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ORIGINAL RESEARCH

Dynamic collaborative optimization for disaster relief supply chains under information ambiguity

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Abstract

Large-scale disasters occur worldwide, with a continuing surge in the frequency and severity of disruptive events. Researchers have developed several optimization models to address the critical challenges of disaster relief supply chains (e.g., emergency material reserving and scheduling inefficiencies). However, most developed algorithms are proven to have low fault tolerance, which makes it difficult for disaster relief supply chain managers to obtain optimal solutions and meet the emergency distribution requirements within a limited time frame. Considering the uncertainty and ambiguity of disaster relief information and using Interval Type-2 Fuzzy Set (IT2TFS), this paper presents a collaborative optimization model based on an integrative emergency material supplier evaluation framework. The optimal emergency material suppliers are first selected using a multi-attribute group decision-making ranking method. Multi-objective fuzzy optimization is then run in three emergency phases: early -, mid-, and late-disaster relief stages. Focusing on a massive flash flood disaster event in Yunnan Province as a case study, a comprehensive numerical analysis tests and validates the developed model. The results revealed that the proposed optimization method can optimize emergency material planning while ensuring that reserve material safety inventory is always maintained at a reasonable level. The presented method suggests a fuzzy interval to prevent emergency materials' safety inventory shortage and minimize continuous life/property losses in disaster-affected areas.

Keywords Collaborative fuzzy optimization · Emergency material reserve structure · Disaster relief supply chains · Fuzzy multi-goal decisions

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1 Introduction

Every year, large-scale disasters (man-made and natural) severely affect human lives across the globe, causing casualties, community disturbance, and property losses (Guha-Sapir et al., 2016; Zheng & Ling, 2013; Zhou et al., 2017). Over the years, there has been a continuing surge in the number and severity of such events. For instance, the intensity of hurricane events has been increased by 70 percent over the past 60 years (Anderson & Bausch, 2006). Flooding is another catastrophic event that has caused approximately US$ 185 billion in economic losses in the first decade of the twenty-first century (Ali et al., 2020). In 2018, the direct losses caused by weather-related disasters in the United States reached US$91 billion. The direct losses caused by weather-related disasters in China reached RMB 264.46 billion (Hu et al., 2019). It was recently estimated by SEIC Data Information Co. (CEIC) that the economic impact of the COVID-19 pandemic could reach up to the US $8.8 trillion worldwide – equal to 9.7 percent of GDP (Park et al., 2020).

Given the increasing number of disasters that have occurred over the past years (see Table 1), a growing concern is currently focused on developing knowledge and innovations for managing disaster relief operations in a more effective and resourceful manner (Cogato et al., 2019). As a result, developing swift and effective response plans to manage such unpredictable emergency events has become a national priority for some governments (Seraji et al., 2021). Researchers have developed different supply chain strategies to reduce human casualties by ensuring the availability of essential supplies and timely delivery of medical/healthcare assistance. For example, emergency resource scheduling (ERS) is developed as a key tool for managing rescue operations, assisting disaster relief decision-makers in efficiently planning and allocating essential products and services (Zhou et al., 2017). Emergency response activities for major disasters primarily rely on the on-demand information communicated

Table 1 Natural disasters' sub-group classifications

Natural disaster category			
Biological	Geological	Hydrological	Meteorological
Epidemic - Viral Infection Disease - Microbial Infection Disease - Parasitic Infection Disease - Prion Infection Disease Insect Infestation Animal Stampede	Earthquake Volcano Mass Movements (Dry) - Rockfall - Landslide - Avalanche - Subsidence	Flood - General Flood - Flash Flood - Storm Surge/Coastal Mass Movements (Wet) - Rockfall - Landslide - Avalanche - Subsidence	Storm - Tropical Cyclone - Extra-Tropical Cyclone - Local Storm Climatological Extreme Temperature - Heat Wave - Cold Wave - Extreme Winter Conditions Drought Wildfire/Bushfire - Forest Fire - Land Fire
		Hydro-Meteorological	

Guha-Sapir et al. (2016)

in a dynamic state, and this causes ongoing fluctuations in the emergency material reserve (EMR) (Hu et al., 2019; Zhang & Chen, 2016; Zhou et al., 2017).

Nevertheless, large-scale disasters continue to occur, and developing enhanced disaster response models which could contribute to effective relief operations is vital to save lives. Only a few studies incorporate collaborative fuzzy optimization models to optimize EMR and Emergency Material Scheduling (EMS) simultaneously. Given the uncertainty and complexity of disaster relief information (Farahani et al., 2020), the present paper proposes a collaborative optimization model based on emergency material supplier evaluation using IT2TFS. This paper proposes a dynamic collaborative decision-making model based on interval two trapezoidal fuzzy set EMR according to fuzzy uncertainty and complexity characteristics in significant disaster events. This could meet the dynamic demands of emergency disaster relief in the affected area, and fully consider the impact of "disaster relief stage dynamic time factor" on the decision results, realize the coordination between the normal decision and abnormal decision making and fuzzy optimization decision making, it is important to solve the EMR decision problem application value and practical significance.

The remainder of the paper is organized as follows: Sect. 2 provides a literature review and the research background; Sect. 3 describes the EMR and optimization problems; Sect. 4 provides the key assumptions and a list of notations used in the proposed model; Sect. 5 describes the properties used to optimize the structure of EMR; Sect. 6 explains the implications and application of the constructed model in the emergency rescue practice; Sect. 7 provides a summary of key findings and concluding remarks.

2 Research background

The issues in disaster relief supply chains include inefficiencies currently existing across various sectors, such as communication systems, pre-positioning resources, lack of integration between central governments and inter-state logistics systems, understaffed and lack of skilled personnel, limited asset visibility, and lack of appropriate planning that could handle and distribute donations and procurement compellingly. A basic set of suggestions corresponding to the issues mentioned above were earlier made to generate optimization models (Van Wassenhove, 2006). A comprehensive literature review on emergency inventory management in disasters was earlier published by Ozguven and Ozbay (2014) and will not be discussed hereafter. However, brief overviews of disaster events and disaster events categories with respective timelines are provided in Tables 1 and 2.

Humanitarian researchers recognize the lack of essential infrastructure support to plan for a quick response to major disasters and uncertainties (Ghorbani & Ramezanian, 2020). Some researchers argue that these organizations effectively use continuous aid to face disasters (Venkatesh et al., 2019). The international relief agencies, such as Red Cross, use these contractual arrangements to guarantee and stock the materials at the predetermined locations involving stakeholders and donors (Balcik & Ak, 2014). Many works integrate multi-objective stochastic programming models (Mohammadi et al., 2016). Emergency Material Scheduling (EMS) is another multi-objective and multi-constraint problem involving complex factors and situations (Hu et al., 2019). Some emerging optimization algorithms (e.g., conditional value-at-risk, paddy field algorithm, cuckoo search, biogeographic optimization algorithm, bionic algorithm, fireworks algorithm) have been recently developed (Faghih-Roohi et al., 2016; Hu et al., 2019; Lu et al., 2019; Somarin et al., 2016).

Table 2 Disaster timeline since 2010

No.	Disaster event	Location	Year	Death Toll
1	Earthquake	Haiti	2010	316,000
2	Heat Waves	Russia	2010	56,000
3	Heat Waves	Japan	2010	2000
4	Tsunami	Japan	2011	15,897
5	Tropical Cyclone	Philippines	2012	1901
6	Middle East Respiratory Syndrome (MERS)	South Korea, Saudi Arabia	2012-Present	858
7	Tropical Cyclone	Philippines, Vietnam, Chin	2013	6340
8	Flood	Afghanistan	2014	2655
9	Earthquake	Nepal, India	2015	8964
10	Heat Waves	India	2015	2500
11	Heat Waves	Pakistan	2015	2000
12	Earthquake	Ecuador	2016	676
13	Tropical Cyclone	Puerto Rico, Dominica	2017	3059
14	Tsunami	Indonesia	2018	4340
15	Tropical Cyclone	Mozambique, Zimbabwe, Malawi	2019	1,303
16	COVID-19	Worldwide	2019-Present*	5,382,546

Andharia (2020); Below and Wallemacq (2018); Guha-Sapir et al. (2016)
*According to the data released by the World Health Organization (WHO), the number of deaths from covid-19 was 5,382,546 as of December 22, 2021

For example, a time window-based EMR and scheduling decision model was proposed earlier by Haghani and Oh (1996), yet, the effect of upstream emergency suppliers on the reserve strategy was not investigated. A case study by Guo et al. (2018) was performed on risk aversion stochastic models and material replacement strategies for emergency material inventory systems. Despite achievements made in identifying adequate boundary conditions in the replacement mechanism (Guo et al., 2018), the primary focus was merely on single-objective optimization models-similar to other modeling reports (Zhou & Olsen, 2018) rather than multi-modeling optimization modeling. Earlier reports on multi-objective optimization modeling, reliability, and flexibility of EMR in dynamic disaster relief scenarios, were not thoroughly investigated (Hu et al., 2019). Therefore, assumptions made in disaster relief material scheduling with relevant corresponding optimization schemes often deviate from reality, making the feasibility of previous methods unrealistic (Hu et al., 2019).

Different ERS models and algorithms have been proposed to tackle various aspects of ERS, such as logistics, location, and demand forecast (Hu et al., 2019). However, previous methods implementations are complicated, cumbersome, and poorly supportive of collaborative decision-making environments. For example, in the Wenchuan earthquake, arbitrary distribution of emergency material supplies led to cchaos as structured classification, and various emergency supplies details were missing (Hu et al., 2019). Furthermore, inaccurate demand forecast of emergency materials makes relief material delivery excessive, leading to a certain extent of waste (Hu et al., 2019). In the Yushu disaster event, the geographical altitudes of the region were not systematically taken into account, which resulted in medical emergency supplies shortages, and rescue efficiency being seriously affected (Hu et al., 2019). In the Acapulco flood 2013 in Mexico, many government agencies were employed to address the problem, leading to high organizational costs and poor outcomes (Rodríguez-Espíndola et al., 2018).

