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Multiperiod Optimal Allocation of Emergency Resources in Support of Cross-Regional Disaster Sustainable Rescue

Yanyan Wang[1]

Abstract Cross-regional allocation is necessary for the rational utilization and optimal allocation of resources. It is also the key to effective and sustainable disaster relief. Existing research, however, generally centers on emergency resource allocation only within territories or regions. This article proposes a multiperiod allocation optimization model for emergency resources based on regional self-rescue and cross-regional collaborative rescue efforts. The model targets the shortest delivery time and lowest allocation costs as its efficiency goals and the maximum coverage rate of resource allocation in the disaster-affected locations as its equity goal. An objective weighting fuzzy algorithm based on two-dimensional Euclidean distance is designed to solve the proposed model. A case study based on the Wenchuan Earthquake of 12 May 2008 was conducted to validate the proposed model. The results indicate that our proposed model allows for optimal, multiperiod cross-regional resource allocation by combining interterritorial and nearby allocation principles. Cross-regional relief makes resource allocation more equitable, minimizes dissatisfaction, and prevents losses. Different decision preferences appear to significantly affect the choice of resource allocation scheme employed, which provides flexibility for decision making in different emergencies.

Keywords Cross-regional collaborative rescue · Efficiency and equity · Emergency resource allocation · Multiperiod allocation · Wenchuan Earthquake

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1 Introduction

Large-scale disasters such as earthquakes, floods, wildfires, and hurricanes have grown increasingly frequent in recent years (Eshghi and Larson 2008; Qin et al. 2017; Ogie and Pradhan 2019), causing huge amounts of property damage, injuries, and fatalities (Chang et al. 2007; Najafi et al. 2013; Zhao and Liu 2017; Green et al. 2019). These disasters typically surpass urban and provincial boundaries and have significant cross-regional effects. In situations such as these, cross-regional emergency response becomes extremely important for post-disaster rescue (Shao et al. 2018). Government agencies have grown increasingly attentive to cross-regional collaborative emergency rescue as it can reduce disposal costs, optimize resource allocation processes, and improve the overall effectiveness of rescue operations. For example, the *Twelfth Five-Year Plan for Earthquake Emergency Rescue*, a guiding document issued by the China Earthquake Administration, notes that the emergency rescue agency should "strengthen cross-regional emergency cooperation, improve regional coordination mechanism, and promote linkage among government departments" (China Earthquake Administration 2012, p. 6).

Emergency resource allocation is the key factor to keep victims safe and facilitate the recovery and development of a disaster-stricken area (Hu, Wang et al. 2016). Sustainable emergency resource allocation (ERA) can ensure the effective operation and rational use of rescue-related resources while limiting casualties (Guo et al. 2019). In an actual ERA process in China, cross-regional cooperation is rare; with the "territory management" model, each region gives priority only to disaster-affected locations within its own territorial scope. Cross-regional disasters that result in multiple disaster-stricken sites require simultaneous ERA

in many separate locations, while resources may be limited in the initial stage of an emergency response. It is difficult to respond properly to a cross-regional disaster by solely relying on the emergency resources in a single administrative region. Therefore, it is necessary to develop a scientific and reasonable cross-regional ERA scheme to improve the overall effects of rescue operations, safeguard citizens' lives and property, and reduce the losses otherwise caused by insufficient total reserves of resources in a single disaster location.

Compared with traditional intraregional resource allocation problems, the cross-regional ERA problem constitutes a new research topic (Shao et al. 2018). The preferences of emergency managers play an important role in the selection and implementation of effective ERA schemes (Amailef and Lu 2013). The balance of different relief objectives, such as efficiency and equity, is a matter of great concern to policymakers (Hu, Liu et al. 2016).

A multiperiod resource allocation optimization model was established in this study as an extension of the traditional model from the cross-regional collaborative perspective. The proposed model centers on both the efficiency and equity of cross-regional resource allocation. The purpose of this model is to obtain an optimal ERA scheme by balancing these two objectives. The main contributions of this work can be summarized as follows:

- A cross-regional ERA model is developed that simultaneously considers efficiency and equity, and the trade-off between these two decision criteria is explored.
- An objective weighting fuzzy algorithm based on two-dimensional Euclidean distance (OWFA-TDED) is designed to analyze the impact of different managerial preferences on the multiperiod ERA scheme selection.
- The advantages of cross-regional ERA in achieving equitable resource allocation and sustainable relief are illustrated by comparing the multiperiod schemes of cross-regional and intraregional allocation.

The remainder of this article is organized in the following fashion. Section 2 introduces and analyzes the related work through a literature review. Section 3 describes the problem and assumptions. In Sect. 4, a cross-regional multiperiod ERA model is proposed. Section 5 designs the OWFA-TDED to solve the model. A case study of the Wenchuan Earthquake is used to test the feasibility and effectiveness of the proposed model in Sect. 6. Finally, the conclusion is stated in Sect. 7.

2 Literature Review

Many researchers have explored resource allocation in emergency logistics scenarios in recent years as the frequency and severity of disasters have continued to increase (Sheu and Pan 2014). Emergency resource allocation is a special type of resource allocation problem that mainly refers to the process of distributing limited resources to potentially competitive institutions and individuals in an optimized manner (Luss 1999; Yi and Özdamar 2007).

Previous research on ERA models has centered mainly on two objectives: efficiency and equity (Hoyos et al. 2015; Özdamar and Ertem 2015). The efficiency goal of the ERA model is primarily reflected in the shortest delivery time (Berkoune et al. 2012; Wex et al. 2014; Wang and Sun 2020) or the lowest allocation costs (Haghani and Oh 1996; Equi et al. 1997; Barbarosoğlu et al. 2002; Özdamar et al. 2004; Balcik and Beamon 2008; Arrubla et al. 2014; Minas et al. 2015; Zhou and Erdogan 2019). For example, Wang and Sun (2020) proposed an ERA model for natural hazard-related disaster rescue with the goal of minimizing the total delivery time for essential rescue and support resources. Zhou and Erdogan (2019) developed an integer two-stage stochastic goal programming model for wildfire response, which considers the lowest total emergency operation costs as an objective. Other models combine delivery time and allocation cost indicators—for example, Zhan et al. (2014) constructed an ERA model for super-typhoon emergency rescue based on disaster scenario information updates that minimizes both the total operating time and the resource transportation/procurement costs. Sheu and Pan (2014) designed a seamless centralized supply network for emergency logistics operations in response to large-scale natural hazard-related disasters, the main goals of which are minimal travel time and operational costs.

In addition to efficiency, another important objective of an ERA model in humanitarian relief operations is equity. When resources are limited in the early post-disaster stages, equitable allocation is very important for improving overall rescue effects (Huang and Rafiei 2019). Holguín-Veras et al. (2013) introduced deprivation cost into an ERA optimization model for post-disaster humanitarian logistics, which mainly depicts equity through a series of negative impacts caused by a lack of resources for certain victims. Wang et al. (2019) reflected equity through disutility losses in the case of emergency resource shortages. Cotes and Cantillo (2019) built a facility location model for prepositioning and allocating resources after flood disasters, where equity is measured by the lowest total social costs (including facilities costs, deprivation costs, inventory costs, and transportation costs).

More recent ERA researchers have considered both equity and efficiency (Bertsimas et al. 2012; Hu, Liu et al. 2016; Zhou et al. 2017). Tzeng et al. (2007) designed a multiobjective ERA model for natural hazard-related disaster relief that minimized total costs and total travel time while maximizing satisfaction. The first two objectives represent efficiency criteria and the third represents fairness (equity). Wang and Sun (2018) proposed a multiobjective ERA model for earthquake disaster relief, where efficiency is measured by allocation costs and equity is measured by losses due to insufficient resources. Liu et al. (2019) proposed a bi-objective medical resource allocation model that considers minimizing total operational costs as well as maximizing the number of expected survivals. These studies all centered on the intraregional allocation of emergency resources.

