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RESEARCH

Design and Application of Vague Set Theory and Adaptive Grid Particle Swarm Optimization Algorithm in Resource Scheduling Optimization

Yibo Han · Pu Han · Bo Yuan · Zheng Zhang · Lu Liu · John Panneerselvam

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Abstract The purpose of resource scheduling is to deal with all kinds of unexpected events that may occur in life, such as fire, traffic jam, earthquake and other emergencies, and the scheduling algorithm is one of the key factors affecting the intelligent scheduling system. In the traditional resource scheduling system, because of the slow decision-making, it is difficult to meet the needs of the actual situation, especially in the face of emergencies, the traditional resource scheduling methods have great disadvantages. In order to solve the above problems, this paper takes emergency resource scheduling, a prominent scheduling problem, as an example. Based on Vague set theory and adaptive grid particle swarm optimization algorithm, a multi-objective emergency resource scheduling model is constructed under different conditions. This model can not only integrate the advantages of Vague set theory in dealing with uncertain problems, but also retain the advantages of adaptive grid particle swarm optimization that can solve multi-objective optimization problems and can quickly converge. The research results show that compared with the traditional resource scheduling optimization algorithm, the emergency resource scheduling model has higher resolution accuracy, more reasonable resource allocation, higher efficiency and faster speed in dealing with emergency events than the traditional resource scheduling model. Compared with the conventional fuzzy theory emergency resource scheduling model, its handling speed has increased by more than 3.82 times.

Keywords Resource scheduling · Vague set theory · Particle swarm optimization algorithm · Model · Multi objective

Y. Han
Nanyang Institute of Big Data Research, Nanyang Institute of Technology, Nanyang 473004, China
e-mail: hanyibo@nyist.edu.cn

P. Han
School of Information Engineering, Nanyang Institute of Technology, Nanyang 473004, China
e-mail: hanpu@nyist.edu.cn

B. Yuan · L. Liu · J. Panneerselvam
Department of Informatics, University of Leicester, University Rd, Leicester LE1 7RH, UK
e-mail: b.yuan@leicester.ac.uk

L. Liu
e-mail: l.liu@leicester.ac.uk

J. Panneerselvam
e-mail: j.Panneerselvam@leicester.ac.uk

Z. Zhang (✉)
School of Computer and Software, Nanyang Institute of Technology, Nanyang 473004, China
e-mail: zhangzheng@nyist.edu.cn

1 Introduction

In recent years, with the rapid growth of population and the rapid rise of urbanization, a number of intelligent technologies have emerged to meet people's growing daily needs, including human resources, logistics, transportation, security and finance [1]. On this basis, people's demand for various social resources has seen an overall growth, in which both the allocation of social resources and the demand for resources by major enterprises are gradually increasing, which further intensifies the optimization of resource scheduling by society and enterprises, especially in the face of some unexpected events, such as the outbreak of SARS in China in 2002 [2, 3], The Wenchuan earthquake that occurred in China on May 12, 2008 [4], and the worldwide novel coronavirus [5, 6] in 2019 have all seen a substantial increase in demand for growth of most social resources, including medical resources, social security resources, food resources, etc. [7]. In order to reduce the impact of disasters on people's production and life, reduce personnel injuries after disasters, and ensure the timeliness and efficiency of post disaster rescue, how to improve the allocation efficiency and utilization of related resources, build an effective scheduling model, and design efficient algorithms to reduce resource allocation time has become one of the hot issues in the current academic community.

In order to reduce the impact of disasters and provide rapid and effective response for emergency rescue after disasters, many researchers have proposed different emergency decision-making models combined with the rapidly developing intelligent neural network algorithm. Kemball Cook et al. [8–10] proposed targeted management of the supply and transportation of emergency resources, however, due to technical reasons, the transportation optimization model can only achieve the optimization of a single objective, which is difficult to meet the actual demand; Wang et al. [11] took deep-sea emergency resources as an example to study the optimization of deep-sea emergency resource scheduling scheme with environmental impact, although this model can effectively solve the optimization problem of deep-sea emergency resource scheduling scheme, it does not promote the relevant model; Liu et al. [12] established an emergency resource scheduling model with the minimum time and cost as the multi-objective; Jiang [13] established an emergency material vehicle scheduling model by considering the transportation time, road traffic degree and material scheduling demand; Wang [14–16] et al. proposed a mathematical model, which proposed a centralized scheduling scheme to reduce the time delay in emergency resource scheduling, and arrange limited resources as much as possible for better application. Huang [17] proposed a mixed optimization model, and proposed a fast optimization algorithm for this model, and applied this algorithm to a scheduling scheme of emergency materials, making the limited resources more reasonable. Chai [18] proposed an emergency material scheduling model from a single supply point to multiple demand points. The purpose of this model is to minimize the impact of disasters on the affected areas and ensure the safety of people's lives and property. Wu [19–22] et al. proposed a scheduling model based on multiple supply points to a single demand point and used for an emergency resource. The purpose of this model is to minimize the number of supply points and the start time of emergency rescue. In view of the complexity of emergency resources, some researchers have built corresponding multi-objective models [20, 23–25]. Stevenson K A [26–28] et al. proposed a three-dimensional mesh model related to ambulance scheduling, which is designed to solve the problem of rapid and reasonable scheduling of a large number of ambulances. Chang [29, 30] et al. proposed a multi-objective model based on the characteristics of the quantity of emergency materials required at demand points. The purpose of this model is to minimize the unsatisfied amount of emergency materials at the demand point, the total scheduling time of emergency materials and the total transportation cost in the emergency scheduling process. And according to the characteristics of the model, a multi-objective evolutionary algorithm based on greedy search is proposed, and this algorithm is applied to a specific example, and has achieved good optimization results. Sheng [31] and others analyzed the differences between the daily phase and the emergency phase, and proposed a relevant two-stage scheduling model. A corresponding polynomial algorithm was designed to minimize the weighted completion time of emergency resource scheduling. BCSA [32] et al. proposed two maintenance duration models for the single machine scheduling problem. The purpose is to find the best maintenance frequency, the best maintenance position and the best job sequence to minimize the completion time of all jobs. The corresponding polynomial time algorithm is proposed for the relevant models, and good optimization results are achieved.

Through analysis, at present, the research of domestic and foreign scholars on the emergency scheduling problem mostly stays at the theoretical level. In general, the prevention of disasters and the timely rescue after disasters are strengthened from the aspects of emergency resources before and after the occurrence.