Prior examples imply that the EMS should be treated as a multi-objective and multi-constraint problem where all complex situations and factors are involved. Currently, it is difficult to obtain optimal solutions within a limited timeframe using existing optimization algorithms. Most algorithms have a low fault tolerance rate, and the optimization results cannot meet the distribution requirements. Therefore, algorithms tend to produce local and sub-optimal solutions (Hu et al., 2019). Most algorithms are focused on common heuristics to solve an EMS mode. Few studies are dedicated to developing new algorithms, but their efficiency has not been adequately validated (Hu et al., 2019).

As emergency resource optimizations and decision-making are carried out in real-time and uncertain settings, former model-based decision-making results could not ideally meet a realistic rescue requirement. The interval type-2 fuzzy set (IT2TFS) algorithms have recently become an essential tool for proposing a new probability measure. An IT2TFS with a three-dimensional membership function can be represented by fuzzy sets in the [0, 1] interval, providing a higher degree of freedom and flexibility than a type-1 fuzzy set (IT1TFS) (Qin & Liu, 2019). IT2TFSs are generally considered suitable applications in areas where multi-attribute group decision-making is involved. In modeling uncertainty, the IT2TFS offers higher accuracy than IT1TFS (Qin & Liu, 2019). A comprehensive model based on the IT2TFS reasoning method and analytic hierarchy process for the urban air quality assessment was recently reported by Debnath et al. (2018).

When a large-scale disaster occurs, different stages require additional EMR resources. Over multiple periods of early-, mid-and late- disaster relief optimization stages, the efficiency of rescue operations is necessary to minimize EMR waste to the greatest possible extent (Zheng & Ling, 2013). Such measures are pivotal due to the ambiguous and multifaceted nature of disaster relief information across different stages of emergency rescue missions. To advance the existing body of literature, this paper presents a collaborative optimization model for the EMR structure, which operates based on an evaluation of the emergency material supplier. A numerical analysis is also performed to evaluate the proposed model. The model serves as a typical response strategy to EMR (living, medical, and biological material reserve) and supplier selection (ESS) problems, aiming to optimize the delivery time for early-, mid- and late- disaster relief optimization stages, the number of shipments, and reserve costs. An IT2TFS model for ESS and a multi-objective fuzzy optimization (MOFO) model for EMR have been constructed (see Fig. 1).

3 Problem description

Most solution algorithms developed so far have a low fault tolerance rate when applied to solve the EMR optimization problems. As a result, the algorithm efficiency cannot be accurately validated. Currently, most of the data are generated arbitrarily by computers (Tang et al., 2018, and a small proportion of which originates from real-life datasets (Chen et al., 2017; Anh Ninh et al., 2020). Only a few reports exist on the successful implementation of heuristic algorithms for solving practical rescue operations. However, most of these solution algorithms would not meet the expectations under ambiguous and uncertain situations.

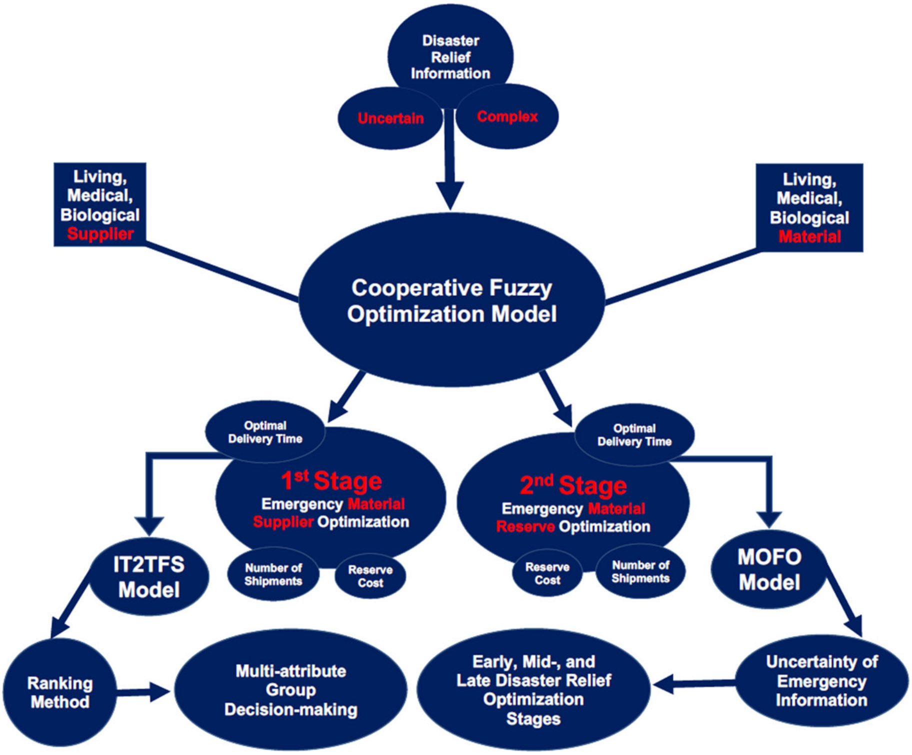

Fig. 1 A schematic of the proposed solution methodology

To address the above issues, this paper proposes a dynamic, collaborative decision-making model based on the IT2TFS to solve the EMR decision problem practically. The proposed model incorporates the fuzzy uncertainty and complexities which are inherent in significant disaster events, making it challenging for planners to meet the dynamic demands of emergency disaster relief in the affected area, fully consider the impact of the "disaster relief stage dynamic time factor" on the decision results, realize the coordination between the normal, abnormal, and fuzzy optimization decision-making.

4 Assumptions and definitions

Based on Zhang and Chen's Definition of emergency materials (2016), the present work assumes that emergency materials refer to the urgently required items in disaster-prone areas, primarily categorized as living materials, medical materials, and biological resources. Considering the influence of dynamic time factors on planners' collaborative decision-making, the EMR process can be divided into three stages (early-, mid-, and late-disaster relief). Sub objectives considered for each disaster relief stage include optimal delivery time, reserve cost, and the number of shipments. We also assume that the urgent time requirements for emergency supplies, the demand, and the cost of reserves fluctuate due to the changes in rescue phases. Based on the modeling of an uncertain disaster relief environment, our collaborative optimization process consists of two levels; (1) Evaluation of emergency material suppliers and (2) Optimization of EMR structure. Further, the following assumption is made:

(1) A minimum amount of EMR should exist after the occurrence of a significant disaster event,
(2) The reserve capacity of emergency suppliers is directly related to the effective control of various emergencies,
(3) The amount of funds available to an EMR decision is associated with a significant disaster event.

A goal planning approach is an effective tool for solving multi-objective decision-making problems, where multiple objectives of the decision-makers are considered in order of their importance. Following the model developed by Chen and Hong (2014), in this paper, different priority factors are assigned to each optimization objective as per the decision-maker's preferences. All symbols and variables are provided as follows:

$\tilde{\tilde{x}}_{ijk}$	Elements in the IT2TFS ($\tilde{\tilde{x}}_{ijk} \geq \tilde{\tilde{0}}$)
$\tilde{\tilde{A}}$	Reserve amount of emergency supplies associated with the kth emergency supplier in the ith disaster relief stage
t_{ijk}	Timeliness index of the jth emergency supply item of the kth emergency material supplier in the ith disaster relief stage
u_{ijk}	Quantity index of the jth emergency supply item delivered by the kth emergency supplier in the ith disaster relief stage
w_i	First-order optimization sub-objective
w_{ijh}	Secondary fuzzy subobjective
Q_{ij}	Reserve capacity of the kth emergency supplier for the jth emergency item
θ_{ij}	Impact factor of the jth emergency item in the jth disaster relief stage
T	Restriction on funds available for EMR activities
A_{ij}	Safety stock of the jth emergency item in the jth disaster relief stage ($A_{ij} \geq 0$)
i	Stage of disaster relief ($i = 1, 2, 3$)
j	Type of emergency relief items ($j = 1, 2, 3$)
h	Timeliness reflected by the delivery volume, reserve cost, and other indicators ($h = 1, 2, 3$)
k	EMR mode number ($k = 1, 2, 3, 4$)
d^+	Positive deviation variable ($d^+ > 0$)
d^-	Negative deviation variable ($d^- > 0$)
d^+_{ijh}	Fuzzy positive deviation variables corresponding to each index for each category of materials ($d^+_{ijh} > 0$)
d^-_{ijh}	Fuzzy negative deviation variables corresponding to each index for each category of materials($d^-_{ijh} > 0$)

5 Methodology

5.1 Interval type-2 trapezoidal fuzzy set (IT2TFS)

Definition 1 If A_α denotes an interval type-1 fuzzy trapezoidal set, α denotes the degree of membership $\alpha \in [0, 1]$ (Zadeh, 1975), then $\tilde{\tilde{A}}$ denotes an extension of the IT1TFS A_μ, as shown in Eq. (1). The IT2TFS is shown in Table 3 (Bortolan & Degani, 1985).. IT1TFS and IT2TFS are shown in Figs. 2 and 3.

$$\tilde{\tilde{A}} = \left\{ \left((x, u), u_{\tilde{\tilde{A}}}(x, u) \right) \middle| \forall x \in X, \forall u \in J; x \subseteq [0, 1], 0 \leq u_{\tilde{\tilde{A}}}(x, u) \leq 1 \right\} \tag{1}$$

In Eq. (1), let x denotes the domain of $\tilde{\tilde{A}}$; $U_{\tilde{\tilde{A}}}$ denotes secondary membership function; J_x denotes the primary membership function, $J_x \in [0, 1]$.

