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Research Article

Two-Stage Robust Counterpart Model for Humanitarian Logistics Management

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In the early stages of a major public emergency, decision-makers were troubled by the timely distribution of a large number of donations. In order to distribute caring materials reasonably and efficiently, considering the transportation cost and time delay cost, this paper takes the humanitarian logistics management as an example to study the scheduling problem. Based on the actual situation of insufficient supply during the humanitarian logistics management, this paper using optimization theory establishes a two-stage stochastic chance constrained (TS-SCC) model. In addition, due to the randomness of emergency occurrence and uncertainty of demand, the TS-SCC model is further transformed into the two-stage robust counterpart (TS-RC) model. At the same time, the validity of the model and the efficiency of the algorithm are verified by simulations. The result shows that the model and algorithm constructed are capable to obtain the distribution scheme of caring materials even in worst case. In the TS-BRC (with box set) model, the logistics service level increased from 89.83% to 93.21%, while in the TS-BPRC (with mixed box and polyhedron set) model, it increases from 90.32% to 94.96%. Besides, the model built in this paper can provide a more reasonable dispatching plan according to the actual situation of caring material supply.

1. Introduction

In recent decades, the global ecological environment has deteriorated dramatically. The frequent occurrence of major public emergencies not only poses a great threat to people's life and health but also hinders the national economic operation. In disaster area, not only casualties and economic losses will occur but also local transportation and communication will be paralyzed. Emergencies generally cover a wide range and have a great impact on current society and long-term development. Muhammad et al. found that dengue fever causes about 100 million infections per year [1]. Due to the randomness of emergencies, management departments cannot cope with excessive relief work in time in actual relief work, which leads to further aggravation of the severity of emergencies [2, 3]. It is necessary to study humanitarian logistics. Humanitarian logistics is an activity for emergency rescue in response to natural disasters, production accidents, and other emergencies [4]. When the emergencies occur, humanitarian logistics can quickly make judgments and deliver materials to disaster areas and personnel. In the process of crisis resolution, reasonable planning of humanitarian logistics plays an important role. Humanitarian logistics can effectively respond to emergencies and not only improve logistics efficiency but also accelerate the rescue speed, which helps to reduce the adverse impact of emergencies.

At present, many scholars focus their research on humanitarian logistics mainly on deterministic conditions, but do not discuss uncertainties. The research on humanitarian logistics can be divided into two aspects: location selection and distribution. In terms of logistics facility location, Amideo et al. discussed the challenges of optimizing models in the context of deterministic shelter location and evacuation routes [5]. Yi and Özdamar established the deterministic humanitarian logistics location model to minimize material relief and personnel treatment delays [6]. Widener et al. discussed material issues and established a layered location model for disaster relief materials [7]. Wohlgemuth et al. established a dynamic vehicle routing optimization model for deterministic demand with minimum time delay [8]. Chou et al. developed a dynamic optimal path model to study resource allocation and vehicle routing problems [9]. These studies provide a good reference for emergency management, but can be further incorporated into uncertain optimization studies. In terms of emergency material allocation, some scholars have studied its uncertainty and irregularity [10, 11]. Okumura studied the distribution and delivery of local, municipal and national warehouses for emergency material management [12]. The above study discussed the distribution, management, and system of emergency materials, but neglected the uncertainty of emergency demand and distribution of emergency resources. These research studies have explored the system model of humanitarian logistics location and material distribution, respectively, and provided effective suggestions for emergency management, but the disadvantage is that they neglect the uncertainty of the problem itself and data on the premise of defining conditions. Therefore, these studies have shortcomings in practical application and cannot cope with the situation of stochastic.

In traditional emergency dispatch management research, many scholars focus on single-stage uncertainty research, while few experts focus on two-stage stochastic programming. The two-stage stochastic optimization model is widely used in financial investment, supply chain management, emergency material dispatching, industrial engineering, and smart grid. Some scholars have studied the problem of random or uncertain real scenes [13, 14]. Yasari et al. established a two-stage stochastic chance constrained model for the two-stage optimization problem and solved it by heuristic algorithm [15]. Dillon et al. studied the optimization of blood supply chain network using a two-stage stochastic optimization model [16]. Christoph et al. studied two-stage optimization of supply chain network with delayed payment strategy under uncertain demand [17]. Chen et al. studied the problem of the size of a dedicated service station with opportunity constraints using two-stage distributed robust optimization models [18, 19]. All of the above are recent studies on the two-stage optimization model. Research involves how to model, how to solve the model, and even how to upgrade the algorithm. These phenomena show that the two-stage optimization model has been recognized by the majority of scholars and gradually widely used in practice. Solving a two-stage stochastic optimization model is usually complicated because it requires calculating the expected value of a multivariable. Scenario-based stochastic optimization is a common method to solve two-stage stochastic optimization problems. Maggioni et al. [20] and Venkitasubramony and Adil [21] considered using the discrete scenario optimization model to study supply chain optimization. However, the solution of the scenario-based stochastic optimization model depends heavily on the defined scenario and its probability of occurrence [22], and the solution of such a model is prone to fall into dimension disaster problem as the number of scenarios increase. Sainathuni et al. studied inventory transportation to determine the optimal distribution plan from the supplier to the customer to minimize total costs [23]. Rong et al. established a mixed integer linear programming model [24]. Rezaee et al. considered the design of a green supply chain network with stochastic demand and carbon price [25]. The above optimization models usually assume that the probability distribution is known beforehand, which is inconsistent with the actual situation. In addition, these models are not robust enough for small disturbances in input parameters, i.e., small changes in actual demand will affect the results.