At the same time, many scholars have introduced intelligent algorithms into other fields, such as Mehrdad, Rostami and others, who have applied them to the study of accurate food recommendation [33, 34]. Some researchers mainly explored the problem of transporting emergency supplies from a single emergency supply point to multiple disaster-affected points, while others mainly explored the problem of transporting emergency supplies from multiple emergency supply points to a single disaster-affected point. Most of the current research is idealized, and the impact of some uncertain factors on emergency resource scheduling is rarely considered, such as weather conditions, traffic conditions and road damage. The emergency that can be effectively handled is also a single target, or theoretical modeling is conducted from a single cost perspective, and the problem is rarely considered from the perspective of optimizing the number of supply points and the order of emergency material scheduling. But the reality is that in the process of emergency resource scheduling, we should not only consider the time cost in the ideal situation, but also consider the freight cost caused by time delay, and consider the possibility that multiple targets may occur at the same time. We should try to use the shortest time to achieve the timeliness and efficiency of rescue under the condition of meeting the constraints.

Therefore, based on the research on different scenarios of emergencies, this paper constructs multi-objective emergency resource scheduling models in different situations based on Vague set theory and adaptive grid particle swarm optimization algorithm. By grasping the rescue characteristics in different scenarios, we design scheduling models for different scenarios, which can not only ensure the minimization of rescue time and rescue delay time, It can ensure that the disaster stricken areas can be rescued in a relatively short period of time and reduce the property loss of the people. Moreover, through the design of reasonable algorithms, it can ensure that the rescue materials can be efficiently and reasonably distributed on the premise of ensuring the timeliness of rescue time, which, to a certain extent, reduces the cost of rescue, ensures that the rescue materials can be used better and faster, and ensures that more people can be rescued in the same time. Through the design of effective models and efficient algorithms, the impact of disasters can be greatly reduced, the safety of people's lives and property can be guaranteed to the greatest extent, and the impact of disasters can be minimized. The optimized scheduling model built in this paper can not only be applied to the emergency resource scheduling studied in this paper, but also be adapted to other resource scheduling due to the variability of the algorithm design of the model, with good applicability.

2 Basic Theory and Problem Description

2.1 Basic Theory

2.1.1 Basic Theory of Vague Set

Vague set is a mathematical set method proposed by Gau and Buehrer in 1993 to deal with fuzzy information and data problems Supplement and extension of Zadeh fuzzy set. The most basic feature of traditional fuzzy set theory is to recognize the transition state between different things. It uses a membership function with a value range of [0,1] to describe the degree of membership of an object belonging to a fuzzy set, which is an extension of the classical set feature function. Fuzzy sets can well express some fuzzy things and concepts with unclear boundaries in the real world, reflecting the "fuzzy" relationship between things [35]. However, Fuzzy Set also has some defects. It uses single value membership to describe the probability that an object "to some extent" belongs to a fuzzy set, which can only express the object's "positive" and "negative" tendencies on the fuzzy set, but cannot represent an uncertain or neutral position. When assigning a membership value belonging to [0,1] interval to each object, Vague set contains both evidence supporting object $x \in A$ and evidence opposing object $x \in A$, which makes Vague set more expressive and flexible than traditional fuzzy set when dealing with uncertain information.

In the Vague set, the relationship between the elements in the universe U and the sets on the universe U is the relationship of "belonging within a certain range", which is the representation of an interval. This interval gives the degree of supporting evidence and the degree of opposing evidence, which has a stronger ability to represent information [36].

Let a vague set A on U be described by a membership function t_{A} and a non membership function f_{A}, where t_{A}: $U \rightarrow [0,1]$, f_{A}: $\mathrm{U} \rightarrow [0,1]$. For $x \in \mathrm{U}$, t_{A} (x) is the positive membership derived from the perspective of supporting $x \in$ A, f_A (x) is the negative membership derived from the perspective of opposing $x \in$ A, and t_A $(x)+f_A$ $(x) \leq 1$. Say [t_A (x), 1- f_A (x)] is the Vague value of x in the Vague set A. Mark $x=$[t_A (x), 1- f_A (x)], as shown in Fig. 1. Say π_A (x) = 1- t_A (x)—f_A (x) is the hesitation degree of x with respect to A.

Hypothetical universe:
$X = \{x_1, x_2 \cdots x_n\}, A = \{[x_1, t_A(x_1), f_A(x_1)] | x_1 \in X\}$.

Then there are: $E(A) = \frac{1}{n}\sum_{i=1}^{n}\frac{1-(t_A(x_i)-f_A(x_i))^2+2\pi_A^2(x_i)}{2-(t_A(x_i)-f_A(x_i))^2+\pi_A^2(x_i)}$

$$S_A^*(x) = t_A(x) + \frac{t_A(x)}{t_A(x)+f_A(x)}\lambda\pi_A(x) - f_A(x) - \frac{f_A(x)}{t_A(x)+f_A(x)}\lambda\pi_A(x) \tag{1}$$

$E(A)$ is called the Vague entropy of A. Use W(A) = 1-E(A) and normalize to calculate the index weight of A. $S_A^*(x)$ is the scoring function of x, where the parameter λ Is the conversion rate of the hesitation degree π A (x), and 0 ≤ λ ≤ 1。

Set: $S_A^*(x) < S_A^*(y)$, then: $x < y$.

2.1.2 Adaptive Mesh Particle Swarm Optimization Algorithm

The PSO algorithm is inspired by the birds in the nature. When birds are looking for food, they should not only fly according to their own goals, but also refer to the flight tracks of other birds in the group, especially the bird close to the food. In PSO, each bird is regarded as a particle, and the bird swarm is regarded as a particle swarm. Each particle is coded as a task resource scheduler. The essence of the adaptive grid particle swarm optimization algorithm is that a particle exchanges experience with other particles in the population through memory and updates the existing memory, adjusts its travel direction by itself, so that it gradually approaches the optimal position. Its main goal is to find the optimal particle from the population after multiple iterations, that is, the optimal task resource scheduler. The update formula of the particle is as follows:

$$\begin{cases} v_i^{(t+1)} = wv_i^t + c_1 r\left(\mathrm{pb}_i^{(t)} - x_i^{(t)}\right) + c_2 R\left(\mathrm{gb}^{(t)} - x_i^{(t)}\right) \\ x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)} \end{cases} \tag{2}$$

Where: $v_i^{(t)}$ and $x_i^{(t)}$ represent the velocity and position of the particle, $\mathrm{pb}_i^{(t)}$ represents the historical individual optimum of the i-th particle, $\mathrm{gb}^{(t)}$ represents the global optimum of the whole population, r and R are random values within [0,1] respectively, and w, c_1 and c_2 are weight values.