IT2TFS $\tilde{\tilde{A}}$ is expressed in Eq. (2).

$$\tilde{\tilde{A}} = \int_{x \in X} \int_{u \in J_X} u_{\tilde{\tilde{A}}}(x, u)/(x, u) \tag{2}$$

Table 3 Twelve fuzzy input sets

Fuzzy set	Serial no	Interval type-2 trapezoidal blur	Fuzzy set	Serial no	Interval type-2 trapezoidal blur
Set1	$\underset{1}{\overset{\approx}{A}}$ $\underset{2}{\overset{\approx}{A}}$	((0.35, 0.4, 0.4, 1; 1, 1), (0.35, 0.4, 0.4, 1; 1, 1)) ((0.15, 0.7, 0.7, 0.8; 1, 1), (0.15, 0.7, 0.7, 0.8; 1, 1))	Set 7	$\underset{1}{\overset{\approx}{A}}$ $\underset{2}{\overset{\approx}{A}}$	((0.2, 0.5, 0.5, 0.8; 1, 1), (0.2, 0.5, 0.5, 0.8; 1, 1)) ((0.4, 0.5, 0.5, 0.6; 1, 1), (0.4, 0.5, 0.5, 0.6; 1, 1))
Set 2	$\underset{1}{\overset{\approx}{A}}$ $\underset{2}{\overset{\approx}{A}}$	((0, 0.1, 0.5, 1; 1, 1), (0, 0.1, 0.5, 1; 1, 1)) ((0.5, 0.6, 0.6, 0.7; 1, 1), (0.5, 0.6, 0.6, 0.7; 1, 1))	Set 8	$\underset{1}{\overset{\approx}{A}}$ $\underset{2}{\overset{\approx}{A}}$ $\underset{3}{\overset{\approx}{A}}$	((0, 0.4, 0.6, 0.8; 1, 1), (0, 0.4, 0.6, 0.8; 1, 1)) ((0.2, 0.5, 0.5, 0.9; 1, 1), (0.2, 0.5, 0.5, 0.9; 1, 1)) ((0.2, 0.6, 0.7, 0.8; 1, 1), (0.2, 0.6, 0.7, 0.8; 1, 1))
Set 3	$\underset{1}{\overset{\approx}{A}}$ $\underset{2}{\overset{\approx}{A}}$	((0, 0.1, 0.5, 1; 1, 1), (0, 0.1, 0.5, 1; 1, 1)) ((0.6, 0.7, 0.7, 0.8; 1, 1), (0.6, 0.7, 0.7, 0.8; 1, 1))	Set 9	$\underset{1}{\overset{\approx}{A}}$ $\underset{2}{\overset{\approx}{A}}$	((0, 0.2, 0.2, 0.4; 1, 1), (0, 0.2, 0.2, 0.4; 1, 1)) ((0.6, 0.8, 0.8, 1; 0.8, 0.8), (0.6, 0.8, 0.8, 1; 0.8, 0.8))
Set 4	$\underset{1}{\overset{\approx}{A}}$ $\underset{2}{\overset{\approx}{A}}$ $\underset{3}{\overset{\approx}{A}}$	((0.4, 0.9, 0.9, 1; 1, 1), (0.4, 0.9, 0.9, 1; 1, 1)) ((0.4, 0.7, 0.7, 1; 1, 1), (0.4, 0.7, 0.7, 1; 1, 1)) ((0.4, 0.5, 0.5, 1; 1, 1), (0.4, 0.5, 0.5, 1; 1, 1))	Set 10	$\underset{1}{\overset{\approx}{A}}$ $\underset{2}{\overset{\approx}{A}}$	((0.4, 0.6, 0.6, 0.8; 1, 1), (0.4, 0.6, 0.6, 0.8; 1, 1)) ((0.8, 0.9, 0.9, 1; 0.2, 0.2), (0.8, 0.9, 0.9, 1; 0.2, 0.2))
Set 5	$\underset{1}{\overset{\approx}{A}}$ $\underset{2}{\overset{\approx}{A}}$ $\underset{3}{\overset{\approx}{A}}$	((0.5, 0.7, 0.7, 0.9; 1, 1), (0.5, 0.7, 0.7, 0.9; 1, 1)) ((0.3, 0.7, 0.7, 0.9; 1, 1), (0.3, 0.7, 0.7, 0.9; 1, 1)) ((0.3, 0.4, 0.7, 0.9; 1, 1), (0.3, 0.4, 0.7, 0.9; 1, 1))	Set 11	$\underset{1}{\overset{\approx}{A}}$ $\underset{2}{\overset{\approx}{A}}$	((0, 0.2, 0.2, 0.4; 0.2, 0.2), (0, 0.2, 0.2, 0.4; 0.2, 0.2)) ((0.6, 0.8, 0.8, 1; 1, 1), (0.6, 0.8, 0.8, 1; 1, 1))
Set 6	$\underset{1}{\overset{\approx}{A}}$ $\underset{2}{\overset{\approx}{A}}$ $\underset{3}{\overset{\approx}{A}}$	((0.3, 0.5, 0.8, 0.9; 1, 1), (0.3, 0.5, 0.8, 0.9; 1, 1)) ((0.3, 0.5, 0.5, 0.9; 1, 1), (0.3, 0.5, 0.5, 0.9; 1, 1)) ((0.3, 0.5, 0.5, 0.7; 1, 1), (0.3, 0.5, 0.5, 0.7; 1, 1))	Set 12	$\underset{1}{\overset{\approx}{A}}$ $\underset{2}{\overset{\approx}{A}}$	((0.2, 0.6, 0.6, 1; 1, 1), (0.2, 0.6, 0.6, 1; 1, 1)) ((0.2, 0.6, 0.6, 1; 0.2, 0.2), (0.2, 0.6, 0.6, 1; 0.2, 0.2))

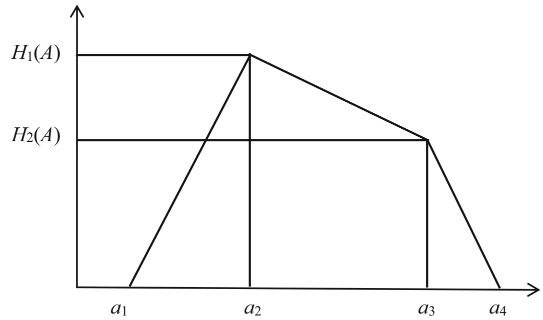

Fig. 2 An interval type-I trapezoidal fuzzy set (IT1TFS)

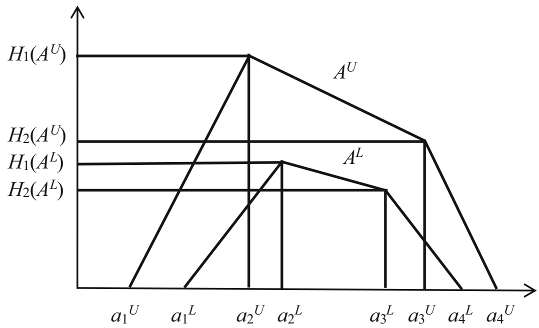

Fig. 3 An interval type-2 trapezoidal fuzzy set (IT2TFS)

Definition 2 If $\tilde{\tilde{A}}$ is an IT2TFS in the universal set U, $\tilde{\tilde{A}}_\alpha^L$ denotes the lower α-cut of $\tilde{\tilde{A}}$, $\tilde{\tilde{A}}_\alpha^L$=$\left\{ \mathrm{x} \in \mathrm{X}|\mu_{-\tilde{\tilde{A}}(x)} \geq \alpha \right\}$. $\tilde{\tilde{A}}_\alpha^H$ denotes the upper α-cut of $\tilde{\tilde{A}}$, $\tilde{\tilde{A}}_\alpha^H$=$\left\{ \mathrm{x} \in \mathrm{X}|\overline{\mu}_{\tilde{\tilde{A}}(x)} \geq \alpha \right\}$. Then, it is easy to show that $\tilde{\tilde{A}}_\alpha^L \subseteq \tilde{\tilde{A}}_\alpha^H$ for $\alpha \in [0, 1]$.

Definition 3 If $\tilde{\tilde{A}}_\alpha = \left(\tilde{\tilde{A}}_\alpha^L, \tilde{\tilde{A}}_\alpha^H \right)$, where $\tilde{\tilde{A}}_\alpha^L$ denotes the lower α-cuts of an IT2TFS $\tilde{\tilde{A}}$, and $\tilde{\tilde{A}}_\alpha^H$ the upper α-cuts of an IT2TFS $\tilde{\tilde{A}}$. Then $\tilde{\tilde{A}}_\alpha^L \backslash \tilde{\tilde{A}}_\alpha^H$ can reflect the uncertainties in $\tilde{\tilde{A}}_\alpha$ at α the level.

Definition 4 If $\rho_{\tilde{\tilde{A}}}(\alpha)$ denotes the uncertainty degree of $\tilde{\tilde{A}}_\alpha$, then, $\rho_{\tilde{\tilde{A}}}(\alpha) = \frac{\left| \tilde{\tilde{A}}_\alpha^H \backslash \tilde{\tilde{A}}_\alpha^L \right|}{\tilde{\tilde{A}}_\alpha^H} = 1 - \frac{\left| \tilde{\tilde{A}}_\alpha^L \right|}{\tilde{\tilde{A}}_\alpha^H}$.

Property 1 For an IT1TFS $\tilde{A}$, we have $\rho_{\tilde{A}}(\alpha)$= 0.

Property 2 For an IT2TFS $\tilde{\tilde{A}}_\alpha$, we have $0 \leq \rho_{\tilde{\tilde{A}}(\alpha)} \leq 1$.

Property 3 For two IT2TFSs $\tilde{\tilde{A}}$ and $\tilde{\tilde{B}}$, if $\mathrm{FOU}\left(\tilde{\tilde{A}}\right) \subseteq \mathrm{FOU}\left(\tilde{\tilde{B}}\right)$, then $\rho_{\tilde{\tilde{A}}}(\alpha) \leq \rho_{\tilde{\tilde{B}}}(\alpha)$**.** In an IT2TFS, the union of all subranges is denoted as Footprint of Uncertainty (FOU).

Property 4 If $\tilde{\tilde{A}} \approx \tilde{\tilde{B}}$, $|s_1| = 0$, $|s_2| = 0$, where $s_1 = \left\{ x \in X | \underline{\mu}_{\tilde{\tilde{A}}}(x) \neq \underline{\mu}_{\tilde{\tilde{B}}}(x) \right\}$, $s_2 = \left\{ x \in X | \underline{\mu}_{\tilde{\tilde{A}}}(x) \neq \underline{\mu}_{\tilde{\tilde{B}}}(x) \right\}$, then $\rho_{\tilde{\tilde{A}}}(\alpha)$=$\rho_{\tilde{\tilde{B}}}(\alpha)$.

