Heliyon 10 (2024) e31758

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

A multi-period optimal distribution model of emergency resources for responding to COVID-19 under uncertain conditions

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ARTICLE INFO

Keywords:
Emergency resource distribution
Uncertain conditions
IMGA algorithm
COVID-19

ABSTRACT

Ideally, optimal emergency resource allocation would have been vital for effective relief work during the COVID-19 outbreak. However, the suddenness of the epidemic and uncertainty of its spread added some difficulties to distributing emergency resources. First, this study introduces triangular fuzzy numbers to describe the uncertainty of supply and demand of emergency resources, and interval numbers to describe the time required for resource transportation under disaster conditions. To minimize the total delivery time and difference in the total satisfaction rate, this study constructs an optimal model for emergency resource distribution under uncertain conditions that considers both efficiency and equity. Subsequently, an improved genetic algorithm (IMGA) is proposed to obtain the optimal decision scheme. Finally, a case study on emergency resource distribution during the COVID-19 pandemic is conducted for model verification. The results demonstrate that the proposed model can improve the efficiency and effect of emergency resource distribution. The model allocates some emergency resources to each demand site during each emergency period, which can help avoid large losses caused by extreme shortages of resources at a certain demand point. The emergency resource allocation scheme considers the transportation time and degree of impact, which is beneficial for enhancing the flexibility of decision-making and practical applicability of distribution operations. A comparative analysis of the algorithms shows that the proposed IMGA is an effective method for managing emergency resource distribution optimization problems because it has higher solving efficiency, better convergence, and stronger stability. These findings can provide decision support for the optimal distribution of large-scale, multiperiod emergency resources during the COVID-19 pandemic.

1. Introduction

In recent years, the occurrence of public health emergencies such as SARS, Ebola virus, MERS, and COVID-19, has caused severe casualties and economic and property losses, and attracted widespread concern around the world [1–3]. Therefore, efficiently implementing emergency rescue in public health emergencies is highly valued by countries worldwide [4,5].

In various emergency rescue and disposal works, emergency resource distribution is a key link in the emergency response to public health emergencies and vital for guaranteeing the appropriate allocation of the resources required for emergency rescue. It directly affects the overall effect and disposal level of the rescue [6]. While combating major infectious diseases with strong transmission and spread, the scientific, efficient, equitable and reasonable distribution of rescue resources is conducive to preventing the large-scale spread these diseases and improving the effectiveness of emergency rescue. Meanwhile, inappropriate or untimely distribution

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https://doi.org/10.1016/j.heliyon.2024.e31758
Received 6 November 2023; Received in revised form 17 May 2024; Accepted 21 May 2024
Available online 23 May 2024
2405-8440/

plans may cause secondary damage to, and increase casualties and property losses in the disaster-affected area [7].

In addition, due to the suddenness of the pandemic and urgency of emergency rescue, as well as the rapid impact of transmission and spread, accurately obtaining relevant information during the rescue operations is usually impossible. This compounds the difficulties to emergency resource distribution [8]. Therefore, formulating a scientific and reasonable optimal decision scheme for emergency resource distribution and achieving a multi-period effective supply of rescue resources under various information uncertainties are important issues in epidemic emergency rescue.

The remainder of this study is organized as follows: Section 2 reviews the relevant literature. Section 3 constructs a bi-objective and multi-period optimal distribution model for emergency resources under uncertain conditions that considers both efficiency and equity. Section 4 proposes an improved genetic algorithm (IMGA) for solving multi-objective optimization problems. Section 5 conducts a case study of emergency resource distribution during COVID-19 to verify the validity of the proposed model and algorithm. Finally, conclusions and future research directions are presented in Section 6.

2. Literature review

In recent years, owing to the frequent occurrence of various types of emergencies, an increasing number of scholars have been greatly concerned about the issue of post-disaster emergency logistics [9,10]. Emergency resource distribution is a key link in post-disaster emergency rescue, with an extensive literature on the same [11,12]. Studies usually obtain the optimal resource distribution decision scheme by building models, but these studies focus on different decision criteria, especially efficiency or equity [13,14].

Because the primary goal of post-disaster emergency rescue is to minimize casualties, most studies efficiency as the first decision-making criterion, including the shortest total distribution time [15–19], shortest total distribution route [20–22] and lowest total transportation cost [23–30]. For example, Berkoune et al. [15] and Wang et al. [17] established a network flow model for emergency resource distribution to minimize total distribution time. Wex et al. [16] developed a multi-disaster-oriented emergency material distribution model to minimize the total distribution time. Tang and Ye [19] proposed an emergency medical resource distribution model with multiple relief centers and multiple affected locations with the objective of minimizing the total time of transportation, loading and unloading. Hu et al. [22] constructed a distribution model for emergency medical resources considering the urgency of affected locations with the objective of minimizing vehicle distribution paths. Bruce et al. [25] proposed an emergency resource distribution model to minimize transportation and penalty cost of unmet demand. Hu et al. [26] constructed a resource distribution model to optimize for minimizing the penalty cost incurred by delaying disaster relief. Yu et al. [28] built a multi-stage emergency resource distribution model with the goal of minimizing total costs, including accessibility, starting state-based deprivation, and terminal penalty costs. Han et al. [30] presented an emergency resource distribution for post-disaster rescue operations with time-window constraints to minimize total transportation costs.

Equity is another important decision-making criterion for emergency resource distribution. Scholars have explored the optimization of emergency resource distribution focus on the minimization of cost and time, however, the distribution scheme with the lowest cost or shortest time often causes unfair distribution and may even cause secondary damage to disaster-affected people [31]. Therefore, considering equity in emergency resource distribution [32]. Altay [33] believed that fair allocation of emergency resources plays a positive role in promoting post-disaster recovery. Gralla et al. [34] used expert evaluation and analysis to determine the relative importance of cost, efficiency and equity in emergency aid logistics, their results showed that the importance of equity was far higher than that of cost. Extant research on fairness of emergency resource distribution mainly focuses on models and algorithms. Some scholars considers fairness as one of the objective functions in multi-objective optimization, while others consider equity as an important constraint condition solving optimization problems [35]. For example, Huang et al. [36] considered equity as an important objective functions for establishing the emergency resource distribution path model. Orgut et al. [37] considered the issue of food donation and distribution, and regarded the fairness of food distribution as an important restriction for the optimization of operations. Considering the need to alleviate the fairness of victims' psychological trauma, Ju et al. [38] proposed the use of relative deprivation cost to depict the equity of resource distribution and then built an optimal distribution model.

With the deepening of research, scholars have gradually realized that various uncertain factors in the emergency rescue process significant affect emergency resource distribution [39–41]. Zhang et al. [42] used interval number to represent the material demand at disaster sites and studied the optimization of emergency material distribution to minimize the total cost. Huang and Fan [43] studied the emergency resource distribution of multiple vehicles under uncertain conditions by establishing stochastic programming and robust optimization model. Zhang et al. [44] focused on the problem of emergency material distribution under demand uncertainty, comprehensively considered the matching degree of demand and demand time, and built an interval robust optimization model with the maximum average comprehensive matching degree as the target. Bozorgiamiri et al. [45] presented a multi-objective stochastic planning model for emergency resources under demand and, supply uncertainties, and procurement and transportation costs. Qin et al. [46] proposed a vehicle routing optimization model with the goal of minimizing the total cost for emergency relief resource distribution considering insufficient materials and uncertain demand.

In summary, considering uncertain disaster information is important in emergency resource allocation, providing the theoretical basis for this study. However, some gaps remain in extant research. First, most studies build a deterministic resource distribution model based on deterministic information, despite the large amount of fuzzy and uncertain information in the rescue process due to various characteristics of crises, such as the suddenness and rapid spread of the COVID-19 pandemic.

Second, the few emergency resource distribution studies involving uncertain disaster information generally only consider the fuzzy uncertainty of supply or demand. Moreover, these studies mostly focus on earthquake disasters and rarely consider major infectious diseases. The emergency resource distribution greatly differs for infectious diseases and earthquake disasters. Previous experience in the emergency resource distribution of natural disasters, such as earthquake may not be directly applicable to the emergency resource distribution of infectious diseases. The multi-period resource distribution optimization problem based on uncertain disaster conditions can be more in line with the actual needs of emergency relief resources for major infectious diseases.

In this sense, this study's contributions are both methodological and practical: Methodologically, this study develops an emergency resource distribution decision problem that considers uncertain disaster information (e.g., uncertainty of demand, supply and road transportation time). Practically, this study proposes a multi-period optimal distribution model and algorithm for emergency resources in response to the COVID-19 pandemic. Overall, this study aims to provide decision support for multi-period optimal distribution of emergency rescue resources.

