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A novel min–max robust model for post-disaster relief kit assembly and distribution

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ABSTRACT

In disaster response phase, different types of emergency relief materials are prepared simultaneously. Assorting and packing a proportion of relief items into relief kits will benefit in improving relief distribution agility and efficiency. This study focuses on the relief kit assembly and distribution problem, which includes two stages. The first stage solves the facility location and relief kit assembly problem with the minimum operation cost. The second stage optimizes the relief kit distribution plan with the minimum distribution cost and maximum demand satisfaction, in which an epsilon-constraint method is adopted to transfer the bi-objective model into a single one with the minimum total cost. Then, a min–max robust model is developed to cope with the uncertain demand and travel time. Computational experiments are provided to validate the effectiveness of the min–max robust model compared with deterministic model and two-stage stochastic model. A realistic case study based on earthquakes in Yunnan Province is provided to illustrate the applicability of the proposed min–max robust model. Some managerial insights are obtained by sensitivity analyses as follows. Assembling relief kits in the distribution centers is more effective than that in the demand points. Specifically, the average cost and 95% percentile of the former are 19.45% and 20.52% lower than those of the latter respectively. The vehicle loading capacity has a greater influence on the optimal solution than that of the available working time. Decision makers can balance the total cost and uncertainty budget by adjusting the conservatism level under expected demand satisfaction.

1. Introduction

As the highest likelihood risks of the next 10 years, extreme weather frequently causes natural disasters, such as earthquake, storm, flood, etc. (WEF, 2021). In the last 20 years, 7348 disasters claimed approximately 1.23 million lives and led to approximately $2.97 trillion in economic losses worldwide (Cred Crunch EM-DAT, 2021). In 2021, 306 natural catastrophes worldwide resulted in economic losses around $270 billion. For example, Haiti suffered a 7.3 magnitude earthquake on August 14, which killed 2248 people and destroyed more than 138,000 buildings. Several days of torrential rains struck the central Chinese province of Henan and caused 120 billion CNY losses in July. Waterlogging led to a power failure of an underground metro system, in which more than 900 people were trapped on a subway and 14 of them died.

Relief distribution is recognized to be one of the core missions in the post-disaster response stage, which can satisfy the demand of affected areas and mitigate the effect of catastrophes (Yánez-Sandivari et al., 2021). Two main factors affect the effectiveness of relief distribution (Ye et al., 2020): (i) the place and the volume of the pre-positioning emergency relief supplies and (ii) the efficiency of the operations in the relief distribution, such as establishing distribution centers (DCs), assorting and picking, loading and unloading, etc. Given that the place and the stored emergency relief supplies are determined in the pre-disaster, speeding up the assorting and picking as well as loading and unloading operations is critical to improve the efficiency of the relief distribution by establishing some temporary cross-dockings.

Nevertheless, relief kit assembly (assorting and picking operation) not only can be applied in manufacturing but also in humanitarian logistics to improve flexibility and effectiveness, especially during the COVID-19 pandemic (Kovács and Sigala, 2021). Emergency relief supplies are divided into several groups, including equipment for transportation, information, energy and reparation, items for medical aid, shelter, and food assistance (National Development and Reform Commission of China, 2005). In real cases, some individual commodities are supposed to be bundled with a fixed proportion to make sure that they are provided together, which are referred to as relief kits. The kits in

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humanitarian logistics mainly concentrate on whether they can complete a whole rescue operation, instead of focusing on sizes for standardized transportation in manufacturing (Vaillancourt, 2016). However, the characteristics of emergency relief supplies matter for relief kit assembly, e.g., the size of each transportation unit and the shelf life of items (Zhu et al., 2022). For food supplies, the WHO suggests that cereal, pulses, oil, fish/meat, fortified blended foods, sugar, and iodized salt can be rationed altogether in terms of energy, protein, and fat for populations entirely reliant on food assistance. However, regional preferences in taste and satiety duration may influence the elements and their proportions in food kits. Furthermore, emergency relief supplies are usually pre-positioned in different warehouses, so packing the relief kits completely in disaster preparedness may be impossible. Therefore, delivering kits within specific items is vital to support disaster response operations.

Moreover, given that communication and transportation infrastructure is interrupted, obtaining information will be difficult; thus, decisions made after a disaster will be based on unknown and uncertainties, such as how much emergency aid is needed and how long it will take to get there (Kovacs and Moshtari, 2019). To address uncertain parameters, researchers have proposed many approaches, such as stochastic programming and robust optimization. However, due to the lack of sufficient and valid historical data, the probability distribution may be difficult to estimate (Nayeri et al., 2022). As for scenario-based programming, the scale will influence the computational time and solution quality significantly (Amideo et al., 2019). Thus, we deal with the deep uncertainty with robust convex optimization. Uncertainty sets are adopted to represent the parameters, and decision makers can balance conservatism and risk preference.

This paper aims to contribute to the literature by assembling and distributing relief kits efficiently and effectively, considering the hybrid uncertainties of demand and travel time. The main contributions of this paper are as follows. (i) Two mathematical models are developed to optimize post-disaster relief kit assembly and distribution, minimizing total cost and maximizing demand satisfaction. (ii) The epsilon-constraint method is utilized to transfer the bi-objective model into a single one. A min–max robust optimization method is adopted to handle the uncertain demand and travel time. (iii) Computational experiments are conducted to validate and test the feasibility and quality of optimal solutions of the min–max robust model with deterministic model and two-stage stochastic model. (iv) The proposed model is applied to solve a real case extracted from Yunnan earthquake. Sensitivity analyses are conducted to obtain some valuable managerial insights.

The rest of this paper is organized as follows. Section 2 reviews the related literature and highlights the research gaps. In Section 3, the relief kit assembly and distribution problem are formulated as a two-stage model. Section 4 mainly elaborates on the epsilon-constraint method and min–max robust optimization. Section 5 provides a simulation study to compare the performance of the min–max robust approach against its deterministic and stochastic counterparts. A case study, along with several sensitivity analyses of the key parameters and some managerial implications, is provided in Section 6. A summary of the paper and the possible future research directions is presented in Section 7.

2. Literature review

A considerable number of papers have been published on the optimization problem of disaster relief logistics. This paper focuses on relief kit assembly and distribution, considering demand and travel time uncertainty. Therefore, the related papers can be classified into three categories: (i) relief distribution, (ii) relief kit management, and (iii) robust optimization methods to deal with uncertainties.

2.1. Relief distribution in disaster response phase

Emergency logistics management includes relief distribution, evacuation planning, resource allocation, emergency response and operational performance (Kundu et al., 2022). As one of the initial activities in disaster response phase, general relief distribution represents emergency resource delivery from origins to destinations. A supplier can serve more than one demand point (DP). Then, the visiting sequence of DPs makes sense, which can be formulated as a vehicle routing problem with different constraints (Zhang et al., 2012, Balcik and Yanıkoğlu, 2020, Fang et al., 2021, Aliakbari et al., 2022). However, after a catastrophe, the victims will evacuate to safe places, which can be called as demand clusters. The requirements are considerably more than usual. Thus, many scholars have only considered the point-to-point allocation of relief items or even combining with the casualty transportation (Liu et al., 2018, Gao and Cao, 2020, Nabavi et al., 2022).

The distribution network in disaster response consists of permanent facilities, temporary facilities, and unpredictable affected areas (Kamyabniya et al., 2021). Some papers have only considered the supply and demand sides (Barzinpour and Esmaeili, 2014, Rodríguez-Espíndola et al., 2018). Given that the construction of a system has a great effect on planning, resource allocation is always optimized with the location of facilities. Facilities can be DCs to transfer materials (Erbeyoğlu and Bilge, 2020, Jiang and Ouyang, 2021) and shelters for gathering victims (Chapman and Mitchell, 2018). Furthermore, many scholars have focused on mobile facilities, which can cover affected areas more flexibly (Jenkins et al., 2020).

Various characteristics of distribution lead to different humanitarian logistics processes. As the network has more than one echelon, there exist many available transportation modes, such as air, road, and railway. For the damage of the road network, Chang et al. (2022) simulated the relationship between earthquake attributes and the resulting status of the transportation network and speed of vehicle traffic to optimize the relief distribution under uncertain conditions. However, given the emergence of drones, the combination of drones and trucks has been noticed by scholars (Chowdhury et al., 2017, Zhang et al., 2021). The characteristics of relief items also affect the planning. Injuries are divided into several levels by the severity, and each level has a different priority (Camur et al., 2021). Some emergency materials (e.g., vaccines and palates) have a specific transportation requirement (e.g., temperature and replenishment) (Akbarpour et al., 2020).

When it comes to disaster response, the goals of humanitarian logistics are efficiency, effectiveness, and equity (Gralla et al., 2014). Efficiency is basically reflected by minimizing the total economic cost, which may include the transportation cost, flow cost, construction cost, and other operational costs. Effectiveness is defined as the extent of a decrease in harm and suffering. Deprivation cost, which represents humanitarian equality, also adds to the total cost (Ismail, 2021). Equity requires a timely response to all victims during the relief process. The minimum of travel time is the most common equity objective. However, in real cases, the response management should achieve more than one objective. Wang et al. (2022) addressed the relief distribution problem, which aims to minimize the expected total cost and maximize supply shortage rate of health care coalition simultaneously. In recent years, the multi-objective optimization methods attract extensive attention of emergency logistics management (Jenkins et al., 2020, Tang et al., 2022).

2.2. Relief kit management

Some emergency items will be assorted and bundled into kits to improve the agility of the humanitarian supply chain (Chandes and Paché, 2010). Relief kit management can be divided into three aspects: kit design, kit supply, and kit assembly (Vaillancourt, 2016).

The two types of relief kit are as follows. One is kitted as standardized size for easier transportation. For example, lightweight relief items (e.g., vaccine, water, and purification tablets) can be bundled into packages for distribution via a drone (Rabta et al., 2018). The other one consists of resources in fixed proportion to complete the rescue operations. It includes water and food for survival, and tents and beds for sheltering.

Important actors in disaster management (e.g., government and non-governmental organizations) make strategic agreements with suppliers of relief kits in advance. Then, kits will be pre-assembled and pre-positioned (Maon et al., 2009). Although some relief kits will lead to postponement in time and place, the manufacturing process can consider the leading time for bundling and packing.

As for relief kit assembly, some researchers have regarded kits only as transportation units and optimized a single commodity relief distribution (Rawls and Turnquist, 2010). Only one paper focused on the process of kit packing or assembling in operational research. Rivera-Royero et al. (2020) considered kit assembly to optimize the relief distribution in earliest response for catastrophe. Relief kits contain items within the same category and are packed into specific pallets. However, the kits are still regarded as a commodity for loading.

2.3. Robust optimization for humanitarian logistics uncertainties

Unpredictable disasters make it difficult for decision makers to obtain exact information in the response phase. The uncertainties are always in the demand side, supply side, and transportation, such as travel time, relief demand, and facility disruption risk (Liu et al., 2019, Ahmadi et al., 2020). Scholars have attempted to address these uncertain factors in different ways, such as updating information timely by rolling horizon methodology (Fang et al., 2021, Ismail, 2021), fuzzy programming (Shaw et al., 2022) and multi-stage stochastics programming (Acar and Kaya, 2019, Doodman et al., 2019, Li et al., 2021).