Definition 5 For an IT2TFS $\tilde{\tilde{A}}_{\alpha}$, $0 \leq \rho_{\tilde{\tilde{A}}(\alpha)} \leq 1$, the uncertainty degree of $\tilde{\tilde{A}}$ is $\rho_{\tilde{\tilde{A}}} = \int_0^1 2\alpha \rho_{\tilde{\tilde{A}}(\alpha)} d\alpha$.

Definition 6 If L denotes a set of alternative emergency suppliers, where $L = \{l_1, l_2, l_3 ..., l_n\}$; R denotes a set of evaluation attributes, where $R = \{r_1, r_2, ..., r_n\}$; The decision group consists of decision-makers $D_1, D_2, ..., D_k$.Then, a group decision matrix M_{γ} consisting of γ decision-makers is expressed in Eq. (3) (Vahdani & Hadipour, 2011).

$$M_{\gamma} = [\tilde{\tilde{X}}_{ij}^{\gamma}]_{n \times m} = \begin{bmatrix} \tilde{\tilde{X}}_{11}^{\gamma} & \tilde{\tilde{X}}_{12}^{\gamma} & \cdots & \tilde{\tilde{X}}_{1m}^{\gamma} \\ \tilde{\tilde{X}}_{21}^{\gamma} & \tilde{\tilde{X}}_{22}^{\gamma} & \cdots & \tilde{\tilde{X}}_{2m}^{\gamma} \\ \cdots & \cdots & \cdots & \cdots \\ \tilde{\tilde{X}}_{n1}^{\gamma} & \tilde{\tilde{X}}_{n2}^{\gamma} & \cdots & \tilde{\tilde{X}}_{nm}^{\gamma} \end{bmatrix}, \tag{3}$$

where $\tilde{\tilde{X}}_{ij}^{\gamma}$ denotes the evaluation value of the group decision for the alternative emergency material supplier l_i with an attribute $r_j (i = 1, ..., n; j = 1, ..., m; \gamma = 1, ..., k)$.

Definition 7 Let $\tilde{\tilde{X}}_{ij} = ((\tilde{\tilde{X}}_{ij}^1 \oplus \tilde{\tilde{X}}_{ij}^2 \oplus \ldots \oplus \tilde{\tilde{X}}_{ij}^k)/k)$. We consider an average judgment matrix $\overline{Y} = \left[\overset{\approx}{X}_{ij} \right]_{n \times m}$ for the evaluation value $\tilde{\tilde{X}}_{ij}^{\gamma}$ of the group decision; So, the weight matrix W_{γ} is denoted as $W_{\gamma} = \left[\tilde{\tilde{w}}_j^{\gamma} \right]_{m \times 1} = \left[\tilde{\tilde{w}}_1^{\gamma} \tilde{\tilde{w}}_2^{\gamma} ... \tilde{\tilde{w}}_m^{\gamma} \right]^T$, where $\tilde{\tilde{w}}_j^{\gamma}$ is the weight of the assessment of the jth attribute r_j by the decision-maker $(i = 1, ..., n; j = 1, ..., m; \gamma = 1, ..., k)$.

Definition 8 Let $\overline{W}$ denote an average weight matrix for the multi-attribute evaluation matrix $\tilde{\tilde{w}}_j = ((\tilde{\tilde{w}}_j^1 \oplus \tilde{\tilde{w}}_j^2 \oplus \ldots \oplus \tilde{\tilde{w}}_j^k)/k)$, where $\overline{W} = \left[\tilde{\tilde{w}}_j \right]_{m \times 1}$. A normalized matrix is shown as $N = [\tilde{\tilde{n}}_{ij}]_{n \times m}$; $\overline{Y}$ denotes the weighted normalized decision matrix; the weighted normalized decision matrix $E = \left[\overset{\approx}{\underset{ij}{e}} \right]_{n \times m}$ can be then determined by $\tilde{\tilde{e}}_{ij} = \tilde{\tilde{n}}_{ij} \otimes \tilde{\tilde{w}}_j$ $(i = 1, ..., n; j = 1, ..., m; \gamma = 1, ..., k)$.

Definition 9 Let $\overset{\approx}{\underset{+i}{S}}$ denote the benefit attributes, $\tilde{\tilde{S}}_{+i} = (\tilde{\tilde{e}}_{+i1} \oplus \tilde{\tilde{e}}_{+i2} \oplus \ldots \oplus \tilde{\tilde{e}}_{+im}), i = 1, ..., n$, and $\overset{\approx}{\underset{-i}{S}}$ denote the non-benefit attributes $\tilde{\tilde{S}}_{-i} = (\tilde{\tilde{e}}_{-i1} \oplus \tilde{\tilde{e}}_{-i2} \oplus \ldots \oplus \tilde{\tilde{e}}_{-im}), i = 1, ..., n$. Then $\overset{\approx}{\underset{+i}{S}}$ and $\overset{\approx}{\underset{-i}{S}}$ describe how close each emergency supplier is to the desired goal.

Property 5 Let $Rank_{\min}(\tilde{\tilde{S}}_{-i})(i = 1, ..., n)$ denote the minimum value describing the relative satisfaction of emergency suppliers. Then, the relative significance of the emergency supplier Q can be determined using Eq. (4).

$$Q_i = Rank(\overset{\approx}{\underset{+i}{S}}) + \frac{Rank_{\min}(\overset{\approx}{\underset{-i}{S}}) \sum_{i=1}^{n} \left(Rank(\overset{\approx}{\underset{-i}{S}}) \right)}{Rank(\overset{\approx}{\underset{-i}{S}}) \sum_{i=1}^{n} \left(Rank_{\min}(\overset{\approx}{\underset{-i}{S}}) \Big/ Rank(\overset{\approx}{\underset{-i}{S}}) \right)}, \quad i = 1, ..., n \tag{4}$$

Furthermore, Eq. (4) can be simplified and converted to Eq. (5).

$$Q_i = Rank(\underset{+i}{\overset{\approx}{S}}) + \frac{\sum_{i=1}^{n}\left(Rank(\underset{-i}{\overset{\approx}{S}})\right)}{Rank(\underset{-i}{\overset{\approx}{S}})\sum_{i=1}^{n}\left(1\Big/Rank(\underset{-i}{\overset{\approx}{S}})\right)},\quad i = 1, ..., n \tag{5}$$

The emergency utility supplier quantified by the utility value U_i can then be used to determine the relative significance of the optimal solution, denoted as $U_i = (Q_i/Q_{\max}) \times 100$, where $Q_{\max}$ is the maximum value of the relative importance. The greater the value of U_i, the higher the priority of the emergency supply provider $l_i (i = 1, ..., n)$.

5.2 Fuzzy optimization model for EMRs

Let min $\tilde{f}_i$ denote the optimization objective of the ith disaster relief stage; α_{ijh} denotes the second-level optimization sub-objective of the hth indicator of the jth emergency item in the ith disaster relief stage, where $\alpha_{ijk} = \sum_{k=1}^{4} t_{ijk}\tilde{\tilde{x}}_{ijk} / \sum_{k=1}^{4} \tilde{\tilde{x}}_{ijk}$. If the EMR process is divided into three stages: early, mid-and late-disasandelief stages, sub-objectives for designing each disaster relief stage include the optimal delivery time, number of shipments, and reserve cost. Thus, a first-level sub-objective fuzzy optimization model can be established as follows:

$$\mathrm{M}in\ p_{i1}\sum_{j=1}^{13}\theta_{ij}d_{ij1}^{-} \vee 0 + p_{i2}\sum_{j=1}^{13}\theta_{ij}d_{ij2}^{+} \vee 0 + p_{i3}\sum_{j=1}^{13}\theta_{ij}d_{ij3}^{-} \vee 0 \tag{6}$$

Subject to

$$\alpha_{ij1} + d_{ij1}^{-} \vee 0 - d_{ij1}^{+} \vee 0 = W_{ij1},\quad i = 1, 2, \cdots 3,\ j = 1, 2, ..., 13, \tag{7}$$

$$\alpha_{ij2} + d_{ij2}^{-} \vee 0 - d_{ij2}^{+} \vee 0 = W_{ij2},\quad i = 1, 2, 3,\ j = 1, 2, ..., 13, \tag{8}$$

$$\alpha_{ij3} + d_{ij3}^{-} \vee 0 - d_{ij3}^{+} \vee 0 = W_{ij3},\quad i = 1, 2, 3 j = 1, 2, ..., 13, \tag{9}$$

$$\tilde{x}_{ijk} \geq \tilde{0},\quad i = 1, 2, 3,\ j = 1, 2, ..., 13,\ k = 1, 2, 3, 4\,, \tag{10}$$

where p_{i1} denotes the time objective priority factor, p_{i2} denotes the reliability objective priority factor, and p_{i3} denotes the cost objective priority factor. d_{ij1}^{+}, d_{ij1}^{-} denote the fuzzy positive and negative bias variables for Phase I with time prioritized; d_{ij2}^{+}, d_{ij2}^{-} denote the fuzzy positive and negative bias variables of Phase II with reliability prioritized, and d_{ij3}^{+}, d_{ij3}^{-} denote the fuzzy positive and negative bias variables of Phase III with cost prioritized.