3. Problem description and model construction

3.1. Problem description

Owing to its rapid spread, wide range of infections, and difficult prevention and control, the COVID-19 pandemic was characterized by substantial uncertain disaster information in the actual emergency response, which resulted in many difficulties in emergency resources distribution. This study focuses on, choosing a scientific multi-period distribution optimization plan and strategy for emergency resources under the condition of multiple uncertain disaster information in the emergency response process.

In this paper, triangular fuzzy numbers and interval numbers are used to describe the uncertainty of related parameters, which aligns with the real emergency resource allocation situation. The rapid spread and serious destructiveness of the COVID-19 outbreak make it impossible to obtain completely accurate information during emergency relief operations. The demand and supply of emergency resources, as well as transportation time (especially in the case of road closures), are highly uncertain. Uncertain information can be input into the emergency resource distribution model in the form of fuzzy numbers and interval numbers that adhere to specific distribution rules. Previous researchers have successfully achieved this. For example, Liu et al. [47] used triangular fuzzy numbers to describe the uncertainty of resource demand at the disaster-affected locations; Wang et al. [48] introduced interval numbers to describe the uncertainty of material transportation time; Chen et al. [49] used triangular fuzzy numbers to represent resource demand, transportation time, and cost. In this study, we drew on these ideas and established parameters according to our own research questions.

Based on the above considerations, this article introduces triangular fuzzy numbers to describe the fuzzy uncertainty of emergency resource supply and demand, and introduces interval numbers to describe the time required for resource transportation in disaster situations. Due to the high demand for resources and the continuous surge over time in the COVID-19 emergency response scenario, the required resource supply is also large. However, the demand and supply information obtained in an emergency situation may be relatively inaccurate or arrive late. Therefore, this paper represents the demand and supply of resources as triangular fuzzy numbers. Meanwhile, some roads are restricted during the epidemic, and the timing of resource transportation cannot be precisely determined, but it can be estimated within a certain range. Based on the above considerations, this paper introduces triangular fuzzy numbers to describe the fuzzy uncertainty of the supply and demand of emergency resources, and interval numbers to represent the time required for resource transportation in disaster situations. The aim is to make the model construction more consistent with the realistic situation of emergency resource distribution during the epidemic.

This article examines the uncertainty of emergency resource demand, supply, and transportation time in each time period due to sudden occurrences, rapid and complex evolution, and urgent rescue efforts of the epidemics. It reflects the efficiency and equity criteria of multi-period distribution of emergency resources by minimizing the total distribution time and the difference in total satisfaction rates, respectively. Combining the dynamic relationship between the supply and demand of resources during various emergency periods, a multi-period distribution optimization model was developed. This model involves multiple rescue centers, demand sites, and types of emergency resources. It aims to achieve both efficiency and equity by minimizing the total distribution time and minimizing the difference of total satisfaction rate throughout the emergency period.

3.2. Model construction

Notations

The sets, parameters and decision variables used in the model formulation are described as follows:

(1) Sets

N is the set of all rescue centers, $n \in N$;
M is the set of demand sites, $m \in M$;
E is the set of types of emergency resources, $e \in E$;
K is the set of periods for emergency resource distribution, $k \in K$.

(2) Variables

Z_{nm}^{k} is the binary variable indicating whether emergency relief resources are distributed to demand sites $m \in M$ from rescue center $n \in N$ during the period $k \in K$. If so, its value is 1 and 0, otherwise.

Q_{nme}^{k} is the amount of resource $e \in E$ distribute to demand sites $m \in M$ from rescue center $n \in N$ during the period $k \in K$.

(3) Parameters

$\widetilde{Tran}_{nme}^{k}$ is the road transportation time required to distribute relief resources $e \in E$ from rescue center $n \in N$ to demand sites $m \in M$ during period $k \in K$. Owing to the impact of the pandemic, the road transportation time for emergency resource distribution can not be accurately obtained during the actual rescue operation, which is expressed by the interval number $\widetilde{Tran}_{nme}^{k} = \left[\widetilde{Tran}_{nme}^{k}{}^{-}, \widetilde{Tran}_{nme}^{k}{}^{+}\right]$ in this study, where $\widetilde{Tran}_{nme}^{k}{}^{-}$ and $\widetilde{Tran}_{nme}^{k}{}^{+}$ are the predicted shortest and longest resource transportation times, respectively.

$Tload_{nme}^{k}$ is the loading and unloading time per unit of emergency resource $e \in E$ at rescue center $n \in N$ and demand sites $m \in M$ during period $k \in K$.

$Tpun_{me}^{k}$ is the time penalty coefficient per unit resource $e \in E$ delay at demand sites $m \in M$ at the end of the period $k \in K$, $Tpun_{me}^{k} \geq 1$. The more severely the demand site is affected by the pandemic, the more urgent the demand for resource, the greater the time cost of lacking such resources.

G is the large enough arbitrary constant.

$\widetilde{Dnew}_{me}^{k}$ is the new demand for emergency resource $e \in E$ at the demand site $m \in M$ at the beginning of the period $k \in K$. Owing to the rapid spread and latency of the pandemic, it was impossible to accurately determine the specific new needs of each demand site in each period. In this study, the new demand is represented by the interval number $\widetilde{Dnew}_{me}^{k} = \left(Dnew_{me}^{k}{}^{L}, Dnew_{me}^{k}{}^{O}, Dnew_{me}^{k}{}^{R}\right)$, where $Dnew_{me}^{K\,L}$, $Dnew_{me}^{k\,o}$ and $Dnew_{me}^{k}{}^{R}$ are respectively the lowest, the most likely, and highest predicted new demand.

$\widetilde{Snew}_{ne}^{k}$ is the new supply for emergency resource $e \in E$ at the rescue center $n \in N$ at the beginning of period $k \in K$. Due to the urgency of emergency response to the pandemic, it may not be possible to accurately know the latest available resources at each rescue center $n \in N$ in each period $k \in K$. Supply is also represented by a triangular fuzzy number in this study. $\widetilde{Snew}_{me}^{k} = \left(Snew_{me}^{k}{}^{L}, Snew_{me}^{k}{}^{O}, Snew_{me}^{k}{}^{R}\right)$, where $Snew_{ne}^{k\,L}$, $Snew_{ne}^{k}{}^{o}$ and $Snew_{ne}^{k}{}^{R}$ are respectively the lowest, the most likely, and highest predicted new supply.

$Dact_{me}^{k}$ is the actual demand for emergency resource $e \in E$ at demand site $m \in M$ during period $k \in K$.

$Sact_{ne}^{k}$ is the actual supply of emergency resource $e \in E$ at rescue center $n \in N$ during period $k \in K$.

$Lack_{me}^{k}$ is the percentage shortfalls in the required emergency relief resource $e \in E$ at the demand site $m \in M$ at the end of the period $k \in K$.

$Inve_{ne}^{k}$ is the inventory of emergency relief resource $e \in E$ at the rescue center $n \in N$ after distribution at the end of period $k \in K$.

3.2.1. Mathematical model

Based on the above-mentioned sets, parameters, and decision variables, this paper formulates a multi-period optimal distribution model of emergency resources for responding to COVID-19 under uncertain conditions. The objective functions and constraints of the proposed model in this paper are as follows.

(1) Objective functions

To optimize the balance between efficiency and equity in the multi-period allocation process of emergency resources, this paper aims to minimize the total delivery time and the difference of total satisfaction rates. Furthermore, the efficiency objective aims to minimize the total delivery time, while the equity objective aims to minimize the difference of total satisfaction rate in the resource allocation.

$$\min F_1 = \sum_{n\in N}\sum_{m\in M}\sum_{e\in E}\sum_{k\in K}\widetilde{Tran}_{nme}^{k} \cdot Z_{nme}^{k} + Tload_{nme}^{k} \cdot Q_{nme}^{k} + Tpun_{me}^{k} \cdot Lack_{me}^{k} \tag{1}$$

$$\min F_2 = \sum_{m\in M}\sum_{e\in E}\sum_{k\in K}\left[\max\left\{\sum_{n\in N}Q_{nme}^{k} \Big/ Dact_{me}^{k}\right\} - \sum_{n\in N}Q_{nme}^{k} \Big/ Dact_{me}^{k}\right] \tag{2}$$

In the proposed model, the objective function (equation (1)) aims to minimize the total time of rescue resource allocation across all emergency periods to pursue the efficiency criterion. The total time for emergency resource allocation is the sum of road transportation time, loading and unloading time, and resource delay penalty time. Where, $\widetilde{Tran}_{nme}^{k} \cdot Z_{nme}^{k}$ represents the road transportation time for distributing emergency resources, $Tload_{nme}^{k} \cdot Q_{nme}^{k}$ is the loading and unloading time of resources, and $Tpun_{me}^{k} \cdot Lack_{me}^{k}$ represents the penalty time caused by the shortage of required emergency resources.

