69	1.46	3.11	2.88	3.18
D_4	1.52	2.20	3.55	3.41	1.94	2.70	2.85
D_5	2.88	1.57	2.71	1.64	1.65	1.67	2.92

resettlement of disaster victims. The optimal rescue time for each disaster site is U = {4.4,3.7,5.5,6.8,4.6} hours. The time taken by each volunteer rescue organization to travel to the disaster site is shown in Table 3 below in hours (h).

5.2 Model solution

The whole simulation and algorithm is implemented in MatlabR 2022b version on Microsoft Windows 10 with 64 bits Core i-7 processor with 1.80 GHz and 8 GB of main memory. The parameters of the MOPSO algorithm are set as follows: the maximum number of iterations is 100, the number of particles in a single iteration is 100, the Pareto optimal solution set archive is 100, the inertia weights are 0.9, the inertia weight decay rate is 0.99, the individual learning coefficient is 2, the global learning coefficient is 2, the number of meshes per dimension is 7, the mesh expansion parameter is 0.1, the leader selection pressure is 1.5, the Deletion selection pressure is 1.2, and the variation rate is 0.01; the parameters of the HGWPSO algorithm are set as follows: the maximum number of iterations is 100, the number of gray wolves is 50, the amount of Pareto optimal solution set storage is 20, the grid expansion parameter is 0.1, the number of grids in each dimension is 10, the leader selection pressure is 4, and the deletion selection pressure is 2.

Based on z_{ij}, the matching results of the rescue skills of each volunteer rescue organization for each disaster-affected areas can be obtained as shown in Table 4, and the closer the value is to 1, the more suitable the volunteer

Table 4 Rescue skills matching results (z_{ij})

Disaster area	Volunteer rescue organizations						
	M_1	M_2	M_3	M_4	M_5	M_6	M_7
D_1	0.708	0.708	0.500	0.750	0.583	0.708	0.917
D_2	0.875	0.792	0.583	0.667	0.500	0.708	0.833
D_3	0.778	0.926	0.889	0.741	0.741	0.704	0.741
D_4	0.852	0.926	0.667	0.741	0.889	0.630	0.667
D_5	0.630	0.778	0.667	0.889	0.889	0.778	0.889

rescue organization is to be dispatched to the disaster-affected areas to carry out rescue activities, and the lower the cumulative fatigue value of the rescue organization is.

5.3 Solution results considering the satisfaction of victims

First, the existence of robustness of the Pareto solution to the bi-objective optimization problem when only the time sensitivity coefficient θ_i is varied is considered. The solution results of the two algorithms are shown in Fig. 6. Setting λ = 0.01, when θ_i=5, the average value of the objective function E1 in the set of pareto solutions is smaller, and the decrease of pareto solutions is larger, which is the time pressure effect caused by the smaller θ_i, and the victim's time sensitivity is a smaller value means that their demand for quick access to emergency services is more urgent; when θ_i=20, the average value of the objective function E1 in the set of pareto solutions increases significantly, which confirms that when the time sensitivity coefficient θ_i increases, the urgency of the victims for the current need for rescue decreases, i.e., the time pressure effect of the victims decreases, and at this time, despite the increase in the time of obtaining the emergency services, the victims' satisfaction is not significantly reduced; when θ_i=30, the number of pareto solutions increases significantly, and the time pressure effect is reduced. When θ_i=30, the number of pareto solutions becomes less, and the range of changes in the average value of the objective function E1 decreases, indicating that with the increase of the time sensitivity coefficient θ_i, its impact on the objective function E1 has a decreasing tendency, and there is a phenomenon of diminishing marginal benefit, and even if there is a situation in which the θ_i is infinitely large, its ability to influence the satisfaction of the victims cannot be infinitely large.

The above situation can be explained by trying to use the following three reasons: (1) Urgency needs: In a disaster event, the victims are faced with emergencies such as life safety and property damage, so they are very concerned about the speed of access to emergency services. The less time-sensitive victims are in more urgent need of timely rescue, medical care, infrastructure repair and other services to mitigate the impacts of the disaster; (2) Psychological stress and anxiety: Disaster events can lead to an increase in psychological stress and anxiety among the victims. Less time-sensitive victims may have increased anxiety due to the fear of not being able to access emergency services in a timely manner, and are therefore more time-sensitive; (3) Limited relief resources: after a disaster, emergency relief resources are usually in short supply. Less time-sensitive victims may realize that rescue resources are limited, and therefore more urgently want to obtain emergency services as early as possible. Understanding and considering the time pressure effect is very important for emergency service planning and implementation, which can help decision makers to rationally allocate resources and improve response speed, so as to better meet the needs of the victims.