The model's objective (6) is to minimize the delivery time, the reserve cost, and the optimal number of shipments for emergency material suppliers based on Eqs. (4) and (5). The priority of the three objectives is to achieve the shortest time, the highest reliability, and the lowest cost. The delivery time is the priority optimization factor in the optimization model where constraint (7) ensures the delivery quantity is reliable. Constraint (8) is the fuzzy component for the reserve cost, a soft constraint. Constraint (9) is another fuzzy constraint for the reserve cost, also a soft constraint. Constraint (10) is to ensure all decision variables are non-negative. To facilitate the optimization solution of the EMR structure and simplify the calculation steps, we establish a fuzzy optimization model as follows:

$$\mathrm{M}in\ W = \sum_{i=1}^{3} \tilde{p}_i . d_i^- \vee 0 \tag{11}$$

Subject to

$$\min \tilde{f} + d_i^- \vee 0 - d_i^+ \vee 0 = W_i \tag{12}$$

$$d_i^- \vee 0 \geq \tilde{0}, d_i^+ \vee 0 \geq \tilde{0} \tag{13}$$

$$d_i^- \vee 0 \cdot d_i^+ \vee 0 = \tilde{0} \tag{14}$$

Model (11) ensures the optimality of a total fuzzy objective. Constraint (12) guarantees the optimal allocation of emergency material items in the three stages of an emergency rescue while ensuring timely delivery. Constraint (13) ensures that all the fuzzy positive and negative bias variables are non-negative. Constraint (14) indicates that the positive or negative bias variable is zero. The total fuzzy objective optimization model of the EMR structure can be rewritten as follows:

$$\mathrm{M}in\ W = \sum_{i=1}^{3} \tilde{p}_i . d_i^- \vee 0 \tag{15}$$

Subject to

$$\min \tilde{f}_i = p_{i1} \sum_{j=1}^{13} \theta_{ij} d_{ij1}^- \vee 0 + p_{i2} \sum_{j=1}^{13} \theta_{ij} d_{ij2}^- \vee 0 + p_{i3} \sum_{j=1}^{13} \theta_{ij} d_{ij3}^+ \vee 0, \quad i = 1, 2, 3,\ j = 1, 2, ..., 13, \tag{16}$$

$$\min \tilde{f}_i + d_i^- \vee 0 - d_i^+ \vee 0 = W, \quad i = 1, 2, 3 \tag{17}$$

$$\sum_{k=1}^{4} t_{ijk} \tilde{\tilde{x}}_{ijk} / \sum_{k=1}^{4} \tilde{\tilde{x}}_{ijk} - d_{ij1}^+ \vee 0 = W_{ij1}, \quad i = 1, 2, 3,\ j = 1, 2, ..., 13, \tag{18}$$

$$\sum_{k=1}^{4} u_{ijk} \tilde{\tilde{x}}_{ijk} / \sum_{k=1}^{4} \tilde{\tilde{x}}_{ijk} - d_{ij2}^+ \vee 0 = W_{ij2}, \quad i = 1, 2, 3,\ j = 1, 2, ..., 13, k = 1, 2, 3, 4, \tag{19}$$

$$\sum_{k=1}^{4} p_{ijk} \tilde{\tilde{x}}_{ijk} / \sum_{k=1}^{4} \tilde{\tilde{x}}_{ijk} - d_{ij3}^+ \vee 0 = W_{ij3}, \quad i = 1, 2, 3,\ j = 1, 2, ..., 13, k = 1, 2, 3, 4, \tag{20}$$

$$\tilde{\tilde{x}}_{ijk} \geq \tilde{0}, \quad i = 1, 2, 3,\ j = 1, 2, ..., 13, k = 1, 2, 3, 4, \tag{21}$$

$$d_i^- \vee 0 \geq \tilde{0}, d_i^+ \vee 0 \geq \tilde{0} \tag{22}$$

$$d_i^- \vee 0 \cdot d_i^+ \vee 0 = \tilde{0} \tag{23}$$

where i indicates the number of the emergency rescue phase ($i = 1, 2, 3$);j indicates the type of emergency material ($j = 1, 2, ..., 13$). Model (15) ensures the optimality of the total fuzzy objective. Constraint (16) is based on Eq. (6). Constraint (17) ensures optimality of the total objective and that the minimum positive and negative deviations are achieved. Equations (18)-(20) ensure that the sub-objectives of the three rescue phases are optimized. Constraint (21) is the same as Eq. (10). Constraint (22) ensures that all the fuzzy positive and negative bias variables remain non-negative. Constraint (23) ensures that at least one fuzzy positive and negative bias variable is zero.

5.3 Numerical analysis

To evaluate the performance of the proposed collaborative optimization method, a numerical analysis of a massive flash flood disaster in Yunnan Province in 2012 is performed as a case study. Located in southwest China, Yunnan Province is heavily influenced by the summer monsoons (from East Asia and India) and air flows from the Qinghai-Tibet Plateau. The region has a plateau monsoon climate characteristic and is particularly vulnerable to climate change due to rainfall and monsoons (Shi & Chen, 2018).

The emergency response time in the Yunnan province disaster is divided into three disaster relief phases: Phases I, II, and III, referred to as early-, mid-, and late-disaster, respectively. The sub-objectives of the multi-objective decisions in each disaster stage are set as an optimal reserve, optimal delivery time, and optimal delivery quantity. Five emergency material supplier evaluation attributes (i.e., responsiveness, cost, defect rate, delivery reliability, and flexible distribution) are used at different disaster relief stages. Twenty representatives having profiles such as procurement experts, humanitarian organization executives, logistics coordinators, distribution centre managers, and academicians were grouped into three anonymous decision-making groups (D_1, D_2, and D_3) to evaluate the emergency material suppliers ($l_1, l_2, l_3, l_4, l_5, l_6$). Their industry background and practical experience are the key grouping attributes (See Appendix Table A1). Each group registered their feedback about the material positioning and collaborations within humanitarian supply chains. Due to the diversity of groups and reduced response bias, a fuzzy optimization model of the EMR structure based on IT2TFS is constructed to examine the optimal reserve structure of emergency materials (e.g., general goods, pharmaceuticals, and life-saving products). Tables 4, 5, and 6 detail the deployment of the Fuzzy scales in this study.

The parameter $\alpha = 0.8$ is set based on the work conducted by Chen and Hong (2014). Therefore, fewer calculation steps are required for the fuzzy set than for other parameter

Table 4 Fuzzy scales and their corresponding fuzzy sets

Fuzzy scale	Interval type-2 trapezoidal fuzzy set	Fuzzy scale	Interval type-2 trapezoidal fuzzy set
Very low (VL)	((0, 0, 0, 0.1; 1, 1), (0, 0, 0, 0.05; 0.9, 0.9))	Medium high (MH)	((0.5, 0.7, 0.75, 0.9; 1, 1), (0.6, 0.7, 0.75, 0.8; 0.9, 0.9))
Low (L)	((0, 0.1, 0.15, 0.3; 1, 1), (0.05, 0.1, 0.15, 0.2; 0.9, 0.9))	High (H)	((0.7, 0.85, 0.9, 1; 1, 1), (0.8, 0.85, 0.9, 0.95; 0.9, 0.9))
Mid low (ML)	((0.1, 0.3, 0.35, 0.5; 1, 1), (0.2, 0.3, 0.35, 0.4; 0.9, 0.9))	Very high (VH)	((0.9, 1, 1, 1; 1, 1), (0.95, 1, 1, 1; 0.9, 0.9))
Medium (M)	((0.3, 0.5, 0.55, 0.7; 1, 1), (0.4, 0.5, 0.55, 0.6; 0.9, 0.9))		

Table 5 The weights given by the decision-making groups for multi-objective attributes

Attributes	Decision-making groups		
	D_1	D_2	D_3
Responsiveness	VH	H	VH
Cost	MH	M	M
Defect rate	H	H	MH
Delivery reliability	VH	MH	VH
Flexibility	ML	L	M

types. Table 4 summarizes the survey outcome, illustrating the fuzzy scale and corresponding fuzzy sets to evaluate emergency material suppliers' group decision attributes. Table 5 shows the weights provided by the decision-making groups for multi-objective attributes. Table 6 shows the fuzzy scale values provided by the decision-making groups for emergency material suppliers' evaluation.

5.4 Calculation steps

(1) According to Tables 3 and 4 and Eqs. (1)-(3), we first construct the decision matrix structures M_1, M_2, and M_3 for emergency supplies and $l_1, l_2, l_3, l_4, l_5, l_6$.

$$M_1 = \begin{bmatrix} VL & H & H & M & H & VH \\ VH & ML & L & ML & VL & VL \\ M & L & ML & VL & M & L \\ L & H & MH & H & M & VH \\ VL & MH & M & M & H & VH \end{bmatrix}, M_2 = \begin{bmatrix} L & MH & MH & M & H & VH \\ V & ML & M & L & ML & VL \\ ML & L & L & ML & VL & VL \\ ML & H & M & ML & MH & VH \\ L & MH & M & MH & MH & MH \end{bmatrix},$$

$$M_3 = \begin{bmatrix} ML & VH & MH & ML & MH & H \\ H & VL & ML & ML & L & L \\ M & VL & L & L & M & VL \\ MH & VH & M & H & MH & MH \\ ML & H & ML & M & M & MH \end{bmatrix}.$$

(2) According to the step 1 results and Definition 3–5, the average decision matrix $\overline{Y}$ is obtained as follows:

$$\overline{Y} = \begin{bmatrix} \tilde{\tilde{X}}_{11} & \tilde{\tilde{X}}_{12} & \tilde{\tilde{X}}_{13} & \tilde{\tilde{X}}_{14} & \tilde{\tilde{X}}_{15} & \tilde{\tilde{X}}_{16} \\ \tilde{\tilde{X}}_{21} & \tilde{\tilde{X}}_{22} & \tilde{\tilde{X}}_{23} & \tilde{\tilde{X}}_{24} & \tilde{\tilde{X}}_{25} & \tilde{\tilde{X}}_{26} \\ \tilde{\tilde{X}}_{31} & \tilde{\tilde{X}}_{32} & \tilde{\tilde{X}}_{33} & \tilde{\tilde{X}}_{34} & \tilde{\tilde{X}}_{35} & \tilde{\tilde{X}}_{36} \\ \tilde{\tilde{X}}_{41} & \tilde{\tilde{X}}_{42} & \tilde{\tilde{X}}_{43} & \tilde{\tilde{X}}_{44} & \tilde{\tilde{X}}_{45} & \tilde{\tilde{X}}_{46} \\ \tilde{\tilde{X}}_{51} & \tilde{\tilde{X}}_{52} & \tilde{\tilde{X}}_{53} & \tilde{\tilde{X}}_{54} & \tilde{\tilde{X}}_{55} & \tilde{\tilde{X}}_{56} \end{bmatrix}$$