The objective function (equation (2)) minimizes the difference in the total satisfaction rate of emergency resource distribution for all demand sites in all emergency periods to pursue the equity criterion. Where $\max\left\{\sum_{n\in N} Q_{nme}^{k} / Dact_{me}^{k}\right\}$ is the maximum satisfaction rate of resource allocation within the emergency period, and $\sum_{n\in N} Q_{nme}^{k} / Dact_{me}^{k}$ is the satisfaction rate of resource allocation at the current disaster site during the emergency period.

(2) Constraints

Demand Constraint:

During emergency rescue operations, resources are precious and should be fully utilized to avoid redundancy or waste. The actual demand for relief resources at a demand site in a given time period is equal to the sum of the latest demand of the current period and the shortage from the previous period. Equation (3) represents the demand constraint, which ensures that the quantity of resources received at the demand site does not surpass its actual demand within a given time period.

$$\sum_{n\in N} Q_{nme}^{k} \leq \widetilde{D}new_{me}^{k} + Lack_{me}^{k-1} \qquad \forall m \in M, e \in E, k \in K \tag{3}$$

Supply Constraint:

During emergency rescue operations, the resources available at the rescue center are typically limited. The actual supply of resources at the center is determined by the sum of the most recent supply of resources in the current period and the inventory of resources from the previous period. To align with the realistic emergency rescue resource distribution scenario, the allocation of resources per period should not surpass the actual supply of resources available. Equation (4) represents the supply constraint, indicating that the quantity of resources distributed from the rescue center must not surpass its actual supply within a given time period.

$$\sum_{m\in M} Q_{nme}^{k} \leq \widetilde{S}new_{ne}^{k} + Inve_{ne}^{k-1} \qquad \forall n \in N, e \in E, k \in K \tag{4}$$

Shortage Constraint:

Equation (5) expresses the shortage of emergency resources at the demand site at the end of a given emergency period. The emergency resource shortage at the demand site is equal to the actual demand minus the allocated resources. If the result value is greater than or equal to 0, then there is no resource shortage at the demand site; conversely, if the result value is less than 0, then the demand site will face a resource shortage problem.

$$Lack_{me}^{k} = Dact_{me}^{k} - \sum_{n\in N} Q_{nme}^{k} \qquad \forall m \in M, e \in E, k \in K \tag{5}$$

Inventory Constraint:

Equation (6) represents the inventory of emergency resources at the rescue center at the end of a given emergency period. If the result value is greater than or equal to 0, the rescue center has resource inventory; conversely, if the result value is less than 0, then the available resources at the rescue center are insufficient.

$$Inve_{ne}^{k} = Sact_{ne}^{k} - \sum_{m\in M} Q_{nme}^{k} \qquad \forall m \in M, e \in E, k \in K \tag{6}$$

Meet the Demand Constraint:

Equation (7) means that the demand at the demand site should be met to the greatest extent possible. When the actual supply exceeds the actual demand, the resource demand at the demand site should be fully met. Conversely, when the actual supply is less than the actual demand, then all the resources at the rescue center should be allocated to the disaster site to fulfill the resource demand to the greatest extent possible.

$$\sum_{n\in N}\sum_{m\in M} Q_{nme}^{k} = \min\left\{\sum_{m\in M} Sact_{me}^{k}, \sum_{n\in N} Dact_{ne}^{k}\right\} \qquad \forall e \in E, k \in K \tag{7}$$

Logical Relationship Constraint between Variables:

Equation (8) is the logical relationship constraint between variables, ensuring that the amount of resources allocated in a given time period is not zero. The value of Z_{nm}^{k} should be 1; conversely, the value of Z_{nm}^{k} is 0.

$$\sum_{e\in E} Q_{nm}^{k} \leq G \cdot Z_{nm}^{k} \qquad \forall m \in M, n \in N, k \in K \tag{8}$$

Expression of Actual Resource Supply:

Equation (9) represents the actual supply of resources at the rescue center during a given time period. In the first emergency period, the actual resource supply of the rescue center equals the new supply for that period. In the second and subsequent periods, the actual resource supply of the rescue center is equal to the sum of the new supply in that period and the inventory from the previous period.

$$Sact_{ne}^{k} = \begin{cases} \widetilde{Snew}_{ne}^{k} & k = 1 \quad \forall m \in M, n \in N, e \in E, k \in K \\ \widetilde{Snew}_{ne}^{k} + Inve_{ne}^{k-1} & k \geq 2 \quad \forall m \in M, n \in N, e \in E, k \in K \end{cases} \tag{9}$$

Expression of Actual Resource Demand:

Equation (10) represents the actual demand at the specific demand site during a given time period. In the initial emergency period, the actual resource demand at the site matches the new demand for that period. In the second and subsequent periods, the actual resource demand at the demand site equals the sum of the new demand in that period and the shortage from the previous period.

$$Dact_{me}^{k} = \begin{cases} \widetilde{Dnew}_{me}^{k} & k = 1 \quad \forall m \in M, n \in N, e \in E, k \in K \\ \widetilde{Dnew}_{me}^{k} + Lack_{me}^{k-1} & k \geq 2 \quad \forall m \in M, n \in N, e \in E, k \in K \end{cases} \tag{10}$$

Binary Variable Constraint:

Equation (11) requires that the variables be binary (either 0 or 1). If emergency resources are allocated, $Z_{nm}^{k} = 1$; otherwise, $Z_{nm}^{k} = 0$.

$$Z_{nm}^{k} \in \{0, 1\} \qquad \forall m \in M, n \in N, e \in E, k \in K \tag{11}$$

Non-negative Constraints on Decision Variables:

Equation (12) indicates that the decision variables must be non-negative because the amount of emergency resources distributed from the rescue center to the demand site cannot be negative.

$$Q_{nme}^{k} \geq 0 \qquad \forall m \in M, n \in N, e \in E, k \in K \tag{12}$$

4. Algorithm design and model solving

The algorithm for solving the proposed model in this article is divided into two steps. Firstly, the triangular fuzzy numbers and interval numbers in the objective functions and constraints of the proposed model are converted into deterministic parameters. Subsequently, an improved genetic algorithm is developed to solve the model.

4.1. Deterministic transformation of triangular fuzzy numbers and interval numbers

This article introduces triangular fuzzy numbers to describe the fuzzy uncertainty of emergency resource supply and demand, and introduces interval numbers to describe the time required for resource transportation under disaster relief conditions. Although it increases the difficulty of the problem, it aligns with the actual disaster information situation of disaster emergency rescue. It can be seen that the proposed model includes both triangular fuzzy numbers and interval numbers, which cannot be directly calculated using traditional methods. Therefore, it is necessary to first convert the triangular fuzzy numbers and interval numbers clearly to general deterministic real numbers.

4.1.1. Deterministic transformation of triangular fuzzy numbers

Based on solving related research problems in uncertain situations, Zadeh [50] first proposed the theory of fuzzy sets in 1965, which led to the development of the triangular fuzzy theory. Triangular fuzzy numbers can be viewed as a fuzzy set within the studied domain U. In other words, there is such a relationship: for any $x \in U$, there exists a corresponding number $\mu(x) \in [0, 1]$, then $\mu(x)$ is called the membership of x to U, μ is called the membership function of x.

Theorem 1. *The triangular fuzzy number $\widetilde{B} = \left(b^L, b^O, b^R\right)$, and its membership function is $\mu_{\widetilde{B}}(x)$, then for any given confidence level α $(0 \leq \alpha \leq 1)$, $\mathrm{Pos}\{\widetilde{B} = c\} \geq \alpha$, if and only the following* equation (13) *is satisfied*:

$$\begin{cases} c \geq (1-\alpha)b^L + \alpha b^O \\ c \leq (1-\alpha)b^R + \alpha b^O \end{cases} \tag{13}$$

According to the relationship between the left and right membership functions (Zhang et al., 2004) [51], as well as the research by Guo and Qi (2011) [52], the equations (3), (4), (9) and (10) of the proposed model can be transformed into deterministic forms at a given optimization level α (α ∈ [0, 1]).

