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Multiperiod scheduling optimization of postearthquake emergency supply based on real-time environmental information

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A B S T R A C T

The advancement of Internet of Things technology enables the collection and transmission of real-time environmental and vehicle information, aiding the scheduling of postearthquake emergency supplies. Earthquakes often cause victims psychological pain due to insufficient supplies, and secondary disasters during transportation complicate supply scheduling. This study used a questionnaire to determine the psychological pain perception cost function of victims and identify the parameter value ranges under various environmental conditions. A fuzzy inference system was applied to ascertain the function parameters based on actual earthquake losses. Subsequently, a mixed-integer programming model for the multiperiod scheduling of emergency supplies was developed. An improved particle swarm optimization (IPSO) algorithm with a nondominated solution adjustment strategy was devised to solve the model and compared with the traditional particle swarm optimization (PSO) algorithm. The efficacy of the IPSO algorithm was validated through multiple examples. Additionally, a sensitivity analysis of factors such as supply satisfaction proportion was conducted. Results indicated that when remaining supplies fail to meet the minimum needs of undistributed disaster points, setting a minimum satisfaction percentage effectively reduces the total psychological pain cost. This study offers significant theoretical value in alleviating victims' psychological pain and enhancing rescue efficiency.

1. Introduction

The Chinese provinces of the southwest, northwest, north, southeast coast and other regions are situated between the Circum-Pacific seismic belt and the Eurasian seismic belt, where earthquakes are a frequent occurrence. China is one of the countries with the highest levels of earthquake-related disaster losses (Gerstenberger et al., 2020). Earthquakes frequently occur in conjunction with a range of secondary geological disasters, including landslides, collapses, mudslides and ground collapses. These events can result in damage to roads and the creation of new disaster points, which present challenges to rescue and emergency supply scheduling. Furthermore, earthquakes can cause considerable psychological pain among victims, which can have a detrimental impact on their ability to resume production and lead to further distress. Following an earthquake, the implementation of scientific and efficient emergency management can not only reduce the losses caused by the earthquake itself but also avoid the exacerbation of the psychological pain experienced by victims due to the lack of rescue time and supplies. Consequently, the enhancement of the effectiveness of postearthquake emergency management has become a crucial issue (Zhang, 2022) . The challenge of reducing the psychological pain of victims whilst simultaneously acquiring and utilising environmental data to devise emergency supply scheduling plans and modifying them over time has become a pressing issue that requires immediate resolution. In the context of emergency management of natural disasters, such as earthquakes, the Internet of Things (IoT) technology has enhanced the efficiency and accuracy of emergency supply scheduling through the utilisation of its real-time data acquisition, transmission and processing capabilities. In the field of seismic monitoring, the

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real-time data acquisition and transmission of IoT is realised by connecting the network with seismic monitoring equipment. This process facilitates the rapid acquisition of environmental information by decision-makers, including the occurrence time, accurate magnitude and source location of the earthquake. Furthermore, IoT is employed in the field of supply statistics. The traditional method of supply statistics is labour intensive and resource intensive and has a high error rate. The IoT technology enables the integration of information from key nodes, such as warehouses and distribution centres, into a unified data platform in real time. This integration facilitates the automatic and real-time updating of supply inventories, thereby enhancing the accuracy and timeliness of statistics. In the context of postearthquake disaster supply distribution, IoT offers the potential for real-time monitoring of supply transportation vehicles, thereby enabling the implementation of flexible scheduling adjustments and improvements in the accuracy of the supply scheduling scheme.

The losses caused by different earthquakes and the urgency of the victims' demand for supplies are different. The lack of technical support for IoT often precludes the use of environmental information collected by equipment in the traditional emergency supply scheduling model. This limitation results in the construction of a fixed objective function and model, which may lead to an excessive or insufficient response to supply scheduling. Furthermore, secondary disasters triggered by earthquakes may result in the continuous emergence of new disaster points. The absence of real-time monitoring of secondary disasters and disaster points has resulted in a lack of attention to the multiperiod rescheduling problem following vehicle departure in existing research. In light of the issues mentioned above, decision-makers frequently rely on experience to inform their decisions during actual rescue operations, with a lack of unified standards and schemes. Consequently, in the context of emergency supply scheduling, the transportation cost and the psychological pain of victims must be considered holistically, and the target function parameters must be adjusted in accordance with the extent of damage caused by the earthquake to reflect the urgency of supply scheduling in different earthquakes.Consequently, this study considers the potential of IoT technology to obtain real-time environmental information in the aftermath of an earthquake. This information is then used to determine the target function parameters through a fuzzy inference system, followed by the construction of a multiperiod scheduling model of emergency supplies. The particle swarm optimisation (PSO) algorithm is improved by integrating the grey wolf algorithm and the nondominated solution adjustment strategy to address the model mentioned above.The remainder of this article is structured as follows: The second section presents a review of the literature on emergency logistics issues, demonstrating the paucity of research in this field. The third section presents the research problem, outlines the construction of the fuzzy inference system and establishes the multiperiod scheduling model of postearthquake emergency supplies. The fourth section presents an improved particle swarm optimisation (IPSO) algorithm, which combines the grey wolf algorithm to enhance the flight mode of the particles. In addition, a nondominated solution adjustment strategy is proposed for the problem of solving efficiency. The fifth section verifies the model and algorithm. The proposed algorithm is compared with the Gurobi solver and the PSO algorithm to assess its efficacy in the context of small-scale examples. Given the inherent limitations of the Gurobi solver in terms of solution efficiency, it cannot achieve the desired results within the specified time frame. Consequently, in the large-scale experiment, the IPSO algorithm is compared with the PSO algorithm to verify the accuracy and efficiency of the IPSO algorithm. The sixth section presents a series of sensitivity analyses, which is conducted to test the performance of the model proposed in the previous sections, and management implications are obtained. Subsequently, the seventh section demonstrates the viability of the model and algorithm through case analysis. Finally, the eighth section draws the conclusion.

2. Literature review

In terms of emergency supplies and personnel scheduling strategies, most of the relevant literatures take the minimization of distribution time and cost as the scheduling goal. Sarma et al. (2019) take the minimization of total cost and total time in the redistribution stage as the goal and construct a mixed integer programming model for application resource redistribution. So as to quickly respond to emergencies. Huang et al. (2018) established an emergency logistics distribution path model based on uncertainty theory considering the customer 's demand, the unloading time of materials, the travel time from the distribution centre to the disaster point, and the travel time between the disaster points. Lassiter et al. (2015) aimed at minimizing unmet needs, aiming to allocate and train a limited number of volunteers for various tasks, and designed a robust optimization method to deal with the uncertainty in the problem. In the rescue operation personnel allocation planning, in the face of new events, Rauchecker et al. (2019) proposed an improved branch pricing algorithm for the binary linear minimization problem with the goal of minimizing the use time. Tanmoy et al. (2022) established an emergency logistics self-organizing response system with the goals of survival maximization, cash exposure risk minimization, undersupply cost, and psychological cost minimization. In addition, different literatures focus on different influencing factors of emergency material scheduling. First of all, secondary disasters will affect the road. Fang et al. (2021) established a multi-depot multi-vehicle dynamic vehicle routing model considering the influencing factors such as secondary disasters and road damage. Vahdani et al. (2018) considered the problem of locating the distribution centre and designing the route from the distribution centre to the affected point in the case of demand diversion. In order to improve the safety of workers and the possibility of vehicles arriving at the affected point in time and to repair the damaged road as the goal, a mixed integer programming model was established. Secondly, after the earthquake, due to the changes in the environment of the earthquake area and the progress of rescue, the demand for the affected points of various materials is uncertain. Taking into account the limited nature of relief supplies and the randomness of rescue needs, Zhan et al. (2021) designed a new decision-making framework and established a dynamic optimization model. Wan et al. (2023) used fuzzy numbers to describe uncertain demand and established a multi-period dynamic emergency material allocation model under uncertain demand. Kim et al. (2023) proposed a dynamic vehicle routing problem model with fuzzy customer response, which uses triangular fuzzy numbers to represent customers' response to delayed delivery of orders and optimizes the path with the goal of reducing customer complaints and costs. Shen et al. (2019) constructed a fuzzy low-carbon location-routing model with the goal of minimizing delivery time, total cost and carbon emissions. In addition, the relevant literature makes a reasonable plan before the start of distribution and makes a realistic adjustment after the start, considering the two-stage optimization, that is, making two decisions. Bozorgi-Amiri et al. (2016) proposed a multi-objective dynamic stochastic programming model to make decisions before and after the disaster to reduce the total cost and improve efficiency. Sakiani et al. (2020) studied the problem of relief redistribution in the rolling horizon with the objective of minimizing the deprivation cost, operation cost and violation of the original decision cost. Fan et al. (2022) proposed a two-stage optimization model with the goal of minimizing distribution costs. In the pre-optimization stage, an improved adaptive genetic algorithm is designed to obtain the initial delivery scheme. In the dynamic adjustment stage, the path planning is carried out by considering the change in the demand of the disaster point and the change in the speed of the distribution network. In terms of emergency material scheduling objectives, less literature considers the impact of victims ' psychological pain on material scheduling and incorporates it into the objective function. In terms of emergency material scheduling strategy, although relevant research has considered factors such as road damage and demand uncertainty, emergency material scheduling under the background of continuous changes in environmental conditions (such as multiple new disaster sites) still needs to be further studied. The research scope and objective function of the above emergency logistics management research articles are summarized in Table 1.