The algorithm flow of particles is shown in the following Fig. 2:

At the beginning of the algorithm process, we first initialize the sample population (the total size is N), including the random position and speed. Then we evaluate the fitness of each particle according to the fitness function. secondly, for cach particle, compare its current fitmessvalue with the fitness vlue oorresponding to itsindividual historical best position (Pbest). If thecurrent fitncss value is higher, the historical bestposition pbest will be updated with the currentposition。After completing the above operations, ftncss value with the fitncss valuccorresponding to the global optimal position (Gbest).If the current fitness vallue is higher, the globa!optimal position gbest will be updated with thecurrent particle position. Thereafter,Update the welocity amd pasitiom of eachparticle acoording to the formnula. Last output.

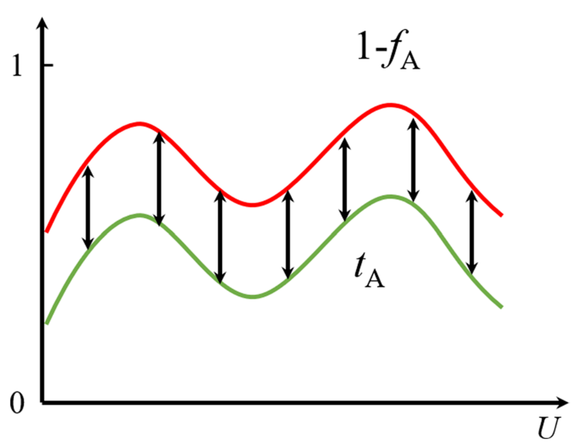
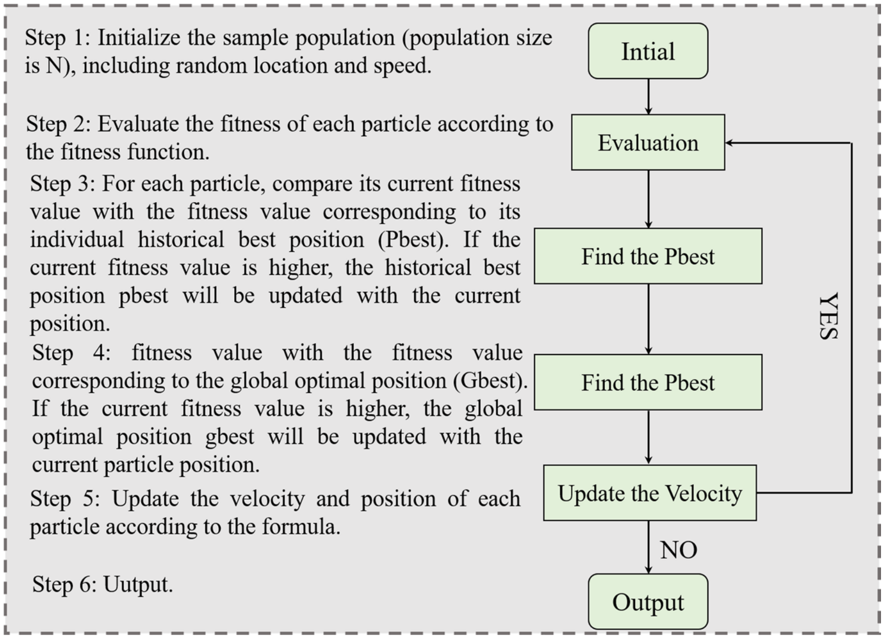


Fig. 1 Vague set

2.2 Problem Description

The problems studied in this paper can be described as follows: during the planning period, there are J possible accident demand points E_1, E_2,..., E_J, and I emergency rescue points S_1, S_2,..., S_I in the studied

Fig. 2 Optimization process of adaptive grid particle swarm optimization algorithm



highway area. The quantity of the k-th ($k=1, 2,\ldots,$ K) emergency resource reserved on the emergency rescue point S_i ($i=1, 2,\ldots,$ I) is qki. When an accident occurs on the demand point E_j ($j=1, 2,\ldots,$ J), its uncertain demand for the k-th emergency resource is determined by the fuzzy number. The time required from the rescue point Si to the demand point Ej is recorded as t_{ij}, and the unit emergency cost of the k-th emergency resource is. When multiple accident points in the region apply for rescue at the same time, the decision-maker needs to determine the optimal scheduling scheme with the goal of minimizing the emergency resource scheduling time and the total emergency cost, on the premise of ensuring the priority of rescue for trunk lines or major accidents.

One of the difficulties of emergency resource scheduling optimization under uncertainty is the measurement and processing of uncertain information. The uncertain information involved in this study mainly includes the priority evaluation of experts on each demand point, the resource demand of demand points and the emergency scheduling time. Considering the incompleteness of the initial information of the accident, the difference in the evaluation experts' understanding of the different attributes of various indicators and the impact of different indicators on the priority, and the fuzziness of the evaluation language, this paper intends to use Vague set theory to describe these uncertain parameters. definition φ It is the overall emergency rescue scheduling scheme, and φ^k represents the scheduling sub scheme of the corresponding k-th resource. Emergency resource scheduling time represents the maximum time required to deliver all emergency resources to all emergency demand locations, and $t(\varphi)$ And $t(\varphi^k)$ represent the overall scheduling scheme respectively φ And sub scheme φ^k, the corresponding mathematical expression is:

$$\varphi = \left[\varphi^1, \varphi^2, \cdots, \varphi^k\right]^{\mathrm{T}} \tag{3}$$

$$t(\varphi) = \max\left\{t\left(\varphi^1\right), t\left(\varphi^2\right), \cdots, t\left(\varphi^k\right)\right\} \tag{4}$$

Emergency rescue dispatching plan φ In, the scheduling sub scheme φ^k of the k-th resource can be expressed as the following matrix:

$$\varphi^k = \begin{bmatrix} x_{11}^k & x_{12}^k & \cdots & x_{1j}^k & \cdots & x_{1,}^k \\ x_{21}^k & x_{22}^k & \cdots & x_{2j}^k & \cdots & x_{2J}^k \\ \vdots & \vdots & & \vdots & & \vdots \\ x_{i1}^k & x_{i2}^k & \cdots & x_{ij}^k & \cdots & x_{iJ}^k \\ \vdots & \vdots & & \vdots & & \vdots \\ x_{I1}^k & x_{I2}^k & \cdots & x_{Ij}^k & \cdots & x_{IJ}^k \end{bmatrix} \tag{5}$$

Where: x_{ij}^k is the quantity of the kth emergency resource allocated from the rescue point Si to the demand point

Ej. $x_j^k = \sum_{i=1}^{I} x_{i,j}^k$ which is the total amount of the kth emergency resource allocated to the demand point E_j by all emergency rescue points under the priority rule.

When making optimization decisions, because the actual demand of emergency demand points is uncertain, x_j^k and x_{ij}^k are also unknown. When solving the model, x_j^k and x_{ij}^k must first be determined according to the priority of the accident point and the actual demand.