Taking equation (3) as an example, we will perform a deterministic transformation of the model's constraints. The new demand $\widetilde{Dnew}_{me}^{k}$ for emergency resources at the demand site at the beginning of each time period is expressed as shown in equations (14) and (15):

$$\left[\widetilde{Dnew}_{me}^{k}\right]_{\alpha}^{L} = \left[Dnew_{me}^{k}\right]^{L} + \alpha * \left(\left[Dnew_{me}^{k}\right]^{O} - \left[Dnew_{me}^{k}\right]^{L}\right) \tag{14}$$

$$\left[\widetilde{Dnew}_{me}^{k}\right]_{\alpha}^{R} = \left[Dnew_{me}^{k}\right]^{R} + \alpha * \left(\left[Dnew_{me}^{k}\right]^{R} - \left[Dnew_{me}^{k}\right]^{O}\right) \tag{15}$$

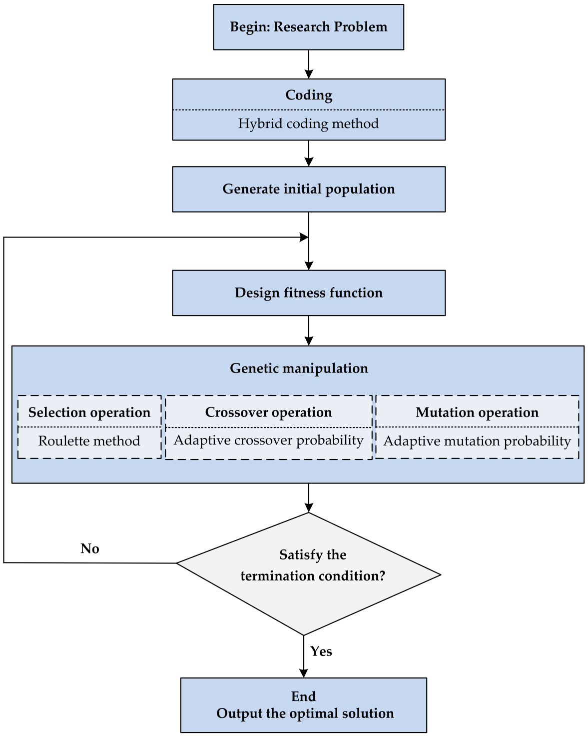


Fig. 1. Flow of improved genetic algorithm.

thus, the triangular fuzzy number in equation (3) of the proposed model can be transformed into the following deterministic form equation (16):

$$\sum_{n\in N} Q_{nme}^{k} \le \left[\left[Dnew_{me}^{k}\right]^{R} + \alpha * \left(\left[Dnew_{me}^{k}\right]^{R} - \left[Dnew_{me}^{k}\right]^{O}\right)\right] + Lack_{me}^{k-1} \tag{16}$$

Similarly, the equations (4), (9) and (10) *can be translated into a deterministic form using the above method.*

4.1.2. *Deterministic transformation of interval numbers*

For deterministic transformations of interval numbers, the following Theorem 2 can be applied.

Theorem 2. For any solution $x \in X$ of a general interval linear programming model, define $\gamma = \text{poss}\left(\sum_{i=1}^{n} Q_{ij}x_i \le P_j\right)$ as the optimization level of X for the constraint condition $\sum_{i=1}^{n} Q_{ij}x_i \le P_j$, define $\beta = \text{poss}\left(\sum_{i=1}^{n} C_i x_i\right)$ as the optimization level of X for the objective function $\sum_{i=1}^{n} C_i x_i$, then the solutions of the general interval linear programming model with the optimization level β and γ can be respectively obtained [53].

According to Theorem 2, given the optimization level β, the objective function (equation (1)) of the basic model of general interval linear programming can be transformed into the following deterministic form (equation (17)):

$$\max \quad F(X) = f(x_1, x_2, \cdots, x_n) = (1-\beta)\sum_{i=1}^{n} c_i^{-} x_i + \beta \sum_{i=1}^{n} c_i^{+} x_i \tag{17}$$

Taking the objective function (equation (1)) of the proposed model as an example, perform a deterministic transformation on it according to Theorem 2, and the transformed objective function (equation (1)) is as shown in the following equatison (18):

$$\min F_1 = (1-\beta)\sum_{n\in N}\sum_{m\in M}\sum_{e\in E}\sum_{k\in K} Tran_{mne}^{k-} \cdot Z_{nme}^{k} + \beta\sum_{n\in N}\sum_{m\in M}\sum_{e\in E}\sum_{k\in K} Tran_{mne}^{k+} \cdot Z_{nme}^{k} + Tload_{nme}^{k} \cdot Q_{nme}^{k} + Tpun_{me}^{k} \cdot Lack_{me}^{k} \tag{18}$$

So far, all the triangular fuzzy numbers and interval numbers in the proposed model have been converted into deterministic real numbers, which lays a foundation for solving the model using an improved genetic algorithm.

4.2. *Improved genetic algorithm*

The multi-period optimal distribution of emergency resources under uncertain conditions is a complicated decision. To solve this problem, a fast and effective algorithm is needed to improve the efficiency and effectiveness of decision making in emergency rescue. Practice has proven that the genetic algorithm is a type of search optimization algorithm that simulates the biological evolution process, with strong global search ability, and is more effective for solving multi-objective optimization problems [54]. However, the classical genetic algorithm can easily fall into a local optimal solution, resulting in prematurity [55]. In addition, the mathematical description of multiple uncertain factors in the proposed model complicates the solution to the problem, and the efficiency of classical genetic algorithm is not ideal. Therefore, this study constructs adaptive cross and adaptive variation probability functions to improve the solving efficiency of the genetic algorithm. The flowchart of the algorithm is illustrated in Fig. 1.

Step 1 *Code.* A hybrid coding method is used for genetic coding. The emergency period, rescue center, demand site and emergency resources are coded by symbols, whereas the number of emergency resources required is coded by natural numbers. Suppose that there are 5 demand sites that need relief resources, and the demands are 8, 5, 9, 6, and 7 units of resources, respectively; then, the corresponding genetic code representation is: 85967. The basic gene is that the rescue center completes an emergency resource distribution task, for example, (n_2, m_4, e_1, k_3) indicates that the rescue center n_2 distributes the emergency resource e_1 to the demand site m_4 during time period k_3.

Step 2 *Build initial population.* Repeated and effective screening is performed to form the initial population by randomly generating a certain number of chromosomes. The specific steps are as follows: randomly select the rescue center n_2 and use it as the starting point of resource distribution, randomly select the demand site m_4, rescue resource e_1 and emergency period k_3, and form the above situation into a gene. Similarly, the above steps are repeated to obtain the relief distribution gene segments for all emergency periods, and the population size is determined according to the specific complexity of the research problem.

Step 3 *Design fitness function.* The proposed objective functions are the difference between the total time F_1 and shortage rate F_2. Each objective function is normalized to obtain F_1^* and F_2^*, and weights λ_1 and λ_2 respectively, are assigned, where $\lambda_1 + \lambda_2 = 1$. Then, the fitness function is shown in equation (19):

$$Fitness\left(Q_{nme}^{k}\right) = \lambda_1 \cdot F_1^* + \lambda_2 \cdot F_2^* \tag{19}$$

Step 4 Genetic manipulation.

① Selection. The roulette method is used to select the new population. The dominant individuals obtained in Step 3 are added to the new population to improve the population quality. φ_c represents the probability that the *cth* individual is selected, and $Fitness_c$ represents the fitness of *cth* individual. This equation (20) indicates that the selection probability of an individual is proportional to its fitness value.

$$\varphi_c = Fitness_c \Big/ \sum_{c \in C} Fitness_c \tag{20}$$

② Adaptive crossover and mutation operations.

Crossover and mutation operations are crucial components of a genetic algorithm. When performing crossover and genetic operations, it is typically necessary to establish a crossover probability and mutation probability to indicate the probability of chromosome crossover and mutation. However, if we use fixed crossover operators and genetic operators, we need to continuously adjust them to determine their values for a given optimization problem. Generally speaking, the search for solutions in genetic algorithms is guided by fitness values. Therefore, crossover and mutation operators should be dynamically adjusted based on the magnitude of fitness values to expedite convergence speed. The larger the crossover operator Pr_{cross}, the faster the speed of generating new individuals, and the stronger the global search ability of the algorithm. However, the larger Pr_{cross} is, the more easily the genetic model is destroyed, and individuals with high fitness values are less likely to be maintained; if Pr_{cross} is too small, the search speed will slow down again. Meanwhile, if the mutation operator Pr_{muta} is too small, it is not easy to generate new individuals; If Pr_{muta} is too large, the search process can easily become a random search.

Based on this, an adaptive mechanism for dynamically adjusting crossover and mutation operators is proposed in this paper. The crossover probability Pr_{cross} and mutation probability Pr_{muta} are adaptively adjusted according to the following formula.