There is also a real need for large-scale, disaster emergency response that may be satisfied by effective cross-regional rescue operations (Groothedde et al. 2015). Tüfeki (1995) built a cross-regional comprehensive rescue system for hurricane response. Green and Kolesar (2004) found that cross-regional collaboration is an important development direction in the emergency management field. Researchers have since begun to prioritize cross-regional collaborative emergency response, achieved mainly via qualitative framework descriptions and quantitative modeling analyses. The former centers mostly on policy formulation (Rose and Kustra 2013), coordination modes (Calixto and Larouvere 2010; Xu et al. 2017), linkage systems (Wang and Lv 2016), collaborative mechanisms (Ansell et al. 2010; Liu et al. 2018), influencing factors (Boin et al. 2014; Olsson 2015), and decision support systems (Kutanoglu and Mahajan 2009; Li et al. 2014). The latter includes quantitative approaches such as the emergency coordination super-network model (Cao and Zhu 2014), fractal emergency coordination organization model (Li et al. 2017), system dynamics model of collaborative emergency (Zhu et al. 2017), regional collaborative game strategy selection model (Zhang et al. 2016; Qiu et al. 2019), and resource allocation model (Arora et al. 2010; Toro-Díazet al. 2013; Lv et al. 2018; Cao et al. 2019). Cao and Zhu (2014) developed a supernetwork model of urban agglomeration emergency coordination based on the stochastic user equilibrium assignment theory; they tested it via a case study of a cyanobacteria event at Taihu Lake in Jiangsu Province in 2007. Li et al. (2017) used fractal theory to build an emergency coordination organization model with the emergency task, emergency capacity, and emergency command units as key elements. They verified the flexibility and efficiency of the model by using a production safety accident in Tianjin Port as an example. Zhu et al. (2017) constructed a system dynamics model for the cross-regional, collaborative allocation of infectious disease emergency materials, which could be adjusted according to the demand in different regions. Zhang et al. (2016) presented a cross-regional emergency scheduling model for farm machinery with the goal of minimizing costs, and then designed a scheduling algorithm based on noncooperative game theory. Qiu et al. (2019) proposed an adaptive regional coordinated response strategy choice model for safety accidents under longitudinal administrative constraints based on evolutionary game theory; the primary concern of Qiu et al. was the impact of such constraints on cross-regional coordination. They analyzed the collaborative strategy selection and evolution path of local governments accordingly. Arora et al. (2010) proposed a resource allocation model for public health emergencies that prioritized equitable distribution through mutual aid between regions. Toro-Díaz et al. (2013) established a cross-regional joint location and distribution model for emergency medical services with the goal of minimizing the average response time. Lv et al. (2018) developed a cross-regional petroleum emergency distribution model based on a supernetwork theory that targeted minimal allocation costs and time. Cao et al. (2019) built a cross-regional emergency material allocation model centered on equity that considers survivors' risk acceptability and perceived satisfaction.

In summary, it is crucial to consider both efficiency and equity in the allocation of emergency resources. This brief review of research on cross-regional rescue operations provides a theoretical basis for our proposed cross-regional ERA model. There are still gaps in the existing quantitative cross-regional modeling research. Previous researchers have, for instance, mostly focused on public health events or safety accidents; there is a lack of cross-regional ERA research on earthquake disasters. Cross-regional ERA modeling analyses have rarely included both the efficiency and equity of multiple periods across their decision criteria and objectives. This article proposes a multiperiod and multiobjective ERA optimization model for earthquake disaster relief based on regional self-rescue and cross-regional collaborative rescue operations. The proposed model was designed to consider both the efficiency and the equity of the cross-regional ERA model. New metrics were developed to support these two criteria. This model allows decision makers to strike a balance between time and cost with the coverage rate in a manner that balances the efficiency and equity of ERA. An OWFA-TDED algorithm was established to solve the proposed model. This OWFA-TDED also reveals the impact of different decision-making preferences on the selection of multiperiod ERA schemes, which makes the proposed model applicable in different contexts.

3 Problem Description and Basic Assumptions

This section introduces the research problem in this study and presents the assumptions of model formulation.

3.1 Problem Description

As shown in Fig. 1, the research problem discussed in this article is the process of a large-scale disaster emergency rescue in which there are two or more administrative areas. Each administrative area has multiple resource supply points (rescue sites) and multiple resource demand points (affected locations). The multiperiod ERA optimization decision-making process is based on regional self-rescue and cross-regional collaborative rescue. To allocate emergency resources sustainably, a multiobjective optimization problem must be solved to minimize both the delivery time and costs and to maximize the ERA coverage rate across the disaster-affected locations. Sustainable rescue should not only meet the resource demand of the disaster-stricken locations in the current emergency period to the greatest extent, but also ensure that the ability of the rescue site to meet the needs of the disaster-stricken points will not be harmed in the future emergency period. It refers to making a scientific emergency resource allocation plan to achieve the multiperiod global optimal rescue effect. It is to formulate a resource allocation plan from the perspective of the optimal rescue effect of the entire emergency period (not only considering the resource allocation plan of a certain emergency period).
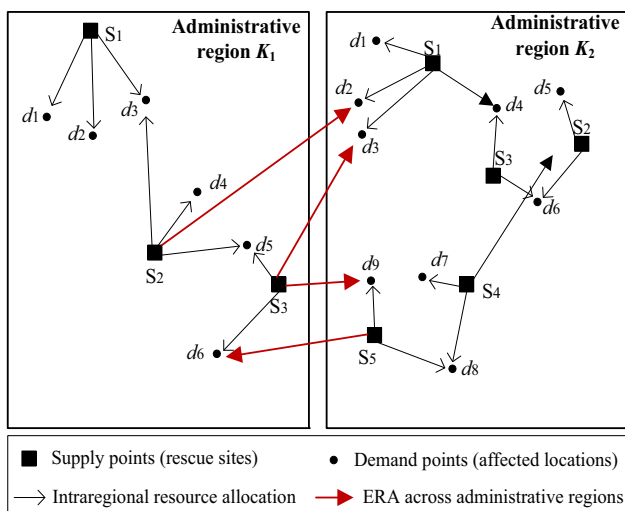
Fig. 1 Schematic diagram of emergency resource allocation (ERA) based on regional self-rescue and cross-regional collaborative rescue

3.2 Basic Assumptions

Assumption 1 The administrative regions are independent of one another and emergency relief resources can be transported among them.

Assumption 2 Each rescue site carries out ERA activities independently; there is no transfer and exchange of resources between them nor is there any interference between allocation routes.

Assumption 3 Large-scale disasters damage public infrastructure (for example, roads, bridges). The road from the rescue site to the disaster-affected location is considered here to be passable, but it may be damaged to some extent due to the disaster.

4 Model Formulation

This section explains the notation for model formulation and proposes a cross-regional multiperiod emergency resource allocation (ERA) model.

4.1 Notation

The notation (sets, indices, parameters, and variables) for a cross-regional multiperiod emergency resource allocation model is listed in Table 1.