Secondly, sorting the matching results of rescue skills in Table 4 can obtain the preference sequence of the affected place to the volunteer rescue organization, and the satisfaction matrix of the affected place is obtained as shown in Tables 5 and 6 by considering the two cases when c_i=1 and c_i=C = {1,2,2,1,1}:

Obtaining the Pareto solution is shown in Fig. 7:

When c_i=1, the number of volunteer rescue organizations required by the disaster site D_i is the same and all of them are 1, and a single volunteer rescue organization is able to satisfy all the rescue needs of the disaster site. Observing the left graph, we can see that the mean value of the objective function E1 is slightly higher than that of the right graph, which may be due to the small scale of the disaster and the unstrained demand for rescue services in the disaster-affected areass; when $c_i = C$, the number of volunteer rescue organizations needed in each disaster-affected areas D_i varies, and the mean value of the objective function E1 slightly decreases compared with that of the left graph, which may be due to the limited number of volunteer rescue organizations and inconsistent proportion of the distribution of the dispatching theme. However, comparing the left and right graphs, it is found that the range of changes in the mean values of the objective function E1 and the objective function E2 is not large, so the preference of the victims has little effect on the satisfaction. In addition, by analyzing the solution results in all cases, it is obtained that the stable matching groups are: $\langle D_1, M_5\rangle$,$\langle D_3, M_1\rangle$,$\langle D_4, M_2\rangle$, and the rest are unstable matching groups.

5.4 Solution results considering fatigue effects

In this section, the influence of different values of the fatigue accumulation exponent λ on the fatigue effect is considered, and the Pareto front surface is shown in Fig. 8.

When $\lambda = 0.01$, the degree of fatigue accumulation is slow, the speed of accumulation of fatigue degree of volunteer rescue organizations in the process of rescue services is at a slower level, and the absolute value of the mean of the objective function E2 is small, which represents that under the condition of slower fatigue accumulation, the fatigue degree of the volunteer rescue organizations due to the rescue services is low, and the rescue organizations are able to participate in the rescue services while maintaining a good mental and health status; when $\lambda = 0.03$, the speed of accumulation of fatigue degree of volunteer rescue organizations in the process of rescue service is at a medium level, at this time, the absolute value of the mean of the objective function E2 is increasing rapidly, which represents the acceleration of the accumulation rate of the fatigue effect of the volunteer rescue organizations, combined with the obtained dispatching scheme, the dispatching scheme with the largest absolute value of the mean of the objective function E2 in the condition is the one that takes the longest time to dispatch. The dispatch program with the largest absolute value of the mean value of the objective function E2 under this condition is the program with the longest dispatching time, so the accumulation of the fatigue effect of the volunteers has a certain correlation with the dispatching time; when $\lambda = 0.05$, the fatigue effect of the volunteer rescue organization accumulates faster, and the absolute value of the mean value of the objective function E2 reaches the maximum level at this time, and it is more easy for volunteer rescue organizations to feel fatigue in the process of rescuing and negatively affects the performance of their rescue services. Specifically, as fatigue increases, individuals in volunteer rescue organizations may experience the following changes: (1) decreased attention, difficulty in maintaining focus and concentration, which may affect work accuracy and efficiency; (2) decreased responsiveness, decreased ability to handle emergencies, which may affect work safety and emergency response; (3) decreased learning ability, increased fatigue may lead to a decrease in information processing and memory abilities, reducing learning effectiveness and knowledge accumulation; (4) increased error rates, fatigue affects decision-making and judgment abilities and may lead to incorrect behaviors or decisions, which may negatively affect work outcomes.

Since the pareto solution is a non-dominated solution, the rescue efficiency formula is introduced to compare the rescue benefits of each dispatch result, as shown in Table 7:

From the above table, it can be seen that with the increase of fatigue exponent λ, the mean value of fatigue of volunteer rescue organizations increases significantly, while the satisfaction of the victims does not show significant changes, so it can be considered that the fatigue exponent λ is [0.01,0.03,0.05] three values of the satisfaction of the victims has less impact. In the results of MOPSO algorithm solution, when $\lambda = 0.01$, Program 5 performs better in terms of rescue duration and satisfaction, which is the best choice among all the programs, Program 4 performs worse in terms of fatigue value and satisfaction, which is the worse choice among all the programs, and the rescue duration of Program 1 is the longest, but the benefit is not the highest, which indicates that the rescue efficiency can be further improved; continue to compare $\lambda = 0.03$ and $\lambda = 0.05$ when obtaining the dispatching options, the following conclusions can be drawn: option 5 still performs well under different fatigue accumulation indices, especially in terms of rescue duration and satisfaction of the victims, and option 8 shows the shortest rescue duration at $\lambda = 0.05$. Therefore, based on the comprehensive analysis, either Option 5 or Option 8 can be considered as the preferred option, as shown in Table 8 below, and further evaluated and adjusted in light of the specific needs and circumstances.