Table 1
Summary of emergency logistics management research articles

Author	Topic	Delivery Period	Objective Function			
			Transport cost	Time	Psychological pain of victims	Other objective functions
Sarma et al.	Redistribution for cost minimization in disaster management under uncertainty with trapezoidal neutrosophic number.	Single Period	√	√		
Huang & Song	An emergency logistics distribution routing model for unexpected events.	Single Period		√		
Lassiter et al.	A robust optimization approach to volunteer management in humanitarian crises.	Single Period				Unmet demand value
Rauchecker & Schryen	An exact branch-and-price algorithm for scheduling rescue units during disaster response.	Single Period		√		
Tanmoy et al.	Emergency logistics management—Review and propositions for future research.	Single Period			√	Exposure risk, number of victims & undersupply cost
Wan et al.	Multi-objective Emergency Scheduling for Geological Disasters.	Multi Period				Total distance & priority errors
Vahdani et al.	Multi-objective, multi-period location-routing model to distribute relief after earthquake by considering emergency roadway repair.	Multi Period	√	√		
Zhan et al.	Disaster relief logistics under demand-supply incongruence environment: A sequential approach.	Multi Period				Total relief demand states
Wan et al.	Multi-period dynamic multi-objective emergency material distribution model under uncertain demand.	Multi Period	√			Unsatisfied demand & risk
Kim	Dynamic Vehicle Routing Problem with Fuzzy Customer Response.	Multi Period	√			Complaints
Shen et al.	Optimization of Location-Routing Problem in Emergency Logistics Considering Carbon Emissions.	Single Period	√	√		
Bozorgi-Amiri	A dynamic multi-objective location-routing model for relief logistic planning under uncertainty on demand, travel time, and cost parameters.	Multi Period	√	√		Maximum amount of shortages
Sakiani et al.	Inventory routing and dynamic redistribution of relief goods in post-disaster operations.	Multi Period	√			Deprivation cost & original decision violation cost
Fan et al.	Dynamic Allocation and Path Optimization of Heterogeneous Vehicles in Time-varying Road Networks	Multi Period	√			

In the research on the application of Internet of Things technology to path optimization and related issues, many literatures have applied the functions of vehicle positioning and information transmission of the Internet of Things to different fields. For the last mile distribution problem, Lim et al. (2020) combined the Internet of Things with green logistics and proposed a green distribution method combining shared cars (private cars) and the Internet of Things. The system includes customer data layer, information collection layer, cloud optimization layer and delivery task execution layer, which provides a solution to the two-stage shared vehicle routing problem in the Internet of Things environment. Yao et al. (2022) developed an intelligent distribution system based on positioning technology by introducing blockchain system and location information encryption, which improved the security and efficiency of the distribution process. Using the information interaction technology in the

Internet of Things, Lei (2022) constructed an intelligent distribution model with the goal of minimizing delivery time by considering the work efficiency and packaging space utilization of distribution personnel for different devices. KhosravI et al. (2021) established a unified coverage scheduling system to solve the problem of UAV material distribution by combining real-time information and wireless power transmission and monitoring technology. In terms of logistics and transportation management, Zhang et al. (2021) constructed a railway vehicle scheduling model using Internet of Things technology, and designed a logistics vehicle scheduling system to realize functions such as information management, railway vehicle scheduling and transportation management. Based on the vehicle networking technology, Zhang et al. (2024) proposed a mixed integer quadratic programming model with the goal of minimizing the power fluctuation of the power grid for the charging problem of electric vehicles in the city. In terms of disaster emergency response and multi-modal transportation scheduling, Yan et al. (2023) established an optimal scheduling model for multi-period and multi-modal transportation supported by the Internet of Things with the goal of minimizing system response time and total cost. Through the use of emergency production and rescue materials, market procurement and inventory information, the needs of affected points are met. Qing(2018) used the Internet of Things to monitor vehicles, established a vehicle scheduling model for emergency material distribution, and used the genetic-ant colony combination algorithm to improve the efficiency of the model solution. Although many literatures apply the Internet of Things to optimization problems, there is still a lack of in-depth research on how to apply the information collected by the Internet of Things to adjust the model in multiple periods.

In the aspect of emergency logistics problem-solving algorithm, due to the emergency resource allocation and ship scheduling decision-making, it is impossible to obtain the corresponding time-varying parameter values in advance. Therefore, Zhang et al. (2021) improved the particle swarm optimization algorithm, combined the dynamic programming with the algorithm, and iteratively adjusted the relevant decision variables to meet the time-varying constraints so as to plan the emergency action. Xu et al. (2022) studied the reinforcement learning (RL) of vehicle routing problem, considered the dynamic network structure, dynamically modeled the state transition and action selection, and used several existing VRP problems to verify the algorithm. Sun. and Cai. (2024) use an improved quantum particle swarm algorithm to solve the problem of emergency facility location selection, with the goal of minimizing the response time and storage cost of emergency rescue. Meng et al. (2023) considered the risk of facility disruption and network uncertainty. In order to enhance the adaptability of the system to various emergency supply, a two-stage chance-constrained stochastic programming model was established, and the evolutionary algorithm was improved to optimize the network design and improve the network resilience. Yu et al. (2018) transformed the nonlinear model into an equivalent programming model, proposed the heuristic rules of the cyclic delivery method, and designed a piecewise linear method to solve large-scale instance problems. Zhang et al. (2018) established an uncertain multi-objective path planning model for emergency response by using uncertainty theory and considering travel time, emergency rescue cost and carbon dioxide emissions, and designed a hybrid intelligent algorithm combining uncertain simulation and genetic algorithm to solve the problem. In summary, in terms of algorithm solving, existing algorithms mostly use particle swarm optimization, genetic algorithm, and various heuristic algorithms for solving and focusing on single period and single decision, lacking multiperiod decision support for continuous environmental changes.

The objective of this paper is to enhance the efficacy of post-earthquake emergency management and mitigate the psychological pain experienced by those affected. In order to minimise the distribution cost and the psychological pain perception cost of the victims, a multi-period scheduling model of post-earthquake emergency materials is constructed. In order to enhance the environmental adaptability of the scheduling plan, a fuzzy inference system is employed to adjust the parameters of the objective function. In terms of solution, this paper employs an enhanced particle swarm optimisation algorithm in conjunction with a non-dominated solution adjustment strategy. This approach not only enhances the precision of the solution, but also fulfils the decision-making requirements of multiple new disaster points across multiple time periods.

3. Problem description and model construction

This paper presents a study of the multiperiod scheduling problem of emergency supplies in the context of a period of supply shortage following an earthquake. In the event of an earthquake, emergency supplies are distributed in a uniform manner from the emergency supply warehouse. Initially, the supplies are distributed in an even manner to a number of designated distribution centres. Subsequently, these centres proceed to distribute the supplies to the various disaster points. However, the recurrence of secondary disasters, such as aftershocks, may result in the emergence of new disaster points. Once the transport vehicle has departed, the distribution centre no longer has a surplus of supplies. In such instances, the addition of a new disaster point typically necessitates the reliance on historical expertise to redistribute the remaining supplies in transit or the postponement of distribution until further supplies are available. The aforementioned methods are inherently flawed. The former is devoid of an objective and scientific decision-making basis, whilst the latter may result in delayed rescue times and more severe consequences. To address these issues, this study develops a multiperiod emergency supplies scheduling model. Upon the emergence of a new disaster point, the subsequent period of supply rescheduling is initiated. The integration of real-time environmental information and data pertaining to the newly identified disaster point facilitates the input of data into a fuzzy inference system, thereby enabling the retrieval of output target function parameters. This, in turn, allows for the adjustment of the model, the implementation of an IPSO algorithm and the resolution of the unallocated supplies in the vehicles. This process continues until all delivery tasks have been completed.

Taking vehicle k from a certain material distribution center as an example, when no other disaster points appear, it indicates that this stage is the occurrence stage of event P ($P = 0$), and its original planned route only includes disaster points 1 and 2. On the way to disaster point 1, a new event occurs, which is the addition of disaster point 3. At this time, $P = 1$, disaster point 3 is included in the undelivered set, and the algorithm is run to obtain a re planned route: the vehicle first goes to disaster point 3, then goes to disaster point 2, and changes the quantity of materials allocated to disaster point 2, thereby achieving real-time adjustment of the original plan. If a new event occurs again during the delivery process, which adds several disaster points at once, then $P = 2$. To improve the rationality of supply scheduling, this study takes the minimisation of the total cost of supply scheduling as the optimisation goal, including vehicle transportation cost and the cost of psychological pain perception of victims. Among them, the cost of psychological pain perception of the victims is quantified as a function of the proportion of supply satisfaction and the time of shortage, which is quantified by the 1–10 score system of the NRS rating scale (Wang, 2020). In this study, this perceived cost is expressed as the sum of two linear functions with the proportion of supply satisfaction and the time of supply shortage as independent variables, and the minimisation of total cost is taken as the goal of scheduling scheme design. The parameter and symbol descriptions are shown in Table 2.