4.2 Mathematical Model

The proposed cross-regional multiperiod emergency resource allocation (ERA) model aims to allocate all emergency resources to all demand points during all time periods with the shortest total delivery time (objective function 1), the lowest total costs (objective function 2), and the maximum coverage rate (objective function 3). Objective functions (1) and (2) pursue the efficiency goal and objective function (3) pursues the equity goal.

$$\min Z_1 = \sum_{i \in K} \sum_{j \in K} \sum_{s \in S} \sum_{d \in D} \sum_{u \in U} \sum_{t \in T} \beta_{s_i d_j}^t \cdot w_{s_i d_j}^u \cdot x_{s_i d_j}^{ut} \qquad (1)$$

$$\min Z_2 = \sum_{i \in K} \sum_{j \in K} \sum_{s \in S} \sum_{d \in D} \sum_{u \in U} \sum_{t \in T} c_{s_i d_j}^{ut} \cdot x_{s_i d_j}^{ut} \qquad (2)$$

$$\min Z_3 = \sum_{j \in K} \sum_{d \in D} \sum_{u \in U} \sum_{t \in T} \partial_{d_j}^{ut} \qquad (3)$$

$$\sum_{i \in K} \sum_{s \in S} x_{s_i d_j}^{ut} \le h_{d_j}^{ut} \quad \forall j \in K, d \in D, u \in U, t \in T, i \neq j \qquad (4)$$

$$\sum_{j \in K} \sum_{d \in D} x_{s_i d_j}^{ut} \le q_{s_i}^{ut} \quad \forall i \in K, s \in S, u \in U, t \in T, i \neq j \qquad (5)$$

Table 1 Notation for a cross-regional multiperiod emergency resource allocation model

Sets and indices

K Set of all administrative regions, $K = \{1, 2, \ldots, i, j, \ldots, n\}$, $i, j \in K$, $i \neq j$

S Set of supply points (rescue sites), $S = \{s | s = 1, 2, \ldots p\}$, $s \in S$, where S_i is the set of rescue sites in administrative region $i \in K$

D Set of demand points (affected locations), $D = \{d | d = 1, 2, \ldots v\}$, $d \in D$, where D_j is the set of affected locations in administrative region $j \in K$

U Set of types of emergency relief resources, $u \in U$

T Set of time periods of ERA, $t \in T$

Parameters

$h'^{ut}_{d_j}$ New demand for emergency resource u at affected location d in administrative region j during time period t

$h^{ut}_{d_j}$ Actual demand for emergency resource u at affected location d in administrative region j during time period t

$q'^{ut}_{s_i}$ New supply of resource u at rescue site s in administrative region i during time period t

$q^{ut}_{s_i}$ Actual supply of resource u at rescue site s in administrative region i during time period t

$c^{ut}_{s_i d_j}$ Variable cost per unit of allocating resource u from site s in region i to location d in region j during time period t

$w^{u}_{s_i d_j}$ Normal transporting time per unit of resource u from site s in region i to location d in region j during time period t

$\delta^{ut}_{d_j}$ Preset minimum coverage rate of resource u at location d in region j during time period t

$\beta^{t}_{s_i d_j}$ Road damage coefficient from site s in region i to location d in region j during time period t, where $\beta^{t}_{s_i d_j} \geq 1$; when the value is larger, the road condition is worse

Variables

$x^{ut}_{s_i d_j}$ Amount of resource u allocated to location d in region j from site s in region i during time period t

$\partial^{ut}_{d_j}$ Actual allocation coverage rate of resource u at location d in region j during time period t

$$\sum_{i \in K} \sum_{j \in K} \sum_{s \in S} \sum_{d \in D} x^{ut}_{s_i d_j} = \min \left\{ \sum_{j \in K} \sum_{d \in D} h^{ut}_{d_j}, \sum_{i \in K} \sum_{s \in S} q^{ut}_{s_i} \right\} \quad (6)$$
$$\forall u \in U, t \in T, i \neq j$$

$$\partial^{ut}_{d_j} \geq \delta^{ut}_{d_j} \quad \forall j \in K, d \in D, u \in U, t \in T \quad (7)$$

$$h^{ut}_{d_j} = h'^{ut}_{d_j} + \sum_{r=1}^{t-1} \left(h^{ur}_{d_j} - \sum_{i \in K} \sum_{s \in S} x^{ur}_{s_i d_j} \right) \forall j \in K, d \in D, u \in U, t \in T, i \neq j \quad (8)$$

$$q^{ut}_{s_i} = q'^{ut}_{s_i} + \sum_{r=1}^{t-1} \left(q^{ur}_{s_i} - \sum_{d \in D} \sum_{j \in K} x^{ur}_{s_i d_j} \right) \forall i \in K, s \in S, u \in U, t \in T, i \neq j \quad (9)$$

$$\partial^{ut}_{d_{b_j}} = \sum_{i \in K} \sum_{s \in S} x^{ut}_{s_i d_j} \Big/ h^{ut}_{d_j} \quad (10)$$
$$\forall j \in K, d \in D, u \in U, t \in T, i \neq j$$

$$x^{ut}_{s_i d_j} \geq 0 \quad \forall i \in K, j \in K, i \neq j, s \in S, d \in D, u \in U, t \in T \quad (11)$$

Constraint (4) shows the demand constraint, which ensures that the total amount of resources allocated to an affected location in a given period should not exceed the

actual demand at this affected location. Constraint (5) indicates the supply constraint, which guarantees that the amount of resources allocated from a rescue site to a demand point in a given period cannot exceed the actual available supply of the rescue point. Constraint (6) demonstrates the constraint to satisfy as much need as possible, which confirms that all relief resources should be allocated when demand outstrips supply in a given period. Constraint (7) defines that the ERA should meet the minimum allocation coverage rate. Constraint (8) denotes the dynamic change of the demand for emergency resources at the affected location in each time period. Constraint (9) represents the dynamic change of the supply at the rescue site in each time period. Constraint (10) is a formula for measuring the allocation coverage rate. Constraint (11) gives the nonnegative constraints of the decision variables.

5 Solution Method

This section analyzes the reasons for the selection of the solution method, introduces the basic definition of the objective weighted fuzzy algorithm based on two-dimensional Euclidean distance (OWFA-TDED), and designs an OWFA-TDED algorithm to solve the proposed model.

5.1 Basis for Method Selection

The proposed model is a multiobjective programming model that can be solved under multiobjective optimization theory. Commonly used solving methods mainly include the ideal point method, stratified sequencing method, step method, linear weighted method, constraint method, and minimax method (Xu and Li 2005). These approaches generally neglect decision-maker preferences in the process of multiobjective transformation (Yao and Xiao 2006). The various preferences of the decision maker influence the optimal solution of the model. In the proposed multiperiod ERA model, decision makers can choose a scientific resource allocation plan based on the actual disaster information of each time period in order to optimize the resource allocation in the entire period. The objective weighted fuzzy algorithm based on two-dimensional Euclidean distance (OWFA-TDED) can effectively resolve multiobjective optimization problems (Tang et al. 2012); an OWFA-TDED algorithm was designed in this study to solve the proposed multiobjective model, to obtain a highly scientific ERA scheme in various time periods, and to achieve sustainable disaster relief.

5.2 Basic Definition of the Objective Weighted Fuzzy Algorithm Based on Two-Dimensional Euclidean Distance (OWFA-TDED)

Definition 1 For a general model of multiobjective decision problems,

$$\max/\min \quad Z(x) = [Z_1(x), Z_2(x), \ldots, Z_n(x)] \tag{12}$$

$$s.t. x \in Z(x) \tag{13}$$

let

$$\begin{cases} Up_y = \underset{x \in X}{large}\{Z_y(x)\} \\ Down_y = \underset{x \in X}{small}\{Z_y(x)\} \end{cases} \quad y = 1, 2, \ldots, n \tag{14}$$

then, Up_y and $Down_y$ are the upper and lower bounds of the objective $Z_y(x)$ in X, respectively.