An excessive number of scenarios will take a long time to obtain the optimal solutions, especially in the cases with several sources of uncertainty and interdependent decisions (Sanci and Daskin, 2021). Thus, robust optimization is a more appropriate approach for real-world applications (Tirkolaee et al., 2020). Uncertain parameters are addressed into uncertain sets, which can be box or even coaxial box uncertain sets (Balcik and Yanıkoğlu, 2020, Dalal and Üster, 2021). If the probability distribution of parameters is known partially, then the problem can be solved by distributionally robust optimization methods (Yang et al., 2021). Zhang et al. (2022) proposed a mean-absolute-deviation-based ambiguity set. Based on the worst-case mean-conditional value-at-risk criterion, Wang et al. (2021) adopted distributionally robust optimization method to deal with the supply, demand, and road link capacity uncertainties.

For a two-stage problem, Cheng et al. (2021) located the facilities in Stage 1 and distributed the relief kits in Stage 2, considering the uncertain demand and disruption simultaneously. Seraji et al. (2021) transported victims to shelters in Stage 1 and delivered emergency materials in Stage 2. Lu and Cheng (2021) compared the basic two-stage robust optimization model, the worst-case bounded two-stage robust optimization model, and the nominal-cost bounded two-stage robust optimization model of facility establishment under disruption risk. Apart from the two-stage robust optimization, the min–max robust framework proposed by Ben-Tal et al. (2011) and Najafi et al. (2013) can also solve the multi-stage decision respectively, but can only cope with considers the right-hand-side uncertainties. Ni et al. (2018) proposed a novel min–max robust optimization model which can deal with both right- and left- hand uncertainties. Akbarpour et al. (2020) adopted the method to design an integrated pharmaceutical relief chain network.

To update the solution with the change of situation, the adaptive robust model is also adopted to decrease conservatism (Wang and Paul, 2020). Furthermore, Paul and Wang (2019) considered uncertain parameters in a scenario and regretting of several scenarios.

There also exist some hybrid methodologies. Nabavi et al. (2022) used machine learning to predict the travel and service time, and adopted a distribution robust optimization model to deal with uncertain predicting of time. Li et al. (2020) proposed a scenario-based stochastic robust optimization model to optimize the disaster response operations considering subsequent shocks.

2.4. Research gap

The main related studies according to five criteria are divided into two groups, namely, disaster management operations and modeling, as shown in Table 1. The two classes of disaster management operation are resource distribution and relief kit assembly. The first class defines the operation of emergency materials, whereas the second class investigates the relief kit management. For the second group, the number of objective functions, the types of uncertainty, and the optimization methods are included. On the basis of the first criterion, papers are categorized into two classes: single objective (SO) and multiple objectives (MO). The second criterion includes uncertainties in the supply side (S), demand side (D), and transportation (T). The third criterion, the optimization method, classifies the papers into three classes: deterministic modeling (DEM), stochastic programming modeling (SPM), and robust optimization modeling (ROM).

In summary, the following conclusions can be drawn from the literature review:

Many studies have been conducted on multi-objective relief distribution with uncertainties.

(i) Many studies have been conducted on multi-objective relief distribution with uncertainties.
(ii) Most studies deal with uncertainties by SPM and ROM.
(iii) Few studies consider relief kits in operational research.
(iv) No study has considered relief kit assembly with hybrid uncertainties in a multi-objective relief distribution plan.

Therefore, in this paper, we focus on relief kit assembly and distribution considering the uncertain demand and travel time to minimize the logistics cost and maximize the demand satisfaction simultaneously. Therefore, we use the min–max robust model that was introduced by Ni et al. (2018) to cope with uncertainties. Furthermore, we shrink the right-hand side uncertainty set further and consider two conflict objectives in the second stage.

3. Modeling

3.1. Problem description

We design a post-disaster logistic network for relief kit assembly and distribution, as shown in Fig. 1. The network is composed of three types of nodes: supply points (SPs), distribution centers (DCs), and demand points (DPs).

(i) SP: SPs can be divided into public and private groups. Public warehouses are established by the government to pre-position relief and adopt a territorial management scheme. Thus, public warehouses are in different capacities based on the level of government department. Private SPs are factories of emergency material manufacture. Companies sign contracts with local government to hold part of inventory for disasters. No matter the type of SP is, the affected area government can reach agreements with them for the disaster response operations, which will cost a fixed cost. An SP can store more than one type of emergency items. The location, inventory, and fixed cost of potential SPs are collected by decision makers in advance. SPs are always far from disasters, which will seldom be disrupted and can be called as permanent facilities.
(ii) DC: In the urban logistic network, DCs should store different types of commodities from all SPs for a short time and divide them into several groups depending on the destinations. In

Table 1
Literature review summary.

Reference	Disaster management operations		Modeling		
	Resource distribution	Relief kit assembly	Objective functions	Uncertain conditions	Optimization method
Tang et al. (2022)	√		MO		DEM
Nabavi et al. (2022)	√		MO	S	ROM
Aliakbari et al. (2022)	√		SO	DT	ROM
Zhang et al. (2022	√		SO	D	ROM
Chang et al. (2022)	√		SO	T	DEM
Seraji et al. (2021)	√		MO	D	ROM
Kamyabniya et al. (2021)	√		SO		DEM
Dalal and Üster (2021)	√		SO	DS	ROM
Jenkins et al. (2020)	√		MO		DEM
Balcik and Yanıkoğlu (2020)	√		SO	T	ROM
Gao and Cao (2020)	√		MO	DT	SPM
Akbarpour et al. (2020)	√		MO	D	ROM
Rivera-Royero et al. (2020)	√	√	SO		DEM
Liu et al. (2019)	√		SO	DT	ROM
Ni et al. (2018)	√		SO	DS	ROM
Najafi et al. (2013)	√		MO	D	ROM
This paper	√	√	**MO**	**DT**	**ROM**

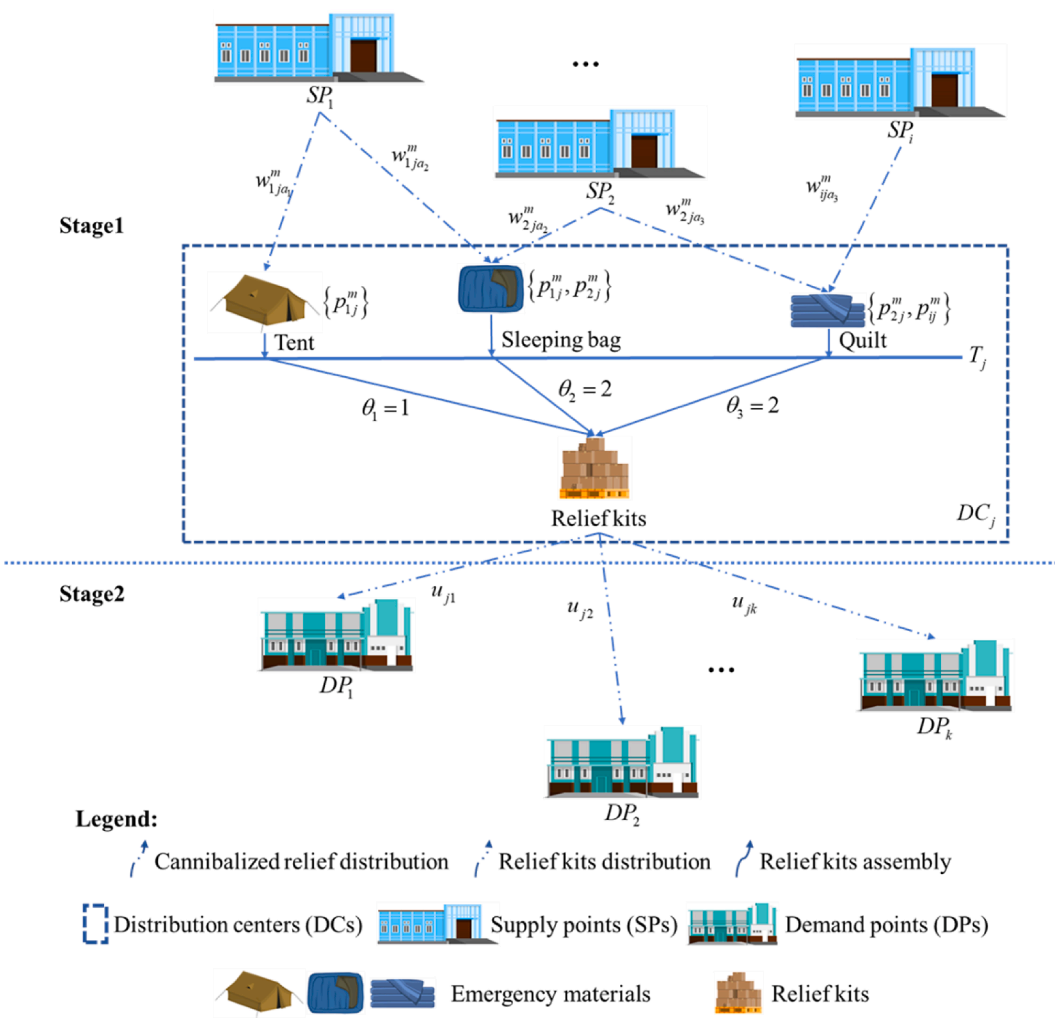

Fig. 1. Relief kit logistic network.

addition to the operations mentioned before, DCs need to assort and pack cannibalized commodities into kits in the relief kit logistic network when materials arrive. All types of emergency material will be bundled into kits with a fixed proportion based on the rescue operation requirements. As shown in Fig. 1, a shelter relief kit consists of a tent, two sleeping bags, and two quilts. Once disasters occur, DCs will be established, which are not extremely far from the affected areas and near the transportation hubs for efficient delivery. However, depending on the severity of disasters, DCs can be built in different levels, which implies different spaces, transportation capacities, and fixed costs. Thus, DCs are the temporary facilities for better rescue operations.

(iii) DP: In post-disaster phase, evacuees are transported to safe places, such as shelters, schools, and gymnasiums. People need several supplies to survive (e.g., food, water, and electricity). Furthermore, the injured need additional medical services. Thus, the victim clusters require different types of relief kit (e.g., food and medical kits). In view of the disasters, the exact amount of demand is difficult to estimate. Obviously, the requirements in DPs are considerably more than that in an urban logistic network. Then, the relief transportation optimization adopts point-to-point strategy instead of modeling vehicle routing problem or shortest path problem. Moreover, DCs are not excessively far from the affected areas, and the disruption of road infrastructure may lead to travel time uncertainty.

According to the distribution unit, the relief kit assembly and distribution can be divided into two stages. For clarity, we will describe each stage operation as follows.

Stage 1.

Because of the authority and knowledge about the affected areas, local governments will command rescue operations in disaster response phase. First, decision makers will define SPs, including public and private groups, and then collect information of agreement fixed cost and relief inventory. Second, on the basis of location and severity of disasters, there exist some potential DCs that can be established in several levels. Third, the distribution plan of cannibalized relief is constructed. SPs are far from the affected areas in a safe place, and the available inventory will not be influenced by disasters. However, due to the long distance between SPs and DCs, there exist many transport modes for delivery, such as air, road, or even high-speed railway. For the long-distance transportation, transportation capacity is unlimited. Finally, the relief from different SPs arrive at DCs. In DCs, the cannibalized relief will be packed into relief kits to satisfy different rescue requirements. Suppose a relief kit$A$, which consists of n types of emergency supplya_1, $a_2, \cdots, a_n$. The proportion of material quantity θ_n depends on the consumption in the same period. Then, relief kit A can be noted as$A = \{\theta_1 a_1, \theta_2 a_2, \cdots, \theta_n a_n\}$. The relief categories and the ratio in kits are decided by the decision makers based on experiences and emergency preparation. Only when all types of material arrive can the process of assorting and packing begin. The work time T_j should be obtained to improve the assembly and distribution efficiency.