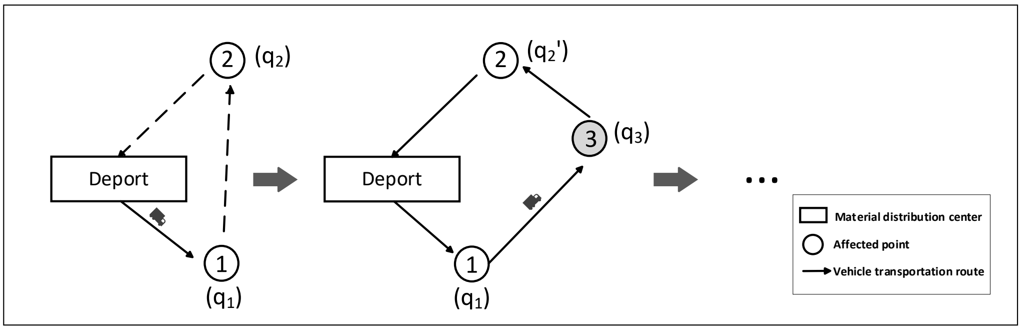


Fig. 1. Post-earthquake emergency supplies scheduling network diagram

Table 2
Definition of notation

Symbol	Description
N_p	The set of all disaster points at the time of the P event, j is the disaster point， $j \in N_p, N_p = \{0,1,2,3, \dots, \mathrm{n}\}$.
M	Emergency Supplies Distribution Centre assembly, m for Emergency Supplies Distribution Centre,$m \in M, M = \{1,2,3, \dots m_0\}$.
V_P	The set of disaster points j that are undistributed at the time of the P event, $j \in V_p, V_p = \{1,2,3, \dots, n_p\}$.
M_p	The set of key points at the time of the P-event, $M_p = \{1,2,3, \dots m_p\}$.
V	The set of all points， $V = M \cup N_P \cup M_p$.
K_m	The set of transport vehicles k， $k \in K_m, K_m = \{1,2,3, \dots, k_0\}, m \in M$.
D_j	The total supply-demand of disaster point j,$\forall j \in N_p$.
Dr_j	The minimum supply-demand of disaster point j,$\forall j \in N_p$.
d_{ij}	The driving distance of the vehicle from node i to node j,$\forall i, j \in V$.
t_{ij}	Travel time of vehicle from node i to node j,$\forall i, j \in V$.
c_k	Unit distance transportation cost of vehicle $k, \forall k \in K_m, m \in M$.
f_k	The fixed cost of vehicle k, $\forall k \in K_m, m \in M$.
α_j,	Supplies satisfied proportional coefficient of disaster point j,$\forall j \in N_p$.
β_j	Supplies shortage time coefficient of disaster point j,$\forall j \in N_p$.
γ_j	The constant value of the supplies satisfied proportional of the disaster point j,$\forall j \in N_p$.
δ_j	The constant value of the supplies shortage time of the disaster point j,$\forall j \in N_p$.
S_j	Supplies loading and unloading time of disaster point $j, \forall j \in N_p$.
G	Unit supplies loading and unloading time.
l_j	The time period from the beginning of distribution to the completion of distribution of supplies at the disaster point j , $\forall j \in N_p$.
Z	An infinite number.
q	Capacity of each vehicle.
Q	Emergency supplies total warehouse reserve supplies quantity.
x_{ij}^{mk}	1 denotes that the vehicle k belonging to the emergency supplies distribution centre m travels from i to j, otherwise $0, \forall i, j \in V, m \in M, k \in K_m$.
y_{ij}^{mk}	The amount of supplies distributed to j by vehicle k belonging to the emergency supplies distribution centre m through i,$\forall i, j \in V$.

3.1 Construction and operation of fuzzy inference system

In the context of actual events, the transportation of emergency supplies is frequently subject to unforeseen challenges, including aftershocks, mudslides and landslides. Such occurrences may not only result in the emergence of new disaster points but may also exacerbate the psychological pain of victims due to the lack of supplies. The 2008 Wenchuan earthquake provides a case in point. The large-scale geological disasters that occurred in the wake of the earthquake, including landslides and collapses in Wenchuan County, not only led to the emergence of additional disaster points but also inflicted considerable damage to the transportation network. This, in turn, further exacerbated the psychological pain of the victims and increased the urgency of their demand for supplies. Furthermore, the natural phenomena of precipitation and debris flow subsequent to the seismic event have introduced considerable challenges to the rescue and transportation of supplies. Consequently, the advent of secondary disasters serves to render the scheduling of supplies more intricate. The scientific nature of decision-making processes is difficult to guarantee when relying solely on expert experience. To address this issue, this study develops a fuzzy inference system that can adapt the parameters of the objective function to align with the actual loss scenario. This system aims to reflect the varying urgency of the supply needs of the victims in response to different levels of loss.

Two trigger conditions have been established to ensure the effective operation of the fuzzy inference system: firstly, an increase in adverse environmental conditions, encompassing the deterioration of the living environment and the traffic environment; secondly, the emergence of new disaster points. The fuzzy inference system comprises five distinct components: input, fuzzification, fuzzy inference machine, defuzzification and output. The fuzzification and defuzzification processes are based on membership functions, whilst the fuzzy inference machine is based on fuzzy inference rules. The construction of a fuzzy inference system involves the following steps:When constructing the fuzzy inference system, three input variables are firstly set and divided into three levels: traffic environment loss (low, medium and high), living environment loss (low, medium and high) and aftershock loss loss (low, medium and high). At the same time, four output variables and their levels are set, including the pain perception cost coefficient α_j(low, medium and high) of the proportion of supplies satisfaction, the pain perception cost constant γ_j (low, medium and high) of the proportion of supply satisfaction, the pain perception cost coefficient β_j (low, medium and high) of the time of supply shortage and the pain perception cost constant δ_j (low, medium and high) of the time of supply shortage.

Initialize the membership values V, U, u_{ij}, c_i, J^t, T, t, ε.

```
begin
V ← Ø, U ← Ø, t ← 0
while t < T do
  for i ← 1 to n do
    for j ← 1 to c do
      calculate u_ij
        u_ij = 1 / Σ_{l=1}^{K} ( (x_j − c_i) / ||x_j − c_l|| )^{2/(m−1)}
    end for
  end for
  for j ← 1 to c do
    calculate c_j :
        c_j = Σ_{j=1}^{N} u_ij x_j / Σ_{j=1}^{N} u_ij
  end for
  calculate J^t :
    t += 1
    if ||J^t − J^{t−1}|| ≤ ε then
      return V, U
    end if
end while
return V, U
end
```

$$u_{ij} = \frac{1}{\sum_{l=1}^{K}\left(\frac{x_j - c_i}{\left\|x_j - c_l\right\|}\right)^{\frac{2}{m-1}}}$$

$$c_j = \frac{\sum_{j=1}^{N} u_{ij} x_j}{\sum_{j=1}^{N} u_{ij}}$$

Output: V, U

In the absence of precise criteria for the aforementioned classification, this study established the range of values for the input and output variables by collating data on earthquakes exceeding magnitude 5 in China over the past 15 years and integrating expert insights. This paper presents a detailed account of the specific conditions pertaining to the loss of the traffic environment (yuan), the living environment (number of houses damaged) and the aftershock loss (number of aftershocks above magnitude 4). Furthermore, it employs the Delphi method to conduct a questionnaire survey among experts with the objective of quantifying the impact of earthquakes on the psychological pain experienced by victims. By analysing and fitting the opinions of experts, a cost function for victims' psychological pain perception is established, and the value range of input and output variable parameters is determined. The aforementioned data serve as a foundation for the construction of membership functions and the establishment of fuzzy inference rules.

Subsequently, the fuzzy C-means clustering algorithm is employed to cluster the specific data pertaining to the input and output variables. The specific value $c_j$of the cluster centre is determined through an iterative optimisation process, and the membership degree u_{ij} (ranging from 0 to 1) belonging to each category is assigned to each sample, indicating the degree of belonging to each category. The iterative process entails the continuous optimisation of the membership degree of the sample and the position of the cluster centre until the convergence condition is reached. The pseudocode of the fuzzy clustering algorithm is as follows. Once the clustering process is complete, the specific loss values associated with each earthquake are classified in accordance with the category with the highest membership degree. This allows the loss levels of the input and output variables to be determined and summarised, thereby establishing the inference rules of the fuzzy inference system.

Ultimately, the centre of gravity method is chosen as the defuzzification technique, with the objective of outputting the parameter value of the psychological pain perception cost function for the victims. The composition of the fuzzy reasoning system is shown in Figure 2.

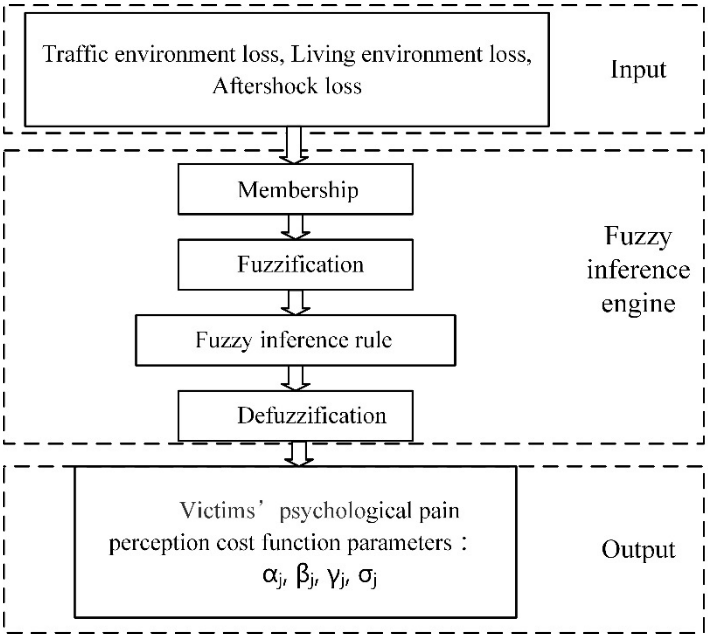


Fig. 2. Components of Fuzzy Reasoning System

Once the fuzzy inference system has been constructed, the decision-maker collates the specific loss data resulting from the earthquake and inputs it into the system. The system's built-in reasoning mechanism ultimately yields precise target function parameters. The parameters are employed to construct the objective function in the supply scheduling model, thereby facilitating the decision-making process regarding the allocation of supplies based on data that are scientific and accurate and can be used in different emergency environments. As a result, the psychological pain experienced by victims is reduced.