Definition 2 The optimal membership degree (satisfaction function) $\lambda_y(x)$ of the decision maker to the objective $y(y = 1, 2, \ldots, n)$ is defined as follows:

For benefit-oriented objectives $Z_y(x)$,

$$\lambda_y(x) = \left(Z_y(x) - small\{Z_y(x)\}\right) / \left(large\{Z_y(x)\} - small\{Z_y(x)\}\right) \tag{15}$$

For cost-oriented objectives $Z_y(x)$,

$$\lambda_y(x) = \left(large\{Z_y(x)\} - Z_y(x)\right) / \left(large\{Z_y(x)\} - small\{Z_y(x)\}\right) \tag{16}$$

Definition 3 The fuzzy negative ideal solution x^- and fuzzy positive ideal solution x^+ make $\lambda_y(x)$ of all $Z_y(x)$ take the minimum value and the maximum value, respectively. The optimal membership degree vectors at the fuzzy negative and positive ideal solutions are, respectively,

$$u = (\lambda_1(x^-), \lambda_2(x^-), \ldots, \lambda_n(x^-))^T = (0, 0, \ldots, 0)^T \\ \lambda_y(x) = 0, y = 1, 2, \ldots n \tag{17}$$

$$v = (\lambda_1(x^+), \lambda_2(x^+), \ldots, \lambda_n(x^+))^T = (1, 1, \ldots, 1)^T \\ \lambda_y(x) = 1, y = 1, 2, \ldots n \tag{18}$$

5.3 Solution Steps and Procedures

Step 1 Calculate the maximum and minimum values (upper and lower bounds) of each objective function $Z_y(x)$ within the given constraints, which are recorded as $large\{Z_y(x)\}$ and $small\{Z_y(x)\}$, respectively.

Step 2 Calculate the optimal membership degree $\lambda_y(x)$ of each objective function $Z_y(x)$.

Step 3 Determine the ideal weight (decision preference coefficient) ω_y of each objective function $Z_y(x)$ and satisfy $\sum_{y=1}^{n} \omega_y = 1$. The weighting coefficient can be determined by decision makers according to various factors such as the severity of the disaster, the urgency of demand, and the actual situation of supply in the time period at hand. The effective solution of the model should be as close as possible to the positive fuzzy ideal solution. A two-dimensional Euclidean distance is used here to represent the maximum and minimum values.

$$\sum_{y=1}^{n} \omega_y^2 \left[\lambda_y(x) - u_y\right]^2 = \sum_{y=1}^{n} \omega_y^2 \lambda_y^2(x) \tag{19}$$

$$\sum_{y=1}^{n} \omega_y^2 \left[v_y - \lambda_y(x)\right]^2 = \sum_{y=1}^{n} \omega_y^2 \left[1 - \lambda_y(x)\right]^2 \tag{20}$$

Step 4 Convert the original multiobjective model into a single-objective model

$$\max \sum_{y=1}^{n} \omega_y^2 \lambda_y^2(x) + \left[1 - \sum_{y=1}^{n} \omega_y^2 \left[1 - \lambda_y(x)\right]^2\right] \tag{21}$$

and meet the following constraint:

$$\sum_{y=1}^{n} \omega_y = 1, \quad x \in X \tag{22}$$

Step 5 Solve the converted single-objective model in MATLAB software. Construct a Lagrangian function and make the partial derivatives of ω_y, x_y, and σ all equal to zero.

$$Z(\omega_y, x_y, \sigma) = \sum_{y=1}^{n} \omega_y^2 \lambda_y^2(x) + \left[1 - \sum_{y=1}^{n} \omega_y^2 [1 - \lambda_y(x)]^2\right]$$
$$- \sigma\left(\sum_{y=1}^{n} \omega_y - 1\right)$$

(23)

The solution idea and process of the proposed model are shown in Fig. 2, and defined below.

6 Computational Case

In this section, a case study of the Wenchuan Earthquake is used to test the feasibility and effectiveness of the proposed model.

6.1 A Case Study of the Wenchuan Earthquake

A magnitude 8.0 earthquake occurred at 14:28:04 a.m., China Standard Time, on 12 May 2008 in Wenchuan County, Sichuan Province. More than 100,000 km^2 were seriously damaged. There were 10 counties (cities) in the most severe disaster area, 41 counties (cities) in the moderately severe disaster area, and 186 counties (cities) in the general disaster area. Many provincial-level administrative regions, including Sichuan, Gansu, Shaanxi, Guizhou, Yunnan, Chongqing, Hubei, Hunan, and Henan, were affected by the earthquake (China News Network 2008). This study considered some of the severely affected administrative regions, such as Sichuan Province (SC), Gansu Province (GS), and Shaanxi Province (SX), as shown in Table 2. Chengdu (CD), Lanzhou (LZ), and Xi'an (XA) were selected as the rescue sites for ERA; tents (TT) and instant noodles (IN) were selected as the required emergency resources. We used 24 hours as a period to analyze the ERA in the first five days after the disaster.

Relevant data for the computation were chosen by using a combination of real and hypothetical data, since some disaster data could not be obtained through official reports. The demand for resources at different affected locations (Table 3) can be estimated based on the number of victims and the severity of the disaster. For example, the demand for TT and IN in Wenchuan County in the first period was estimated in the following way. Wenchuan County (WC) had 18,000 victims in the first period, a tent is assumed to be 5 m by 6 m and able to hold 10−12 people, and a case of instant noodles contains 16 containers of 108 g each, which can feed 4−5 people for a day; therefore, the demand for TT is equal to 18,000/[10, 12] ≈ 1,800, and the demand for IN is 18,000/[4, 5] ≈ 4,000. The resource storage of three supply sites before the disaster and the mobilization ability during the disaster were obtained via

field investigation and interviews with relevant personnel. The resource supply at each supply site was estimated accordingly, as shown in Table 4. There were 2,500 tents stored in Chengdu before the disaster and 500 gathered during rescue operations, so the total tent supply was 3,000. The road damage coefficients from rescue sites to affected locations per period (Table 5) were estimated based on the intensity and number of aftershocks. The value of the road damage coefficient is greater than or equal to 1. In this case, the value range was assumed to be [1, 1.5]. Among the eight selected affected locations, WC is the most severely damaged by the earthquake and is the location of the highest earthquake intensity and most aftershocks, so it has the largest road damage coefficient (1.5) in the first period of post-earthquake rescue. Conversely, Chencang District (CC) is relatively far away from the epicenter and its roads were less damaged by the earthquake, so its road destruction coefficient is the smallest in the first period (1). The minimum coverage rate of ERA at affected locations in each period was set here as $\delta = 0.6$, as 60% typically represents a passing level. Each affected location could obtain 60% or more of the required rescue resources in this case, which allows the proposed model to effectively serve disaster victims by providing resources. The transportation time of allocating resources from rescue sites to affected locations in nondisaster situations was obtained through
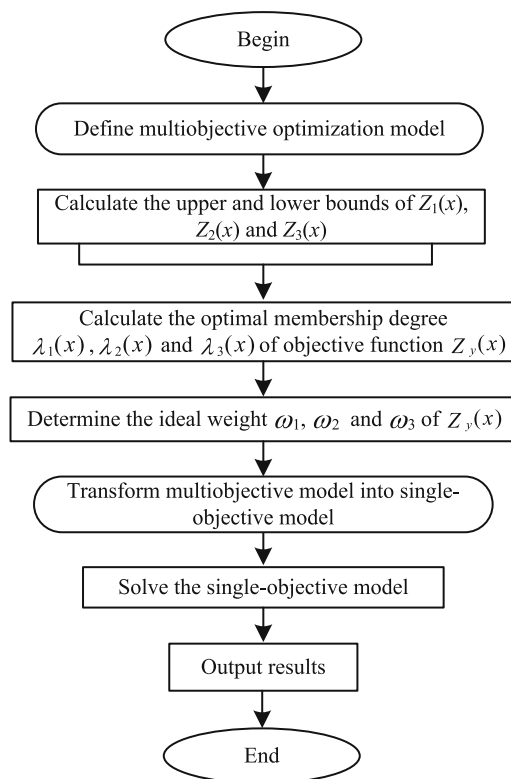