Generally, Stage 1 should optimize the cannibalized relief distribution plan by answering the following questions.

(i) Which SPs will be chosen to service the DCs?
(ii) Where will DCs be established and in which level?
(iii) How long will it take to complete the assorting and packing of relief kits?
(iv) How can the emergency materials be transported from the SPs to the DCs via several transportation modes?

Stage 2.

When cannibalized relief is transferred as a relief kit in Stage 1, it can be transported as a unit in Stage 2. Given that DCs are not far from DPs, only road transportation is available. Suppose that the trips from DCs to DPs are fully loaded, and the back trips from DPs are unloaded. However, the infrastructure may be destroyed, and the road network needs repair. Then, the travel time will be uncertain. Moreover, in view of the fuzzy affected population, the demand of DPs is also uncertain. On the basis of this information, the demand and travel time can be determined and set as uncertain parameters with the upper bound, lower bound, and most likely value. A penalty cost is defined for the unmet demand. Each DP can be served by more than one DC. The DC levels limit the relief kit distribution in three aspects. First, different DC levels hold different numbers of vehicles. The number of rent vehicles is limited. Second, each vehicle can only load a specific weight of goods. The weight of relief kits cannot exceed the vehicle capacity in any trip. Third, in view of the work time of drivers, vehicles can only work for a certain time.

Stage 2 will optimize the relief kit distribution by answering the following questions.

(i) How many vehicles should the DCs rent?
(ii) How can the relief kits be transported from the DCs to the DPs under uncertain demand and travel time?

3.2. Mathematical formulation

Stage 1.

Set and indices.

I	Set of SPs, indexed by $i \in I$
J	Set of candidate DCs, indexed by $j \in J$
N	Set of DC levels, indexed by $n \in N$
M	Set of transportation modes, indexed by $m \in M$
A	Set of types of relief supplies, indexed by $a \in A$

Parameters.

FS_i	Fixed cost for agreement with SP i (CNY)
FD_j^n	Fixed cost for establishing DC j with level n (CNY)
CK_j^n	Capacity for relief kits at DC j with level k
v	Speed of assembling relief kits (unit/hour)
p_{ij}^m	Required travel time between SP i and DC j via mode m (hour)
c^m	Unit distribution cost in mode m (CNY/hour)
qs_{ia}	Inventory of relief supply a at SP i
θ_a	Number of relief supply a in a relief kit
B_u	A large positive number (e.g., 1000000)

Decision variables.

X_i	1 if there exists an agreement with SP i, and 0 otherwise
Y_j^n	1 if DC j in level n is established, and 0 otherwise
H_{ij}^m	1 if any relief supply is transferred from SP i to DC j via mode m, and 0 otherwise
T_j	Earliest start time of assembling in DC j
w_{ija}^m	Number of emergency materials a transferred from SP i to DC j via transport mode m
Q_j	Number of relief kits in DC j

3.2.1. Objective function

In Stage 1, we minimize the total operation cost, including the fixed cost of SP agreements, the fixed cost of establishing DCs in specific levels, and the transportation cost of different modes.

$$\min \Pi_1 = \sum_{i \in I} FS_i X_i + \sum_{n \in N} \sum_{j \in J} FD_j^n Y_j^n + \sum_{i \in I} \sum_{j \in J} \sum_{m \in M} w_{ija}^m p_{ij}^m c^m \tag{1}$$

Constraints

$$\sum_{n \in N} Y_j^n \leqslant 1, \forall j \in J \tag{2}$$

$$\sum_{m \in M} \sum_{j \in J} w_{ija}^m \leqslant qs_{ia} X_i, \forall i \in I, a \in A \tag{3}$$

$$\sum_{a\in A} w_{ija}^{m} \leqslant B_u H_{ij}^{m}, \forall i \in I, j \in J, m \in M \tag{4}$$

$$T_j = \max_{i,m}\left\{p_{ij}^{m} H_{ij}^{m} - \frac{Q_j}{v}\right\}, \forall j \in J \tag{5}$$

$$Q_j \theta_a = \sum_{i\in I}\sum_{m\in M} w_{ija}^{m}, \forall j \in J, a \in A \tag{6}$$

$$Q_j \leqslant CK_j^{n} Y_j^{n}, \forall j \in J, n \in N \tag{7}$$

$$X_i, Y_j^{n}, H_{ij}^{m} \in \{0,1\} \tag{8}$$

$$w_{ija}^{m}, Q_j, T_j \geqslant 0 \tag{9}$$

Constraint (2) requires that a candidate DC can only be established in one level. Constraint (3) ensures that the number of cannibalized reliefs transported from SPs cannot exceed its inventory. Constraint (4) indicates that transportation modes will be chosen only if there exists a relief delivery. Referring to Li et al. (2020) Theorem 3, Constraint (5) denotes that the earliest start time of assembly equals the longest travel time from SPs to the DC minus the minimum time of continuous bundling cannibalized relief into relief kits. Constraint (6) guarantees the proportion of different types of arrived materials that meet the relief kit requirements. Constraint (7) denotes the number of relief kits in each DC, which cannot exceed its capacity. Constraint (8) enforces the binary restriction on the corresponding decision variable. Constraint (9) defines the nonnegative constraints of decision variables.

Stage 2.

Set and indices.

K Set of DPs, indexed by $k \in K$

Parameters.

$\widetilde{d}_k$	Demand for relief kits at DP k
$\widetilde{t}_{jk}$	Required travel time between DC j and DP k (hour)
V_j^n	Number of available vehicles at DC j with level n
δ	Available working time of a vehicle (hour)
g	Weight of a relief kit (kg)
G	Maximum vehicle capacity (kg)
c^o	Fixed cost for renting a vehicle (CNY)
c^f	Unit operating cost of a vehicle with a full load (CNY/hour)
c^e	Unit operating cost of a vehicle without load (CNY/hour)

Decision variables.

u_{jk}	Number of relief kits transferred from DC j to DP k
E_j	Number of renting vehicles at DC j
N_{jk}^D	Number of trips from DC j to DP k with a full load
N_{jk}^B	Number of trips from DP k to DC j without load

3.2.2. Objective function

In Stage 2, we aim to optimize the cost and improve the demand satisfaction simultaneously. Objective Function (10) minimizes the total distribution cost, including the fixed cost of renting vehicles and the operating cost of transportation. Objective Function (11) maximizes the minimum demand satisfaction, which is calculated by the number of received kits and demand.

$$\min \Pi_2 = \sum_{j\in J} E_j c^o + \sum_{j\in J}\sum_{k\in K} \widetilde{t}_{jk} N_{jk}^D c^f + \sum_{j\in J}\sum_{k\in K} \widetilde{t}_{jk} N_{jk}^B c^e \tag{10}$$

$$\max \Pi_3 = \min\left\{\frac{\sum_{j\in J} u_{jk}}{\widetilde{d}_k}, \forall k \in K\right\} \tag{11}$$

Constraints

$$\sum_{k\in K} u_{jk} \leqslant Q_j Y_j^{n}, \forall j \in J \tag{12}$$

$$E_j \leqslant V_j^{n} Y_j^{n}, \forall j \in J, n \in N \tag{13}$$

$$\sum_{k\in K} N_{jk}^D = \sum_{k\in K} N_{jk}^B, \forall j \in J \tag{14}$$

$$\sum_{k\in K} u_{jk} g \leqslant \sum_{k\in K} N_{jk}^D G, \forall j \in J \tag{15}$$

$$\sum_{k\in K} \widetilde{t}_{jk}\left(N_{jk}^D + N_{jk}^B\right) \leqslant \delta E_j, \forall j \in J \tag{16}$$

$$u_{jk}, E_j, N_{jk}^D, N_{jk}^B \geqslant 0 \tag{17}$$

Constraint (12) ensures that the number of relief kits transported from SPs cannot exceed its inventory. Constraint (13) indicates that the number of rent vehicles cannot exceed its capacity. Constraint (14) balances the inbound and outbound flows of vehicles for each DC. Constraint (15) defines the weight capacity limitation. Constraint (16) implies that the duration of any dispatched vehicle does not exceed its available working time. Constraint (17) defines the nonnegative constraints of decision variables.

4. Solution approach

To solve the relief kit assembly and distribution problem with muti-objective and uncertainties, we propose a tailored solution approach, as shown in Fig. 2. First, we linearize the nonlinear equations in models mentioned in Section 3. Second, we adopt an epsilon-constraint method to address the two conflict objectives in the Stage 2 model. Third, on the basis of min–max robust optimization and the real-case situation, we obtain a novel min–max robust model, which can be solved by commercial optimization packages.

4.1. Linearization of the functions

From the formulation presented in the previous section, Constraint (5) and Objective Function (11) are nonlinear equations.

We introduce $\pi_{im} \in \{0,1\}, i \in I, m \in M$ to linearize the Constraint (5), which is shown as follows.

$$\begin{cases} p_{ij}^{m} H_{ij}^{m} - \dfrac{Q_j}{v_j} \leqslant T_j, \forall i \in I, m \in M \\ p_{ij}^{m} H_{ij}^{m} - \dfrac{Q_j}{v_j} \geqslant T_j - B_u(1-\pi_{im}), \forall i \in I, m \in M \\ \sum_{i\in I}\sum_{m\in M} \pi_{im} \geqslant 1 \\ \pi_{im} \in \{0,1\}, \forall i \in I, m \in M \end{cases} \tag{18}$$

Objective Function (11) aims to maximize the minimum demand satisfaction. Thus, suppose that the relief kit satisfaction should not be less thanγ. Objective Function (11) can be rewritten as follows:

$$\max \gamma \tag{19}$$

$$\sum_{j\in J} u_{jk} \geqslant \gamma \widetilde{d}_k, \forall k \in K \tag{20}$$

Then, all objectives and constraints are linear equations.