In the results of the HGWPSO algorithm solution, λ is 0.01, the rescue benefit of result b is the highest, and the rescue benefit of result c is the lowest. Result b performs similarly to result 5 in terms of rescue benefit and has a mean value of 2.1603, which is also closer to the results solved by result 5; $\lambda = 0.03$, result d has the highest rescue benefit and result a has the lowest rescue benefit, and compared with λ is 0.01, result b's rescue benefit decreases slightly, while result d's rescue benefit improves significantly; When $\lambda = 0.05$, result e has the highest rescue benefit and result d has the lowest rescue benefit. Compared with the previous results, the performances of result e and result f show some changes, especially the performance of scheme e in rescue benefit is improved, while the performance of scheme d shows a significant decrease. Comparing the results obtained by solving the two algorithms, it can be seen that they basically come to the same conclusion, i.e., as λ increases, the performance of certain results will change.

In the optimization process of the above multi-objective optimization problem using MOPSO and HGWPSO algorithms, both algorithms show their respective advantages and disadvantages. MOPSO algorithm can effectively solve multi-objective optimization problems, obtain a set of non-inferiority solution set, which has better searchability and convergence, obtains a more balanced and diversified solution, and can cope with the complex search space, which is suitable for a variety of optimization problems, but when dealing with high dimensional problems, the average computation time may be reduced by 25.4063 s. However, it may be affected by dimensional catastrophe when dealing with high-dimensional problems, and the search efficiency may decrease, and the average computation time in this case is 25.4063 s. Moreover, MOPSO is sensitive to the selection of initial parameters and needs to tune the parameters to obtain better performance. In addition, MOPSO may not perform well in solving non-convex and discontinuous problems, and there is a local optimal solution problem; The HGWPSO algorithm combines the advantages of PSO and GWO, has better global and local search ability, and can quickly converge to the near-optimal solution, and achieves a good balance between the search performance and convergence, in addition, the HGWPSO is relatively insensitive to the selection of parameters, which reduces the complexity of the parameter tuning, but there is a precocious convergence problem, i.e., it converges to the locally optimal solution rather than to the global optimal solution, and when dealing with high-dimensional problems, it may face the problem of decreased search efficiency due to the increase of the search space, and the average computation time in this case is 98.4115 s. In addition, HGWPSO may likewise perform poorly when dealing with complex constraints and non-convex problems, which requires further improvement and optimization. The shorter algorithm computation time is more reasonable and feasible as the focus needs to be on the execution speed and efficiency of the algorithm in emergency situations. In summary, the MOPSO algorithm is more suitable than the HGWPSO algorithm for solving emergency dispatch scenarios. Although the MOPSO algorithm has a shorter computation time, it still needs to be evaluated comprehensively based on the characteristics of the specific problem, constraints, and the quality of the solution to ensure that the selected algorithm can provide a fast and feasible dispatch solution in emergency situations.

6 Conclusions

6.1 Managerial insights

Section 5.3 discusses the scheduling scheme that takes into account the satisfaction of the victims of the disaster and concludes that there is an increasing trend in the satisfaction of the victims of the disaster as the time sensitivity coefficient rises. It is important to note that in reality the urgency requirements for relief services are different for each disaster site, thus leading to inconsistent time sensitivity for each site. For those disaster areas where the need for relief is less urgent, their time sensitivity factor is greater, so the emergency response center can give priority to dispatching volunteer relief organizations to those disaster areas where relief services are urgently needed. But in any case, volunteer rescue organizations should arrive at the disaster site and provide rescue services within the best possible rescue time.

In addition, Sect. 5.3 considers scheduling solutions when there is variability in the number of volunteer organizations needed to provide relief services at the disaster site, and solved for several pairs of affected sites and volunteer rescue organizations that could be stably matched. This means that these affected places are assigned to the most appropriate relief organizations, and these relief organizations are assigned to the most appropriate affected places. This can provide the following rare insights into emergency management: (1) By understanding the needs of the disaster-affected areas and the skill level of volunteer rescue organizations, we can better optimize the allocation of rescue resources and improve the efficiency of rescue and the satisfaction of the victims. (2) Multiple matches between disaster-affected sites and volunteer organizations (e.g., a disaster-affected site needs the support of multiple volunteer relief organizations) should be taken into account when matching and maximize stable matches during multiple matches. (3) Stable matching algorithms can be applied to different scenarios, such as rescue, employment, marriage and other fields. Therefore, managers can further develop and improve the matching algorithms to adapt to different applications.