Adaptive crossover operation:

The standard genetic algorithm uses fixed crossover operator, which seriously affect the convergence and it can easily fall into local optima. Therefore, to improve the search ability of the crossover operator, this study proposes an adaptive crossover probability function Pr_{cross} to guide the crossover operation. The basic idea of adaptive crossover assigning different crossover probabilities to different chromosomes. To protect individuals with high fitness values, a smaller crossover probability is assigned to them, whereas the crossover probability is correspondingly increased for individuals with low fitness values, to ensure population diversity and avoid the destruction of good chromosomes. The crossover probability Pr_{cross} of adaptive genetic algorithm is as shown in equation (21):

$$\mathrm{Pr}_{cross} = \begin{cases} h_1 (Fitness_{cross} - Fitness_{\min}) / (Fitness_{\mathrm{ave}} - Fitness_{\min}) & Fitness_{cross} < Fitness_{\mathrm{ave}} \\ h_2 & Fitness_{cross} \geq Fitness_{\mathrm{ave}} \end{cases} \tag{21}$$

Table 1
Demand for resources at each affected site at the beginning of each period.

Demand sites	Resources	Period 1	Period 2	Period 3	Period 4	Period 5
m_1	e_1	(30,33,35)	(35,40,45)	(40,45,50)	(50,53,56)	(50,58,66)
	e_2	(5,6,7)	(4,5,6)	(3,4,5)	(2,2.5,3)	(2,2.25,2.5)
m_2	e_1	(20,23,26)	(26,28,30)	(25,30,35)	(30,33,36)	(35,40,45)
	e_2	(3,4,5)	(2,2.5,3)	(1.6,1.8,2)	(1,1.3,1.6)	(0.6,0.8,1)
m_3	e_1	(15,17,19)	(16,18,20)	(15,20,25)	(20,25,30)	(30,35,40)
	e_2	(2,2.5,3)	(1.6,1.8,2)	(1.2,1.4,1.6)	(0.6,0.8,1)	(0.4,0.5,0.6)
m_4	e_1	(10,12,14)	(10,13,16)	(12,14,16)	(10,15,20)	(20,25,30)
	e_2	(1,1.5,2)	(0.6,0.8,1)	(0.4,0.6,0.8)	(0.2,0.4,0.6)	(0.2,0.3,0.4)

Note: The unit of masks (e_1) and medicines (e_2) are ten thousand pieces and boxes, respectively.

Table 2
Supply of resources at each rescue center at the beginning of each period.

Rescue centers	Resources	Period 1	Period 2	Period 3	Period 4	Period 5
n_1	e_1	(16,18,20)	(35,40,45)	(40,45,50)	(60,65,70)	(90,100,110)
	e_2	(4,4.5,5)	(5.5,6.5,7.5)	(7,7.5,8)	(3,4,5)	(2,3,4)
n_2	e_1	(30,34,38)	(45,50,55)	(75,80,85)	(80,85,90)	(110,115,120)
	e_2	(5,5.5,6)	(4.5,5,5.5)	(4.4,4.6,4.8)	(3.5,4,4.5)	(2,3,4)

Note: The units of emergency resources here are the same as those in Table 1.

Table 3
Road transportation time and time penalty coefficient from rescue center to demand site.

Rescue centers	Demand sites			
	m_1	m_2	m_3	m_4
n_1	[4,5]; 1.8	[4.6,5.2]; 1.5	[4,4.6]; 1.4	[6,7]; 1.3
n_2	[3.5,4]; 1.7	[4,4.4]; 1.4	[4,5]; 1.3	[3,4]; 1.2

Note: The data format in the table is [A,B]; C, where [A,B] represents the road transportation time (in hour, A and B are the estimated shortest and longest transportation times, respectively), and C represents the time penalty coefficient.

where $Fitness_{cross}$ is the smaller fitness value of the two individuals to be crossed, $Fitness_{ave}$ is the average fitness value of each population generation, $Fitness_{\min}$ is the smallest fitness value of the population, h_1 and h_2 are real numbers between $[0,1]$.

Adaptive mutation operation:

Similarly, to avoid a standard genetic algorithm using fixed genetic operators affecting the convergence of the algorithm, this study proposes adaptive mutation probability function Pr_{muta} to improve the searching ability of mutation operators. As shown in the following equation (22):

$$\mathrm{Pr}_{muta} = \begin{cases} h_3(Fitness_{muta} - Fitness_{\min})/(Fitness_{\mathrm{ave}} - Fitness_{\min}) & Fitness_{muta} < Fitness_{\mathrm{ave}} \\ h_4 & Fitness_{muta} \geq Fitness_{\mathrm{ave}} \end{cases} \tag{22}$$

where, $Fitness_{muta}$ is the individual fitness value of the mutation operation; $Fitness_{ave}$ is the average fitness value of each population generation; $Fitness_{\min}$ is the smallest fitness value in the population; h_3 and h_4 are real numbers belonging to $[0,1]$.

Step 5 Determine whether the algorithm can be terminated. Determine whether the termination criterion is met or the maximum algebra is reached. If so, proceed to Step 7; otherwise return to Step 3.

Step 6 End the program, output the best fit value and chromosome code, and obtain the global optimal solution.

5. Computational case and result analysis

5.1. Introduction of a computational example

This section considers the case of emergency resources distribution during the COVID-19 pandemic to design a case study to verify the effectiveness and feasibility of the proposed model. Hefei City (n_1) and Changsha City (n_2) in neighboring provinces in China are selected as emergency rescue centers. Meanwhile, Wuhan City (m_1), Xiaogan City (m_2), Huanggang City (m_3) and Jingzhou City (m_4) in Hubei Province, which were seriously affected by the pandemic, are selected as emergency resource demand points. With a 7-day emergency period, masks (e_1) and medicines (e_2) are set as urgently needed materials in the pandemic-affected area in units of ten thousand and boxes, respectively. Notably, owing to the impact of the pandemic, it was challenging know the exact requirements of

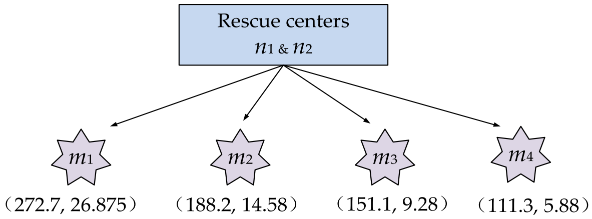


Fig. 2. The network structure diagram of overall emergency material allocation.

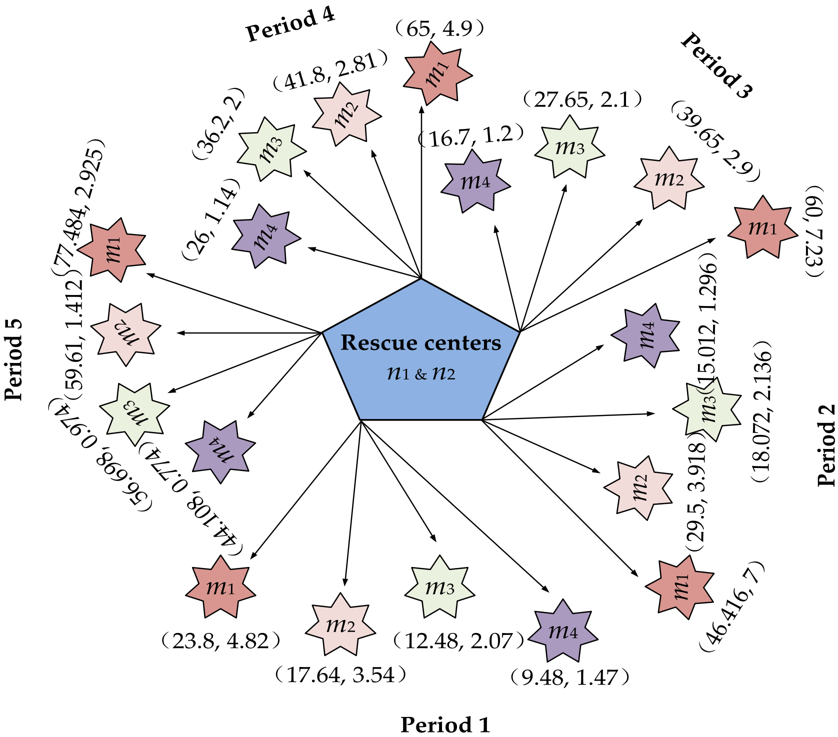


Fig. 3. Quantity of allocation at each demand site per period.