The model for Stage 1 is

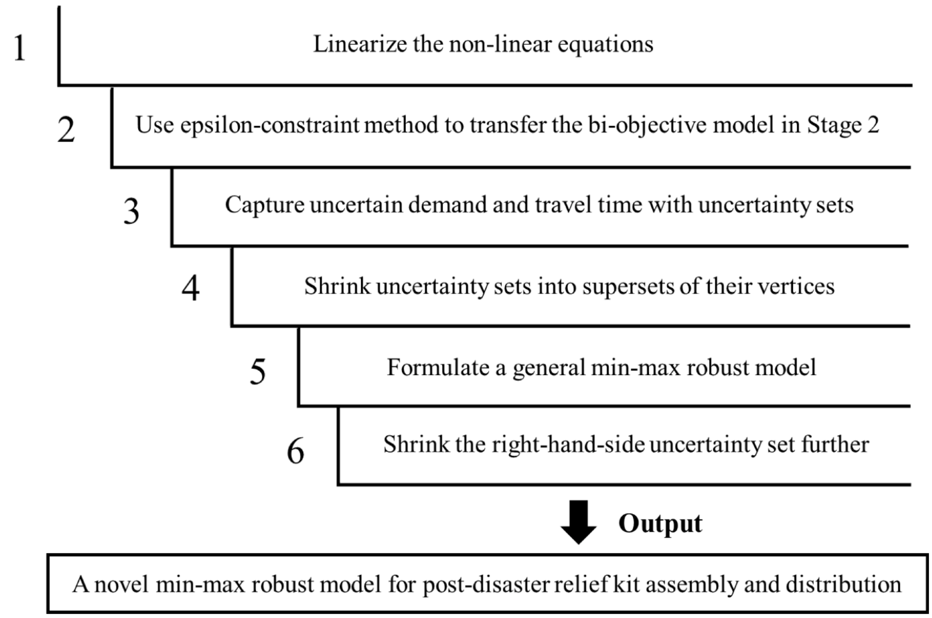

Fig. 2. The framework of the novel min–max robust model formulation.

$$\begin{cases} min\Pi_1 = \sum_{i\in I} FS_i X_i + \sum_{n\in N}\sum_{j\in J} FD_j^n Y_j^n \\ \quad + \sum_{i\in I}\sum_{j\in J}\sum_{m\in M} w_{ija}^m p_{ij}^m c^m \\ s.t.(2)-(4),(6)-(9), and\ (18) \end{cases} \tag{21}$$

The model for Stage 2 is

$$\begin{cases} min\Pi_2 = \sum_{j\in J} E_j c^o + \sum_{j\in J}\sum_{k\in K} \tilde{t}_{jk} N_{jk}^D c^f \\ \quad + \sum_{j\in J}\sum_{k\in K} \tilde{t}_{jk} N_{jk}^B c^e \\ max\gamma \\ s.t.\ (12)-(17)\ and\ (20) \end{cases} \tag{22}$$

4.2. Transformation of the bi-objective model

In the rescue process, government decision makers will pay for all the operations. Therefore, the relief distribution plan should minimize the total cost. However, the rescue service level should be guaranteed in humanitarian logistics. Decision makers usually try their best to help victims as much as possible. To improve the quality of rescue operations, we maximize the minimum demand satisfaction of DPs, which can reduce the extreme value impacts.

Obviously, the two targets are in conflict. Considerably more resources are required to improve effectiveness, which will increase the budget. However, a distribution plan with a lower cost may reduce the availability of materials and influence the quality of rescue. The inventory of relief kits in each DC can be obtained in Stage 1. In Stage 2, the decision makers only need to transport the supplies to the DPs. Then, the demand satisfaction of DPs can be estimated approximately at the beginning of Stage 2. The core mission is how the relief kits can be distributed from DCs to DPs with the lowest cost and highest demand satisfaction. In other words, the minimum of the total cost of Stage 2 is the major objective function.

Many methods can solve the problems with multiple objectives, such as weighted sum method (Sarma et al., 2019) and fuzzy method (Haeri et al., 2020). However, the coefficient of the objective has a great influence on the solution quality. On the basis of the characteristics of our proposed model, we adopt the epsilon-constraint method. The epsilon-constraint method controls the effective solutions by relaxing each objective as a constraint with different thresholds (Mavrotas, 2009).

Assume a maximization model:

$$\begin{cases} \max(f_1(x), f_2(X), \cdots, f_n(x)) \\ s.t.\ x\in X \end{cases} \tag{23}$$

The constraint part of the model is as follows:

$$\begin{cases} \max f_1(x) \\ s.t.\ f_2(X) \geqslant \varepsilon_2 \\ \cdots \\ f_n(x) \geqslant \varepsilon_n \\ x\in X \end{cases} \tag{24}$$

Suppose that the first objective function is the main objective. $f_2(X)$, $f_3(X),\ldots,f_n(X)$ are transferred into constraints with thresholds$\varepsilon_2,\varepsilon_3,\ldots,\varepsilon_n$. The appropriate parameters $\varepsilon_2,\varepsilon_3,\ldots,\varepsilon_n$ should be determined in advance to obtain the optimal solutions of the model.

As mentioned before, the demand satisfaction can be estimated roughly before the relief kit distribution. Thus, Stage 2 mainly focuses on minimizing the cost. Then, we regard Objective Function (10) as the major objective and converts Objective Function (19) into constraints. We introduce auxiliary variableε. Objective Function (19) can be depicted by the following inequation (25).

$$\gamma \geqslant \varepsilon \tag{25}$$

Decision makers propose an expectation demand satisfaction level ε in advance. Moreover, different ε will obtain different optimal solutions, which can be seen as the pareto front.

Therefore, the model for Stage 2 is

$$\begin{cases} min\Pi_2 = \sum_{j\in J} E_j c^o + \sum_{j\in J}\sum_{k\in K} \tilde{t}_{jk} N_{jk}^D c^f \\ \quad + \sum_{j\in J}\sum_{k\in K} \tilde{t}_{jk} N_{jk}^B c^e \\ s.t. + \sum_{j\in J}\sum_{k\in K} \tilde{t}_{jk} N_{jk}^B c^e (12)-(17),(20), and\ (25) \end{cases} \tag{26}$$

4.3. Formulation of the min–max robust model

Given that disasters are unpredictable, the demand of DPs is difficult to estimate exactly and timely. Furthermore, the road network in the affected area may be destroyed, and the travel time between DCs and DPs is uncertain. Then, the relief kit distribution faces hybrid uncertainties with demand and travel time. Nowadays, many methods can address uncertainties, such as stochastic programming, fuzzy methods, and robust optimization. For multi-stage optimization model, the main methods are the two-stage stochastic programming model and two-stage robust model. However, SPM has many weaknesses. In real cases, the sufficient historical data for estimating the distribution of uncertain parameters are impossible to obtain. As for the scenario-based optimization, the potential scenarios and the probability of occurrences are difficult to define. In comparison with SPM, ROM introduces uncertainty sets for modeling uncertainties, which provide a series of solutions depending on the risk preferences of decision makers. The traditional robust framework proposed by Bertsimas and Sim (2004) and Ben-Tal et al. (2009) make all decisions simultaneously, which is not suitable for our two-stage problem, although they can deal with the uncertainties in right and left hands. The traditional min–max robust framework proposed by Ben-Tal et al. (2011) and Najafi et al. (2013) only considers the right-hand-side uncertainties, which cannot deal with our proposed model. Therefore, we adopt the min–max robust optimization method proposed by Ni et al. (2018) to solve our problem. In Stage 1, decision makers will sign contracts with SPs, establish DCs in specific levels, transport cannibalized relief from SPs to DCs, and pack individuals into relief kits in DCs. Then, on the basis of the decision variables in Stage 1, decision makers will rent vehicles and distribute the relief kits in Stage 2. The min–max robust model minimizes the sum of the cost in Stage 1 and the worst-case cost in Stage 2. The main process of min–max robust model formulation is shown as follows.

Step 1: Define the uncertainty sets D and T with the most likely value, the upper bound and the lower bound of the parameters, which are polytopes. The corresponding model can be called as **min–max *robust Model 1(MMRM1)***.
Step 2: Prove the vertices of sets D and T are contained in the set V_d andV_t. Reformulate ***MMRM1*** to the equivalent **min–max *robust Model 2 (MMRM2)***.
Step 3: Shrink the set V_d into $V_d^{'}$ and obtain the equivalent **min–max *robust Model 3 (MMRM3)***.

First, we capture uncertain demand and travel time by uncertain sets. Instead of defining the distribution of parameters, we obtain the upper bound, the lower bound, and the most likely value to construct the uncertain sets.

For the uncertain demand of DPs$\widetilde{d}_k$, suppose that the information of the lower boundd_k^L, the upper boundd_k^U, and the most likely value d_k^M is available. Then, we can define the uncertainty set D as follows:

$$D=\left\{\widetilde{d}_k\in R\;\middle|\;\begin{array}{l}\eta_k=\begin{cases}\left(d_k^M-\widetilde{d}_k\right)\Big/\left(d_k^M-d_k^L\right),\ \widetilde{d}_k\leqslant d_k^M\\ \left(\widetilde{d}_k-d_k^M\right)\Big/\left(d_k^U-d_k^M\right),\ \widetilde{d}_k>d_k^M\end{cases},\forall k\in K\\ \widetilde{d}_k\in\left[d_k^L,d_k^M\right]\ ,\forall k\in K\\ \sum_{k\in K}\eta_k\leqslant\rho_d\end{array}\right\}\tag{27}$$

$\widetilde{d}_k$ takes the value in uncertainty set$D$, where ρ_d represents the number of uncertain parameters denoting the level of conservatism. ρ_d controls the size of$D$. The larger ρ_d is, the less risk decision makers will take, and the more conservative the solution will be. However, the summation of decision variable η_k is upper bounded byρ_d. Furthermore, the travel time between DCs and DPs T is defined in a similar manner as

$$T=\left\{\widetilde{t}_{jk}\in R\;\middle|\;\begin{array}{l}\eta_{jk}=\begin{cases}\left(t_{jk}^M-\widetilde{t}_{jk}\right)\Big/\left(t_{jk}^M-t_{jk}^L\right),\widetilde{t}_{jk}\leqslant t_{jk}^M\\ \left(\widetilde{t}_{jk}-t_{jk}^M\right)\Big/\left(t_{jk}^U-t_{jk}^M\right),\widetilde{t}_{jk}>t_{jk}^M\end{cases},\forall j\in J,k\in K\\ \widetilde{t}_{jk}\in\left[t_{jk}^L,t_{jk}^M\right]\ ,\forall j\in J,k\in K\\ \sum_{j\in J}\sum_{k\in K}\eta_{jk}\leqslant\rho_d\end{array}\right\}\tag{28}$$

Then, the ***MMRM1*** can be obtained to deal with the uncertain demand and travel time.

MMRM1

$$\begin{cases}\min\Pi=\Pi_1+\max\limits_{\widetilde{d}_k\in D,\widetilde{t}_{jk}\in T}\Pi_2\\ s.t.\ (1)-(4),\ (6)-(10),\ (12)-(18),\ (20),\ and\ (25)-(28)\end{cases}\tag{29}$$

Furthermore, we can easily infer from D that

$$\eta_k=\begin{cases}\dfrac{\left(d_k^M-\widetilde{d}_k\right)}{\left(d_k^M-d_k^L\right)}\geqslant0\geqslant\dfrac{\left(\widetilde{d}_k-d_k^M\right)}{\left(d_k^U-d_k^M\right)},\widetilde{d}_k\leqslant d_k^M\\ \dfrac{\left(\widetilde{d}_k-d_k^M\right)}{\left(d_k^U-d_k^M\right)}\geqslant0\geqslant\dfrac{\left(d_k^M-\widetilde{d}_k\right)}{\left(d_k^M-d_k^L\right)},\widetilde{d}_k>d_k^M\end{cases},\forall k\in K\tag{30}$$

In other words,

$$\eta_k=\max\left\{\frac{\left(d_k^M-\widetilde{d}_k\right)}{\left(d_k^M-d_k^L\right)},\frac{\left(\widetilde{d}_k-d_k^M\right)}{\left(d_k^U-d_k^M\right)}\right\},\forall k\in K\tag{31}$$

which can be rewritten as

$$\begin{cases}\eta_k\geqslant\dfrac{\left(d_k^M-\widetilde{d}_k\right)}{\left(d_k^M-d_k^L\right)}\\ \eta_k\geqslant\dfrac{\left(\widetilde{d}_k-d_k^M\right)}{\left(d_k^U-d_k^M\right)}\end{cases},\forall k\in K\tag{32}$$

Thus, uncertain set D can be transferred to

$$D=\left\{\widetilde{d}_k\in R\;\middle|\;\begin{array}{l}\begin{cases}\eta_k\geqslant\dfrac{\left(d_k^M-\widetilde{d}_k\right)}{\left(d_k^M-d_k^L\right)}\\ \eta_k\geqslant\dfrac{\left(\widetilde{d}_k-d_k^M\right)}{\left(d_k^U-d_k^M\right)}\end{cases},\forall k\in K\\ \widetilde{d}_k\in\left[d_k^L,d_k^M\right]\ ,\forall k\in K\\ \sum_{k\in K}\eta_k\leqslant\rho_d\end{array}\right\}\tag{33}$$

Given that all constraints are linear equations, (33) is a polytope. In addition to$\widetilde{d}_k\in\left[d_k^L,d_k^M\right]$, it is also a hyperrectangle. Then, (33) is a bounded polytope, which can also be called as a polytope.