The priority of resource allocation at accident points can be determined by establishing triangular fuzzy number evaluation matrix. At the same time, considering that too little resource allocation at the demand point will lead to insufficient rescue force, and too much resource allocation will lead to waste of resources, the k-th resource allocation satisfaction function is introduced for the emergency demand point E_j $\mu(x_j^k)$, and set it to the trapezoidal fuzzy number as shown in Fig. 3.

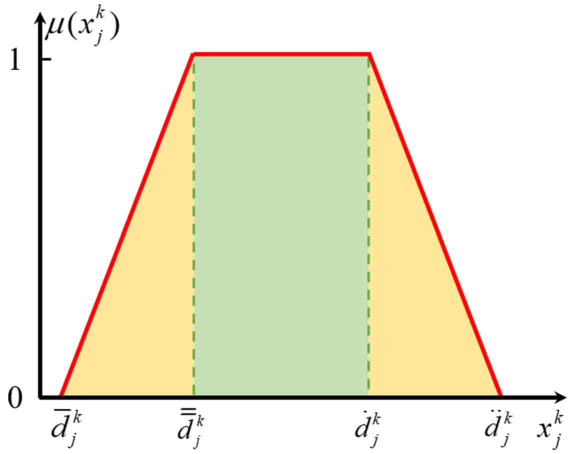


Fig. 3 Satisfaction function of resource scheduling coefficient

In Fig. 3, x_j^k, $\mu(x_j^k)$ are the number of resource scheduling and their satisfaction; $\bar{d}_j^k$, $\bar{\bar{d}}_j^k$, $\dot{d}_j^k$ and $\ddot{d}_j^k$ are respectively the threshold parameters of the trapezoidal fuzzy demand of the demand point E_j for the kth resource.

Define 0–1 decision variables y_{ij}^k and y_{ij} to indicate whether the rescue point Si provides the k-th resource to the demand point E_j and participates in the rescue of the demand point E_j, where:

$$y_{ij}^k = \begin{cases} 1 & x_{ij}^k > 0, \forall k \\ 0 & \text{Other} \end{cases} \tag{6}$$

$$y_{ij} = \begin{cases} 1 & x_{ij}^k > 0, \forall k \\ 0 & \text{Other} \end{cases} \tag{7}$$

By definition, there are:

$$t(\varphi) = \max\left(y_{ij} t_{ij}\right) \quad \forall i, j \tag{8}$$

3 Emergency Resource Scheduling Model Design Based on Vague set Theory and Adaptive Grid Particle Swarm Optimization Algorithm

3.1 Assumptions of Emergency Resource Scheduling Model

In the application process of emergency resource scheduling, there are some differences in its resource data. Therefore, in order to improve the matching degree between emergency dispatching resources and service requests, it is necessary to assume the resources in the resource pool and the emergency locations waiting for rescue, so as to facilitate the adjustment of waiting time, transportation time and dispatching time.

The specific assumptions of the model of multi demand point emergency resource scheduling problem are as follows.

In order to ensure the timeliness of the emergency system to the greatest extent, the direct distribution mode is adopted in the transportation process of emergency resources in the model, that is, there is only one demand point on the distribution path of each material distribution tool;

As the research in this paper is the optimization of resource scheduling, it is assumed that the transport vehicles are sufficient, that is, the capacity limit of single transport vehicle is not considered in this model;

The emergency start time of each demand point is the time when all delivery vehicles from each supply point arrive at the demand point.

It is assumed that the transportation vehicle is absolutely safe to go to the resource demand point, that is, the sudden risk accidents of the transportation vehicle in the transportation process are not considered.

As shown in Fig. 4, emergency resources are provided from multiple supply points to multiple emergency points, which is the multi emergency point resource scheduling problem mainly studied in this paper.

3.2 Construction of Multi-Objective Optimization Function

3.2.1 Construction of Time Optimization Function

The primary optimization objective of the emergency rescue plan should obviously be to deliver the rescue equipment to the demand point in the shortest possible time, that is, the emergency resource scheduling time should be the shortest. In this paper, the weighted average of the emergency start time of each demand point in the emergency system is defined as the average emergency start time T of the system, and the minimum t0 is taken as the start time of the emergency system. By introducing the importance of demand point B_j in the emergency system, w_j, we can get the expression of the sub objective of system timeliness:

$$\min\ T = \sum_{j=1}^{T} \left(t^0 \omega_j\right) \tag{9}$$

According to the previous definition of function, $t^0 \omega_j = \varphi$, where:

$$\min\ T = \varphi(t) \tag{10}$$

3.2.2 Construction of Cost Optimization Function

In the emergency resource model, in addition to the time of the primary element, the resource scheduling cost is also an important factor. Set the total cost as Z, and according to the previous variable definition, the corresponding optimization objective function is:

$$\min Z = \sum_{k=1}^{K} \sum_{i=1}^{I} \sum_{j=1}^{J} c_{ij}^{k} x_{ij}^{k} \tag{11}$$

3.3 Fuzzy Evaluation of Emergency Rescue Site Priority Based on Vague Set Theory

In general, it is difficult to solve the multi-objective optimization model, and it is usually necessary to coordinate among multiple objectives and choose the best among all non inferior solutions.