Section 5.4 conducts a study on how fatigue effects affect scheduling programs and concludes that as fatigue accumulates at an accelerated rate in volunteer organizations, the level of fatigue tends to increase. At the same time, the calculated value of rescue benefit E was introduced to select the most appropriate volunteer organization scheduling plan by combining the characteristics of the bi-objective function. An increase in the fatigue cumulative exponent will lead to a rise in the fatigue value of volunteers. When volunteers engage in high-intensity rescue work

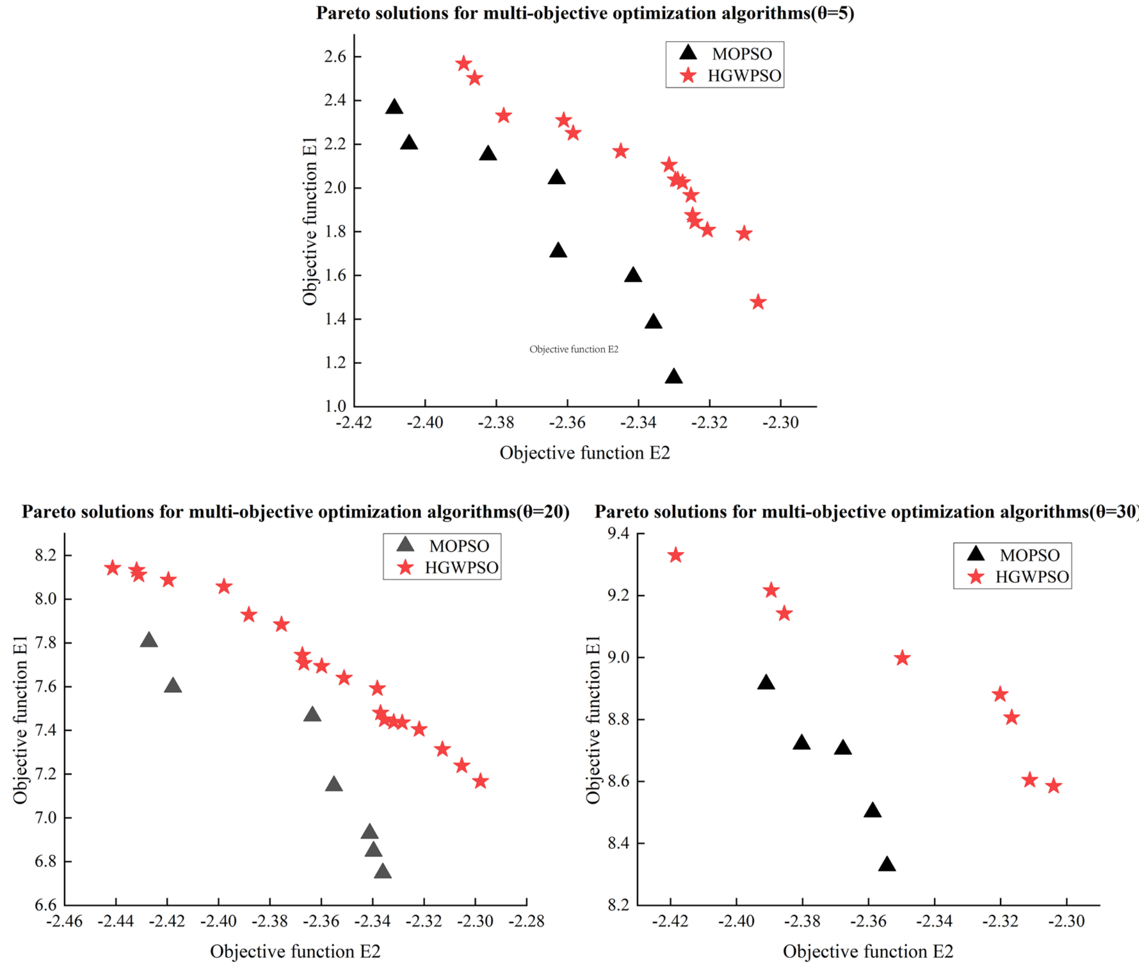

Fig. 6 Pareto solution considering time sensitivity coefficient θ_i

for a long period of time, their physical and mental state may be under great pressure, leading to the accumulation of fatigue. If the fatigue value is too high, volunteers may suffer from physical exhaustion, lack of concentration, and slow reaction time, which may affect their work efficiency and concentration, and may even increase the risk of errors and accidents at work. Management insights include the following: (1) Plan reasonable work schedules and rotation systems: to reduce volunteer fatigue, managers can develop reasonable work schedules and rotation systems to ensure that volunteers have sufficient rest time and opportunities for recovery. (2) Provide psychological support and training: Managers can provide psychological support and training courses to help volunteers cope with stress and fatigue at work and provide methods and techniques to cope with fatigue. (3) Advocating teamwork and mutual assistance: Encourage volunteers to support and collaborate with each other, and distribute work tasks reasonably to avoid over-fatigue or over-burdening of certain volunteers. (4) Monitor and assess fatigue levels: Establish an effective fatigue monitoring mechanism to keep abreast of volunteers' fatigue status and make appropriate adjustments and management measures based on the monitoring results. To sum up, managers should pay attention to the fatigue management of volunteers in volunteer rescue organizations, and reduce the fatigue of volunteers and improve their work efficiency and satisfaction through reasonable work arrangements, psychological support and teamwork.