Table 6 Fuzzy scales given by the decision-making group for emergency material supplier evaluation

Evaluation Index	Emergency supplies	Decision-making groups		
		D_1	D_2	D_3
Responsiveness	l_1	VL	L	ML
	l_2	H	MH	VH
	l_3	H	MH	MH
	l_4	M	M	ML
	l_5	H	H	MH
	l_6	VH	VH	H
Cost	l_1	VH	H	H
	l_2	ML	ML	VL
	l_3	M	M	ML
	l_4	ML	ML	ML
	l_5	VL	L	L
	l_6	L	L	VL
Defect rate	l_1	M	ML	M
	l_2	L	L	VL
	l_3	ML	L	L
	l_4	VL	VL	L
	l_5	M	ML	M
	l_6	L	VL	VL
Delivery reliability	l_1	L	ML	MH
	l_2	H	H	VH
	l_3	MH	M	M
	l_4	H	MH	H
	l_5	M	ML	MH
	l_6	VH	VH	MH
Flexibility	l_1	VL	L	ML
	l_2	MH	MH	H
	l_3	M	ML	ML
	l_4	M	MH	M
	l_5	H	MH	M
	l_6	VH	MH	MH

(3) According to Table 6 and Definition 4, the weighting matrices W_1,W_2 and W_3 are obtained:

$$W_1 = \begin{bmatrix} VH \\ MH \\ H \\ VH \\ ML \end{bmatrix}, W_2 = \begin{bmatrix} H \\ M \\ H \\ MH \\ L \end{bmatrix}, W_3 = \begin{bmatrix} VH \\ M \\ MH \\ VH \\ M \end{bmatrix}.$$

(4) According to Definition 4, a normalized matrix is also constructed as follows:

$$N = \begin{bmatrix} \tilde{\tilde{n}}_{11} & \tilde{\tilde{n}}_{12} & \tilde{\tilde{n}}_{13} & \tilde{\tilde{n}}_{14} & \tilde{\tilde{n}}_{15} & \tilde{\tilde{n}}_{16} \\ \tilde{\tilde{n}}_{21} & \tilde{\tilde{n}}_{22} & \tilde{\tilde{n}}_{23} & \tilde{\tilde{n}}_{24} & \tilde{\tilde{n}}_{25} & \tilde{\tilde{n}}_{26} \\ \tilde{\tilde{n}}_{31} & \tilde{\tilde{n}}_{32} & \tilde{\tilde{n}}_{33} & \tilde{\tilde{n}}_{34} & \tilde{\tilde{n}}_{35} & \tilde{\tilde{n}}_{36} \\ \tilde{\tilde{n}}_{41} & \tilde{\tilde{n}}_{42} & \tilde{\tilde{n}}_{43} & \tilde{\tilde{n}}_{44} & \tilde{\tilde{n}}_{45} & \tilde{\tilde{n}}_{46} \\ \tilde{\tilde{n}}_{51} & \tilde{\tilde{n}}_{52} & \tilde{\tilde{n}}_{53} & \tilde{\tilde{n}}_{54} & \tilde{\tilde{n}}_{55} & \tilde{\tilde{n}}_{56} \end{bmatrix}.$$

Therefore, according to Definition 9, the weighted normalization decision matrix E can be next obtained. The negative deviation $\underset{-i}{\overset{\approx}{S}}$ of emergency resource suppliers use to achieve optimization objectives is calculated in Table 7. The order of positive and negative deviations that emergency resource suppliers use to achieve optimization objectives is sorted in Table 8.

(5) We calculate $S \approx +i$ and sort the values, as shown in Table 8.
According to Eq. 5, we calculate the quantitative utility value U_i as shown in Table 9, which denotes the maximum relative importance value The greater the value of U_i, the higher the priority of the emergency supply provider $l_i (i = 1, 2, ..., 6)$.
As shown in Table 9, the relative significance order of the utility of the six emergency material suppliers is $U_6 \succ U_2 \succ U_4 \succ U_3 \succ U_5 \succ U_1$. Therefore, the emergency material supplier 6 is the best choice.

5.5 Optimization results

To validate the proposed model, we borrow some of the input parameter values from Chen and Hong (2014), where the $minf$ values for the first-level sub-objectives in the three stages are set as 0, 0, and 0.012. It is shown before that the emergency supplier l_6 the best choice (see Table 9), hence we have $k = 6$. Following Zhang et al. (2018), we have $\tilde{\tilde{x}}_{116} =$ ((0,0.4,0.6,0.8;1,1), (0,0.4,0.6,0.8;1,1)), $\tilde{\tilde{x}}_{216} =$ ((0,0,0,0.1;1,1), (0,0,0,0.05;0.9,0.9)), $\tilde{\tilde{x}}_{316} =$ ((0,0.1,0.15,0.3;1,1), (0.05,0.1,0.15,0.2;0.9,0.9)), $\tilde{\tilde{x}}_{126} =$ ((0, 0.1, 0.15, 0.3; 1, 1), (0.05, 0.1, 0.15, 0.2; 0.9, 0.9)), and $\tilde{\tilde{x}}_{136} =$ ((0.3, 0.5, 0.55, 0.7; 1, 1), (0.4, 0.5, 0.55, 0.6; 0.9, 0.9)). Other input parameter values are drawn from the expert survey and are shown in Table 10.

The actual demand data for emergency materials in the three rescue stages is captured from China's Ministry of Civil Affairs (http://www.mca.gov.cn/). We set the fuzzy intervals according to the actual demand data and compared the optimization results with the actual demand data to verify the validity of the proposed collaborative optimization method. The optimization results are summarized in Table 11.

Table 11 shows that the results of collaborative optimization are more consistent with the actual demand for emergency materials, while the individual optimization results deviate from the actual demand. Comparing the optimization results (Table 11) with the actual demand data provided by the Ministry of Civil Affairs of China, we observe that the collaborative optimization method can effectively optimize the reserve materials structure in various rescue stages, ensuring that a safety inventory is maintained at the most reasonable level. The presented plan meets the emergency response requirements of disaster-affected areas and the relevant demand characteristics. Although the proposed collaborative optimization method based on IT2TFS does not yield a specific value, it still provides a fuzzy interval based on which the safety inventory can effectively meet the demand in the affected area. Fuzzy optimization decisions associated with the EMR are next simulated separately. In this

Table 7 The negative deviation to achieve the optimization objectives

	$\tilde{s}_{-i}^{U}$						$\tilde{s}_{-i}^{L}$					
	s_{-i1}^{U}	s_{-i2}^{U}	s_{-i3}^{U}	s_{-i4}^{U}	$H_1\left(s_{-i}^{\sim U}\right)$	$H_2\left(s_{-i}^{\sim U}\right)$	s_{-i1}^{L}	s_{-i2}^{L}	s_{-i3}^{L}	s_{-i4}^{L}	$H_1\left(s_{-i}^{\sim L}\right)$	$H_2\left(s_{-i}^{\sim L}\right)$
$\tilde{\tilde{S}}_{-1}$	0.16	0.49	0.65	1.88	1.00	1.00	0.31	0.49	0.65	0.99	0.90	0.90
$\tilde{\tilde{S}}_{-2}$	0.01	0.09	0.15	0.69	1.00	1.00	0.04	0.09	0.15	0.28	0.90	0.90
$\tilde{\tilde{S}}_{-3}$	0.04	0.21	0.31	1.13	1.00	1.00	0.11	0.21	0.31	0.51	0.90	0.90
$\tilde{\tilde{S}}_{-4}$	0.01	0.10	0.15	0.65	1.00	1.00	0.05	0.10	0.15	0.28	0.90	0.90
$\tilde{\tilde{S}}_{-5}$	0.07	0.27	0.38	1.38	1.00	1.00	0.15	0.27	0.38	0.64	0.90	0.90
$\tilde{\tilde{S}}_{-6}$	0.00	0.03	0.05	0.43	1.00	1.00	0.01	0.03	0.05	0.15	0.90	0.90

Table 8 The order of positive and negative deviations to achieve optimization objectives

i	$Rank\left(\overset{\approx}{s}_{+i}\right)$	$Rank\left(\overset{\approx}{s}_{-i}\right)$	i	$Rank\left(\overset{\approx}{s}_{+i}\right)$	$Rank\left(\overset{\approx}{s}_{-i}\right)$
1	0.2028	0.2665	4	0.2556	0.2324
2	0.2661	0.2336	5	0.2604	0.2607
3	0.2603	0.2552	6	0.2658	0.2239

Table 9 Relative significance of the alternative emergency suppliers

i	Q_i	U_i (%)	i	Q_i	U_i (%)
1	0.4188	78.8	4	0.5035	94.7
2	0.5126	96.4	5	0.4811	90.5
3	0.4856	91.3	6	0.5315	100

Table 10 Other parameters in the EMR structure optimization model

Emergency phase	Target level	Secondary sub-objective		Primary sub-objective	
		W_{ijh}	p_{ih}	W_i	p_i
Pre-rescue	Time efficiency index	0.8	0.6	0.45	0.375
	Number of shipments	0.35	0.35		
	Reserve cost	2.2	0.05		
Mid-rescue	Time efficiency index	0.65	0.41	0.35	0.375
	Number of shipments	0.75	0.41		
	Reserve cost	1.5	0.18		
Late rescue	Time efficiency index	0.35	0.15	0.2	0.25
	Number of shipments	1.0	0.35		
	Reserve cost	0.85	0.5		

approach, individual optimizations are separately run without including emergency supplier selection. To compare the two methods, affected areas were divided into three classes: Mild, Moderate, and Severe. The corresponding collaborative decisions are then made according to collaborative optimization results and the individual choices according to the optimization results. The two decision types are compared, and the results are shown in Figs. 4–6.