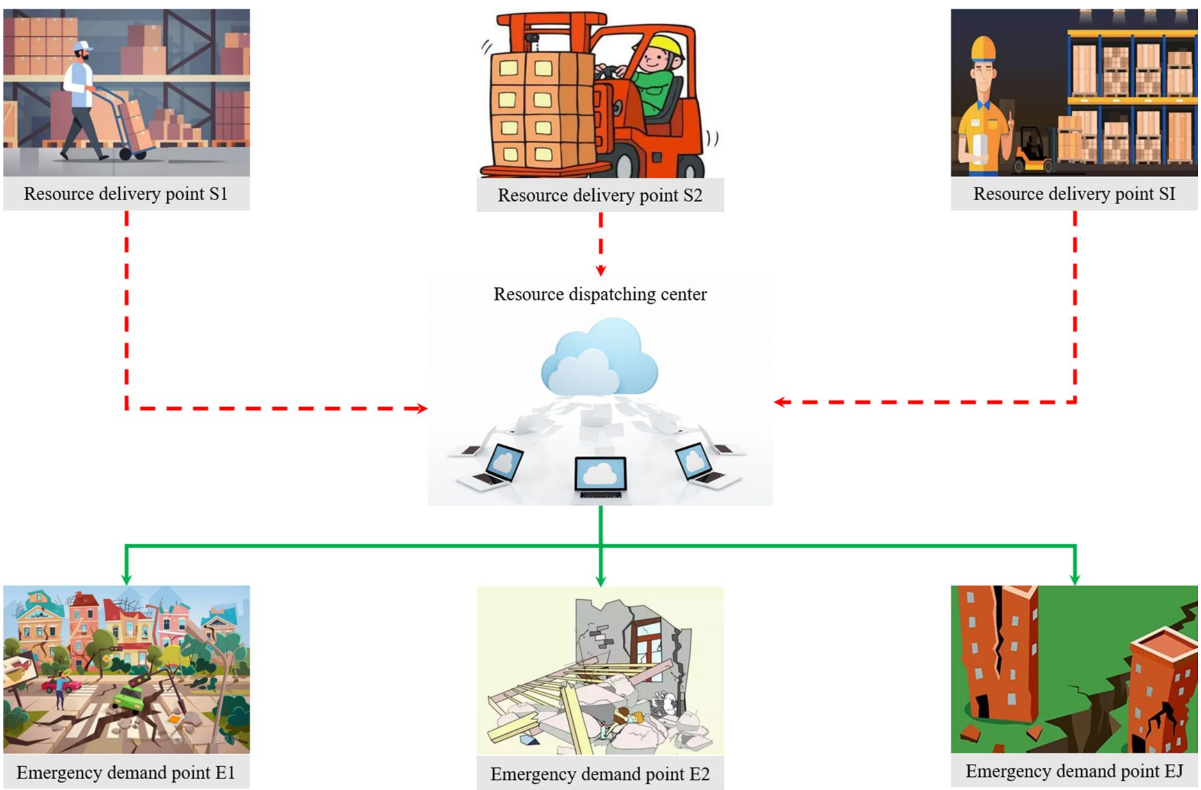


Fig. 4 Schematic diagram of multipoint resource scheduling model

However, in the traditional emergency dispatching model, the traditional weighted fuzzy matrix evaluation method is often used. Although this method controls the subjective factors to a certain extent through the collective determination of weights by experts, it still has a greater subjective judgment, which seriously affects the objective needs of emergency response, and has a greater restriction on emergency resource dispatching. In order to solve the above problems, this paper first uses the theory of vague set in TensorFlow to conduct a fuzzy evaluation of the emergency degree of each emergency point, and quickly defines priority objectives, and gives specific emergency plans to achieve the best balance of each single objective solution.

This paper constructs a vague value matrix to evaluate the rescue priority indicators of each demand point. A relative closeness decision-making method with complementary advantages is constructed by comprehensively using Vague set theory, entropy weight method and other methods to effectively solve the priority ranking problem of demand point rescue in hybrid multi-attribute decision-making. The specific process is as follows:

Step 1: Determine the Vague value evaluation matrix of all schemes on indicator factors;
Step 2: Solve the scoring value of the indicator factors in the scheme;
Step 3: use the entropy weight method to calculate the weight set of all indicators W = {w1, w2,…, wm}, and calculate the scheme weighted score of the secondary indicators according to Formula 1, and calculate the scheme weighted score of the primary indicators according to Formula;

$$S_k^*\left(x_i\right) = \sum_{j=1}^{m} w_j S_{kj}^*\left(x_i\right) \tag{12}$$

$$S^*\left(x_i\right) = \sum_{k=1}^{t} w_k S_k^*\left(x_i\right) \tag{13}$$

Where: x_i represents low i solution, $1 \leq i \leq n$; $S_{kj}^*\left(x_i\right)$ is the score of the k-th factor in the first level index of the scheme.

3.4 Optimal Solution Search Algorithm with Limited Parameter Interval

Because the problem considered in this paper is multi-objective and multi resource emergency resource scheduling optimization problem, which is difficult to achieve with conventional algorithms, in order to effectively reduce the amount of calculation, this paper proposes an adaptive grid particle swarm optimization algorithm with limited parameter interval to search for the optimal solution. The nonlinear search function used in this case is (Fig. 5):

$$f(x,y) = \frac{\sin\sqrt{x^2+y^2}}{\sqrt{x^2+y^2}} + e^{\frac{\cos 2\pi x + \cos 2\pi y}{2}} - 2.71289 \tag{14}$$

4 Example Analysis

4.1 Case Background

This case occurred near a provincial national highway in China. The national highway is located in the western region of China, with complex geological conditions, harsh environment, and perennial strong winds. It is located in the seismic zone and is an accident-prone area. The case accident was caused by the earthquake, affecting 3 villages of different sizes and basically the same population size. After the earthquake, 4 villages were damaged to different degrees.

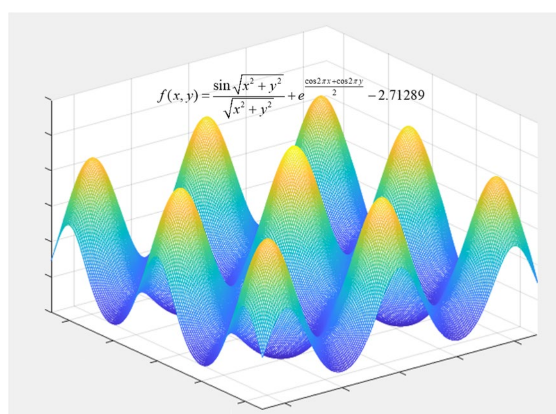


Fig. 5 Function image of adaptive grid particle swarm optimization algorithm

The above 4 villages were named E1, E2, E3 and E4 respectively. After the accident, the command center will start the emergency plan at the first time, and conduct resource scheduling and allocation according to the resource scheduling model established by this stability. It is proposed to dispatch resources from four different resource rescue points S1, S2, S3 and S4 near the disaster area for disposal. The rescue points and villages with different emergency resources are shown in Fig. 6. The horizontal line in the figure represents the safe route available for emergency resource rescue.

The distance from the rescue points of different resources to the affected villages is shown in Table 1 below:

Table 1 Minimum Distance between Rescue Point Si and Affected Village E_j

Material point Affected area	S1	S2	S3	S4
E1	9.1	5.6	10.4	5.4
E2	10.0	3.8	8.6	5.5
E3	12.7	6.4	11.3	2.8
E4	12.2	14.5	19.3	7.9

4.2 Construction of Evaluation Index System of Post Disaster Emergency Rescue Capability Based on Vague Set Theory

4.2.1 *Post Disaster Emergency Rescue Capability Evaluation Index System*

By referring to the research results of emergency rescue capability evaluation at home and abroad, taking emergency rescue capability as the main line, strictly following the design principles of the index system, and referring to the actual situation of Wenchuan earthquake emergency rescue, the evaluation index system of coal mine emergency rescue capability is finally determined in Table 2. The system consists of a target layer, a first level evaluation index and a second level evaluation index, in which the target layer is the emergency rescue capability for the disaster affected areas; The first level evaluation indicators are divided into four aspects according to the implementation time of rescue: hazard monitoring capability, emergency preparedness capability, emergency response capability and post recovery capability; The secondary evaluation indicators consist of 16 indicator factors as shown in Table 2, the selected indicators in Table 2 are all the basic indicators listed in China's emergency response specifications.