Finally, two algorithms, MOPSO and HGWPSO, are utilized in this article to solve the model. In terms of solution speed, MOPSO's has an advantage over HGWPSO in terms of optimization speed in this case. Algorithm runtime is of great importance in emergency management. Following are some aspects related to emergency management that show the importance of algorithm runtime: (1) Emergency response speed: time is critical in emergency situations. Making decisions and taking action quickly can minimize damage and save more people. If algorithms take too long to run, this can lead to a delayed response and delays in taking the necessary action. (2) Resource allocation optimization: emergency management involves the rational allocation of limited resources to meet demand. With efficient algorithms, factors can be evaluated in a short period of time and optimal resource allocation schemes can be developed for different tasks and demands. Rapidly calculating the optimal solution can better meet emergency needs and improve the efficiency of resource utilization. (3) Risk assessment and decision support: in emergency management, it is necessary to assess risks and make corresponding decisions based on the assessment results. Faster algorithms can accelerate the risk assessment process and provide decision makers with timely and accurate information to help them develop appropriate measures and response strategies. (4) Data analysis and prediction: processing and analyzing large-scale data is crucial for emergency management. With efficient algorithms, large amounts of data can be processed faster and useful information and insights can be extracted from it to support emergency response decisions and predict future scenarios. Therefore, the runtime of algorithms has a direct impact on the efficiency and outcomes of emergency management. Fast and efficient algorithms can help emergency management organizations better respond to emergencies by providing real-time data support and decision-making guidance to maximize the protection of people's lives and property. However, HGWPSO outperforms MOPSO in terms of global optimization. Global optimization search has important implications for emergency management. The following are the significance of global optimality seeking aspects of algorithms for emergency management: (1) Optimal Resource Allocation: in emergency management, proper allocation and utilization of resources is crucial. Global optimization seeking algorithms can help determine the optimal resource allocation scheme to achieve the best results in emergency response tasks. Through the HGWPSO optimization algorithm, a solution closer to the optimal solution can be found in a wider search space, thus improving the utilization efficiency of resources. (2) Decision support for emergency response: in the face of an emergency situation, a quick decision needs to be made in order to take the right action. Global optimization algorithms can help emergency managers obtain as comprehensive information as possible through a comprehensive search of the problem space, and provide multiple alternative optimal solutions to support emergency response decision-making. (3) Risk assessment and planning: global optimization algorithms can be applied to the risk assessment and planning process. It can help identify potential risk factors, evaluate the effectiveness of various response measures, and find the optimal planning solution to reduce risk or lower losses. In emergency management, timely global optimization can help to quickly identify risks and develop corresponding preventive measures. (4) Rescue path planning: in emergency rescue, it is very critical to determine the best rescue path. The global optimization algorithm can find the shortest and optimal rescue path by considering various factors, such as geographic conditions, traffic conditions, and resource distribution. This helps to improve the efficiency of rescue, reduce the response time, and maximize the rescue of victims. Therefore, different optimization algorithms should be used as much as possible in emergency management to obtain more scheduling solutions, and these solutions should be compared in various dimensions (e.g., rescue time, rescue efficiency, etc.) and selected from among them, so as to ensure that the emergency rescue is accomplished in an efficient and orderly manner.

6.1.1 Future research

For the satisfaction of the disaster victims at the disaster site, this article constructs functions in terms of rescue time sensitivity and preference. In addition to the above factors, the following factors may affect the satisfaction of disaster victims: (1) Fairness in the distribution of relief resources: disaster victims are concerned about the fairness of the distribution of relief resources. If relief resources are allocated to the victims in a reasonable and fair manner, without favoritism or corruption, then the satisfaction of the victims may be higher. (2) Information transparency: in the event of a disaster, the provision of accurate, timely, and transparent information is very important to the victims. If the victims can be provided with relevant information about the disaster situation, relief progress, and allocation of relief resources, so that they can understand the specifics of the relief operation, it may help to increase satisfaction. (3) Post-disaster reconstruction support: the victims need to be provided with appropriate reconstruction support after a disaster, including housing reconstruction, employment opportunities, education, and healthcare. If effective reconstruction support can be provided to help the victims resume normal life and work, they may be more satisfied. The combination of these factors will have an impact on the satisfaction of the victims. Post-disaster relief work needs to take the above factors into account in a comprehensive manner to ensure the effectiveness, fairness and humanization of relief actions in order to better meet the needs of the victims and enhance their satisfaction.