Fig. 2 Solution idea and process of the proposed model

Table 2 Administrative regions, disaster areas, demand points in the Wenchuan Earthquake impact area

Administrative region	Disaster area	Demand point (affected location)
Sichuan (SC)	Tibetan Qiang Autonomous Prefecture of Ngawa (AB)	Wenchuan County (WC)
		Mao Xian (MX)
	Mianyang City (MY)	Beichuan Qiang Autonomous County (BC)
	Deyang City (DY)	Mianzhu City (MZ)
Ganshu (GS)	Longnan City (LN)	Wudu District (WD)
		Wenxian County (WX)
	Gannan Tibetan Autonomous Prefecture (GN)	Zhouqu County (ZQ)
Shaanxi (SX)	Baoji City (BJ)	Chencang District (CC)

Table 3 Resource demand for locations affected by the Wenchuan Earthquake

Affected locations	Period					Total
	1	2	3	4	5	
WC	(1800;4000)	(600;5000)	(300;6000)	(300;7000)	(100;8000)	(3100;30000)
MX	(1600;4000)	(500;5000)	(300;5000)	(200;6000)	(100;7000)	(2700;27000)
BC	(1500;3500)	(400;4500)	(200;5000)	(100;5000)	(100;6000)	(2300;24000)
MZ	(1300;3000)	(400;4000)	(200;5000)	(100;5000)	(100;5000)	(2100;22000)
WD	(1000;2500)	(400;3000)	(300;4000)	(200;5000)	(100;6000)	(2000;20500)
WX	(800;2000)	(300;2500)	(300;3000)	(100;4000)	(100;5000)	(1600;16500)
ZQ	(600;1500)	(300;2000)	(200;2500)	(100;3000)	(100;4000)	(1300;13000)
CC	(500;1500)	(200;2000)	(100;2500)	(100;3000)	(100;3500)	(1000;12500)
Total	(9100;22000)	(3100;28000)	(1900;33000)	(1200;38000)	(800;44500)	(16100;165500)

A and B columns for each time period represent the demands for TT (tents) and IN (instant noodles), respectively. Tent demand reflects the number of ten-person-capacity tents required to minimally support homeless victims, and food demand is measured by the number of instant noodle cases needed to support the impacted population for a day. Each time period is one 24 hour day. Affected locations are: WC = Wenchuan County; MX = Mao Xian; BC = Beichuan Qiang Autonomous County; MZ = Mianzhu City; WD = Wudu District; WX = Wenxian County; ZQ = Zhouqu County; CC = Chencang District

Table 4 Resource supply at the rescue sites before the earthquake

Rescue sites	Period					Total
	1	2	3	4	5	
CD	(3000;8000)	(2000;16000)	(1300;21000)	(800;25000)	(600;30000)	(7700;100000)
LZ	(1500;4000)	(1000;4000)	(1000;5000)	(500;7000)	(400;13000)	(4400;33000)
XA	(1500;2000)	(1300;5000)	(600;7000)	(500;9000)	(500;12000)	(4400;35000)
Total	(6000;14000)	(4300;25000)	(2900;33000)	(1800;41000)	(1500;55000)	(16500;168000)

A and B columns for each one-day time period represent the stockpiles for TT (tents) and IN (instant noodles), respectively. Rescue sites are: CD = Chengdu; LZ = Lanzhou; XA = Xi'an

Table 5 Road damage coefficients from rescue sites to affected locations per period

Affected locations	Rescue sites														
	CD					LZ					XA				
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
WC	1.5	1.4	1.3	1.2	1	1.4	1.3	1.2	1.1	1	1.4	1.3	1.2	1.1	1
MX	1.4	1.3	1.3	1.1	1	1.3	1.2	1.2	1.1	1	1.3	1.2	1.1	1.1	1
BC	1.4	1.3	1.2	1.1	1	1.3	1.2	1.1	1.1	1	1.3	1.2	1.1	1.1	1
MZ	1.3	1.2	1.2	1.1	1	1.2	1.2	1.1	1.1	1	1.2	1.2	1.1	1.1	1
WD	1.4	1.3	1.3	1.1	1	1.4	1.3	1.2	1.1	1	1.3	1.2	1.2	1.1	1
WX	1.3	1.2	1.2	1.1	1	1.2	1.2	1.1	1.1	1	1.2	1.2	1.1	1.1	1
ZQ	1.4	1.3	1.2	1.1	1	1.3	1.2	1.2	1.1	1	1.4	1.3	1.2	1.1	1
CC	1.2	1.2	1.1	1.1	1	1.2	1.1	1.1	1.1	1	1.2	1.1	1.1	1.1	1

Rescue sites are: CD = Chengdu; LZ = Lanzhou; XA = Xi'an. Affected locations are: WC = Wenchuan County; MX = Mao Xian; BC = Beichuan Qiang Autonomous County; MZ = Mianzhu City; WD = Wudu District; WX = Wenxian County; ZQ = Zhouqu County; CC = Chencang District

Google Maps, as shown in Table 6. The costs of allocating one unit of resources from rescue sites to affected locations (Table 7) can be calculated according to the distance and the transport cost per kilometer. The distance from rescue sites to affected locations was obtained via Google Maps and the average transportation cost per kilometer per unit resource under road transportation mode was determined to be RMB 0.7 yuan.[1] The computational case was solved by using MATLAB R2016a on a computer with an Intel(R) Core(TM) 1.90 GHz processor with 16.0 GB of RAM.

6.2 Result Analysis

This section analyzes the two computational results. The first example illustrates the influence of different ideal weights (preference coefficients) on emergency resource allocation (ERA), and the second example illustrates the advantages of the proposed multiperiod cross-regional ERA model.

6.2.1 Influence of Different Ideal Weights (Preference Coefficients) on Emergency Resource Allocation (ERA)

The objective function values (total delivery time, total cost, and total coverage rate of resource allocation) under different decision-making preference coefficients are shown in Fig. 3. The values of 0, 0, 1 denote $\omega_1 = 0, \omega_2 = 0, \omega_3 = 1$ in this figure, and similarly below. From Fig. 3, we can see that different decision-making preference coefficients (ideal weights) have an important influence on

Table 6 Normal transportation time per unit of resource from rescue sites to affected locations (Unit: hours)

| Rescue sites	WC	MX	BC	MZ	WD	WX	ZQ	CC
CD	2	3	3.5	1.5	6.5	7	8	9
LZ	13	12	13	11.5	6.5	10	7.5	6.5
XA	10.5	10.5	10	8.5	7	9	8.5	2

Rescue sites are: CD = Chengdu; LZ = Lanzhou; XA = Xi'an. Affected locations are: WC = Wenchuan County; MX = Mao Xian; BC = Beichuan Qiang Autonomous County; MZ = Mianzhu City; WD = Wudu District; WX = Wenxian County; ZQ = Zhouqu County; CC = Chencang District

Table 7 Costs of allocating per unit of resource from rescue sites to affected locations (Unit: yuan)

Rescue sites	WC	MX	BC	MZ	WD	WX	ZQ	CC
CD	100	120	150	75	270	280	300	340
LZ	500	380	480	460	270	340	190	250
XA	380	325	350	330	225	310	305	80

Rescue sites are: CD = Chengdu; LZ = Lanzhou; XA = Xi'an. Affected locations are: WC = Wenchuan County; MX = Mao Xian; BC = Beichuan Qiang Autonomous County; MZ = Mianzhu City; WD = Wudu District; WX = Wenxian County; ZQ = Zhouqu County; CC = Chencang District

the ERA scheme selection. As the weight of the time and cost decision coefficients gradually increases, the objective values of the total time and total costs gradually decrease. When the weights of time and costs (efficiency) are greater

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[1] USD 1 = RMB 6.95 yuan.

than the weight of the coverage rate (equity), decision makers are more inclined to send resources to each disaster-affected point with the least time and the lowest cost. Conversely, when the weight of the coverage rate (equity) is greater than the weight of time and costs (efficiency), the decision maker prefers to make the ERA more equitable (maximize the coverage).