4.2.2 *Evaluation and Decision-Making of Post Disaster Emergency Rescue Capability*

Step 1: Determine the Vague value evaluation matrix of all schemes on indicator factors;
Step 2: Solve the scoring value $S_{kj}*(x_i)$ of scheme xi $(1 \le i \le n)$ on index factor B_{kj} $(1 \le j \le m)$, where k is the kth factor in the first level index;

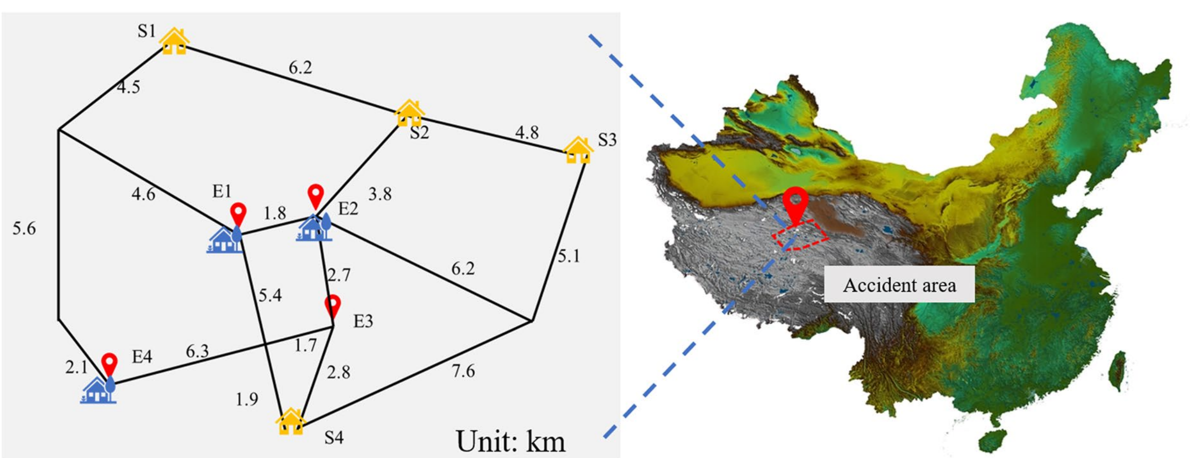


Fig. 6 Overview of rescue points and emergency points in the case area

Step 3: use the entropy weight method to calculate the weight set of all indicators $W=\{w_1, w_2, \ldots, w_m\}$, and calculate the scheme weighted score of the secondary evaluation indicators according to the aforementioned formula 1, and calculate the scheme weighted score of the primary evaluation indicators according to formula 2;

Step 4: Make sorting decision according to the size of $S^*(x_i)$ value.

4.2.3 Solution of Post Disaster Emergency Rescue Capability

Considering the shortcomings of vague set theory such as high fuzziness and slow calculation speed when solving the rescue capability, particle swarm optimization algorithm is used first to improve the calculation efficiency and speed of the model when solving the rescue capability. In this example, the particle swarm size l is 20, the number of rescue points m is 10, the consumption rate of emergency resources v is 1, the end time of emergency activities T is 1000, the penalty cost ratio D is 5, the initial transportation volume of emergency resources x_0 is 10; The upper limit of iteration times is 3000. Observe the calculation effect of learning factors c_1 and c_2 under different values, as shown in Fig. 7. T in the figure is the time required to find the optimal emergency resource scheduling scheme. After calculation with reference to Fig. 7, it is determined that $c_1=0.1$ and $c_2=0.2$ are better.

Taking the affected village E_1 as an example, the route assessment scheme from different emergency points Si to the affected village E_1 is set as SE_i (i = 1, 2, 3, 4). After the expert group has analyzed the emergency rescue capabilities of four different emergency plans SE11, SE12, SE13 and SE14, the evaluation matrix obtained from the evaluation of the above 16 indicator attributes is shown in Fig. 8.

Solve the data in R according to the score value formula to get the matrix S* as shown in Fig. 9, where the conversion rate of hesitation degree λ, The value is 1.

According to the above emergency indicator evaluation matrix in Fig. 7 and the emergency indicator scoring matrix in Fig. 8, when using the vague set theory to evaluate and score the emergency indicators, it can be clearly seen that the evaluation and scoring are positively related to the distance between the disaster area and the emergency point. When the disaster area is farther away from the disaster area of the emergency accident, the corresponding indicator scores are smaller, indicating that the disaster area is less likely to be rescued, On the contrary, when the evaluation value and score value are higher, it indicates that the closer the accident disaster area is to

Table 2 Evaluation Index System of Emergency Rescue Capacity in Disaster Affected Areas

Target layer	Level I evaluation index	Secondary evaluation index
Emergency rescue capacity of disaster affected area A	Hazard monitoring capability B1	Monitoring equipment B11
		Monitoring system B12
		Monitoring control B13
		Alarm system B14
	Emergency preparedness B2	Responsiveness B21
		Emergency Plan B22
		Emergency materials B23
		Emergency personnel B24
	Emergency rescue capability B3	Plan launch B31
		Decision Command B32
		Rescue response B33
		Rescue capability B34
	Post disaster recovery capacity B4	Impact control B41
		Aftermath treatment B42
		Production recovery capacity B43
		Rescue summary B44

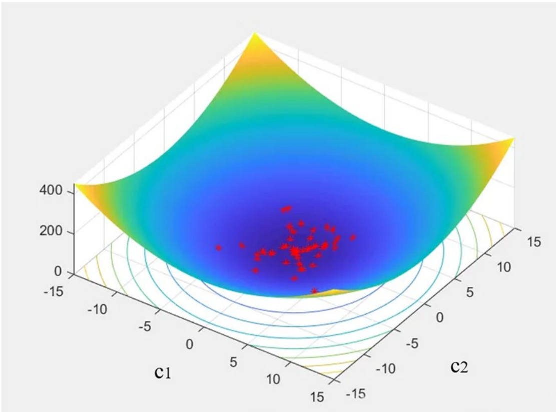


Fig. 7 Relationship between learning factor and optimization time

the emergency point, the higher the score of receiving effective rescue. As above, the emergency indicator evaluation matrix and emergency indicator score matrix are respectively solved for different disaster affected areas.