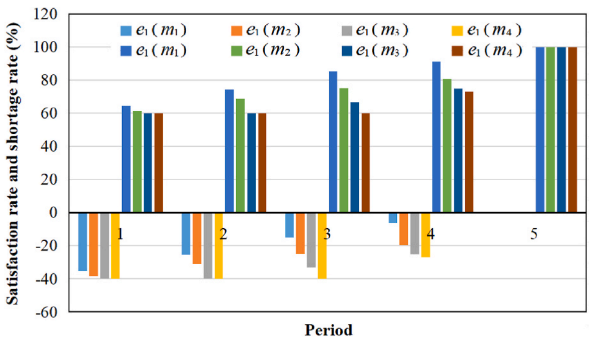


Fig. 4. Satisfaction and shortage rates of emergency resource e_1 at each demand site in each period.

emergency resources per period in reality; nonetheless, the requirements can be estimated within a certain range, as shown in Table 1. The amount of emergency resources supplied by the rescue center in each period is listed in Table 2. The road transportation time and time penalty coefficient for distributing relief resources during the pandemic are shown in Table 3. The loading and unloading times per unit of emergency resource e_1 and e_2 are 0.2 h and 0.4 h, respectively. The computational case in MATLAB R2016a on a computer with an Intel (R) Core (TM) 1.90 GHz processor with 16.0 GB of RAM. The parameters of the IMGA algorithm were set as follows:

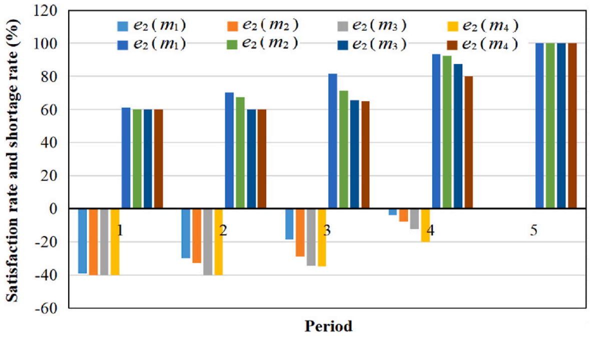


Fig. 5. Satisfaction and shortage rates of emergency resource e_2 at each demand site in each period.

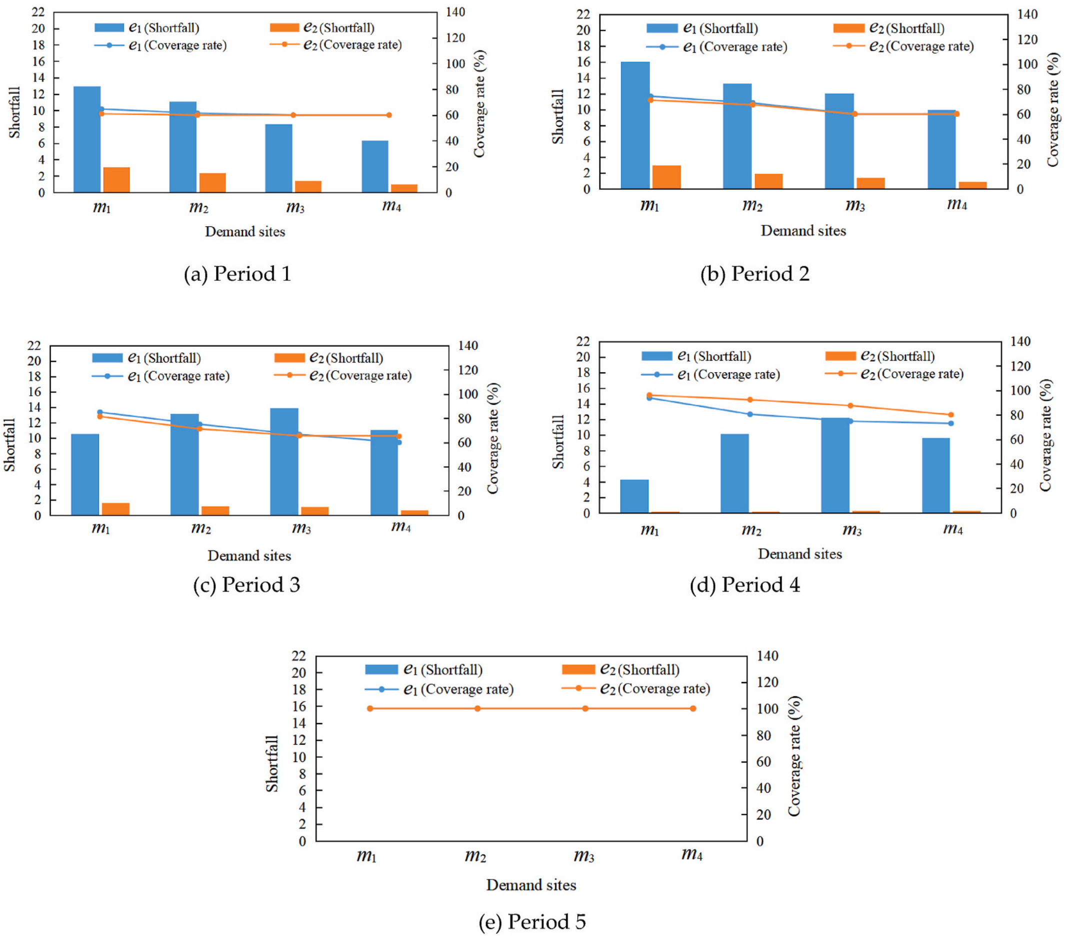


Fig. 6. (a–e). Shortfalls and coverage rate of emergency resources at each demand site per period.

population size $N = 50$, maximum number of iterations $G = 500$, $h_1 = h_3 = 0.8$, $h_2 = h_4 = 0.2$. The optimization levels of deterministic transformation of fuzzy constrained programming were $\alpha = 0.9$ and $\beta = 0.9$.

5.2. *Result analysis*

5.2.1. *Verify the effectiveness of the proposed model*

First, by solving the model, an emergency resource distribution scheme for the entire emergency period is obtained. The overall emergency resource distribution network structure is shown in Fig. 2.

Fig. 2 shows the overall distribution of emergency resources from rescue centers to each demand site. The result is an emergency

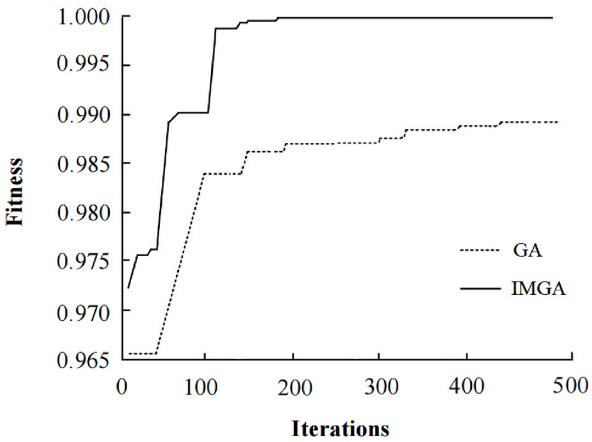


Fig. 7. Fitness evolution curves of IMGA and GA.

resource distribution strategy which comprehensive considers various factors, including the distance between the rescue center and demand site, road transportation time, and distribution delay penalty coefficient.

Secondly, through calculation, the amount of emergency resources at each demand site in each period is obtained, as shown in Fig. 3. The satisfaction and shortage rate for each type of resource are shown in Figs. 4 and 5, respectively. The shortfall and coverage rate of emergency resources at each demand site per period are shown in Fig. 6(a–e).

As shown in Figs. 3–5, each rescue center distributes a certain amount of emergency resources to each demand site in each emergency period according to the actual situation. The lack of resources in the previous period is supplemented in the next period. By the end of the entire emergency period, the demand for various resources at all disaster sites is fully met.

Figs. 4 and 5 show that the proposed model can satisfy the emergency resource demand of each demand site to the greatest extent, especially in the case of resource shortage in the first period of emergency rescue, the resource satisfaction rate of each demand site can still reach 60 % or more.

Compared with other demand sites, demand site m_1 gets the most amount of the two resources e_1 and e_2 per period. This may because compared with the other three demand sites, demand site m_1 is the most seriously affected by the pandemic, requires the largest amount of resources, and is close to the relief center. Under such circumstances, the relief center should allocate resources to demand site m_1 as much as possible, which can not only reduce demand site m_1 but also the overall resource shortage loss to the greatest extent. It can also save the time and cost of resource transportation, which is important in actual emergency rescue resource allocation.

As shown in Fig. 6(a–e), with a gradual increase in supply, the resource coverage rate of each demand site continues to increase (decrease). Finally, all emergency resource needs are fully met in the fifth period, where there is no resource shortage at any demand site.

5.2.2. *Verify the effectiveness of the proposed IMGA algorithm*

To verify the effectiveness of the proposed IMGA, 40 random operations on the algorithm while maintaining the same conditions and parameters. The generated emergency resource allocation paths of 40 schemes are consistent, indicating that the IMGA has strong stability.