Figure 4 shows the trends in delivery time, costs, and coverage rate of ERA per period in the two cases of ideal weights $\omega_1 = 0.1$, $\omega_2 = 0.1$, $\omega_3 = 0.8$ and
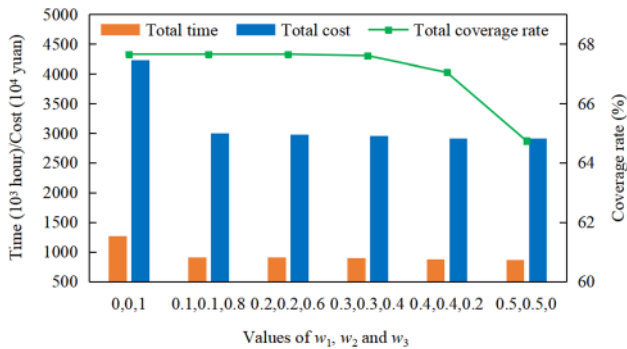
Fig. 3 Total delivery time, total costs, and total coverage of emergency resource allocation (ERA) under different decision-making preferences

$\omega_1 = 0.4$, $\omega_2 = 0.4$, $\omega_3 = 0.2$. In both cases, the delivery time, costs, and coverage rate all gradually increase as the supply of resources per period gradually increases as rescue activities develop. To compensate for the large amount of material shortfalls in the initial period of rescue, a large amount of resources need to be allocated to the disaster sites in the middle and late periods of the emergency. Higher total allocation time and total costs are generated in the middle and later periods versus the early period of the emergency, and, simultaneously, the coverage rate improved.

Higher time and cost (efficiency) weights result in lower delivery time and costs (Fig. 4a and b) but also lead to a relatively low coverage rate (equity) (Fig. 4c). In the case of limited supplies, considering the time and costs, priority is often given to the nearest disaster-stricken locations. Conversely, if the decision maker prefers a higher coverage rate (equity) coefficient weight, this produces higher delivery time and costs. Improving the coverage rate (equity) of ERA may require allocating resources to disaster-stricken locations that are relatively far away and severely affected.

It is not appropriate to consider the efficiency (time and costs) or equity (coverage rate) preference coefficient alone in the process of multiperiod resource allocation. The


(a) Change trend of delivery time

(b) Change trend of costs

(c) Change trend of coverage
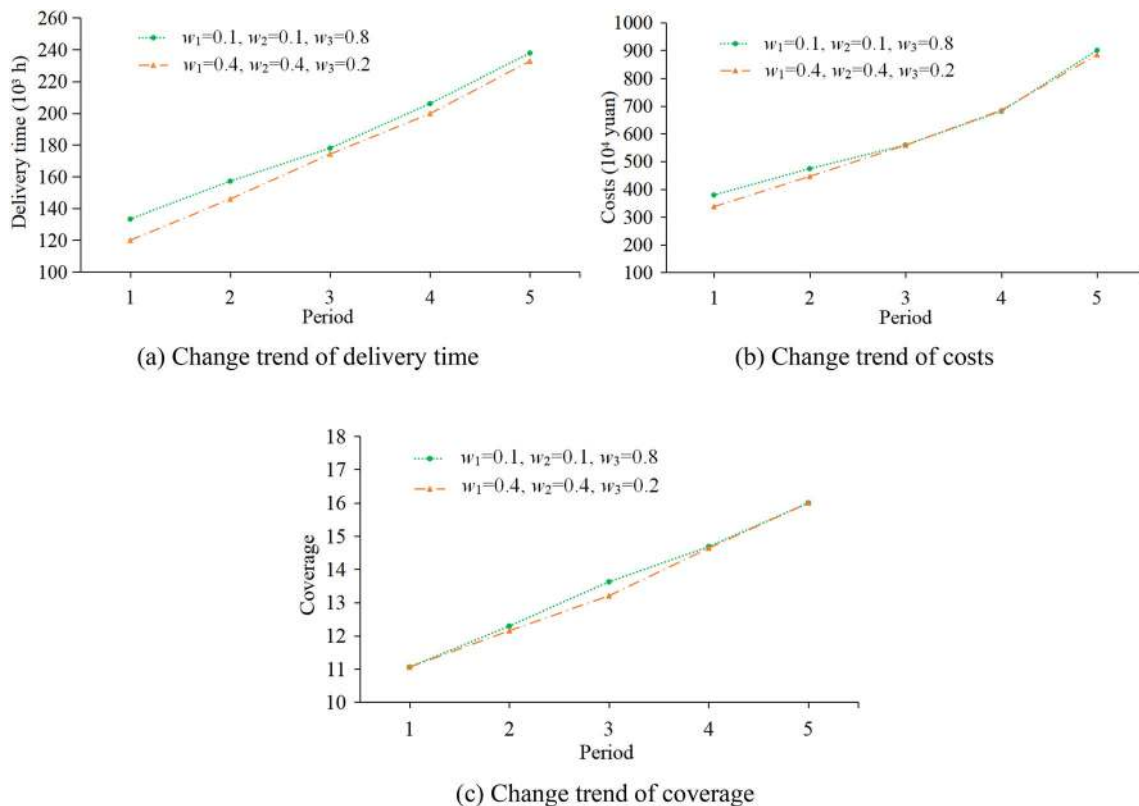
Fig. 4 Change trends of delivery time, costs, and coverage of ERA in each period when $\omega_1 = 0.1$, $\omega_2 = 0.1$, $\omega_3 = 0.8$ or $\omega_1 = 0.4$, $\omega_2 = 0.4$, $\omega_3 = 0.2$. Note: Each time period represents a 24 hour day

optimal weight combination depends on the goal (efficiency or equity) that the decision maker seeks to achieve, which provides some flexibility for decision making. In general, the best combination strikes a balance between efficiency and equity. When choosing the preference coefficient, decision makers should scientifically grasp the choice of "degree" and fully consider the effects of combining efficiency and equity.