4.2.4 *Calculation of Comprehensive Score of Post Disaster Emergency Rescue Capability*

According to the emergency index evaluation matrix and emergency index score matrix values obtained above, $SE_{11}=(0.128, 0.205, 0.207, 0.311, 0.209, 0.276, 0.412, 0.375, 0.501, 0.219, 0.154, 0.177, 0.409, 0.286, 0.522, 0.193)$ can be solved according to the entropy formula, so as to obtain the weight vector

Fig. 8 Emergency indicator evaluation matrix

R	B11	B12	B13	B14	B21	B22	B23	B24	B31	B32	B33	B34	B41	B42	B43	B44
SE11	0.2, 0.1	0.4, 0.3	0.5, 0.4	0.6, 0.3	0.2, 0.4	0.6, 0.3	0.4, 0.4	0.4, 0.5	0.7, 0.3	0.6, 0.5	0.4, 0.6	0.6, 0.7	0.5, 0.8	0.6, 0.6	0.5, 0.7	0.6, 0.9
SE12	0.3, 0.6	0.1, 0.8	0.4, 0.3	0.4, 0.5	0.2, 0.3	0.3, 0.4	0.5, 0.2	0.6, 0.4	0.3, 0.1	0.5, 0.2	0.3, 0.1	0.7, 0.3	0.6, 0.5	0.9, 0.2	0.6, 0.4	0.4, 0.8
SE13	0.4, 0.5	0.5, 0.3	0.6, 0.4	0.12 ,0.7	0.2, 0.4	0.4, 0.6	0.5, 0.4	0.7, 0.6	0.3, 0.7	0.3, 0.6	0.2, 0.5	0.5, 0.7	0.6, 0.8	0.4, 0.9	0.2, 0.8	0.5, 0.5
SE14	0.3, 0.2	0.4, 0.1	0.1, 0.2	0.2, 0.3	0.2, 0.1	0.5, 0.2	0.5, 0.1	0.2, 0.4	0.4, 0.4	0.4, 0.2	0.4, 0.3	0.6, 0.4	0.5, 0.5	0.6, 0.5	0.7, 0.5	0.7, 0.7

Fig. 9 Score matrix of emergency indicators

S	B11	B12	B13	B14	B21	B22	B23	B24	B31	B32	B33	B34	B41	B42	B43	B44
SE11	-0.28	0.22	0.16	0.47	0.11	0.47	0.31	0.39	0.17	0.34	0.29	0.47	0.48	0.74	0.64	0.54
SE12	0.47	0.61	0.22	0.34	0.19	0.22	0.19	0.46	-0.10	0.23	0.16	0.49	0.74	0.39	0.54	0.68
SE13	0.16	-0.31	0.13	-0.16	0.11	0.23	0.11	0.47	0.31	0.47	0.27	0.38	0.41	0.39	0.34	0.58
SE14	0.15	-0.27	-0.28	0.15	-0.28	0.32	0.20	0.11	0.28	0.11	0.22	0.39	0.44	0.66	0.49	0.74

W_2 = (0.343, 0.298, 0.141, 0.207, 0.326, 0.194, 0.187, 0.401, 0.433, 0.274, 0.154, 0.506, 0.271, 0.614, 0.127, 0.133). The weighted sum formula of scores is used to calculate the E1 score of the four rescue sites in the disaster area as S_1*(E1) = (0.298, 0.521, 0.129, 0.575) T. Similarly, the scores of the four rescue sites for E2, E3 and E4 in the disaster area can be calculated as S_1*(E2) = (0.102,0.776,0.309,0.568) T, S_1*(E_3) = (0.104,0.486,0.247,0.952) T, and S_1*(E_1) = (0.171,0.051,0.018,0.324) T.

The comparison between the scores from different rescue sites to the affected areas and the straight distance from different rescue sites is shown in Fig. 10. It can be seen from the figure that the model built in this paper fully considers the distance factor of the target point and various indicators when scoring, and the rescue scores obtained are basically consistent with the characteristics of real rescue, thus verifying the accuracy of the model built in this paper.

In addition, in order to test the effectiveness of particle swarm optimization algorithm on this model, this paper introduces the conventional emergency scheduling model built by fuzzy set evaluation theory for comparative verification, which is marked as Model 1, the model built based on Vague set theory is marked as Model 2, and the scheduling model built based on Vague set theory and adaptive grid particle swarm optimization algorithm is marked as Model 3, The LOSS value during model training and the model iteration calculation time are respectively selected as the evaluation criteria for the advantages and disadvantages of three different models. Figure 11 shows the change of the LOSS value during the training of the model in the process of emergency dispatching resource allocation in this paper for three different models, and Fig. 12 shows the change of the iteration time during the training of the model in the process of emergency dispatching resource allocation in this paper for three different models.

It can be seen from the change chart of the LOSS value of the three different models during the training of the model in the process of emergency dispatching resource allocation in this paper in Fig. 11 that the overall change of the different models is consistent, that is, the LOSS value of the model shows a gradually decreasing trend with the increase of the number of model iterations, and finally tends to be stable. But the difference is that in different resource scheduling models, the initial LOSS value of the model is different, in which Model 2 is the largest, and the initial LOSS value is close to 2.0, indicating that the model has the largest change in searching for the optimal model during training. The second is model 1. The maximum LOSS value is 1.643, the minimum is model 3 built in this paper, and the maximum value is only 1.412. From the minimum LOSS value of the model, except that the LOSS value of model 3 constructed in this paper tends to converge at the end of training, the final LOSS value of the other two models

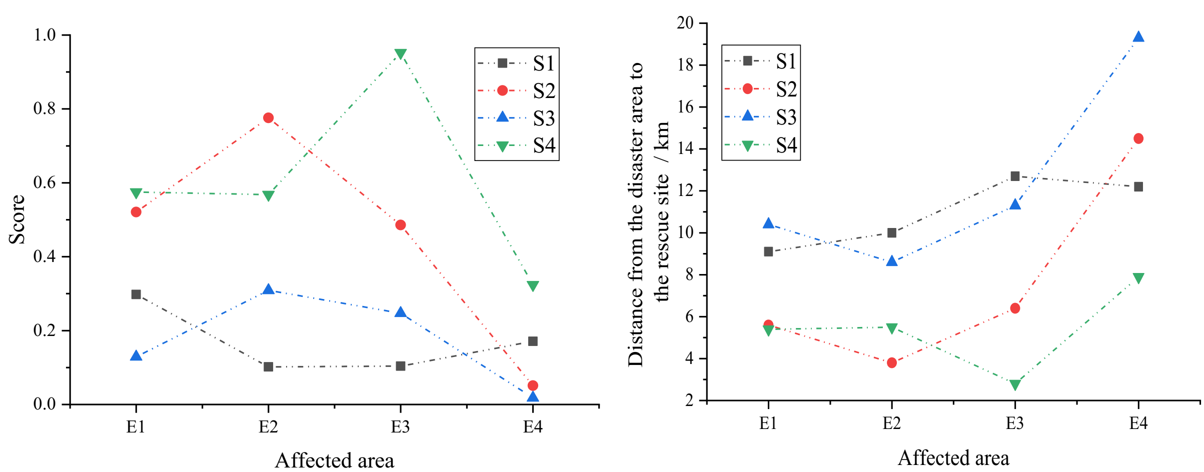


Fig. 10 Comparison between the scores from different rescue sites to the affected areas and the straight-line distances from different rescue sites