Moreover, the proposed IMGA's effectiveness is compared with that of a basic GA. Under the same conditions and parameters, after 500 evolution iterations, the fitness evolution curves of IMGA and GA were obtained respectively, as shown in Fig. 7.

Clearly, the proposed IMGA can achieve a high fitness in the early stage of iteration. With the continuous iteration, the basic GA has a fast search speed at the beginning of operation, but falls into the local optima after 149 iterations. Although the convergence speed of IMGA is slow at the beginning of operation, after 45 iterations, the convergence speed is improved by increasing the crossover probability and reducing the mutation probability. Thus, the ability of IMGA to explore new solutions increasing, making the jump steadily from the local optimal to the optimal solution, and the global optimal solution was effectively obtained in 189 iterations. Therefore, the proposed IMGA can quickly and accurately obtain an appropriate emergency resource allocation scheme, which is vital in emergency rescue operations.

5.2.3. *Verify the applicability of the proposed model in different scenarios or geographic regions*

To verify the applicability of the proposed model in different scenarios or geographic regions, this paper will expand the case and select the emergency resource distribution case in other regions (such as Guangdong Province) during the COVID-19 as the study case to further verify the effectiveness and feasibility of the proposed model. Guangzhou City (m_1'), Shantou City (m_2'), Zhuhai City (m_3') and Shenzhen City (m_4'), which were severely affected by the COVID-19, were selected as emergency resource demand sites; Nanning City (n_1') and Fuzhou City (n_2') in neighboring provinces were selected as emergency rescue centers. Disposable protective clothing (e_1') and disinfectant (e_2') are selected as urgently needed resources in the epidemic affected-area. The demand and supply of emergency re-

Table 4
Demand for resources at each affected site at the beginning of each time period.

Demand sites	Resources	m_1'	m_2'	m_3'	m_4'
Period 1	e_1'	(45,50,55)	(35,37,39)	(20,25,30)	(10,12,14)
	e_2'	(7,7.5,8)	(3,4,5)	(2,2.5,3)	(1,1.5,2)
Period 2	e_1'	(55,60,65)	(40,45,50)	(25,35,45)	(12,14,16)
	e_2'	(7,8,9)	(4,5,6)	(2.5,3.5,4.5)	(1.5,2,2.5)
Period 3	e_1'	(60,70,80)	(50,55,60)	(35,45,55)	(15,20,25)
	e_2'	(8,9,10)	(5.5,6,6.5)	(4,5,6)	(1.5,2.5,3.5)
Period 4	e_1'	(80,90,100)	(60,70,80)	(45,55,65)	(20,25,30)
	e_2'	(10,12,14)	(6,7,8)	(5,6,7)	(3,4,5)
Period 5	e_1'	(100,120,140)	(80,90,100)	(45,55,65)	(25,30,35)
	e_2'	(12,14,16)	(7,8,9)	(6,6.5,7)	(4,5,6)

Note: The unit of disposable protective clothing (e_1') is 10000 pieces, and the unit of disinfectant (e_2') is ten thousand boxes.

Table 5
Supply of resources at each rescue center at the beginning of each time period.

Rescue centers	Resources	Period 1	Period 2	Period 3	Period 4	Period 5
n_1'	e_1'	(50,55,60)	(70,85,100)	(150,160,170)	(180,190,200)	(200,220,240)
	e_2'	(4,5,6)	(8,10,12)	(15,169,17)	(18,20,22)	(24,26,28)
n_2'	e_1'	(25,30,35)	(40,50,60)	(75,80,85)	(90,100,110)	(160,170,180)
	e_2'	(3,4,5)	(8,9,10)	(9,10,11)	(15,16,17)	(20,21,22)

Table 6
Road transportation time and time penalty coefficient from rescue center to demand site.

Rescue centers	Demand sites			
	m_1'	m_2'	m_3'	m_4'
n_1'	[7,9]; 1.9	[11,13]; 1.8	[7,9]; 1.6	[8,10]; 1.5
n_2'	[10,12]; 1.9	[6,8]; 1.7	[10,12]; 1.5	[9,11]; 1.5

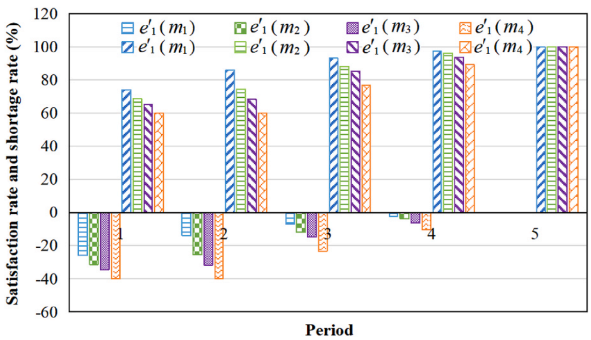


Fig. 8. Satisfaction and shortage rates of resource e_1' at demand sites in each time period (Expanded case).

sources in each period are shown in Tables 4 and 5, respectively. The road transportation time and time penalty coefficient of resources are shown in Table 6. The loading and unloading times per unit of emergency resource e_1' and e_2' are 0.3 h and 0.5 h, respectively.

Calculations are performed while maintaining the same parameter settings and optimization levels as in the previous section. The satisfaction and shortage rates, as well as the shortage amount and coverage rates for each type of resource at each demand site per period, are shown in Figs. 8–10(a-e), respectively.

The results of Figs. 8–10(a-e) show that the proposed model is also suitable for this extended case. Applying the proposed model in response to COVID-19 can enhance the efficiency and effectiveness of emergency resource allocation. The research results can offer decision support for the optimal allocation of large-scale multi-period emergency resources.

In addition, to validate the benefits of the proposed multi-period distribution model, this proposed model is compared with the traditional single-period distribution model. By calculation, the emergency resource allocation coverage rate formed by the multi-period model and the single-period model is shown in Fig. 11(a–e).

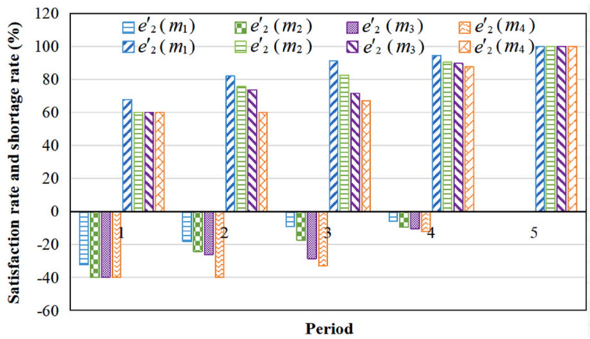
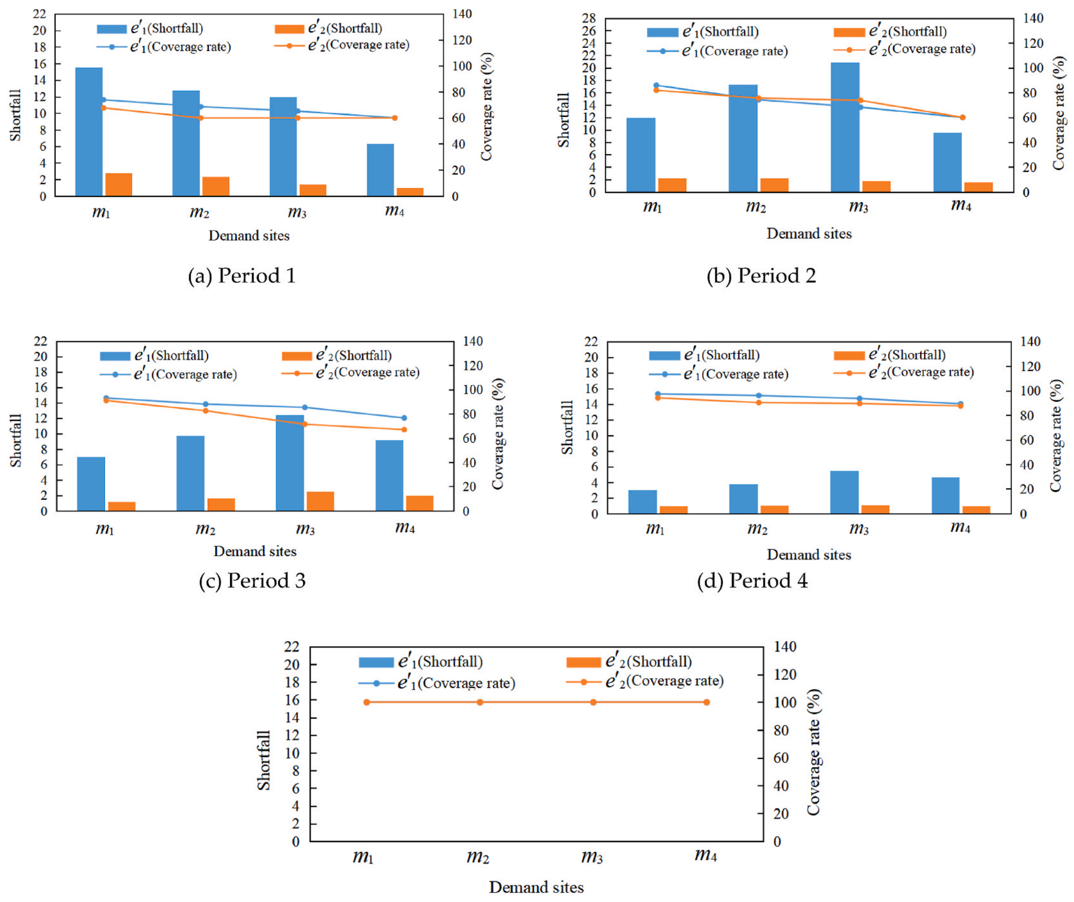


Fig. 9. Satisfaction and shortage rates of resource e_2' at demand sites in each time period (Expanded case).