6.2.2 Advantages of the Proposed Multiperiod Cross-Regional ERA Model

To illustrate the advantages and effectiveness of the proposed multiperiod cross-regional ERA model, this study compared the resource coverage rate between the multiperiod schemes of cross-regional allocation and intraregional allocation ($\omega_1 = 0.3, \omega_2 = 0.3, \omega_3 = 0.4$), as shown in Fig. 5. The resource coverage rates of the two cases differ significantly. In the cross-regional allocation scheme, the coverage rate of the two resources shows an upward trend with the increase in the emergency period. At the end of the fifth period, the overall coverage rate of all types of resources reaches 100%; that is, the demand of all disaster-affected locations is met after the resource allocation of the entire emergency period. In the case of intraregional allocation, however, the coverage rate of tents shows a downward trend with the increase of the emergency period. Although the coverage rate of instant noodles increases after the third period, it only reaches 70% in the fifth period; this does not meet all the resource requirements of the disaster-stricken areas. Cross-regional allocation allows for the free distribution and mutual exchange of resources among different regions. Intraregional allocation requires that supply points only allocate resources to the affected locations in their own regions, and does not allow for allocation to other regions even if there is surplus. As shown in Fig. 6, intraregional allocation may result in extreme redundancy of resources in some regions and scarcity in others (for example, the rescue site XA has a surplus of resources in each period that increases over time, but there is a serious shortfall of resources at the CD and LZ rescue sites). When supply and demand are imbalanced and shortfalls are gradually increasing, if cross-regional allocation is not carried out, disaster-affected locations with extreme shortfalls will face serious losses due to unsatisfied resource demand.

The resource coverage rates between the multiperiod cross-regional allocation and one-period intraregional allocation ($\omega_1 = 0.3, \omega_2 = 0.3, \omega_3 = 0.4$) are shown in Fig. 7. Under the multiperiod cross-regional allocation scheme (Fig. 7a), the coverage rates of TT and IN at each affected location in each time period are all greater than or equal to 60% and gradually increase until the fifth period
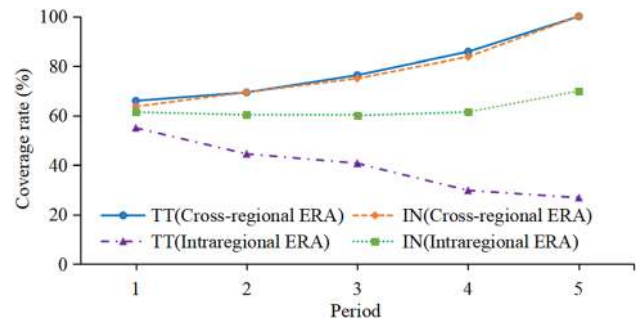
Fig. 5 Multiperiod allocation coverage rate of tents (TT) and instant noodles (IN) with cross-regional versus intraregional model ($\omega_1 = 0.3, \omega_2 = 0.3, \omega_3 = 0.4$)
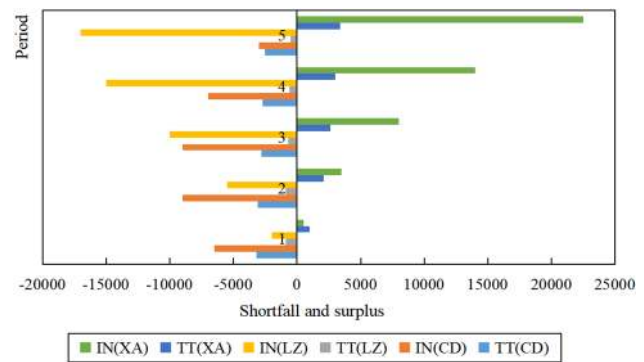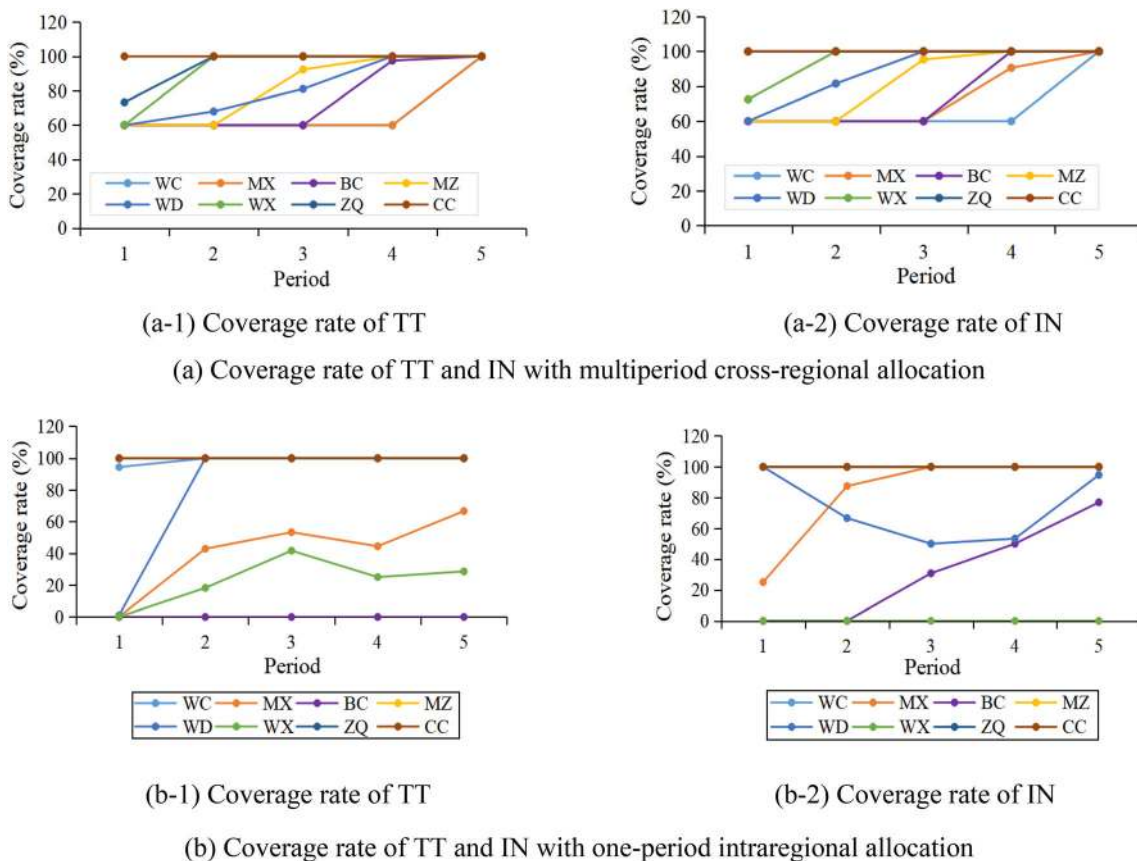

Fig. 6 Shortfall and surplus of resources at rescue site in each period with intraregional allocation Note: Resource availability is indicated for IN (instant noodles) and TT (tents); Shortfalls and surpluses of these commodities occur in XA (Xi'an); LZ (Lanzhou); and CD (Chengdu)

reaches 100%. Conversely, under the one-period intraregional allocation scheme (Fig. 7b), the resource coverage rate of most disaster-affected locations is less than 60% (for example, MX, BC, and WX). The coverage rate of tents at the affected location BC and the coverage rate of instant noodles at the affected location WX are all zero in each period, indicating that these two disaster-affected locations will face serious negative effects due to resource shortfalls.

As also shown in Fig. 7, under the two allocation schemes, the affected location CC has the highest coverage rate and reaches 100% in each period. The supply of resources in administrative region XA, where the disaster-stricken site CC is located, is sufficient throughout the post-disaster period; thus, the demand of CC could be fully met in each period.