The two models are as follows:

$$\begin{cases}Z=\min\left(\sum_{k\in K}a_kd_k\right)\\ s.t.\ d_k\in D\end{cases}\tag{34}$$

$$\begin{cases}Z^{'}=\min\left(\sum_{k\in K}a_k^{'}\eta_k+\sum_{k\in K}a_kd_k^M\right)\\ s.t.\ \eta_k\in[0,1],\forall k\in K\\ a_k^{'}=\begin{cases}-a_k\left(d_k^M-d_k^L\right),a_k\geqslant0\\ a_k\left(d_k^U-d_k^M\right),a_k<0\end{cases},\forall k\in K\end{cases}\tag{35}$$

Suppose η_k^* is an optimal solution of (35). Then, we can construct a vector, as shown as follows:

$$\widehat{d}_k = \begin{cases} d_k^M - \eta_k^*(d_k^M - d_k^L) \in [d_k^L, d_k^M], a_k \geqslant 0, \forall k \in K \\ d_k^M + \eta_k^*(d_k^U - d_k^M) \in [d_k^M, d_k^U], a_k < 0, \forall k \in K \end{cases} \quad (36)$$

Obviously, $\widehat{d}_k \in D$. Then, $\widehat{d}_k$ is a feasible solution for (33). We can refer that

$$\begin{aligned} Z &= \sum_{k\in K} a_k d_k \leqslant \sum_{k\in K} a_k \widehat{d}_k = \sum_{k\in K:a_k\geqslant 0} a_k \widehat{d}_k + \sum_{k\in K:a_k<0} a_k \widehat{d}_k \\ &= \sum_{k\in K:a_k\geqslant 0} a_k [d_k^M - \eta_k^*(d_k^M - d_k^L)] + \sum_{k\in K:a_k<0} a_k [d_k^M + \eta_k^*(d_k^U - d_k^M)] \\ &= \sum_{k\in K:a_k\geqslant 0} a_k d_k^M - \sum_{k\in K:a_k\geqslant 0} a_k \eta_k^*(d_k^M - d_k^L) \\ &+ \sum_{k\in K:a_k<0} a_k d_k^M + \sum_{k\in K:a_k<0} a_k \eta_k^*(d_k^U - d_k^M) \\ &= \sum_{k\in K} a_k d_k^M + \sum_{k\in K:a_k\geqslant 0} a_k' \eta_k^* + \sum_{k\in K:a_k<0} a_k' \eta_k^* \\ &= \sum_{k\in K} a_k d_k^M + \sum_{k\in K} a_k' \eta_k^* \\ &= Z' \end{aligned} \quad (37)$$

Conversely, suppose one of the optimal solutions of (34) is d_k^*. Then, construct a vector:

$$\widehat{\eta}_k = \max\{(d_k^M - d_k^*)/(d_k^M - d_k^L), (d_k^* - d_k^M)/(d_k^U - d_k^M)\} \in [0,1], \forall k \in K \quad (38)$$

For $d_k^* \in D$, $\widehat{\eta}_k$ is a feasible solution of (35). Then,

$$\begin{aligned} Z' &= \sum_{k\in K} a_k d_k^M + \sum_{k\in K} a_k' \eta_k \\ &\leqslant \sum_{k\in K} a_k d_k^M + \sum_{k\in K} a_k' \eta_k^* \\ &= \sum_{k\in K} a_k d_k^M + \sum_{k\in K:a_k\geqslant 0} a_k' \eta_k^* + \sum_{k\in K:a_k<0} a_k' \eta_k^* \\ &= \sum_{k\in K} a_k d_k^M - \sum_{k\in K:a_k\geqslant 0} a_k (d_k^M - d_k^L)\eta_k^* + \sum_{k\in K:a_k<0} a_k (d_k^U - d_k^M)\eta_k^* \\ &\leqslant \sum_{k\in K} a_k d_k^M - \sum_{k\in K:a_k\geqslant 0} a_k (d_k^M - d_k^L) \frac{(d_k^M - d_k^*)}{(d_k^M - d_k^L)} \\ &+ \sum_{k\in K:a_k<0} a_k (d_k^U - d_k^M) \frac{(d_k^* - d_k^M)}{(d_k^U - d_k^M)} \\ &= \sum_{k\in K} a_k d_k^M - \sum_{k\in K:a_k\geqslant 0} a_k (d_k^M - d_k^*) + \sum_{k\in K:a_k<0} a_k (d_k^* - d_k^M) \\ &= \sum_{k\in K} a_k d_k^M + \sum_{k\in K} a_k (d_k^* - d_k^M) \\ &= \sum_{k\in K} a_k d_k^* = Z \end{aligned} \quad (39)$$

Generally, $Z = Z'$.

In Model (35), the objective function indicates that the less $\sum_{k\in K} a_k' \eta_k$ is, the better the solution will be. Obviously, $\sum_{k\in K} a_k d_k^M$ is determined and independent on the decision variables η_k. Thus, we obtain $\{k_1, k_2, \cdots, k_{|K|}\} = |K|$, such that $a_{k_1}' \leqslant a_{k_2}' \leqslant \cdots \leqslant a_{k_{|K|}}'$. Suppose $T = \{k_1, k_2, \cdots, k_{|\rho_d|}\}$. For $a_k' \leqslant 0$, we summarize that the higher the value of a_k' is, the better the results will be. According to the set, the general solution form of the optimal solution is obtained as follows:

$$\eta_k^* = \begin{cases} 1, \forall k \in T \\ 0, \forall k \in K \backslash T \end{cases} \quad (40)$$

Then,

$$d_k = \begin{cases} d_k^L, a_k \geqslant 0, \forall k \in T \\ d_k^U, a_k < 0, \forall k \in T\ T \subseteq K, |T| = \rho_d \\ d_k^M, \forall k \in K \backslash T \end{cases} \quad (41)$$

Thus, the vertices of D (33) are contained in the set, as shown as follows:

$$V_d = \bigcup_{T\subseteq K,|T|=\rho_d} \left\{ d_k \in R \middle| \begin{array}{l} d_k \in \{d_k^L, d_k^U\}, \forall k \in T \\ d_k = d_k^M, \forall k \in K \backslash T \end{array} \right\} \quad (42)$$

Similarity, the vertices of T (28) are contained in the set, as shown as follows:

$$V_t = \bigcup_{T\subseteq J\cup K,|T|=\rho_t} \left\{ t_{jk} \in R \middle| \begin{array}{l} t_{jk} \in \{t_{jk}^L, t_{jk}^U\}, \forall k \in T \\ t_{jk} = t_{jk}^M, \forall k \in J \cup K \backslash T \end{array} \right\} \quad (43)$$

Referring to Ni et al. (2018), ***MMRM1*** is the general min–max ROM, which meets the following constraints:

(i) For all $\widetilde{d}_k \in D, \widetilde{t}_{jk} \in T$, Stage 2 model is feasible.
(ii) For $\widetilde{d}_k \in V_d, \widetilde{t}_{jk} \in V_t$, Stage 2 model is bounded.

Then, ***MMRM1*** is equivalent to ***MMRM2***, which is formulated as follows.

MMRM2

$$\begin{cases} \min \Pi = \Pi_1 + \max_{\widetilde{d}_k} \in V_d, \widetilde{t}_{jk} \in V_t \Pi_2 \\ s.t. \quad (1)-(4), (6)-(10), (12)-(18), (20), (25), (42), \ and \ (43) \end{cases} \quad (44)$$

In our model, the uncertain demand $\widetilde{d}_k$ is in the right-hand side. We also optimize the plan for the worst cases. Then, we transfer (42) into (45), which indicates that if the.

parameter is uncertain, then only the upper bound is obtained.

$$V_d' = \bigcup_{T\subseteq K,|T|=\rho_d} \left\{ d_k \in R \middle| \begin{array}{l} d_k = d_k^U, \forall k \in T \\ d_k = d_k^M, \forall k \in K \backslash T \end{array} \right\} \quad (45)$$

Generally, the ***MMRM3*** for relief kit deployment and distribution optimization in disaster response phase is as follows:

MMRM3

$$\begin{cases} \min \Pi = \Pi_1 + \max_{\widetilde{d}_k} \in V_d', \widetilde{t}_{jk} \in V_t \Pi_2 \\ s.t. \quad (1)-(4), (6)-(10), (12)-(18), (20), (25), (42), \ and \ (45) \end{cases} \quad (46)$$

5. Computational experiments

In this section, several numerical experiments are designed to evaluate the ***MMRM3*** versus its deterministic and two-stage stochastic counterparts. We use MATLAB software coupled with CPLEX 12.9 as the development environment. The tests run on an Intel(R) Core (TM) i5-1135G7 2.40 GHz laptop with 16 GB RAM.

5.1. Experiment generation

The experiment considers three SPs, four DCs with two levels, two transportation modes, three types of relief item, and two DPs. We use $N(\mu, \sigma, l, u)$ to denote a truncated normal distribution, where μ and σ correspond to the mean and stand deviation of the "parent" normal distribution, respectively, and (l, u) specifies the truncation interval. Relief kit demand $\widetilde{d}_k$ in DPs and the required travel time between DCs and DPs $\widetilde{t}_{jk}$ are assumed to follow independent truncated normal distributions $N(\mu_k^d, \sigma_k^d, 0, +\infty)$ and $N(\mu_{jk}^t, \sigma_{jk}^t, 0, +\infty)$. The parameter settings can be found in the supplementary materials.

5.2. Mechanism of comparison

In this mechanism, the demand of DPs and travel time between DCs and DPs are generated randomly for 10 times. Then, the DEM, SPM and ROM are solved iteratively to investigate the performance of the proposed min–max robust approach.

Step 1: Obtain 50 independent samples drawn from truncated normal distributions $N(\mu_k^d, \sigma_k^d, 0, +\infty)$ and$N\left(\mu_{jk}^t, \sigma_{jk}^t, 0, +\infty\right)$. Then, let the average, minimum, and maximum values be the most likely value, lower bound value, and upper bound value, respectively. Thus, the uncertain demand and travel time have available information, e.g., $\left(d_k^L, d_k^M, d_k^U\right)$ and$\left(t_{jk}^L, t_{jk}^M, t_{jk}^U\right)$.

Step 2: Set ε based on the decision makers' preference and the practicality.

Step 3: Construct the DEM, stochastic, and robust models as follows.