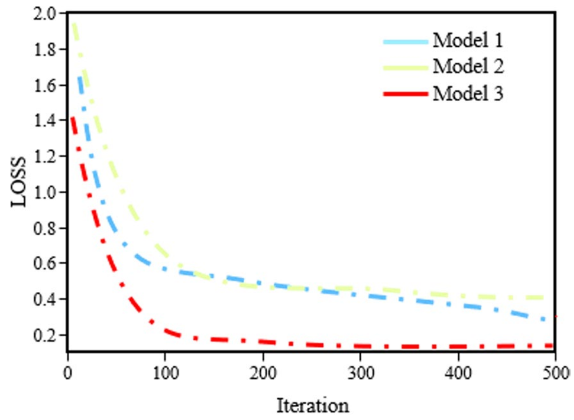


Fig. 11 Change of LOSS value during training of three different resource scheduling models

are not convergent. To sum up, the data show that the model 3 constructed in this paper has high convergence efficiency and training accuracy.

It can be seen from the time change chart of three different models in the training of models in the process of emergency dispatching resource allocation in this paper in Fig. 12 that different models have great differences in the performance of model training, but the overall performance shows that as the number of model iterations increases, the time spent on model training gradually increases, but the difference is that for model 2, due to its insufficient fuzziness compared with model 1, it is worse than model 3 to find the optimal training path, Its efficiency is lower. When the model training iteration reaches about 150 times,

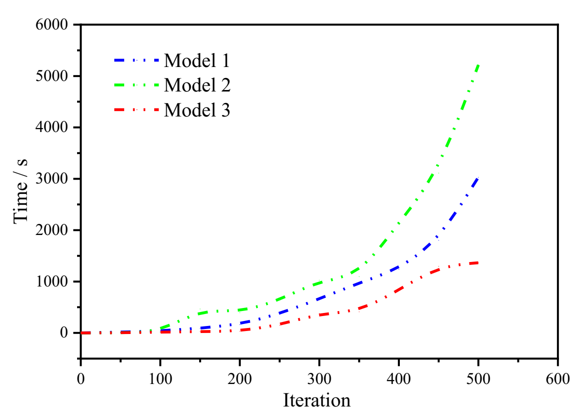


Fig. 12 Time change chart of three different resource scheduling models during training

the model training time is significantly improved, showing an exponential growth trend, and the maximum time consumption is up to 5219 s. Although the training time change of model 1 is consistent with that of model 3, it takes a lot of time as a whole, and does not converge after about 200 iterations, and the training time is more than half an hour. However, from the summary of many emergency rescue cases, we can know that time factor, as the first element of emergency rescue, its allocation is extremely important for emergency rescue and disaster relief resource scheduling. The training time of model 3 is obviously shorter than that of other models, which shows that its training efficiency is high and it can plan and arrange emergency rescue plan in the shortest time. Therefore, model 3 is an ideal resource scheduling model for emergency rescue.

To sum up, it can be found that the multi-objective emergency resource scheduling model based on Vague set theory and adaptive grid particle swarm optimization algorithm in this paper is more accurate than the traditional resource scheduling model in different situations. Under the premise of ensuring reasonable resource allocation, it is more efficient and faster to deal with emergency events. Compared with the conventional fuzzy theory emergency resource scheduling model, its handling speed is about 3.82 times faster, This proves the reliability of this study.

5 Conclusion

In view of the problems of slow decision-making in the traditional resource scheduling system, which is difficult to meet the needs of the actual situation, and the unreasonable resource allocation in the face of emergencies, this paper studies the resource allocation and scheduling of four different resource allocation points to four different damaged villages after the earthquake, taking the village resource scheduling problem caused by the earthquake near a provincial national highway as the background, and draws the following conclusions:

1) In this paper, a multi-objective emergency resource scheduling model is built based on the Vague set theory and adaptive grid particle swarm optimization algorithm in different situations. The example shows that the multi-objective

emergency resource scheduling model based on the Vague set theory and adaptive grid particle swarm optimization algorithm constructed in this paper can achieve the multi-objective emergency resource scheduling in different situations.

2) Through the analysis of resource scheduling under different path conditions, the resource scheduling model constructed in this paper can not only integrate the advantages of Vague set theory in dealing with uncertain problems, but also retain the advantages of adaptive grid particle swarm optimization in solving multi-objective optimization problems and fast convergence. The particle swarm optimization algorithm is used to search the global optimal solution, and the shortest emergency response time is the goal, Quickly allocate resources in the disaster area.
3) The result of the case study shows that compared with the traditional resource scheduling optimization algorithm, the emergency resource scheduling model has higher resolution, more reasonable resource allocation, higher efficiency and faster speed in dealing with emergency events than the traditional resource scheduling model. Compared with the emergency resource scheduling model built by the traditional fuzzy set theory and the emergency resource scheduling model built by the Vague set theory, Its disposal efficiency can be increased by 3.82 times and 2.22 times respectively.

In addition, the model built in this paper can not only provide theoretical and practical reference for similar research, but also solve the problem of resource demand at multiple demand points and fuzzy uncertainty of multiple supply points, as well as the problem of large differences in the importance of each demand point and various resources in the emergency system. However, due to the limitation of time and energy, this paper has not compared with other classical models, The model built in this paper has not been cited in other resource scheduling cases. Therefore, the model has some defects in terms of algorithm advantages and the universality of practical application of the algorithm, but its theory is sufficient to prove the advantages of the model.

Author Contributions Conceptualization, Yibo Han and Pu Han; methodology, Bo Yuan; software, Lu Liu; validation, John Panneerselvam, Zheng Zhang and Yibo Han; formal analysis, Pu Han; investigation,Bo Yuan; resources, Zheng Zhang; data curation, Lu Liu; writing—original draft preparation, John Panneerselvam; writing—review and editing, Yibo Han; visualization, Pu Han; supervision, Bo Yuan; project administration, Zheng Zhang; funding acquisition, Lu Liu All authors have read and agreed to the published version of the manuscript.

Data Availability The experimental data used to support the findings of this study are available from the corresponding author upon request.

Declarations

Competing interests The authors declare no competing interests.

Conflicts of Interest The authors declared that they have no conflicts of interest regarding this work.

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