3.2 Model establishment

Model assumptions: (1) Given the shortage of supplies in the early stage of the earthquake, all the supplies in the emergency supply distribution centre are completely distributed, and the demand for supplies in each disaster point may not be fully satisfied. (2) 'Key points' (the location of the disaster point that has begun to be distributed but has not yet reached and the disaster point that is being served) are introduced. When a new event occurs, the disaster points that have been distributed and that serve as key points are removed from the list of disaster points. (3) The supply and demand between the distribution centre and the disaster point is known. (4) The roads between the distribution centre and the disaster point are interconnected, and emergency vehicles leave at the same time. (5) The case of partially loaded vehicles is considered. (6) Split delivery is not allowed. The postearthquake emergency supply scheduling model considering the psychological pain of the victims and transportation costs is as follows:

$$min\ F_1 = \sum_{i\in V}\sum_{j\in V}\sum_{k\in K_m}\sum_{m\in M}\left(x_{ij}^{mk}\cdot d_{ij}\cdot c_k\right) + \sum_{m\in M}\sum_{k\in K_m} x_{ij}^{mk}\cdot f_k \tag{1}$$

$$\min \quad F_2 = \sum_{j\in N_p} (\alpha_j * \frac{y_{ij}^{mk}}{D_j} + \gamma_j) + \sum_{j\in N_p} \left(l_j * \beta_j + \delta_j\right), \forall m \in M, i \in V, j \in N_p \tag{2}$$

subject to

$$\sum_{j\in N_p} \sum_{k\in KM} x_{ij}^{mk} \leq k_0, \forall i = m \in M, k \in K_m \tag{3}$$

$$\sum_{j\in N_p} x_{ij}^{mk} = \sum_{j\in N_p} x_{ji}^{mk} \leq 1, \forall i = m \in M, k \in K_m \tag{4}$$

$$\sum_{j\in N_p} \sum_{m\in M} \sum_{k\in K_m} x_{ij}^{mk} = 1, \forall i \in V \tag{5}$$

$$\sum_{i\in N_p} \sum_{m\in M} \sum_{k\in K_m} x_{ij}^{mk} = 1, \forall j \in N_p \cup M \tag{6}$$

$$\sum_{i\in M_p \cup V_p} \sum_{j\in M_p} \sum_{m\in M} \sum_{k\in K_m} x_{ij}^{mk} = 0 \tag{7}$$

$$\sum_{m\in M} \sum_{i\in M_p} \sum_{j\in M \cup V_p} \sum_{k\in K_m} x_{ij}^{mk} = m_p \tag{8}$$

$$\sum_{j\in M} x_{ij}^{mk} = \sum_{j\in M} x_{ji}^{mk} = \sum_{j\in M} y_{ji}^{mk} = \sum_{j\in M} y_{ij}^{mk} = 0, \forall i = m \in M, k \in K_m \tag{9}$$

$$y_{ij}^{mk} \leq x_{ij}^{mk} * Z, \forall i,j \in V, m \in M, k \in K_m \tag{10}$$

$$\sum_{i\in V} y_{ij}^{mk} = 0, \forall j, m \in M, k \in K_m \tag{11}$$

$$\sum_{j\in N_p} \sum_{i\in V} y_{ij}^{mk} \leq q, \forall m \in M, k \in K_m \tag{12}$$

$$Dr_j \leq \sum_{i\in V} \sum_{m\in M} \sum_{k\in K_m} y_{ij}^{mk} \leq D_j, \forall j \in N_p \tag{13}$$

$$\sum_{i\in V} \sum_{j\in N_p} \sum_{k\in K_m} y_{ij}^{mk} = \frac{Q}{m_0}, \forall m \in M \tag{14}$$

$$S_j = y_{ij}^{mk} * G, \forall i \in V, j \in N_p, k \in K_m, m \in M \tag{15}$$

$$t_{ij} = \frac{d_{ij}}{60}, \forall i \in V, j \in N_p \tag{16}$$

$$l_j = \left(l_i + S_i + t_{ij}\right) x_{ij}^{mk}, \forall i \in V, j \in N_p, m \in M, k \in K_m \tag{17}$$

$$x_{ij}^{mk} \in (0,1), \forall i,j \in V, m \in M, k \in K_m \tag{18}$$

$$y_{ij}^{mk} \geq 0, \forall i,j \in V, m \in M, k \in K_m \tag{19}$$

Eq. (1) represents the total transportation cost minimisation, including vehicle driving cost and vehicle fixed cost. Eq. (2) represents the minimisation of the perceived cost of the victims' pain, which covers the perceived cost of the victims' psychological pain caused by the proportion of supply satisfaction and the time of supply shortage. Eq. (3) ensures that the number of vehicles dispatched by each distribution centre does not exceed the number of vehicles it has. Eq. (4) ensures that the vehicles sent by the emergency supply distribution centres will return to the starting point. Eq. (5) and Eq. (6) limit each disaster point to be served only once. Eq. (7) and Eq. (8) stipulate that vehicles at 'key points' can only be accessed in one direction, that is, they can only be issued. Eq. (9) prohibits vehicles from one emergency supply distribution centre to go to another emergency supply distribution centre. Eq. (10) stipulates that only the node passed by vehicle k can receive the goods delivered by the vehicle. Eq. (11) shows that the emergency supply distribution centre does not receive supply distribution. Eq. (12) shall not limit the carrying capacity of a vehicle to exceed its capacity. Eq. (13) ensures that the minimum needs of all disaster points are met. Eq. (14) ensures that there are no surplus supplies in the emergency supply distribution centre after the scheduling is completed. Eq. (15) represents the loading and unloading time of supplies. Eq. (16) represents the transportation time. Eq. (17) represents the time from the beginning of the vehicle to the arrival of point j. Eqs (18-19) describe the properties of the independent variables.

Taking 9 disaster points as an example, the process of emergency supplies scheduling in each period is explained : Gurobi is used to solve the above model, in which the set of emergency supplies distribution centres $M = \{A, B, C\}$, the set of vehicles owned by each emergency supplies distribution centre $K_m = \{1, 2, 3\}$, and the set of disaster points $N = \{1, 2, 3, \ldots, 9\}$.After 20 minutes of distribution, 10 disaster points are added. At this time, $V_p = \{1, 6, 9, 10\}, M_0 = \{2, 3, 5\}$, the unit supplies loading and unloading time $G = 0.05\ h$, and the vehicle speed is $60\ km / h$. The travel time between two nodes is calculated by $t_{ij} = \frac{d_{ij}}{60km/h}$. The fixed cost of vehicle k is $f_k = 100$ yuan / vehicle, and the transportation cost per unit distance of vehicle k is 1 yuan. The capacity is 45 units. The minimum supply-demand set $Dr = \{14,14,14,14,14,14,14,14,17,17,17,17,2\}$, and the total supply-demand set $D = \{20,20,20,20,20,25,25,25,25,10\}$. The optimal supply scheduling scheme, obtained by solving the Gurobi solver, is depicted in Figure 3. The brackets in the figure indicate the quantity of supplies allocated to each disaster point by each vehicle. Among the disaster points, the new No. 10 point is included in the distribution path of a vehicle from the emergency supplies distribution centre A. However, due to the limitation of the amount of supplies loaded by the vehicle, this has led to a reduction in the amount of supplies allocated to the subsequent disaster points in the route. Nevertheless, the total amount of supplies allocated to all disaster points still meets the minimum requirements.