- DEM: Replace the demand of DCs and travel time between DCs and DPs by the estimated most likely values d_k^M andt_{jk}^M.
- SPM: Generate 50 scenarios for demand and travel time. Each scenario includes the random generation of independent samples drawn from triangular distributions $T\left(d_k^L, d_k^M, d_k^U\right)$ and $T\left(t_{jk}^L, t_{jk}^M, t_{jk}^U\right)$ with lower boundd_k^L, t_{jk}^L, moded_k^M, t_{jk}^M, and upper boundd_k^U, t_{jk}^U,respectively.
- ROM: The uncertain sets in equation (42) and (43) are defined by $\left(d_k^L, d_k^M, d_k^U\right)$ and $\left(t_{jk}^L, t_{jk}^M, t_{jk}^U\right)$. We consider three levels of conservatism by simultaneously setting the demand and travel time uncertainty budgets$(\rho_d, \rho_t) = \{(1,1), (1,|J|), (|K|,|J|)\}$.

Step 4: Solve all the above models to obtain the optimal solutions in Stage 1, including the agreements, the establishment, and the relief kit inventory.

Step 5: Generate 1000 realizations of$\left(\widetilde{d}_k, \widetilde{t}_{jk}\right)$, following independent truncated normal distributions $N(\mu_k^d, \sigma_k^d, 0, +\infty)$ and$N\left(\mu_{jk}^t, \sigma_{jk}^t, 0, +\infty\right)$. For each solution obtained in ***Step 4***, we solve the corresponding second-stage problem. Then, we obtain the results of the first and second stages for each realization.

Step 6: For each model constructed in ***Step 3***, we use the corresponding results for the 1000 realizations obtained in ***Step 5*** to calculate the average and the 95 % percentile of these results. The average value and the 95 % percentile are estimators of the expectation and the 5 % value-at-risk of the value associated with implementing the corresponding Stage 1 solutions under the true distribution of the uncertain parameters.

5.3. Performance evaluation

Table 2 reports the infeasibility of three models with$\varepsilon = 0.5$, and the budget of uncertainty is set as:$(\rho_d, \rho_t) = \{(1,1), (1,|J|), (|K|,|J|)\}$. Obviously, given that uncertainties will improve the solution feasibility, SPM and ROM have lower infeasibility than DEM. In real cases, the distribution plan, which is determined by the most likely value, may not satisfy emergency disasters. Furthermore, in comparison with SPM and ROM, the infeasibility of ROM is far less than that of SPM. Therefore, the more conservative the decision maker is, the higher the conservatism degree and the more feasible the solution will be.

Table 2
Infeasibility of DEM, SPM, and ROM.

Model	Infeasibility
DEM	54.98 %
SPM	42.67 %
ROM $(\rho_d, \rho_t) = \{(1,1)\}$	7.28 %
ROM $(\rho_d, \rho_t) = \{(1,4)\}$	6.49 %
ROM $(\rho_d, \rho_t) = \{(2,4)\}$	0.47 %

Different settings of ε will influence the results of optimal solutions. We compare average value and the 95 % percentile of the total cost, the ratio of penalty cost, and the demand satisfaction of the three models under different values of ε as follows.

From Table 3, the higher the minimum demand satisfaction is, the higher the total cost will be. If the decision makers want to meet more demand, then they should transport more relief and manage more resources. Thus, the total cost will be higher.

No matter the type of models or the type of values, they all draw the same conclusions. As for the total cost of each model, the more uncertainties the model considers, the higher the total cost will be. The average value and the 95 % percentile show that the total cost of ROM is higher than that of SPM and DEM. In real cases, if the plan considers uncertainties and tries to deal with the worse situation, then the decision makers will spend more money in Stage 1. For instance, they make contracts with more SPs to guarantee relief inventory. Then, the cannibalized relief distribution in Stage 1 will cost more money. The emergency resources require more space to be assembled and stored. Then, the establishment cost of DCs will also be considerably higher.

As for demand satisfaction, as shown in Table 4, ε does not affect the 95 % percentile value. However, the higher the value of ε is, the higher the average demand satisfaction will be. The average service level will also be improved. Obviously, the 95 % percentile demand satisfaction is always equal toε, which is set by the decision makers in advance. The type of models and the uncertainties have no influence on it. It is because that ε is determined by decision-makers in advance as the minimum demand satisfaction. If the solution increases the demand satisfaction, the total cost will increase at the same time. But the main objective of this model is to minimize the total cost. Then, the demand satisfaction will only reach the lowest level and always equal toε. However, the average value of demand satisfaction is different from the 95 % percentile value. The more uncertainties the solution considers, the higher the average demand satisfaction will be, which can be referred from the results of DEM, SPM, and ROM with different conservation degrees.

6. Case study

To investigate the practicality of the min–max robust model and the algorithm, we conduct numerical tests based on the relief kit assembly and distribution plan in the Yunnan earthquake.

6.1. Case study description

Yunnan Province is in the southwest of China with varied topography. The mountainous area and plateau account for 84 % and 10 % of the total area of the province, respectively. Furthermore, the precipitation in the whole province is extremely uneven in season and region. The rainy season is from May to October, with 85 % of the rainfall concentrated. The dry season is from November to April of the next year, and the precipitation accounts for only 15 % of the whole year. Given the complex landforms and climates, various natural disasters occur in Yunnan Province.

According to the Department of Emergency Management of Yunnan Province 2021 Annual Natural Disaster Report, 159 natural disasters affected 16 cities and 124 counties, resulted in 37,640 evacuees, and costed 10.63 billion CNY. More than 23,000 buildings were destroyed. Although the disasters include earthquakes, droughts, and floods, the losses caused by earthquakes are the largest. In 2021, disasters affected 196.1 thousand people, resulted in 12,940 evacuees, and costed 3.4 billion CNY. Furthermore, earthquakes are usually moderately strong and affect a wide area. The transferred population account for 82.79 % of the whole year evacuees. The collapsed building account for 74.69 %

Table 3
Total cost under different values of ε (CNY).

Model	Average			95 %		
	$\varepsilon = 0.4$	$\varepsilon = 0.5$	$\varepsilon = 0.6$	$\varepsilon = 0.4$	$\varepsilon = 0.5$	$\varepsilon = 0.6$
DEM	**2296.91**	**2809.38**	**3395.69**	**2990.26**	**3663.93**	**4189.85**
SPM	2362.34	2978.65	3506.10	3143.77	3803.53	4684.46
ROM $(\rho_d, \rho_t) = (1, 1)$	2734.85	3286.21	4151.36	3866.12	4694.98	5409.85
ROM $(\rho_d, \rho_t) = (1, 4)$	2784.91	3515.32	4221.33	3767.61	4811.05	5699.10
ROM $(\rho_d, \rho_t) = (2, 4)$	2816.82	3788.95	4573.54	3800.13	5242.22	5993.38

Table 4
Demand satisfaction under different values ofε.

Model	Average			95 %		
	$\varepsilon = 0.4$	$\varepsilon = 0.5$	$\varepsilon = 0.6$	$\varepsilon = 0.4$	$\varepsilon = 0.5$	$\varepsilon = 0.6$
DEM	39.99 %	50.00 %	**60.00 %**	**40.00 %**	**50.00 %**	**60.00 %**
SPM	**40.00 %**	50.00 %	**60.00 %**	**40.00 %**	**50.00 %**	**60.00 %**
ROM $(\rho_d, \rho_t) = (1, 1)$	**40.00 %**	50.00 %	**60.00 %**	**40.00 %**	**50.00 %**	**60.00 %**
ROM $(\rho_d, \rho_t) = (1, 4)$	**40.00 %**	50.00 %	**60.00 %**	**40.00 %**	**50.00 %**	**60.00 %**
ROM $(\rho_d, \rho_t) = (2, 4)$	**40.00 %**	**50.02 %**	**60.00 %**	**40.00 %**	**50.00 %**	**60.00 %**

of the destroyed buildings for the whole year. In the future, earthquakes will still occur Yunnan Province. Thus, decision makers should prepare for disasters in advance to improve the response efficiency. However, given the uncertainty of the occurrence of earthquakes, decision makers have difficulty estimating the relief demand accurately. The damage of road conditions and information infrastructure will influence the travel time between DCs and DPs. Thus, we use the earthquake that happened in Yunnan Province, China to evaluate the performance of the min–max robust model.

Suppose that there exist 11 SPs, 5 potential DCs, and 9 DPs in Yunnan Province. Fig. 3 denotes the map of SPs, DCs, and DPs.

According to the locations and types of SP, the fixed cost of agreement is different with one another. Following Akbarpour et al. (2020), we set the fixed cost in the range of [1000, 2000]. The inventories of emergency items are generated as shown in the supplementary materials. On the basis of the severity of disasters, available resources, and the development of the local society, suppose that there exist three levels for the establishment of DCs, namely, large, medium, and small. Different levels of DC will have different capacities and available vehicles. The input parameters about DCs can be found in the supplementary materials.

The transportation in Yunnan Province can take multiple modes, such as railway, road, or even air. However, the railway operating plan will limit the accessibility of SPs and DCs. Then, the travel time between SPs and DCs via railway may not exist. The road transportation time is defined by the fastest driving plan in Baidu Map. The railway transportation time is obtained from the 12,306 China Railway timetable. The air transportation time is calculated by the distance and the speed of

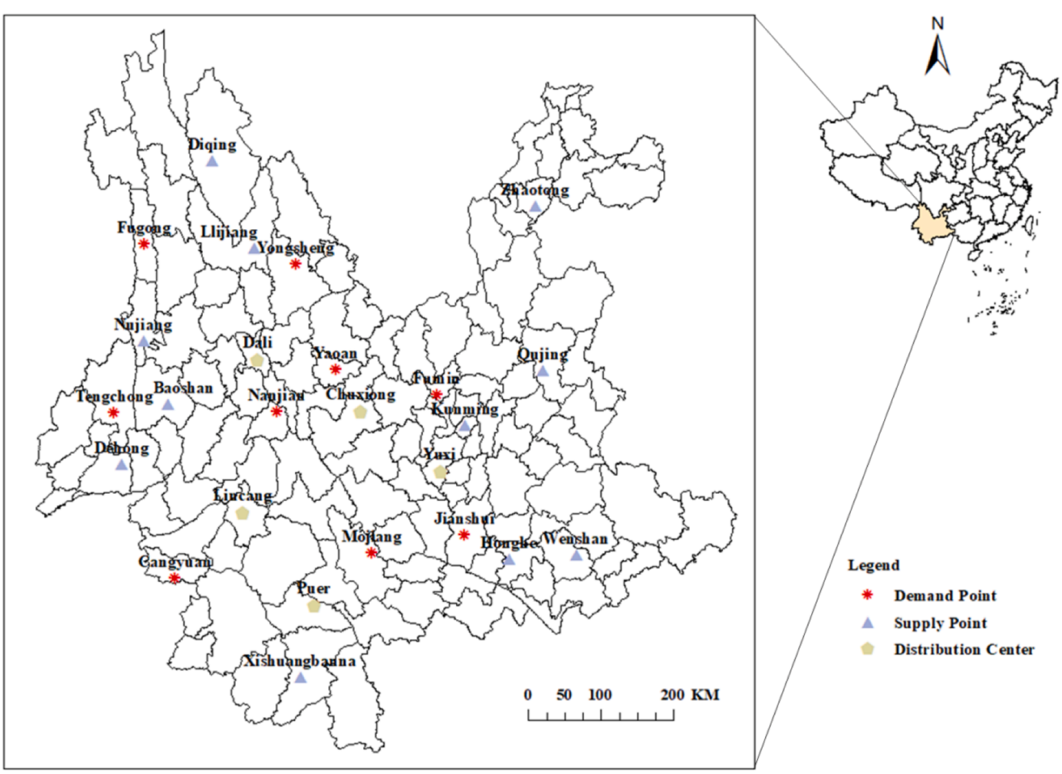

Fig. 3. Map of SPs, DCs, and DPs.