Because the selection of emergency material suppliers influences the subsequent optimization, the comparison of results can also be recognized as a sensitivity analysis for the most relevant parameters. The responsiveness attribute of the emergency supplier affects the time efficiency index in reserve structure optimization. We assume the index setting of time efficiency in the individual optimization method depends on the average responsiveness

Table 11 The optimization results of the safety stocks in the EMR structure

Resource types	Pre-rescue			Mid-rescue			Late-rescue		
	Cooperative	Individual	Actual	Cooperative	Individual	Actual	Cooperative	Individual	Actual
Biological resources	H	MH	H	ML	H	M	L	H	ML
Medical materials	MH	MH	MH	MH	M	MH	ML	H	M
Living materials	ML	MH	L	M	H	ML	MH	H	MH

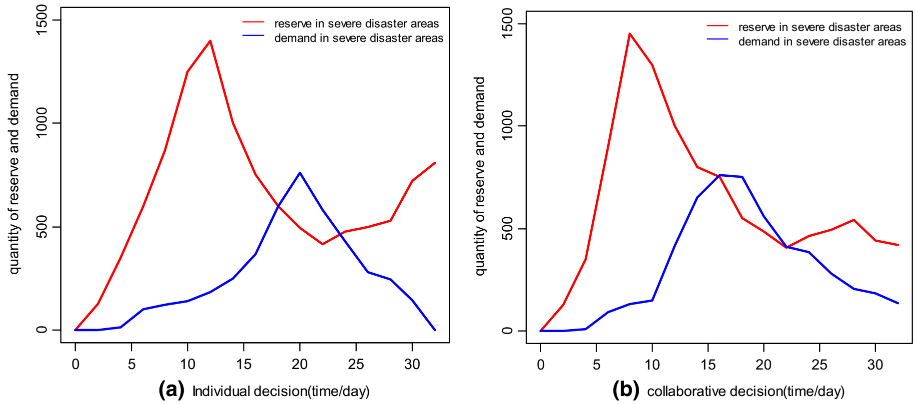

Fig. 4 Equilibrium analysis in severe disaster areas under individual and collaborative decision schemes

attribute of the six considered suppliers. Accordingly, the index setting of time efficiency in collaborative optimization is based on the optimal emergency supplier l_6.

Comparing the effects of the collaborative decisions indicated above and the individual decisions on the supply and demand, the balance time of EMR and demand is evaluated. This result is used to explore the advantages of collaborative optimization. As can be seen in Figs. 3–5, there is a point (the intersection of the red and blue curves) at which the EMR is precisely equal to the demand; that is, the sooner the balance time of the EMR and demand is realized, the better the emergency resource allocation will be, thereby meeting the established optimization objectives and yielding effective emergency rescue work.

Figure 4a shows that when decisions are made separately, the EMR balance times and demand in severe disaster areas are 18 and 25 days, respectively. Figure 4b illustrates EMR results and demand when collaborative optimization decision-making is used. The balance time points are 15 and 23 days, respectively. Hence, the primary emergency control in the disaster area can be done at least three days ahead of schedule. The EMR is greater than the demand data from 23 to 25 days.

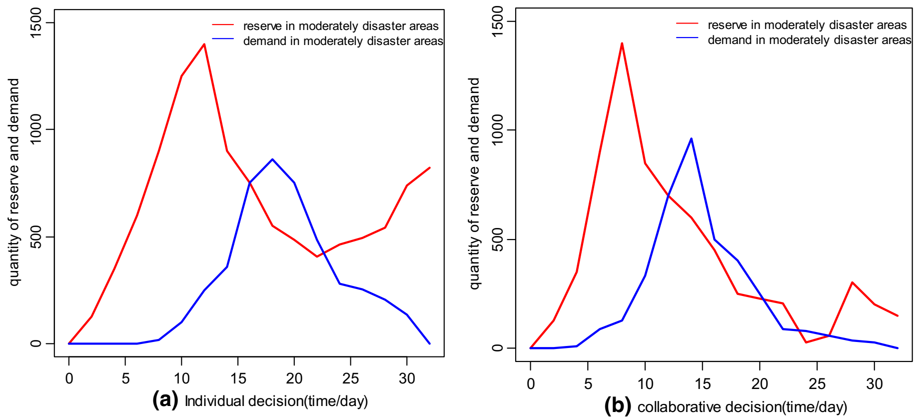

Fig. 5 Equilibrium analysis in moderate disaster areas under individual and collaborative optimization

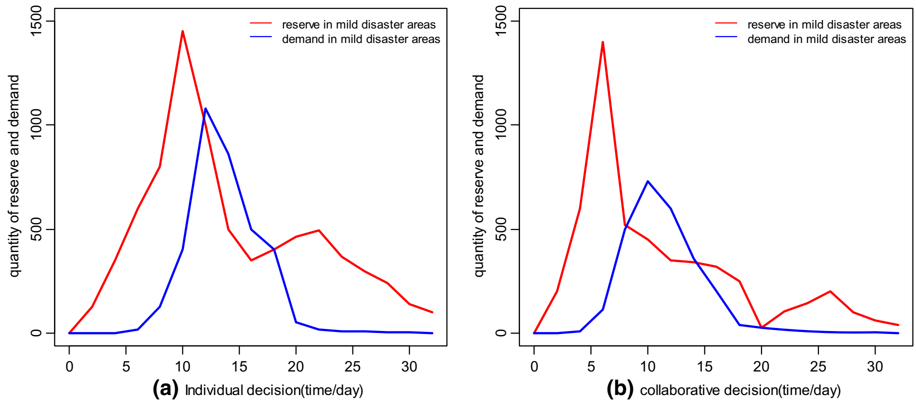

Fig. 6 Equilibrium analysis in mild disaster areas under individual and collaborative decision schemes

Figure 5a illustrates the balance time points of the EMR and demand in moderate disaster areas (15 and 22 days) when the optimization decisions are made individually. Figure 5b shows the emergency disaster area employed in the collaborative optimization decision scheme. The balance times are 11 and 18 days, and hence the primary essential control of the emergency in the disaster area can be achieved four days ahead of that in the individual scheme. The EMR is greater than the demand from 18 to 22 days.

Figure 6a shows the balance time with the demand is between 12 and 18 days. Figure 6b shows that emergency disaster reserve in mild disaster areas is coordinated. The balance time with the demand is eight and 14 days, and the disaster primary control is achieved four days before the individual scheme. The EMR is higher than the demand from 14 to 28 days. Therefore, from a timeliness perspective, collaborative decision-making outperforms individual decision-making processes.

6 Discussion and implications

Given the uncertainty of flood disasters and the urgency for a fast response, a flood disaster response plan or standard operating procedure needs to be carefully arranged for managing rescue equipment, resources, and rescue teams. Once a disaster event has occurred, a rescue plan should be launched to prevent chaos. Regardless of the differences in organizational structures of rescue teams in different countries, flood rescue operations should follow standard guidelines that suggest how to classify disaster-affected areas, plan group distributions, and inter-group backups. Under such systems, a flood emergency logistics network can be viewed as a multi-group and multi-level structure. Given the uncertain demands, planning appropriately for emergency logistics is complex. The existing optimization algorithms have reported low fault tolerance rates, under which optimization results cannot meet the distribution requirements (Hu et al., 2019).

In our study, the issue with flood emergency logistics preparation under uncertainty scenarios is formulated as a collaborative multiple objective fuzzy optimization problem to develop an optimal distribution plan for urban flood disasters. The proposed model considers multiple objectives in managing humanitarian logistics operations during a disaster event and optimizes the structure of the reserve materials in each emergency rescue stage where a safety inventory should be maintained at a reasonable level. This model assigns a fuzzy interval to avoid the safety inventory error of emergency materials being too large. The collaborative optimization model proposed is proven efficient in meeting emergency response requirements in disaster-affected areas and minimizing life/property losses.

Our case study shows that the reserves of various emergency materials continue to change at different stages of emergency relief as the disaster relief process evolves. Therefore, the following suggestions are made when employing an EMR strategy. The EMR should be kept within a reasonable range when dealing with significant disaster events. In addition, emergency material suppliers should be included in the material reserve optimization process to deal with major disasters. Also, an EMR contact should be employed, under which the emergency materials suppliers are allocated specific orders and are responsible for building the sufficient capacity, enabling them to meet demand when the EMR is insufficient.

7 Conclusion

Dynamic time factors have been widely applied in humanitarian logistics optimization and decision-making problems. However, most manage random or uncertain situations, where fuzzy information is gradually collected from different sources and analyzed over time. This paper proposes a collaborative optimization model of the EMR structure to evaluate the emergency material suppliers and optimize the logistics operations. Two models such as IT2TFS for ESS and MOFO or EMR, are investigated. First, the IT2TFS was defined, and a multi-objective group decision-making algorithm for emergency material supplier evaluation was developed; Secondly, we ran the developed fuzzy optimization model in early, middle, and late relief stages; Finally, a case study of sudden flood disasters in 2012 was considered to examine the feasibility and performance of the proposed collaborative decision-making model under dynamic disaster relief environments. The model can be employed as an integrative response to EMR (living, medical, and biological material reserve) and supplier selection problems, aiming to optimize the delivery time, the number of shipments, and reserve costs. Given the uncertainty and complexity of the disaster relief information, the collaborative optimization method for EMR structures was designed based on IT2TFS. The performance of the collaborative optimization method was validated using a data set obtained from a significant disaster event in Yunnan Province.

The results demonstrate that the developed fuzzy optimization decision-making method can effectively capture the impact of the dynamic time factors on decision-making results and enhance interactions between groups who deal with normal and abnormal decision-making tasks. Testing the presented model, it was observed that the method could be confidently employed to optimize the structure of the reserve materials in different emergency rescue stages to ensure that the safety inventory can be maintained at the most reasonable level. We also showed that the method meets the emergency response requirements of disaster-affected areas. By comparing the group and individual optimization schemes, we showed that employing collaborative optimization outperforms the individual method, ensuring material reserves meet the requirement of each emergency rescue stage and saving considerable rescue time.