In the meantime, it is also worthwhile to further consider how to avoid the problem of too much subjectivity in portraying the satisfaction of disaster victims with functions, and further research can be carried out in the following dimensions: (1) Multi-dimensional indicators: evaluation indicators for the satisfaction of disaster victims can be

Table 5 Matrix of satisfaction with volunteer relief organizations in affected areas ($c_i = 1$)

Disaster area	Volunteer rescue organizations						
	M_1	M_2	M_3	M_4	M_5	M_6	M_7
D_1	0.500	0.167	0.250	0.750	0.083	1.000	0.917
D_2	1.000	0.500	0.917	0.250	0.167	0.083	0.583
D_3	0.917	0.417	0.833	1.000	0.333	0.167	0.750
D_4	0.083	0.917	0.667	1.000	0.167	0.417	0.333
D_5	0.750	0.667	0.500	0.083	0.917	0.583	0.250

Table 6 Matrix of satisfaction with volunteer relief organizations in affected areas ($c_i = C$)

Disaster area	Volunteer rescue organizations						
	M_1	M_2	M_3	M_4	M_5	M_6	M_7
D_1	0.500	0.167	0.250	0.750	0.083	1.000	0.917
D_2	0.500	0.250	0.458	0.125	0.083	0.042	0.292
D_3	0.458	0.208	0.417	0.500	0.167	0.083	0.375
D_4	0.083	0.917	0.667	1.000	0.167	0.417	0.333
D_5	0.750	0.667	0.500	0.083	0.917	0.583	0.250

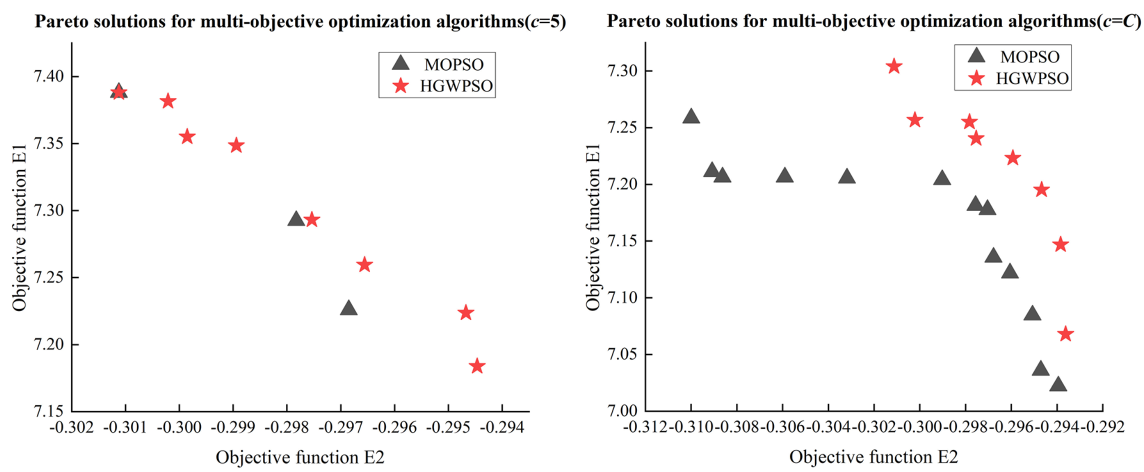

Fig. 7 Pareto solution considering preference satisfaction

decomposed into multiple dimensions, such as rescue effect, fairness in resource distribution, transparency of information, and reconstruction support, etc. Each dimension can be assessed quantitatively using objective indicators, such as the quantity and quality of food and medical services provided. Each dimension can be quantitatively assessed using objective indicators, e.g., rescue effectiveness can be measured using the quantity and quality of food and medical services provided, etc. (2) Weight setting: for the evaluation indicators of multiple dimensions, reasonable weights can be set for each indicator according to the actual situation and professional knowledge. The weights can be set through expert consultation, questionnaires, etc., so as to make the weights as objective and representative as possible. (3) Data collection: collect relevant data to support the evaluation of the satisfaction of the victims. Data samples can be obtained through questionnaires, interviews, statistical data, etc. to provide objective support. (4) Statistical analysis: statistical analysis can be conducted with the collected data, including mean, standard deviation, correlation analysis, etc., to identify the degree of influence of different factors on the satisfaction of disaster-victims. (5) Modeling: based on the collected data and the results of the statistical analysis, mathematical models can be set up to describe the satisfaction function of the disaster-victims. Satisfaction function of the victims. Regression analysis, multivariate analysis and other methods can be used to build the model, and prediction and assessment can be made based on the model. It should be noted that although subjectivity can be reduced through the above methods, there are still certain subjective factors in