Mi-171 helicopter (250 km/h). More detailed information can be found in the supplementary materials. On the basis of Zhang et al. (2019), the unit transportation cost of different types of mode are set as: road (1.2), air (3), and railway (0.5). We adopt the DongfengEQ240 as available vehicles for DCs. The available working time of a vehicle is 18 h. The fixed cost for renting a vehicle is 2000 CNY. The unit operating cost of a vehicle with a full load is 150 CNY/hour, and the unit operating cost of a vehicle without load is 70 CNY/hour. The maximum vehicle capacity is 4000 kg.

There exist various relief kits in the disaster response phase. Especially for earthquakes, buildings are destroyed and the affected people will evacuee to safe shelters. Thus, the requirements in shelters must be met. Some of the emergency materials have limited shelf life and must be supplied more than once, such as food and medical kits. The proposed model aims to optimize the distribution of the relief kit whose quality may not change in a short time. Then, we adopt the kit for accommodation as the explanation example. Suppose that the accommodation kit has one tent, four quilts, and four folding beds. The total penalty cost of a kit is 441.32 CNY, and the total weight is 91.87 kg. Some parameters about the relief can be found in the supplementary materials for more detailed information.

In 2021, the minimum earthquake magnitude in Yunnan Province is 4.2, and the maximum magnitude is 6.4. However, to prepare for the disasters that will truly damage cities, we suppose that the earthquake magnitudes' lower bound is 5.0–5.4, the upper bound is 6.0–6.4, and the most likely range is 5.5–5.9. On the basis of Cai et al. (2017), we obtain the lower bound, upper bound, and most likely value of demand of DPs and the travel time between DCs and DPs, which can be found in the supplementary materials.

6.2. Simulation results

To illustrate a relief kit assembly and distribution plan clearly, we suppose $\varepsilon = 0.6, \rho_d = 4, \rho_t = 20$ and obtain the optimal solution of the min–max robust model.

Fig. 4 depicts the results in Stage 1. Obviously, the government will make contracts with all SPs and build all the five DCs. The values in DCs indicate the level of establishment. The larger the number is, the more capacity the DC will have. The two values in parentheses under DCs represent the inventory of the relief kits and the earliest start time of assembly. For example, the Dali DC will be established in Level 3 and deal with 3276 relief kits with 19.23 completion time. The three values in parentheses near each line between the SPs and DCs represent the distribution plan of cannibalized relief via road, air, and railway. For example, 214 tents are transferred from Lijiang to Dali by railway. As shown in Fig. 4, one SP can service more than one DC; for example, Dehong supplies Lincang and Dali simultaneously. However, the emergency supplies can belong to more than one type; for example, Diqing will transport quilts and folding beds to Dali. The more relief kits the DC hold, the longer the completion time will be. In real cases, it may need

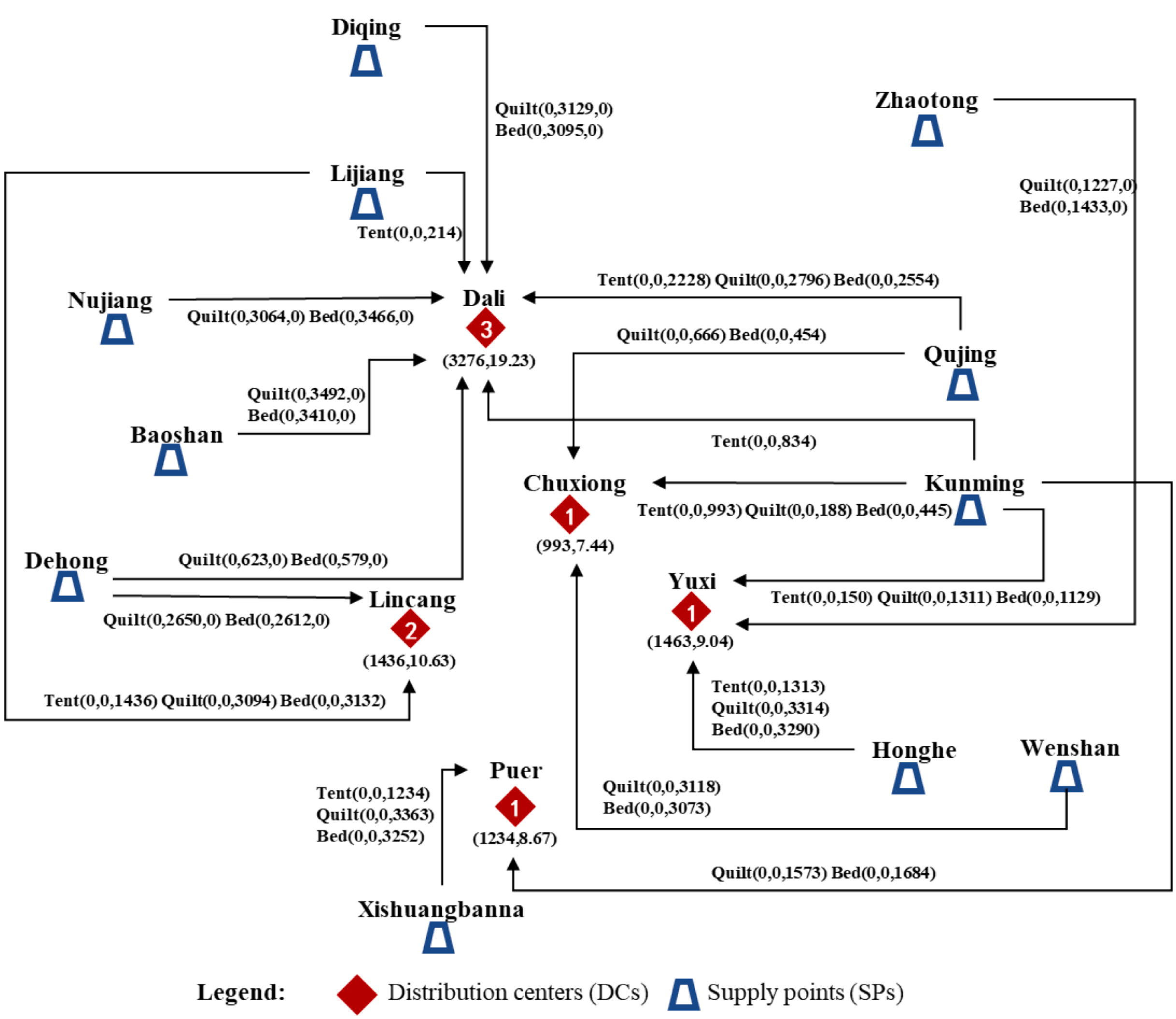

Fig. 4. Cannibalized relief distribution.

more emergency materials supplied by many SPs. The assembly time of relief kits will be longer, too. To assemble more relief kits, the DC will be built in a higher level, which may be serviced by more SPs. As for the transportation modes, no distribution adopts the road transportation. Most of the delivery choose the transportation by railway, and some of them will adopt air. Although the road unit transportation cost is the lowest, the travel time is considerably longer than the other transportation modes in Yunnan Province for the specific geography. Therefore, the railway or air may be the better choice.

Fig. 5 reports the results in Stage 2. The values in DCs indicate the rent vehicles of the DC. For example, Dali will rent 30 vehicles to complete the relief kit distribution. The values near each line between the DCs and DPs represent the relief kit distribution. For example, Puer will transport 1234 relief kits to Mojiang with 6 vehicles. Obviously, one DC can supply more than one DP. The more relief kits the DCs hold, the more DPs the DC will service and the more vehicles the DC will rent.6.3 Effect of relief kit deployment pattern.

6.3. Effect of relief kit deployment pattern

In this paper, emergency supplies will be assorted and packed as relief kits in DCs and then transported to DPs in units. Different from the assembly process, suppose there exists only cannibalized relief distribution in the disaster response phase, and the individual items will be bundled into kits in DPs. DCs, which are the same as hub DCs in urban logistics network, only hold relief items temporarily and then transport them to DPs in cannibalization. The materials will not be assembled in DCs; thus, there exist no relief kit inventories in DCs. However, the total number of items cannot exceed the limitation of DCs. Nevertheless, DPs still need relief kits. Only when the DPs receive the cannibalized relief can the relief kits begin to be assembled, and DPs will keep the relief kit inventory instead. Thus, some extra emergency supplies may be available. As for the rest of the supplies, which are not packed into relief kits, we define a penalty cost for the resource waste. Then, the total cost in Stage 2 will add another part of penalty cost for resource waste. The corresponding mathematical model can be found in the supplementary materials.

Different relief kit assembly patterns are under the same parameter settings as$\varepsilon = 0.6, \rho_d = 4, \rho_t = 20$. We obtain 200 realizations and the average values and 95 % percentile of the total cost and demand satisfaction. The comparisons are shown in Table 5. The average cost of assembling relief kits in the distribution centers is 19.45 % lower than that of in the demand points, even 20.52 % in the 95 % percentile values Obviously, penalty cost for unpacked relief is high. Fixed cost for agreement with SPs,

establishing DCs, renting vehicles and operating cost for full load and without load vehicles are almost the same in two cases. The distribution cost decrease 2.84 % in average and 2.36 % in 95 % percentile values in assembly process. In other words, assorting and packing relief kits in DCs is more effective at making full use of resources than that in DPs. However, the demand satisfaction in the average and 95 % percentile

Table 5
Comparison of two cases.