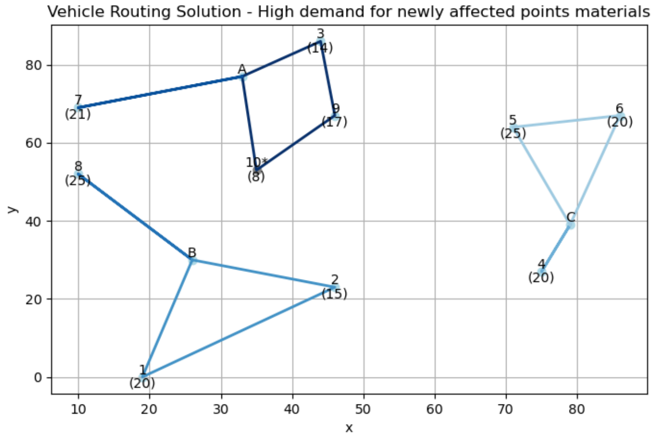


Fig. 3. New No.10 disaster point supplies scheduling scheme

4. Improved particle swarm optimization algorithm

As the classical VRP has been demonstrated to be an NP-hard problem (Montoya-Torres et al., 2014), the multiperiod scheduling problem of emergency supplies, as examined in this study, is also an NP-hard problem. In the case of such problems, the generation method of the initial solution of the algorithm when rescheduling must be improved. As the scale of the demand solution problem continues to expand, the efficiency and accuracy of the algorithm must be improved. Furthermore, in light of the potential emergence of new disaster points during the distribution process, the algorithm must be capable of accommodating real-time restart and rescheduling by incorporating these new disaster points on an ongoing basis. Accordingly, this study proposes the design of an IPSO algorithm. The PSO algorithm can conduct a comprehensive search of the solution space and is therefore a popular choice for path planning. In particular, the improved algorithm integrates the leader–follower mechanism of the grey wolf algorithm and the swarm intelligence search strategy of the PSO algorithm, thereby conferring enhanced stability and solution accuracy upon the classical PSO algorithm when confronted with the multiperiod scheduling problem of emergency supplies. The specific improvements are as follows:

4.1 Coding of particles and initialisation of particle swarm

The particle coding method is as follows : each particle represents a supplies scheduling scheme. In order to accurately record the information of m emergency supplies distribution centres and k vehicles, as well as the path and supplies distribution of n disaster points, this paper encodes the particles into a $(k+1) \times (n+m)$ matrix. Among them, line k represents the driving path of the vehicle k, and the column number of the matrix corresponds to the number of the emergency supplies distribution centre and the disaster point in turn. The element a_{ij} in the matrix indicates whether the i th vehicle passes through the j th node. If it passes through, the corresponding value is 1, otherwise it is 0. The last row of the matrix represents the supplies allocation of each node.

In the initial stages of this study, a supply scheduling plan is generated on the basis of the available information. This plan groups the disaster points and matches them with the emergency supply distribution centre. Subsequently, the disaster points randomly select vehicles for supply distribution, ensuring that the amount of supplies allocated is between the minimum and maximum demand. Upon the occurrence of a new event, the decision-maker inputs the information of the new disaster point to the algorithm manually or via IoT, resulting in the distributed and undistributed disaster points being classified into different sets. Subsequently, the IPSO algorithm randomly incorporates the new disaster points into the supply scheduling plan in turn by the enumeration method and randomly allocates the amount of supplies to generate multiple initial solutions, as shown in Fig. 4. This approach allows for the effective incorporation of new disaster points into the scheduling plan, thereby facilitating the generation of an initial solution.

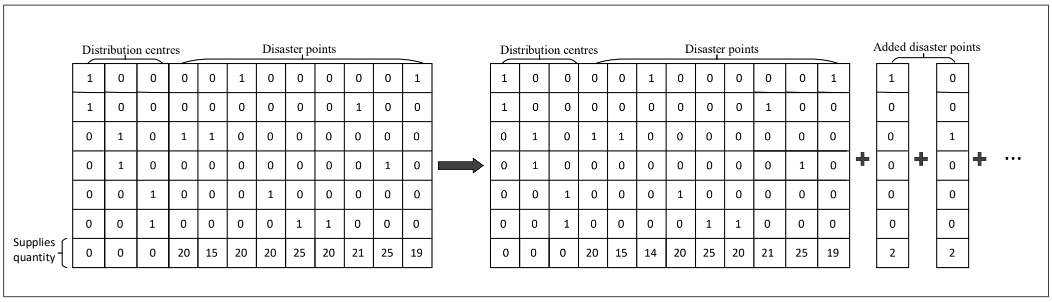


Fig. 4. Insertion of new disaster points

4.2 Defining the fitness function

In the IPSO algorithm, the quality of the solution is evaluated via a fitness function. The smaller fitness value observed in this study indicates that the solution is closer to the optimal solution. A series of constraints is firstly checked on the path represented by each particle to calculate the fitness value. These include location constraints, statistics of the number of visits to the disaster point, whether the vehicle starts from an emergency supply distribution centre and returns to the original emergency supply distribution centre, whether the number of visits to the disaster point is 1, whether the resource allocated by the disaster point is between the minimum and maximum demand and whether the vehicle is overloaded. For particles that contravene the restriction, a penalty term is established. Subsequently, the total transportation cost of each particle, the psychological pain cost of the victims and the penalty term are calculated. The total transportation cost encompasses the driving cost and the fixed cost of all vehicles traversing the particle path, which is represented by the objective function F_1 in the model. Additionally, it incorporates the proportion of emergency supplies at the disaster point and the psychological pain cost of the victims resulting from the shortage of emergency supplies, which is represented by the objective function F_2. Finally, the penalty term is set to infinity due to the violation of the aforementioned constraints. The aforementioned statistics are then aggregated to derive the final fitness value, which is calculated using the formula presented in Equation (20).

$$Fitness = \omega_1 F_1 + \omega_2 F_2 + Penalty \tag{20}$$

4.3 Updating and adjusting the position of particle swarm with grey wolf algorithm

The grey wolf algorithm is an optimisation algorithm that draws inspiration from the behaviour of the grey wolf group. In this algorithm, the candidate solutions within the solution space are regarded as grey wolf individuals, which are searched and adjusted in accordance with the current position and fitness value. The social behaviour of wolves is emulated by grey wolves to find the optimal solution through a process of cooperation and competition. In this paper, the concept of a global suboptimal solution in PSO based on the idea of the grey wolf algorithm is introduced. The position update method is modified to be jointly guided by the historical optimal position, the global optimal solution, and the global suboptimal solution of the particle itself. In this manner, the information pertaining to the global search space is more extensively leveraged to facilitate the search process. The improved speed update formula is presented in Eq. (21).

$$v_{id} = \omega v_{id-1} + c_1 r_1 (p_{best-id} - x_{id}) + c_2 r_2 \left(p_{global_{\text{best}}} + p_{global_{second}} - 2x_{id}\right) \tag{21}$$

In the iterative process of PSO, several unqualified solutions are frequently generated, namely, nondominated solutions, which ultimately reduce the overall solution efficiency.

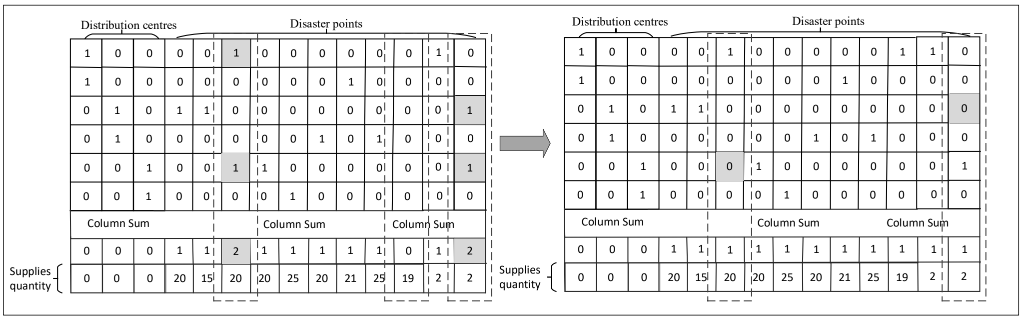


Fig. 5. Solution adjustment of improved particle swarm optimization algorithm

To address this issue, this study proposes a nondominated solution adjustment strategy with the objective of enhancing the probability that the solution meets the specified conditions. In particular, the strategy initially determines whether each disaster point satisfies the condition of 'there is only one vehicle for supply transportation' by summing each column. If the sum of a column is not equal to 1, then the condition is not satisfied. In the case of columns with a value of greater than 1, indicating the presence of multiple vehicles at a given disaster point, the path of one vehicle is maintained, whilst the value $(a_{ij})$of the remaining vehicles in the corresponding column is set to 0. This ensures that only one vehicle is distributed at each disaster point. By contrast, for columns with a value of 0, indicating the absence of vehicles at a given disaster point, a vehicle is randomly selected, and the value $(a_{ij})$of its corresponding position is set to 1. The above process is shown in Fig. 5. This guarantees that all disaster points are visited. The aforementioned strategies serve to reduce the frequency of nondominated solutions and enhance the efficiency of IPSO.

5. Numerical experiments and results analysis

Both Gurobi and Particle Swarm Optimization (PSO) can solve the supplies scheduling problem. In order to verify the effectiveness of the proposed improved particle swarm optimization (IPSO), this section uses the above methods to solve the model. All simulation experiments are implemented on Win10 system and Intel Core i5-7200 dual-core processor computer. The maximum load of the vehicle is $q = 45\ units$, the average speed of the emergency supplies transportation vehicle is $v = 45\ km/h$, the unit distance distribution cost is $c_k = 1$ yuan, and the fixed departure fee is $f_k = 100\ yuan/vehicle$. Two numbers are randomly generated within 100 as the horizontal and vertical coordinates of each node, and the Euclidean distance is used to define the distance between any two regions.