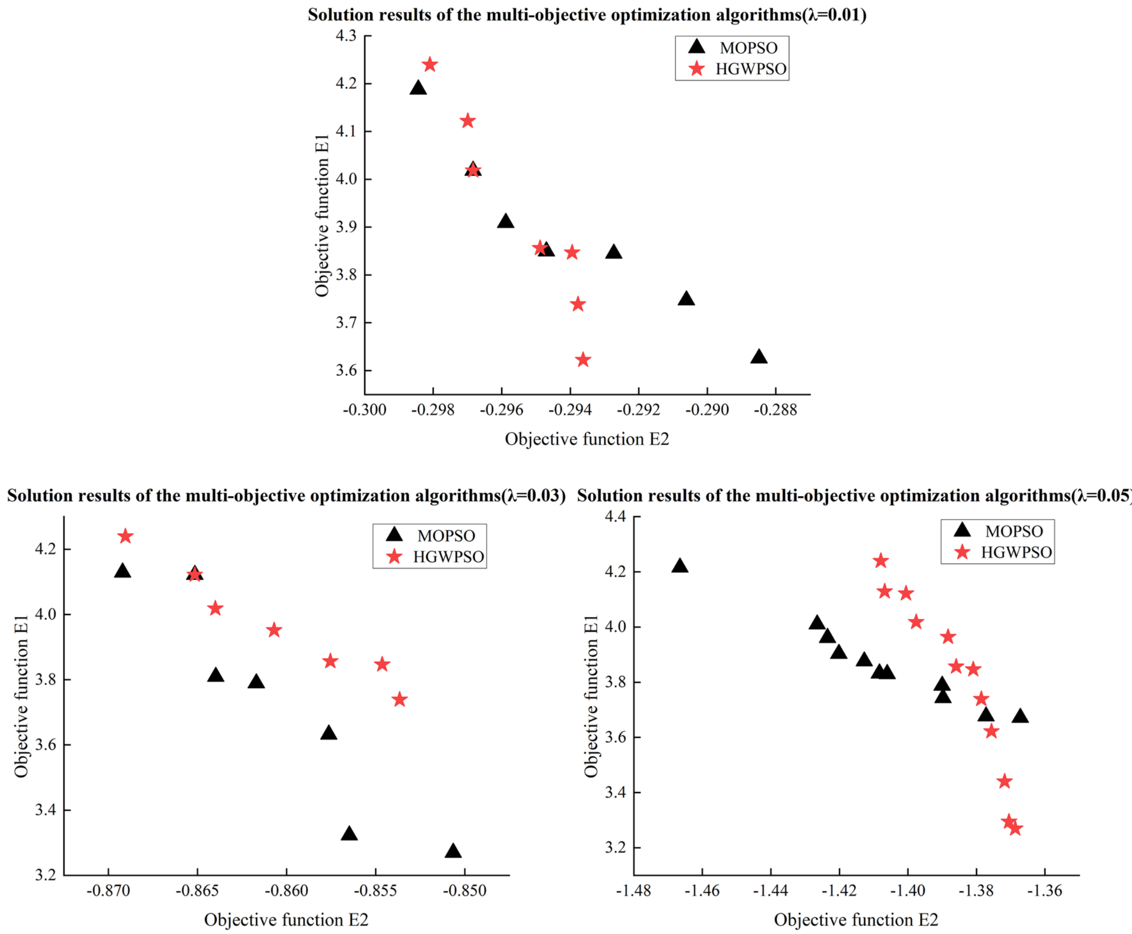

Fig. 8 Pareto solution considering fatigue accumulation indices

evaluating the satisfaction of the victims. Therefore, when designing the evaluation system, the needs and opinions of different groups should be taken into account as much as possible, and the voices of the victims should be fully heard and reasonably weighed and synthesized. At the same time, a continuous feedback mechanism and improvement measures are also key to ensure the scientific and accurate nature of the evaluation system.

For volunteer rescue organizations, the level of fatigue is affected by common factors such as the environment of the rescue work, psychological stress, staffing and cooperation, in addition to the intensity of the rescue work and the length of the rescue service. Understanding these factors helps volunteer rescue organizations take measures to reduce the fatigue level of volunteers, such as rationalizing working hours and rest, providing necessary psychological support, providing appropriate training and skill enhancement opportunities, and strengthening teamwork. The physical and mental health of volunteers is an important factor in guaranteeing the effectiveness of rescue operations and deserves attention and care. All mentioned above can be the future research direction for further volunteer rescue organization scheduling problems.