(a) Period 1

(b) Period 2

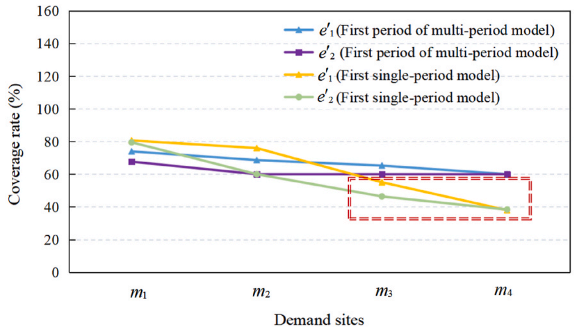
(c) Period 3

(d) Period 4

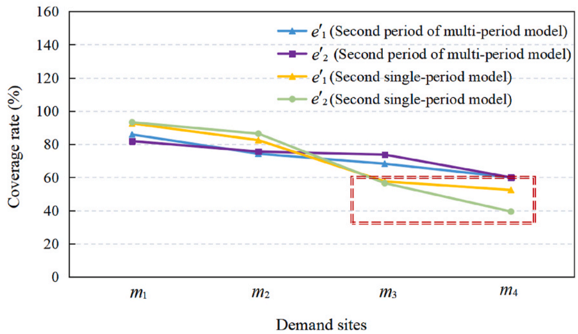
(e) Period 5

Fig. 10. (a–e). Shortfalls and coverage rate of resources at each demand site per period (Expanded case).

The coverage rate of resource distribution is a crucial factor in assessing the effectiveness of emergency resource allocation. The higher the satisfaction, the better the resource distribution effect. Moreover, satisfaction also entails a comprehensive consideration of the total delivery time and total losses in the distribution process of emergency supplies. As can be seen from Fig. 11(a–e), the proposed multi-period model offers significant advantages over the single-period model, particularly during the initial period of emergency resource distribution. For example, in Fig. 11(a), during the first period of the proposed multi-period model, the resource coverage rate for resources e_1' and e_2' at each demand site exceeds 60 %. In contrast, in the first single-period model, the coverage rate for demand sites e_1' and e_2' falls significantly below 60 %. This disparity may result in substantial losses and adverse impacts due to resource shortages at these two demand sites. Therefore, it can be seen that the multi-period model proposed in this article has certain



(a) Coverage rate (the first period of multi-period model versus the first single-period model)



(b) Coverage rate (the second period of multi-period model versus the second single-period model)

Fig. 11. Comparison of coverage between the multi-period model and the single-period model.

advantages.

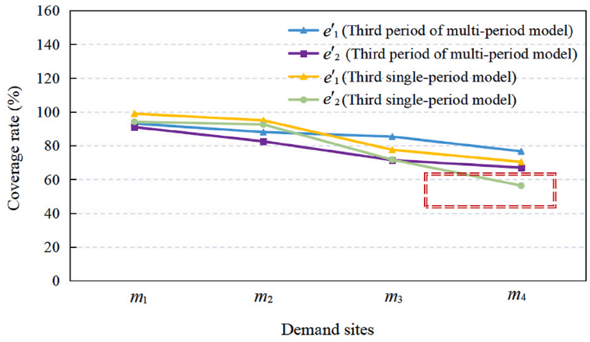
6. Conclusions and future research directions

The proposed model in this study introduces a triangular fuzzy number to describe the uncertainty of the supply and demand of emergency resources, and an interval number to describe the time required for resource transportation in the case of rescue operations. The model's aim is to minimize the total time and difference in the total satisfaction rate of resource allocation. Next, the IMGA is developed to obtain high-quality emergency resource distribution schemes. Finally, a case study based on emergency resource allocation during the COVID-19 pandemic is performed to verify the proposed model.

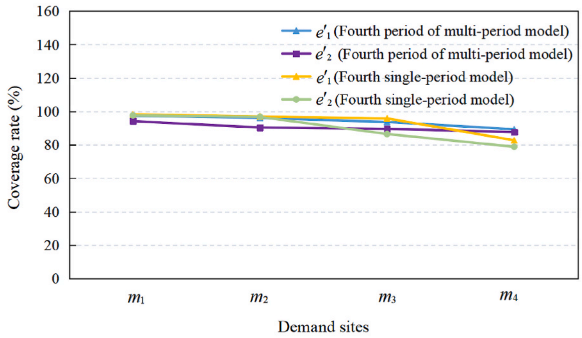
The results show that the proposed model can balance efficiency and equity, and improve the efficiency and effect of emergency resource distribution. First, the model allocates a certain amount of emergency resources to each demand site in each emergency period, which can avoid large losses caused by extreme shortage of resources at a certain demand site. Second, the emergency resource distribution needs to weigh the allocation time of emergency resources and degree of impact. Specifically, the allocation of resources to demand sites with short transportation time and serious impact. Finally, the continuous increase in supply highlights, the advantages of the proposed model. It can continuously improve the resource coverage rate of each demand site and help meet the resource demand of all disaster-affected sites. In addition, the proposed IMGA can be effectively applied to emergency resource distribution decision-making. It has significant advantages in terms of stability, convergence effect and optimization capability. In practice, it can provide decision support to obtain high-quality or optimal emergency resource distribution schemes.

Although the proposed model has achieved significant advantages in case analysis, it also has some limitations. For example, the proposed model only considers a single transportation mode (road transportation) and lacks the incorporation of potential integration of real-time data sources (e.g., big data technology).

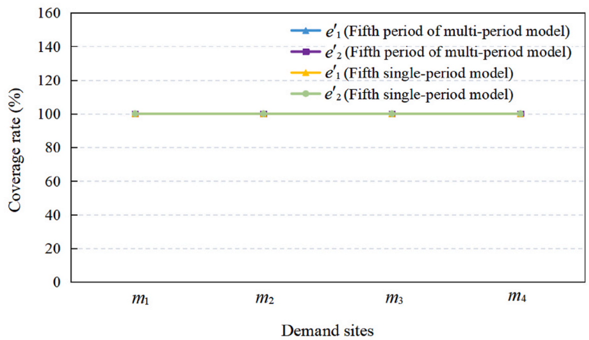
The multi-period distribution of emergency resources is a complex systemic process. Different transportation modes (e.g., air or railway) have different impacts on the efficiency of resource distribution. In response to the COVID-19 epidemic, time is of the essence for the distribution of emergency resources. In this case, multimodal transport is very necessary and important. Multimodal transport can choose the most suitable distribution mode based on the actual disaster situation during resource allocation, aiming to transport the necessary emergency resources to the disaster-affected area in the shortest time possible. Meanwhile, the disaster environment is very complex during the emergency resource distribution process. The disaster information, such as resource demand and supply,



(c) Coverage rate (the third period of multi-period model versus the third single-period model)



(d) Coverage rate (the fourth period of multi-period model versus the fourth single-period model)



(e) Coverage rate (the fifth period of multi-period model versus the fifth single-period model)

Fig. 11. (*continued*).

obtained based on real-time big data is more accurate. This accuracy is beneficial for the precision and scientific nature of resource allocation.

Therefore, in future studies, exploring how to utilize big data technology to acquire real-time information (e.g., supply, demand, and transportation capacity) and to incorporate multimodal transport in the multi-phase allocation process of large-scale disaster emergency rescue operations still necessitates additional investigation and contemplation by practitioners and researchers in this field.

Data availability statement

The data associated with this study are not deposited in a publicly available repository; all data are included in this article.

CRediT authorship contribution statement

Yanyan Wang: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This research was funded by the National Social Science Foundation of China (21CGL044).

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