The number of particles is set to 40, and the number of iterations is 500. Two numbers are randomly generated within 100 as the horizontal and vertical coordinates of each node, and the Euclidean distance is used to define the distance between any two regions. $w_1 \in [0.2\ , 0.5], c_1 \in [0.3,1], c_2 = [0.5,1]$, Three emergency supplies distribution centres are set up, and the examples of 6,9 and 12 disaster points are added one disaster point in each stage as a small-scale example experiment. The results of particle swarm optimization, improved particle swarm optimization and Gurobi are shown in Table 3. The objective function $F = \omega_1 F_1 + \omega_2 F_2$, Gap is the error value between the results of two different algorithms, $Gap1 = \frac{F_{PSO}-F_{MIP}}{F_{PSO}}, Gap2 = \frac{F_{IPSO}-F_{MIP}}{F_{IPSO}}$. For the scale of the example above 12 disaster points, due to the limitation of the solution time, Gurobi cannot solve the optimal result within the specified time. Therefore, the particle swarm optimization algorithm and the improved particle swarm optimization algorithm are used to compare the large-scale example experiments to calculate the total cost of the whole process after the end of distribution. At this time, $Gap3 = \frac{F_{PSO}-F_{IPSO}}{F_{PSO}}$. The results are shown in Table 4.

Table 3
Experimental results of a small-scale example of multi-period scheduling of emergency supplies

Number of vehicles per distribution centre	Number of original disaster points	New number of		Objective function values			Gap1	Gap2
		First added	Second added	Gurobi	PSO	IPSO		
2	6	1	1	862.60	863.63	862.60	0.12%	0%
3	9	1	1	1343.05	1377.79	1343.17	2.52%	0.01%
4	12	1	1	1716.52	1787.65	1755.77	2.24%	3.98%

Table 4
Experimental results of large-scale example of multi-period scheduling of emergency supplies

Number of vehicles per distribution centre	Number of original disaster points	New number of disaster points		Objective function values		Gap3
		First added	Second added	PSO	IPSO	
4	21	2	1	3152.18	2959.54	6.11%
		4	3	3218.17	3137.99	2.49%
		6	5	3432.28	3300.42	3.84%
5	30	2	1	4458.80	4358.82	2.24%
		4	3	4706.55	4473.83	4.94%
		6	5	5005.66	4654.37	7.02%
10	60	2	1	8900.47	8790.46	1.24%
		4	3	9085.92	8907.82	1.96%
		6	5	9187.25	9032.97	1.68%
15	90	2	1	13107.12	12841.83	2.02%
		4	3	13146.06	12982.92	1.24%
		6	5	13274.90	12994.53	2.11%

It can be seen from the above results that Gap is positive in different data settings, and it is basically stable between 1-6%. This means that the improved particle swarm optimization algorithm can improve the objective function value by 1-6 %

compared with the ordinary particle swarm optimization algorithm. This proves that the improved particle swarm optimization algorithm has advantages over the traditional particle swarm optimization algorithm and can better approach the optimal solution.

6. Sensitivity analysis

To enhance the efficacy of postearthquake emergency management and optimise the emergency supplies scheduling strategy, this study develops a multiperiod emergency supply scheduling model with the objective of minimising the transportation cost and the psychological pain perception cost of the victims. In this model, the vehicle-related parameters, the weight of the vehicle transportation cost and the psychological pain perception cost of the victims in the total cost and the supply-demand of the disaster point are all considered important factors that affect the optimal scheduling results. In light of the aforementioned considerations, this study employs a sensitivity analysis to assess the sensitivity of the objective function to these parameters.

In this study, three emergency supply distribution centres (A, B, C) and nine disaster points (1–9) were established. Subsequently, the occurrence of a secondary disaster led to the addition of two disaster points (10, 11). Maintaining a normal vehicle speed during transportation is challenging due to the damage to the road and congestion caused by the earthquake. Therefore, the impact of vehicle speed on the optimal scheduling results must be considered when developing an emergency supply scheduling strategy. In light of the aforementioned considerations, a sensitivity analysis of vehicle speed was conducted. Figure 6 shows the optimal scheduling scheme obtained by executing the IPSO algorithm three times, with only the vehicle speed variable adjusted whilst all other conditions remained constant. The results demonstrate that a notable reduction in vehicle speed leads to an increase in the time required to replenish supplies, which in turn affects the selection of an optimal scheduling scheme. Prior to the occurrence of the disaster, emergency supply distribution centre B was responsible for the distribution of supplies to the new disaster point, designated No. 11. Following the speed adjustment, emergency supply distribution centre A assumed responsibility for supply distribution. This adjustment resulted in an increase in the perceived cost of psychological pain for victims of the disaster at the time of the supply shortage, i.e. from 155.88 to 156.63. Concurrently, the cost of transportation also increased from 738.22 to 748.48. A reduction in vehicle speed results in an increase in the perceived cost of psychological pain for victims due to an extension in the material shortage time, accompanied by a corresponding increase in the cost of material transportation. In the decision-making process, some compromises must be made to reduce the total cost. For instance, some transportation costs may need to be sacrificed, and some disaster points may need to be distributed by vehicles that are far away. This compromise can be made to change the distribution order and reduce the waiting time at the disaster points, thus reducing the psychological pain experienced by victims of the disaster.

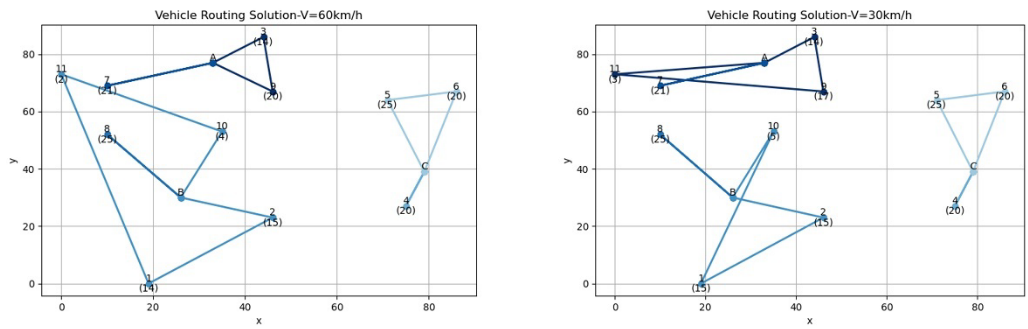


Fig. 6. The optimal emergency supplies scheduling plan under different driving speeds

The total cost in the model is obtained by weighting two objective functions: the vehicle transportation cost and the cost of victims' psychological pain perception. The vehicle transportation cost encompasses the fixed cost of vehicle use and the distribution cost related to the distribution distance. The psychological pain perception cost of victims is a function of the proportion of supply satisfaction and the time of supply shortage. The perceived cost of psychological pain of the victims is negatively correlated with the proportion of supply satisfaction and positively correlated with the time of supply shortage. The aforementioned two objective functions exert a considerable influence on the formulation of a supply scheduling plan. By regulating these two costs, the emergency supply scheduling can be constrained in accordance with the varying effects of the earthquake, thus helping reduce the likelihood of inadequate or excessive responses to the emergency supply scheduling.

Fig. 7 illustrates the specific alterations to the optimal material scheduling plan in response to varying weights. As illustrated in the figure, the alteration of the weight of the victims' psychological pain perception cost in the total cost has a considerable effect on the vehicle transportation path and material distribution outcomes. With the incremental increase in the weight of the psychological pain perception cost of the victims, the transportation path and supply distribution quantity of the vehicles from emergency supply distribution centre B in the optimal distribution scheme have undergone a transformation due to the influence of the proportion of supply satisfaction and shortage time. The vehicle path undergoes a transformation, shifting from 1(14)→11(2)→10(4) to 10(2)→11(2)→1(16). The value in parentheses represents the quantity of supplies. Furthermore, when the ratio of F1 to F2 reaches 1:20, the distribution task of the No. 10 disaster point continues to be borne by emergency supply distribution centre B, whilst the distribution task of the No. 11 disaster point is transferred to the vehicle of emergency supply distribution centre A. In addition, the supply distribution volume of the two new disaster points increases accordingly. As the perceived cost of psychological pain among victims increases, the distribution time for each disaster point gradually decreases, whilst the proportion of satisfied supplies gradually increases. This results in a decrease in the perceived cost of psychological pain among victims from 156.99 to 156.58, whilst the transportation cost of supplies gradually increases from 748.22 to 748.48. It can be seen that with the decrease of vehicle speed, the psychological pain perception cost of the victims increases due to the extension of supply shortage time, and the cost of supply transportation also increases. In the decision-making process, in order to reduce the total cost, some transportation costs will be sacrificed, and some disaster points will be distributed by vehicles far away so as to change the distribution order and reduce the waiting time for the disaster points, thus reducing the psychological pain perception cost of the victims.

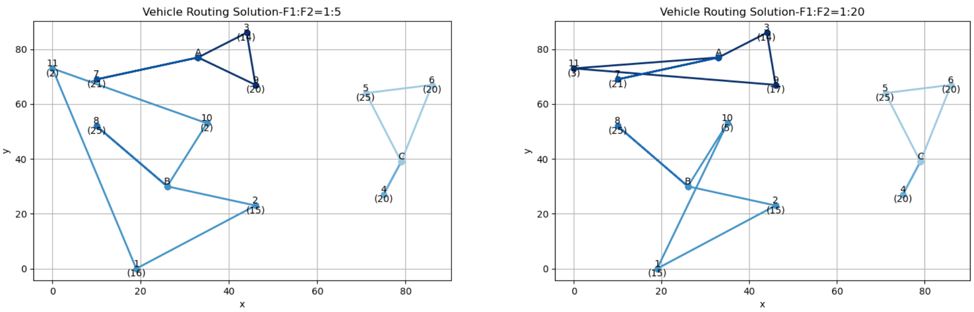


Fig. 7. The solution results of the optimal emergency supplies scheduling plan under different objective function weights

Following an earthquake is a paucity of supplies in the initial stages of rescue operations, and the number of remaining supply to be allocated is constrained when new disaster points emerge. The optimal scheduling scheme is contingent upon the specific requirements of the newly emerging disaster points. Accordingly, this study examines the influence of the supply-demand at new disaster points on the optimal solution. The optimal scheduling scheme results for varying supply demand are presented in Fig. 8. The results demonstrate that when the supply demand of the new disaster point is reduced (within the scope of [2,5]), a greater number of vehicles can meet their supply needs. In this instance, the cost of vehicle transportation is reduced to 745.63. However, in the event of a high demand for supplies at the new disaster point, the restriction that multiple vehicles are not permitted to be delivered to the same disaster point may result in no vehicle remaining with sufficient capacity to meet its minimum requirements. Consequently, the conditions governing the supply of materials can be altered. One such alteration would be to change the quantity of materials allocated to each disaster point, with the aim of meeting at least 60% of the total demand (below the minimum supply-demand).