	Assorting and packing relief kits in DPs		Assorting and packing relief kits in DCs	
	Average	95 %	Average	95 %
Total cost (CNY)	520,646	580,771	419,404	461,597
Fixed cost for agreement with SPs (CNY)	15,417	15,784	15,417	15,784
Fixed cost for establishing DCs (CNY)	18,182	18,736	18,175	18,736
Distribution cost (CNY)	131,837	150,754	135,576	154,316
Fixed cost for renting vehicles (CNY)	126,750	140,000	126,440	140,000
Full load operating cost of vehicles (CNY)	84,870	93,532	84,407	93,205
Without load operating cost of vehicles (CNY)	39,606	43,648	39,390	43,496
Penalty cost (CNY)	103,984	124,801	–	–
Demand satisfaction	60.00 %	60.00 %	60.00 %	60.00 %

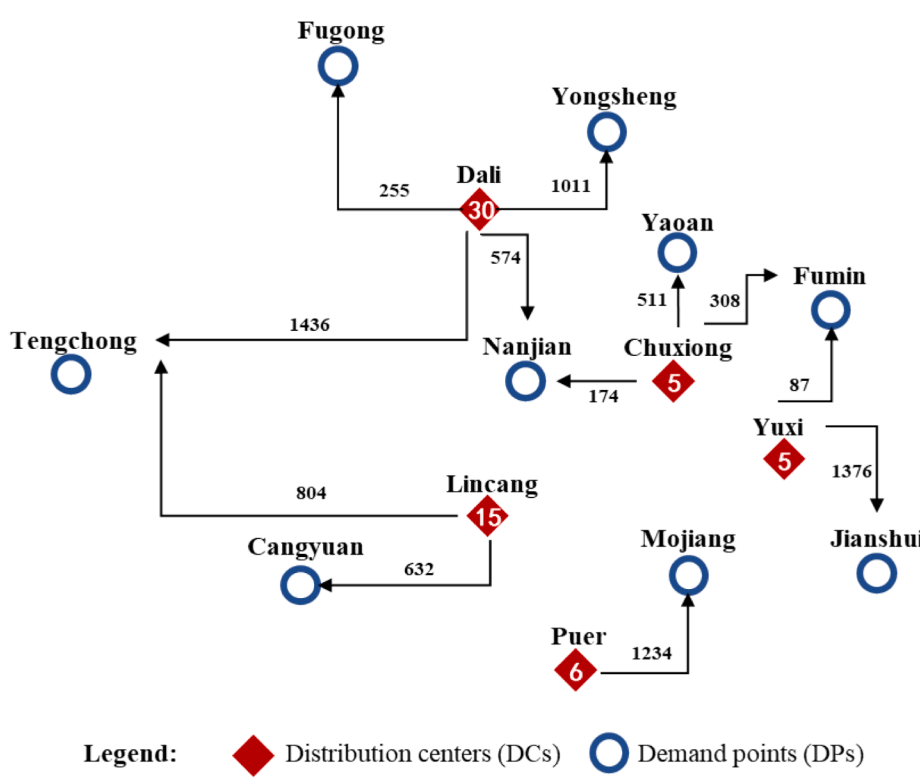

Fig. 5. Relief kit distribution.

values are not changed.

6.4. *Sensitivity analysis*

In view of disasters, hybrid uncertainties exist in post-disaster relief kit distribution, such as travel time and demand. Thus, we analyze the capacity and working time of vehicles and the conservatism preference of decision makers to improve the operations. We systematically change the values of the parameters to evaluate their effects in the performance of the model.

6.4.1. *Increasing vehicle capacity*

Set $\varepsilon = 0.6, \rho_d = 4, \rho_t = 20$ and generate seven scenarios of 70 %, 80 %, 90 %, 100 %, 110 %, 120 %, and 130 % of the vehicle capacity. Then, we obtain 200 realizations in each scenario and the average and 95 % percentile values of the outcomes. As shown in Fig. 6, the average and 95 % percentile total cost decrease with the increase in the vehicle capacity. Obviously, fewer vehicles with higher loading capacity can complete relief distribution in less trips of traveling. Then, the total cost will decrease with the fixed cost of renting vehicles and the operating cost of transportation. Thus, the decision makers may choose vehicles with higher capacity in the same fixed renting cost.

6.4.2. *Increasing the available working time of a vehicle*

Set $\varepsilon = 0.6, \rho_d = 4, \rho_t = 20$ and generate seven scenarios of 70 %, 80 %, 90 %, 100 %, 110 %, 120 %, and 130 % of the vehicle's available working time. Then, we obtain 200 realizations in each scenario and the average and 95 % values of the outcomes. As shown in Fig. 7, the average and 95 % percentile total cost decrease with the increase in the available working time of a vehicle. The main reason is that a vehicle with longer.

working time can transport more relief to reduce the total cost and transportation time. Although increasing the available working time of a vehicle will improve the efficiency of the rescue plan, the labor force may limit the upbound.

6.4.3. *Increasing uncertainty budget*

Set $\varepsilon = 0.6$ to generate 200 realizations in each uncertainty budget scenario, and obtain the average and 95 % percentile values of the outcomes. As shown in Table 6, the more conservative the decision makers are, the more the post-disaster logistics will cost. However, the average and 95 % percentile demand satisfaction remain unchanged. In comparison with travel uncertainty, the demand uncertainty has a greater effect on total cost. Decision makers should establish a trade-off between uncertainty budget and total cost through this sensitivity

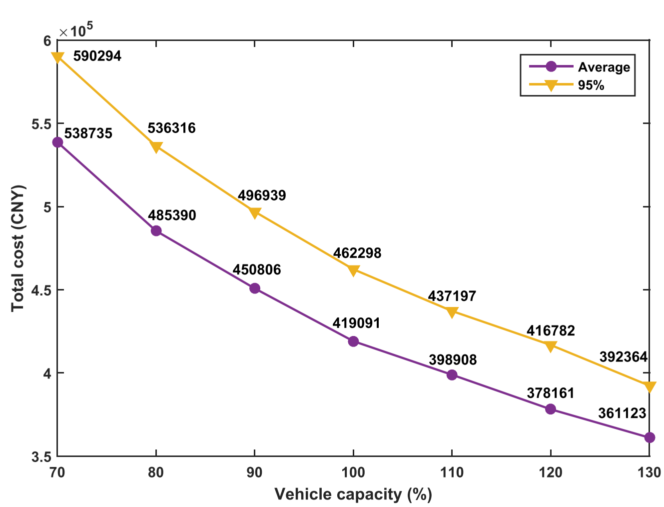

Fig. 6. Sensitivity of total cost to vehicle capacity.

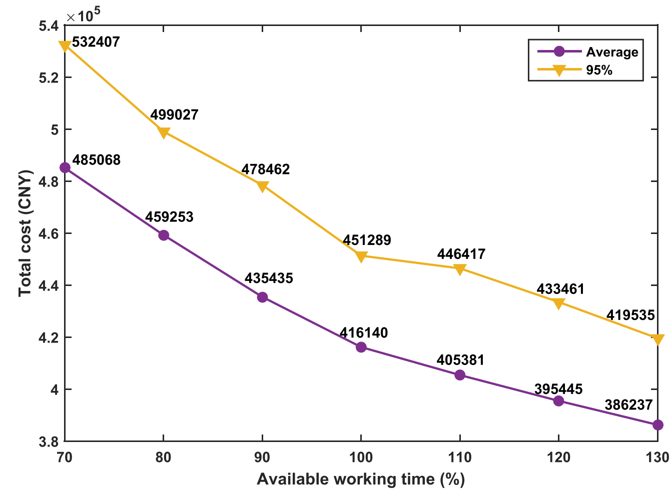

Fig. 7. Sensitivity of total cost to the vehicle's available working time.

Table 6
Outcomes of increasing uncertainty budget.

	Total cost (CNY)		Demand satisfaction	
	Average	95 %	Average	95 %
$(\rho_d, \rho_t) = (2, 20)$	379,779	415,589	60.00 %	60.00 %
$(\rho_d, \rho_t) = (2, 35)$	383,267	421,886	60.00 %	60.00 %
$(\rho_d, \rho_t) = (4, 20)$	419,562	458,297	60.00 %	60.00 %
$(\rho_d, \rho_t) = (4, 35)$	419,946	463,141	60.00 %	60.00 %
$(\rho_d, \rho_t) = (6, 20)$	451,217	477,089	60.00 %	60.00 %
$(\rho_d, \rho_t) = (6, 35)$	451,790	478,215	60.00 %	60.00 %

analysis. Decision-makers can pay more attention to predicting the relief demand. It is useful to use GIS and GPS to obtain the state of road networks and repair damaged roads. Real-time information, especially demand, can be obtained to improve the input parameters' reliability. Decision-makers can set the uncertainty budget depending on the timeless of information.

6.5. *Managerial implications*

The main outputs of the case study are the findings from numerical experiments, which provide many managerial implications to support relief kit assembly and distribution plans. Significantly, the results are not generalizable and depend on the parameter settings. Focusing on minimizing the total cost and maximizing the demand satisfaction, this study can help decision makers improve the effectiveness and efficiency in disaster response operations. The model considers relief kits, establishes DCs in different levels, and completes cannibalized relief distribution and relief kit distribution under demand and travel time uncertainties, which is highly impractical.

Some findings based on the numerical results are proposed as follows:

(i) Finishing relief kit assorting and packing in DCs is more applicable to post-disaster relief distribution systems than in DPs. As mentioned in Section 6.3, assorting and packing relief kits in advance cost less money and keep the same demand satisfaction. Decision makers should adopt the pattern and prepare in DCs to pack relief kits.

(ii) Under the same budget of uncertainty, the increase of vehicle capacity decreases the total cost considerably more than the available working time does, according to the sensitivity analysis in Sections 6.4.1 and 6.4.2. If decision makers have to limit the resources, decreasing the available working time will lead to less cost increase. Otherwise, increasing the vehicle capacity will lead to much more cost decrease. However, they can also make contracts with DCs to provide economies of scale to reduce cost per unit of loading.

(iii) Decision makers should determine the expected demand satisfaction in advance. As mentioned in Section 6.4.3, the more conservative the decision makers are, the higher the total cost will be, but the demand satisfaction will remain unchanged. However, for all SPs chosen to service the DCs in Section 6.2, the government can cooperate with the local potential SPs in advance to achieve economies of scale. Then, the fixed cost of SPs decreases, and the total cost can decrease, whereas the demand satisfaction is still in the same level.

7. Conclusion and future research

In disaster response phase, the affected areas demand several types of supply. Some emergency materials only make sense with the related ones, and there usually exists a fixed proportional relationship between them. Thus, we divide relief items into several kits. Furthermore, in view of the damage of disasters, the hybrid uncertainties of demand and travel time are also considered for relief distribution. In this paper, we optimize the relief kit assembly and distribution with two stages: cannibalized relief distribution and relief kit distribution. First, we propose nominal models for two stages. Stage 2 minimizes the distribution cost and maximizes the demand satisfaction simultaneously. Second, we adopt the epsilon-constraint method to transfer the Stage 2 model into an SO model and then reformulate the two-stage model into a min–max robust model, which minimizes the total cost. Finally, we reduce the uncertain sets into the supersets of their vertices to obtain the pareto fronts with different values of conservatism effectively.

The proposed min–max model is compared with DEM and two-stage stochastic model to demonstrate the robustness and effectiveness of the solution. The model is also implicated in a case study of relief distribution in Yunnan Province earthquakes. Some important practical insights and managerial implications are derived as follows. (i) Finishing relief kit assorting and packing in DCs is better than that in DPs. (ii) Increasing vehicle capacity reduces more total cost than available working time does. (iii) The risk preference of decision makers only influences the total cost, and the expected demand satisfaction should be determined in advance.

The min–max robust optimization method can be easily generalized to deal with two-stage multi-objective problems contain uncertainties in both left- and right- hand sides of its constraints. Apart from relief kit assembly and distribution problem, the method can be used in other cases. For example, power distribution system restoration integrates logistics support and repair crew scheduling and routing. The method can be adopted to optimize materials allocation and restoration schedule with complex geographical features.

On the basis of the limitation of this paper, we suggest further research directions as follows. (i) As the capacity of assembling relief kits plays a huge role in distribution process efficiency, the labor force in DCs must be considered. Thus, the optimization will fit the real situation better. (ii) Some relief items have a short shelf life, such as pharmaceutical and food. Therefore, the model should consider the perishability of items in special relief kits. (iii) As the rescue process will last for a few days, the relief distribution may not be complimented one time. Thus, optimizing a multi-period relief kit distribution would be of value. (iv) Data-driven predict method can be adopted to obtain the uncertainty set boundaries to improve the worst-case performance outcomes.

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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.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eswa.2022.119198.

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