In this article, the MOPSO algorithm is used to solve the problem model, which confirms that the algorithm plays a certain role in emergency rescue, mainly in the optimization of multi-objective, the allocation of human resources in emergency rescue and the scheduling of rescue tasks. Through the evolution and iterative optimization of particle swarm, a set of excellent solutions can be found to provide diversity and flexibility for emergency rescue decision-making. In addition to the emergency response field, MOPSO can also be used in transportation planning, production scheduling, energy management and other fields. However, the MOPSO algorithm can be further optimized in terms of changing the particle swarm initialization strategy, introducing diversity maintenance mechanism, optimizing crossover and mutation operations, considering constraints handling, and adopting adaptive parameter tuning. Innovations can also be attempted by combining other optimization techniques. This can further improve the performance and effect of MOPSO algorithm on multi-objective optimization problems.

Table 7 Results of rescue time, victims' satisfaction, volunteers' fatigue and rescue effectiveness

	MOPSO					HGWPSO				
	Result	Time	Fatigue	Satisfaction	E	Result	Time	Fatigue	Satisfaction	E
λ = 0.01	1	19.89	0.296	4.018	2.225	a	16.35	0.293	3.738	2.059
	2	16.47	0.292	3.844	2.113	b	15.31	0.293	3.622	1.993
	3	16.47	0.294	3.849	2.116	c	19.89	0.296	4.018	2.225
	4	18.59	0.288	3.625	2.017	**d**	**19.06**	**0.298**	**4.239**	**2.330**
	5	**15.63**	**0.298**	**4.188**	**2.280**	e	17.62	0.296	4.121	2.261
	6	18.59	0.290	3.747	2.079	f	17.79	0.294	3.856	2.128
	7	16.72	0.295	3.909	2.148	g	14.96	0.293	3.846	2.103
	AVE	17.48	0.293	3.883	2.139	AVE	17.39	0.295	3.924	2.160
λ = 0.03	**1**	**18.87**	**0.869**	**4.129**	**2.416**	a	14.96	0.854	3.846	2.243
	2	18.4	0.863	3.809	2.252	b	16.35	0.853	3.738	2.199
	3	17.62	0.865	4.121	2.403	c	17.79	0.857	3.856	2.269
	4	16.84	0.857	3.632	2.150	d	18.19	0.860	3.952	2.321
	5	13.60	0.856	3.322	1.972	**e**	**19.06**	**0.869**	**4.239**	**2.473**
	6	14.85	0.850	3.269	1.953	f	17.62	0.865	4.121	2.403
	AVE	16.53	0.860	3.724	2.195	AVE	17.69	0.860	3.967	2.325
λ = 0.05	**1**	**17.33**	**1.466**	**4.216**	**2.598**	a	14.96	1.380	3.846	2.375
	2	16.17	1.412	3.876	2.406	b	17.62	1.400	4.121	2.536
	3	15.39	1.408	3.832	2.378	c	15.79	1.371	3.440	2.176
	4	18.83	1.390	3.787	2.375	d	16.63	1.370	3.294	2.108
	5	16.00	1.420	3.903	2.420	e	19.89	1.397	4.018	2.500
	6	17.12	1.426	4.010	2.483	f	14.85	1.368	3.269	2.083
	7	16.70	1.389	3.743	2.338	g	17.79	1.385	3.856	2.401
	8	13.62	1.406	3.830	2.363	h	16.40	1.388	3.964	2.446
	9	16.05	1.423	3.961	2.451	**i**	**18.87**	**1.406**	**4.129**	**2.551**
	AVE	16.41	1.411	3.883	2.411	AVE	16.81	1.384	3.756	2.344

Bold font shows the results of obtaining the optimal rescue benefit under the conditions of the two algorithms

Table 8 Results of MOPSO solving

Result	Disater area	Volunteer rescue organizations						
		M_1	M_2	M_3	M_4	M_5	M_6	M_7
Result 5	D_1	0	0	1	0	0	0	0
	D_2	0	0	0	0	1	0	0
	D_3	0	1	0	0	0	0	1
	D_4	0	0	0	1	0	0	0
	D_5	1	0	0	0	0	1	0
Result 8	D_1	0	0	1	0	0	0	0
	D_2	0	0	0	0	1	0	0
	D_3	0	1	0	0	0	0	1
	D_4	0	0	0	1	0	0	0
	D_5	1	0	0	0	0	1	0

The HGWPSO algorithm used in this article is a serial combination of GWO and PSO. This approach utilizes the features of both algorithms and can combine the advantages of GWO and PSO to some extent, however, the algorithm is slightly inferior to MOPSO in terms of solution speed. And the reality of emergency rescue requires the algorithm to respond quickly. In the next step of the study, the addition of adaptive strategies, such as dynamic adjustment of the number of iterations, parameter variations, etc., can be considered to further improve the convergence speed and optimization performance. In addition, it is also possible to try to adjust the ratio relationship between GWO and PSO according to the characteristics of the problem.

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Data availability Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Declarations

Competing interests The authors report there are no competing interests to declare.

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