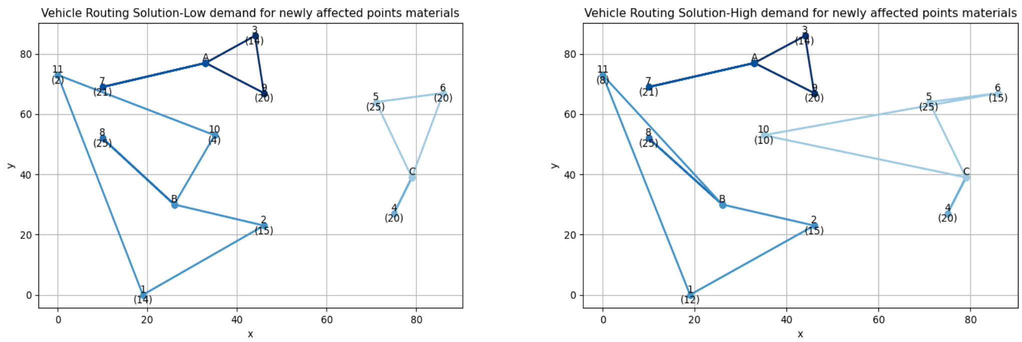
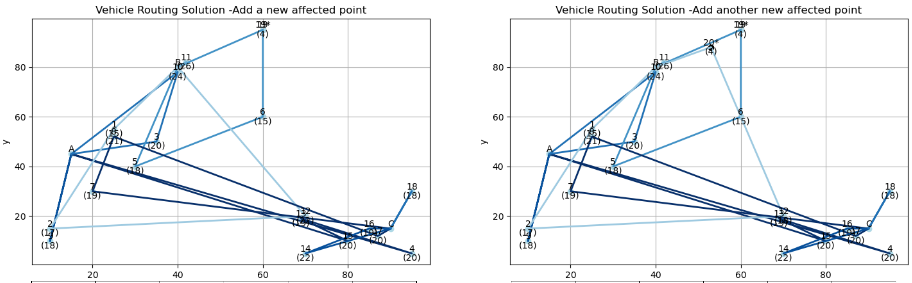


Fig. 8. The solution results of the optimal emergency supplies scheduling plan under different supply-demand satisfaction ratios

This study employs a sensitivity analysis to assess the impact of transportation costs and victims' psychological pain perception costs on the model. This analysis is conducted under the assumption of actual decision-making scenarios. The research demonstrates that decision-makers can evaluate the cost and the psychological pain perception cost of victims in accordance with a range of factors, including the disaster situation. This enables the formulation of a more practical supply scheduling scheme. Furthermore, the sensitivity analysis of the demand for supplies in the newly disaster points revealed that when the remaining supplies cannot meet the minimum supply needs of all undistributed disaster points, including the newly affected ones, the use of the minimum satisfaction rate of supplies in the supply schedule to replace the minimum demand of each disaster point can also effectively reduce the psychological pain perception cost of the victims.

7. Case study

This study inputs the specific loss data into the fuzzy inference system to determine the psychological pain perception cost function parameters of the victims and constructs a multiperiod supply scheduling model based on the 6.2-magnitude earthquake that occurred in Jishishan County, Linxia Prefecture, Gansu Province at 23:59 on 18th, December 2023. The 18 centralised settlements located in Liuji Township, Shiyuan Town, Dahejia Town, Liugou Township, Chuimatan Town, Zhaizigou Township and Hulinjia Township were selected as disaster points for the purposes of obtaining their respective latitude and longitude coordinates. These coordinates were subsequently obtained by processing. The distribution centre for emergency supplies was established at the local government offices of Liuji Township, Dahejia Town and Zhaizigou Township. Following the Jishishan earthquake, a remarkable sand surge was triggered, resulting in the extensive burial of Jintian Village and Caotan Village in Zhongchuan Township, Jishishan County. Upon the commencement of relief supplies, the aforementioned two disaster points were subsequently established and reported their demand for emergency supplies. Consequently, the aforementioned two disaster points were incorporated into the distribution plan in a chronological sequence, and two reschedulings were conducted. The fixed cost of a unit transportation vehicle is 100 yuan, the vehicle driving cost per unit distance is 1 yuan, and the average driving speed of the vehicle is 30 km/h. Table 5 presents the information on each emergency supply distribution centre and disaster point, whilst Fig. 9 displays the scheduling results.



V1	A	4	13	15	A
V2	A	9	A		
V3	A	3	10	A	
V4	B	5	6	19	B
V5	B	11	B		
V6	B	1	2	12	B
V7	C	7	8	17	C
V8	C	14	16	C	
V9	C	18	C		

V1	A	4	13	15	A	
V2	A	9	A			
V3	A	3	10	A		
V4	B	5	6	19	B	
V5	B	11	B			
V6	B	1	2	12	20	B
V7	C	7	8	17	C	
V8	C	14	16	C		
V9	C	18	C			

Fig. 9. Supply scheduling plan

Table 5
The information of each emergency supply distribution centre

Serial number	Emergency supplies distribution centre / disaster point	Coordinate	Minimum supply-demand	Total supply-demand
1	Liuji Township People 's Government	(15, 45)	-	-
2	Dahejia Town People 's Government	(40, 80)	-	-
3	Zhaizigou Township People 's Government	(90, 15)	-	-
4	Taojia Village	(25, 55)	15	19
5	Gaoli Village	(10, 10)	13	18
6	Qiyangwa Village	(35, 50)	16	28
7	Shenjiaping Village	(95, 5)	17	25
8	Songjiagou Village	(30, 40)	18	26
9	Xiaohongping Village	(60, 60)	12	18
10	Qinyin Village	(20, 30)	15	19
11	Shiyuan Village	(25, 52)	16	23
12	Dahe Village	(10, 10)	13	19
13	Chenjia Village	(40, 78)	20	28
14	Liugou Township Government Building	(42, 82)	22	30
15	Kanggaji Village	(70, 20)	16	24
16	Qianzhuang	(69, 19)	14	19
17	Shangping Village	(70, 5)	18	25
18	Dihe Village	(80, 10)	16	23
19	Dongping Temple Village	(85, 15)	16	24
20	Gaoguan Village	(87, 12)	15	22
21	Jintian Village, Nakagawa Township	(95, 30)	15	21
22	Caotan Village, Zhongchuan Township	(60, 95)	8	13
23	Songjiagou Village	(53,88)	4	13

In consequence of the disparate temporal intervals between the occurrence of the disaster and the subsequent shortage of supplies, the new disaster points (19 and 20) are incorporated successively after the vehicle has been driven for 10 and 40 minutes. The optimal total cost obtained after the algorithm was run three times is 2,303.35. The results demonstrate that the model and algorithm proposed in this study can assist decision-makers in addressing the multiperiod scheduling challenge of post-earthquake emergency supplies, reducing the psychological and transportation costs incurred by victims and enhancing the efficiency of emergency management.

8. Summary and prospect

The IoT technology is employed extensively in the fields of earthquake monitoring, real-time statistics and the scheduling of supplies. This study addresses the challenge of supply scheduling in post-earthquake emergency management. A multiperiod scheduling model of emergency supplies is constructed on the basis of real-time environmental information from IoT. The impact of supply shortage time and satisfaction ratio on the psychological pain of victims is quantified. In the decision-making process, the decision-maker adjusts the target function parameters through the fuzzy inference system and solves the problem by using the IPSO algorithm, which combines the grey wolf algorithm and the nondominated solution adjustment strategy. The efficacy of the algorithm is validated through a multitude of case studies. The experimental results demonstrate that the supply scheduling scheme formulated by the proposed model and algorithm is conducive to reducing the time of supply shortage and increasing the proportion of supply satisfaction, thus effectively alleviating the psychological pain of the victims. This research has substantial theoretical value in improving the efficiency of post-disaster emergency supply scheduling and reducing the psychological pain of victims. It also provides support for the decision-making of relevant departments. Furthermore, the utilisation of a fuzzy inference system and an enhanced particle swarm optimisation algorithm provides a framework for addressing analogous issues. In light of the aforementioned research outcomes and conclusions, the following avenues for future investigation can be proposed: Firstly, the incorporation of external donations or supplies procured through alternative means during periods of scarcity into the distribution system in real time, with a vision to enhance the demand satisfaction rate further, represents a key area of future research. Secondly, when the remaining unallocated supplies are insufficient to meet the needs of new disaster points, the question of whether multiple vehicles should be permitted to transport supplies to one disaster point simultaneously to meet the needs of the disaster area to the greatest extent can be the focus of future research.