The multiperiod cross-regional resource allocation path, shortfall, and coverage rate of each affected location are shown in Fig. 8. As cross-regional rescue activities develop, the resource coverage rate of each affected location gradually increases and the number of affected

(a-1) Coverage rate of TT

(a-2) Coverage rate of IN

(a) Coverage rate of TT and IN with multiperiod cross-regional allocation

(b-1) Coverage rate of TT

(b-2) Coverage rate of IN

(b) Coverage rate of TT and IN with one-period intraregional allocation

Fig. 7 Coverage rate of tents (TT) and instant noodles (IN) with a multiperiod cross-regional model versus a one-period intraregional model ($\omega_1 = 0.3, \omega_2 = 0.3, \omega_3 = 0.4$). Note: Coverage rate of TT (tents) and IN (instant noodles) is provided for WC (Wenchuan County); MX (Mao Xian); BC (Beichuan Qiang Autonomous County); MZ (Mianzhu City); WD (Wudu Distric); WX (Wenxian County); ZQ (Zhouqu County), and CC (Chencang District)

locations with resource shortfalls gradually decreases. By the fifth period, all affected locations have met their demand for resources. Among them, the administrative region CD has many disaster-stricken locations (including WC, MX, BC, and MZ), but its resource supply is seriously insufficient (especially in the first three periods) for most of the five day period. To ensure ERA equity, administrative regions LZ and XA carry out cross-regional resource allocation for CD so that the coverage rate at each affected location in administrative region CD for TT and IN reaches 60% in each period. The proposed multiperiod ERA model based on regional self-rescue and cross-regional collaborative rescue thus appears to mitigate resource shortage problems at various affected locations. Although the supply is limited in the early period of the emergency response, a certain proportion of required resources can still be obtained for the affected locations via cross-regional collaborative rescue, thus ensuring the equitable, multiperiod allocation of resources, while optimizing overall effect and efficiency, and ultimately achieving sustainable disaster relief.

7 Conclusion

It is necessary to scientifically and reasonably utilize limited emergency resources for sustainable post-disaster rescue response. This study was conducted to enrich the existing research on multiperiod cross-regional ERA. First, we formulated ERA as a multiperiod and multiobjective programming problem. We then constructed a cross-regional multiperiod ERA optimization model that considers both equity and efficiency. The goal is to optimize the ERA scheme by making a trade-off between these two decision criteria. An objective weighting fuzzy algorithm based on two-dimensional Euclidean distance (OWFA-TDED) algorithm was designed to solve the proposed model.

The computational results presented here provide several insights into cross-regional ERA with respect to the sustainability of multiperiod rescue operations. First, different decision preference coefficients were shown to have an important influence on the ERA scheme selection. A single consideration of efficiency or equity preference coefficient is one-sided; the optimal combination strikes a balance between them. Decision makers should fully

(a) Period 1

(b) Period 2

(c) Period 3
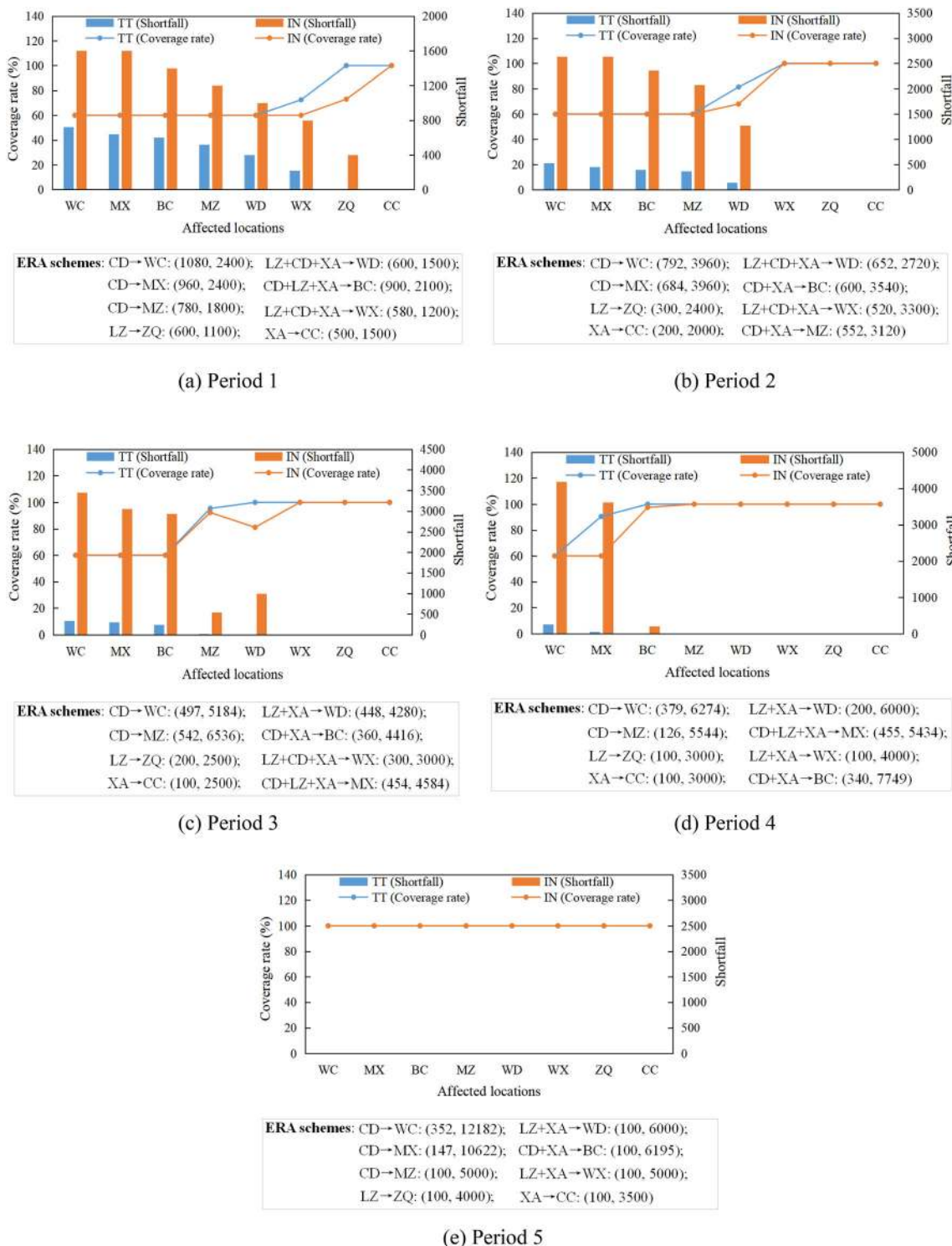
(d) Period 4

(e) Period 5

Fig. 8 Multiperiod cross-regional allocation path, shortfall, and coverage rate with $\omega_1 = 0.3, \omega_2 = 0.3, \omega_3 = 0.4$. Note: Rescue sites are: CD = Chengdu; LZ = Lanzhou; XA = Xi'an. Affected locations are: WC = Wenchuan County; MX = Mao Xian; BC = Beichuan

Qiang Autonomous County; MZ = Mianzhu City; WD = Wudu District; WX = Wenxian County; ZQ = Zhouqu County; CC = Chencang District

consider the advantages of combining efficiency and equity. Second, the proposed multiperiod cross-regional ERA model was compared against a multiperiod

intraregional ERA model and a one-period intraregional ERA model to find that our model effectively improves coverage rates, ensures the multiperiod equity of ERA, and

satisfies the demands for multiperiod sustained emergency rescue. The proposed model was evaluated to emphasize the importance of considering multiperiod ERA from a cross-regional perspective for the realization of sustainable disaster relief.

In the future, the realism and complexity of this model can be further improved. The allocation of emergency resources is affected by many factors, such as vulnerability of the affected location, urgency of demand, and particularity of the victims. These factors affect the quantity, type, and structure of emergency resource allocation. More specificity about these factors would make a much stronger case for support of a more comprehensive and inclusive model. It will be beneficial to consider the influence of such factors on the dynamic multiperiod allocation of large-scale cross-regional emergency resources in real-world scenarios.

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