Apart froBesidesntages of using fuzzy models in uncertain situations, several limitations exist. For instance, it is challenging to tackle all aspects of disaster relief supply chains with fuzzy models, particularly the prediction and pattern recognition aspects. Instead, machine learning and AI-based models can train datasets to improve the optimal solutions and provide an ideal disaster response model that can integrate into a package with a user-friendly interface. The reasoning details associated with the IT2TFS approach used in the developed optimization model are not sufficiently discussed. It is, therefore, of interest for future studies to develop methodologies and expand IT2TFS theories to fill the gap.

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Appendix 1

Proofs of all of the properties described in the present study are detailed below.

Proof of Property 1 Using Eq. (1), this theorem is based on the fact that for any IT1TFS, $\tilde{A}_\alpha^L = \tilde{A}_\alpha^H$ which indicates there is no second-order uncertainty in the α-cuts of IT1TFS, as the upper and lower ranges are the same. This completes the proof.

Proof of Property 2 Using Eq. (2), it is easy to show that $0 \le \rho_{\tilde{\tilde{A}}}(\alpha) \le 1$ for $\tilde{\tilde{A}}_\alpha^L \subseteq \tilde{\tilde{A}}_\alpha^H$.This completes the proof.

Proof of Property 3 According to Definition 4, for two IT2TFSs $\tilde{\tilde{A}}$ and $\tilde{\tilde{B}}$, if $\mathrm{FOU}\left(\tilde{\tilde{A}}\right) \subseteq \mathrm{FOU}\left(\tilde{\tilde{B}}\right)$, then $\underline{\mu}_{\tilde{\tilde{A}}}(x) \subseteq \underline{\mu}_{\tilde{\tilde{B}}}(x)$. Hence $\rho_{\tilde{\tilde{A}}}(\alpha) \le \rho_{\tilde{\tilde{B}}}(\alpha)$.

This completes the proof.

Proof of Property 4 If IT2TFS $\tilde{\tilde{A}}$ and $\tilde{\tilde{B}}$ are equivalent, i.e., $\tilde{\tilde{A}} \approx \tilde{\tilde{B}}$, $|s_1| = 0$, $|s_2| = 0$, and where $s_1 = \left\{x \in X | \underline{\mu}_{\tilde{\tilde{A}}}(x) \ne \underline{\mu}_{\tilde{\tilde{B}}}(x)\right\}$ and $s_2 = \left\{x \in X | \underline{\mu}_{\tilde{\tilde{A}}}(x) \ne \underline{\mu}_{\tilde{\tilde{B}}}(x)\right\}$, then we can obtain $\rho_{\tilde{\tilde{A}}}(\alpha)=\rho_{\tilde{\tilde{B}}}(\alpha)$, $\underline{\mu}_{\tilde{\tilde{B}}}(x) \subseteq \underline{\mu}_{\tilde{\tilde{A}}}(x)$, $\tilde{\tilde{B}}_\alpha^L \subseteq \tilde{\tilde{A}}_\alpha^L$, $\tilde{\tilde{A}}_\alpha^H \subseteq \tilde{\tilde{B}}_\alpha^H$. Hence, $\left|\tilde{\tilde{B}}_\alpha^L\right| \subseteq \left|\tilde{\tilde{A}}_\alpha^L\right|$, $\left|\tilde{\tilde{A}}_\alpha^H\right| \subseteq \left|\tilde{\tilde{B}}_\alpha^H\right|$, so that $\frac{\left|\tilde{\tilde{B}}_\alpha^L\right|}{\left|\tilde{\tilde{B}}_\alpha^H\right|} \le \frac{\left|\tilde{\tilde{A}}_\alpha^L\right|}{\left|\tilde{\tilde{A}}_\alpha^H\right|}$. Hence, $\rho_{\tilde{\tilde{A}}}(\alpha) \le \rho_{\tilde{\tilde{B}}}(\alpha)$.

This completes the proof.

Proof of Property 5 Let $Rank_{\min}(\tilde{\tilde{S}}_{-i})$ denote the minimum value describing the relative satisfaction of emergency suppliers. Then, based on Chen and Hong (2014), the relative significance of the emergency supplier Q is determined as shown in Eq. (24):

$$Q_i = [\tilde{\tilde{n}}_{ij}]_{n\times m} \cdot \left(\left[\tilde{\tilde{w}}_1^\gamma \tilde{\tilde{w}}_2^\gamma \ldots \tilde{\tilde{w}}_m^\gamma\right]^T + \frac{[\tilde{\tilde{n}}_{ij}]_{n\times m} - \left[\tilde{\tilde{w}}_1^\gamma \tilde{\tilde{w}}_2^\gamma \ldots \tilde{\tilde{w}}_m^\gamma\right]^T}{[\tilde{\tilde{n}}_{ij}]_{n\times m} \cdot \left[\tilde{\tilde{w}}_1^\gamma \tilde{\tilde{w}}_2^\gamma \ldots \tilde{\tilde{w}}_m^\gamma\right]^T}\right), \gamma = 1, \ldots, k \quad (24)$$

If $N = [\tilde{\tilde{n}}_{ij}]_{n\times m}$, using N to replace $[\tilde{\tilde{n}}_{ij}]_{n\times m}$ in (24) and obtain Eq. (25):

$$Q_i = N\left(\left[\tilde{\tilde{w}}_1^{\gamma}\,\tilde{\tilde{w}}_2^{\gamma}\ldots\tilde{\tilde{w}}_m^{\gamma}\right]^T + \frac{N - \left[\tilde{\tilde{w}}_1^{\gamma}\,\tilde{\tilde{w}}_2^{\gamma}\ldots\tilde{\tilde{w}}_m^{\gamma}\right]^T}{N\left[\tilde{\tilde{w}}_1^{\gamma}\,\tilde{\tilde{w}}_2^{\gamma}\ldots\tilde{\tilde{w}}_m^{\gamma}\right]^T}\right), \gamma = 1, ..., k \tag{25}$$

Then, we can obtain:

$$Q_i{=}RankN\overline{W} + \frac{rank_{\min}N(1-\overline{W})(\sum_{j=1}^{m}\tilde{\tilde{n}}_{im} - N\overline{W})}{RankN(1-\overline{W})(\sum_{i=1}^{n} rank_{\min}N(1-\overline{W})/\sum_{j=1}^{m}\tilde{\tilde{n}}_{im} - N\overline{W}))} \tag{26}$$

If $\overline{W} = \left[\tilde{\tilde{w}}_j\right]_{m\times 1}$, $N = [\tilde{\tilde{n}}_{ij}]_{n\times m}$ and $E = \left[\overset{\approx}{\underset{ij}{e}}\right]_{n\times m}$ $(i = 1, ..., n; j = 1, ..., m)$ are determined for $\tilde{\tilde{e}}_{ij} = \tilde{\tilde{n}}_{ij} \otimes \tilde{\tilde{w}}_j$, $i = 1, ..., n; j = 1, ..., m$,then we can obtain Eq. (27):

$$\begin{aligned} Q_i &= Rank(\tilde{\tilde{e}}_{+i1}\oplus, \ldots, \tilde{\tilde{e}}_{+im}) \\ &+ \frac{Rank_{\min}(\tilde{\tilde{e}}_{-i1}\oplus, \ldots, \tilde{\tilde{e}}_{-im})\sum_{i=1}^{n}(Rank(\tilde{\tilde{e}}_{-i1}\oplus, \ldots, \tilde{\tilde{e}}_{-im}))}{Rank(\tilde{\tilde{e}}_{-i1}\oplus, \ldots, \tilde{\tilde{e}}_{-im})\sum_{i=1}^{n}\left(Rank_{\min}(\tilde{\tilde{e}}_{-i1}\oplus, \ldots, \tilde{\tilde{e}}_{-im})\Big/Rank(\tilde{\tilde{e}}_{-i1}\oplus, \ldots, \tilde{\tilde{e}}_{-im})\right)} \end{aligned} \tag{27}$$

If $\overset{\approx}{\underset{+i}{S}} = (\tilde{\tilde{e}}_{+i1}\oplus, \ldots, \tilde{\tilde{e}}_{+im})$, and $\tilde{\tilde{S}}_{-i} = (\tilde{\tilde{e}}_{-i1}\oplus, \ldots, \tilde{\tilde{e}}_{-im})$,$i = 1, ..., n$,then we can substitute terms and obtain Eq. (28).

$$Q_i = Rank(\overset{\approx}{\underset{+i}{S}}) + \frac{Rank_{\min}(\overset{\approx}{\underset{-i}{S}})\sum_{i=1}^{n}(Rank(\overset{\approx}{\underset{-i}{S}}))}{Rank(\overset{\approx}{\underset{-i}{S}})\sum_{i=1}^{n}\left(Rank_{\min}(\overset{\approx}{\underset{-i}{S}})\Big/Rank(\overset{\approx}{\underset{-i}{S}})\right)}, i = 1, ..., n \tag{28}$$

Hence,the formula can be simplified as follows:

$$Q_i = Rank(\overset{\approx}{\underset{+i}{S}}) + \frac{\sum_{i=1}^{n}(Rank(\overset{\approx}{\underset{-i}{S}}))}{Rank(\overset{\approx}{\underset{-i}{S}})\sum_{i=1}^{n}\left(1\Big/Rank(\overset{\approx}{\underset{-i}{S}})\right)}, i = 1, ..., n \tag{29}$$

This completes the proof.
(See Table 12).

Table 12 The profile of all 20 participants

S. no.	Group	Expert profile	Experience in years
1	D1	Procurement expert	18
2	D1	Procurement expert	20
3	D1	Academician	15
4	D1	Distribution center manager	19
5	D1	Logistics coordinator	17
6	D1	Logistics coordinator	15
7	D1	Humanitarian organization executive	18
8	D2	Humanitarian organization executive	15
9	D2	Logistics coordinator	19
10	D2	Logistics coordinator	16
11	D2	Academician	12
12	D2	Distribution center manager	15
13	D2	Distribution center manager	18
14	D2	Procurement expert	20
15	D3	Distribution center manager	16
16	D3	Humanitarian organization executive	15
17	D3	Humanitarian organization executive	17
18	D3	Procurement expert	15
19	D3	Logistics coordinator	19
20	D3	Academician	15

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