9. Disclosure statement

9.1. Disclosure of interest

No potential conflict of interest was reported by the authors.

9.2. Disclosure of funding

No funding was received.

9.3. Data availability statement.

The data are available from the corresponding author on reasonable request.

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Appendix A: Under different earthquake background, Materials satisfied proportion and materials shortage time questionnaire on the impact of victims' psychological pain

This questionnaire explores the impact of Materials satisfied proportion and materials shortage time on the victims' psychological pain in the context of different levels of earthquakes. The table shows the time of shortage of the sample materials and the name of the earthquake after the earthquake. Please judge the degree of victims' pain according to the given background and fill in the following table.

The NRS numerical rating scale was used to quantify the degree of pain. The standard was composed of 11 numbers from 0 to 10, and 0 was categorized as no pain ; 1–3 are categorized as mild pain, 4–6 are categorized as moderate pain, and 7–10 are categorized as severe pain. The greater the number, the higher the degree of pain. Among the earthquakes surveyed, the 8-magnitude earthquake in Yingxiu Town, Wenchuan County, Sichuan Province in May 2008 was the worst traffic environment, the worst living environment and the most new disaster areas. In October 2016, the 6.2-magnitude earthquake in Zaduo County, Qinghai Province was the least bad traffic environment, the least bad living environment and the least new disaster areas. In general, the greater the magnitude, the higher the degree of injury, the more urgent the demand for warm clothing, drugs and other materials. At the same time, the impact on the living environment, such as the degree of damage to the house, is also greater. Please use this as a reference background to estimate the degree of victims' pain for different the Materials satisfied proportion and the materials shortage time (The standard consists of 11 numbers of 0-10, 0 is painless; 1–3 are categorized as mild pain, 4–6 are categorized as moderate pain, and 7–10 are categorized as severe pain. The greater the number, the higher the degree of pain.).

	Materials satisfied proportion (Pain value)		
Earthquake name (0-10)	Materials (water, food, warm clothing, basic drugs, etc.) can fully meet needs (100 %).	Materials (water, food, warm clothing, basic drugs, etc.) can only meet basic needs (60 %).	Materials (water, food, warm clothing, basic drugs, etc.) can not meet the basic needs (30 %).
In October 2016, Zaduo County, Qinghai Province, M6.2 earthquake (The least bad traffic environment, the least bad living environment, and the least aftershocks).			
In May 2008 Wenchuan County, Sichuan Province, M8 earthquake (The worst traffic environment, the worst living environment, and the largest number of aftershocks).			

	Materials shortage Time (Pain value)			
Earthquake name (0-10)	Shortage of materials (water, food, warm clothing, basic drugs, etc.) for 12 hours.	Shortage of materials (water, food, warm clothing, basic drugs, etc.) for 24 hours.	Shortage of materials (water, food, warm clothing, basic drugs, etc.) for 48 hours.	Shortage of materials (water, food, warm clothing, basic drugs, etc.) for 72 hours.
In October 2016, Zaduo County, Qinghai Province, M6.2 earthquake (The least bad traffic environment ,the least bad living environment, and the least aftershocks).				
In May 2008, Wenchuan County, Sichuan Province, M8 earthquake (The worst traffic environment, the worst living environment, and the largest number of aftershocks).				

Appendix B: Questionnaire on the impact of various aspects of earthquake losses on the degree of victims' psychological pain

This questionnaire explores the impact of different degrees of losses caused by different levels of earthquakes on the degree of victims' psychological pain. The name of the earthquake is shown in the table, and the traffic economic loss, the number of damaged houses, and the number of aftershocks greater than four are divided into three grades of " Slight," "Medium," and "Serious" for reference. The NRS numerical rating scale was used to quantify the degree of pain. The standard was composed of 11 numbers from 0 to 10, and 0 was categorized as no pain, 1–3 are categorized as mild pain, 4–6 are categorized as moderate pain, and 7–10 are categorized as severe pain. The greater the number, the higher the degree of pain. Please comprehensively consider the magnitude of the earthquake, the traffic loss caused, the number of damaged houses, and the number of aftershocks greater than 4 to determine the degree of victims' pain and fill in the following table.

Earthquake loss / Earthquake name	Traffic loss level	Housing loss level	Aftershocks' loss	Pain value (0-10)
2016 Zaduo County, Qinghai Province, M6.2 earthquake.[1]	Slight	Slight	Slight	
2008 Wuqia, Xinjiang Uygur Autonomous Region, M6.8 earthquake.[2]	Slight	Slight	Medium	
2018 Jiashi County, Xinjiang Uygur Autonomous Region, M5.5, M4.7 earthquake.[3]	Slight	Medium	Slight	

[1] https://news.youth.cn/gn/201610/t20161018_8759652.htm
[2] https://www.gov.cn/govweb/gzdt/2008-10/17/content_1123584.htm
[3] https://www.ndrc.gov.cn/fggz/jjyxtj/yjgl/201809/t20180929_1197391.html

2008 Haixi County, Qinghai Province, M6.3 earthquake.[4]	Slight	Medium	Medium	
2020 Jiashi County, Xinjiang Uygur Autonomous Region, M6.4 earthquake.[5]	Medium	Slight	Slight	
2016 Aketao County, Xinjiang Uygur Autonomous Region, M6.7 earthquake.[6]	Medium	Slight	Medium	
2017 Jinghe County, Xinjiang Uygur Autonomous Region, M6.6 earthquake.[7]	Medium	Medium	Medium	
2008 Dangxiong County, Lhasa City, Tibet Autonomous Region, M6.6 earthquake.[8]	Medium	Medium	Slight	
2017 Jiuzhaigou County, Sichuan Province, M7 earthquake.[9]	Medium	Medium	Slight	
2014 Yutian County, Xinjiang Uygur Autonomous Region, M7.3 earthquake.[10]	Medium	Medium	Medium	
2015 Pishan County, Hotan Prefecture, Xinjiang Uygur Autonomous Region, M6.5 earthquake.[11]	Medium	Medium	Medium	
2021 Maduo County, Guoluo Prefecture ,QinghaiProvince , M7.4 earthquake.[12]	Medium	Medium	Serious	
2008 Renhe District, Panzhihua City, Sichuan Province, M6.1 earthquake.[13]	Medium	Serious	Slight	
2008 Yingjiang County, Yunnan Province, M5.0, M4.9, M5.9 earthquake.[14]	Medium	Serious	Medium	
2013 Lushan County, Ya'anCity, Sichuan Province, M7 earthquake.[15]	Medium	Serious	Medium	
2021 Yangbi County, Yunnan Province, M6.4 earthquake.[16]	Medium	Serious	Serious	
2014 Jinggu County, Yunnan Province, M6.6 earthquake.[17]	Serious	Medium	Slight	
2013 Minxian County, Gansu Province, M6.6 earthquake.[18]	Serious	Serious	Slight	
2010 Yushu County, Qinghai Province, M7.1 earthquake.[19]	Serious	Serious	Medium	
2008 Wenchuan County, Sichuan Province, M8 earthquake.[20]	Serious	Serious	Serious	

[4] https://www.gov.cn/gzdt/2008-12/04/content_1168266.html

[5] https://www.xjdzj.gov.cn/quakeproof/20210225/38379.html

[6] Ali Mujiang Yalikun, Chang Xiangde, Chen Jianbo, Li Shuai, Hu Weihua, Tan Ming. November 25, 2016, Aktao, Xinjiang S6.7 Earthquake Disaster Loss Assessment [J]. Inland Earthquake, 2017,31 (02): 184-189

[7] https://www.chinanews.com.cn/gn/2017/08-09/8300163.shtml

[8] https://news.cctv.com/2017/08/09/ARTIMafaSVqMbPXxDrwnTvAE170809.shtml

[9] https://baike.baidu.com/item/8%C2%B78%E4%B9%9D%E5%AF%A8%E6%B2%9F%E5%9C%B0%E9%9C%87/22069058?fr=ge_ala

[10] https://hea.gov.cn/system/201512/314470.html

[11] https://news.12371.cn/2015/07/04/ARTI1435962503808506.shtml

[12] https://yjgli.ningbo.gov.cn/art/2022/1/26/art_1229076331_58950006.html

[13] https://www.eqsn.gov.cn/info/1058/24644.htm

[14] https://www.gov.cn/govweb/gzdt/2008-09/19/content_1100084.htm

[15] https://www.yaan.gov.cn/xinwen/show/68F7624A-63E7-4F09-80DD-7A48777D4361.html?eqid=aa546ac10000b3950000000464799a6f

[16] http://www.yangbi.gov.cn/ybyz/c102199/202205/4533fcf4f1d54ed19eaec1de67d97c14.shtml

[17] https://www.chinanews.com.cn/gn/2014/10-08/6655708.shtml

[18] Shi Yucheng, Gao Xiaoming, Tan Ming, et al. Evaluation of losses caused by the 6.6 magnitude earthquake in Zhang County, Min County in 2013 [J]. Journal of Earthquake Engineering, 2013,35 (04): 717-723

[19] https://www.gsdzj.gov.cn/info/1025/4668.htm

[20] http://www.npc.gov.cn/zgrdw/npc/zt/2008-09/05/content_1448390.htm