In recent years, scholars have introduced robust optimization methods to various problems of supply chain management to improve the robustness of the model. In addition, optimization theories including robust optimization are found to involve in practical applications, such as the large-scale group decision-making [26] and multicriteria bilevel games [27]. Gülpınar et al. proposed a robust optimization model for equipment location under the worst-case scenario by assuming that the stochastic demand belongs to an uncertain set [28]. Zokaee et al. studied the optimization of a robust supply chain network by assuming that demand, inventory capacity, and some cost parameters belong to box sets [29]. The above robust optimization models consider that uncertain parameters belong to a certain set, and the decision-making problem with minimum total cost in the worst case is studied. In practice, the decision results of stochastic programming model are often too conservative since the probability of stochastic programming model does not usually occur. In order to reduce the chance stochastic problems, the theoretical methods of the robust optimization model have been extensively studied.

In the research of humanitarian logistics management, as far as we know, few scholars have studied it through the two-stage model. The innovation and contribution of this paper is to study how to construct the TS-RC model to discuss uncertainty. The first-stage decision is the selection of temporary warehouse locations and the quantity of basic inventory, and the second-stage decision is the transportation from the warehouse to the point of demand. First, in order to improve the satisfaction of logistics transportation service, a TS-SCC model with opportunity constraints is considered, in which the uncertain set is composed of the first and second moment of stochastic demand. Unlike the classical TS-SCC facility location problem, this model does not assume a preknown probability distribution of stochastic demand. Compared with the stochastic programming model, this model does not assume that uncertain demand belongs to a predetermined set. Secondly, by using the Karush–Kuhn–Tucher (KKT) condition, the TS-SCC model is equivalently transformed into a TS-RC model. In addition, according to the universality of the model, we construct three RC models with different undefined sets. In order to effectively solve the problem of robustness, its convergence is proved by writing an algorithm. Finally, in a numerical example, the emergency dispatching problem is studied. Using historical sales data, the first and second moments of stochastic demand are estimated by data-driven method. Seven different probability distributions are randomly generated for out-of-sample data. The test results show that the model in this paper has better stability than the nonrobust optimization model and the classical stochastic programming model.

The rest of this paper is set up as follows. Section 2 describes two stages of humanitarian logistics management. Section 3 transforms the TS-SCC model into TS-RC models.

Section 4 verifies the solution algorithm of the model by simulation. The performance of the models is analyzed and compared in detail in Section 5. Section 6 summarizes the conclusions of this study and future research directions.

2. Problem Description and Model Establishment

2.1. Problem Description. After disaster incidents, in addition to rescue work, how to protect people's livelihood is also a very important issue. In order to reduce the loss and ensure the safety of life, strict closure measures are generally adopted to minimize the contact behavior of the people. In order to protect people's livelihood, caring materials from all over the country have been flowing into the core area of the incident. How to effectively distribute these caring materials has become an urgent problem to be solved. On the premise of comprehensive analysis of the real scene, this paper constructs a TS-SCC model. The specific model framework is shown in Figure 1.

In an uncertain demand context, the first-stage decision is to choose a warehouse. In the second stage, the base stock of the selected warehouse and the distribution ratio of goods from the warehouse to the point of demand are determined. The goal of optimization problems is to minimize the total cost under the constraints of meeting the demand. Problems with adequate supply: to combat the outbreak, it does not need the material production manufacturer to return to work, expand their capacity, and strengthen the production force of materials loving for plague prevention. At the same time, large volumes of loving material will also need to be called in from other regions to combat the outbreak. Against this background, the rational distribution of charity donations plays an important role in the fight against outbreaks. The problem considered in this paper concerns a material scheduling problem from the distribution center to the site of demand. As far as possible, fairness in the distribution of the charity donations is guaranteed, minimizing the delay loss caused by the inadequate supply of materials and the costs incurred during storage and distribution.

2.2. Basic Assumptions and Symbols. In order to introduce the TS-SCC model and its application to the site selection path planning problem, the related parameters and signs of decision variables are summarized in Table 1.

Considering the practical problem that the material supply under the influence of the new corona pneumonia outbreak is not sufficient, the following assumptions are proposed:

(1) Because materials are uniformly distributed, the manufacturer of materials delivers the manufactured materials to the logistics consolidation center, which is then uniformly distributed by the consolidation center

(2) The paths from the consolidation center to the distribution center and from the distribution center to the fixed hospital are interconnected, and the shortest path is chosen

(3) Since the supplies are dispensed on day by day, the supplies are dispensed in one stage of the day (24 h)

(4) Both the distribution centers are capable of storing supplies that arrive the same day

(5) The individual site-directed hospitals had known requirements for a variety of supplies

2.3. Two-Stage Stochastic Chance Constrained Model. Based on the above basic assumptions, a TS-SCC model is constructed. The model aims to minimize the total cost on the basis of maximizing customer demand. The specific model is shown as follows. Based on a real-world scenario, the first stage of a TS-SCC model is designed to minimize the total cost. Random variables are defined in probability space $(\Xi, \mathscr{F}, P)$ and assume that the first and second moments are known precisely in advance, that is, $E_P[\varepsilon] = \mu_0, E_P[(\varepsilon - \mu_0)(\varepsilon - \mu_0)^T] = \Sigma_0 \succ 0$. Assume $\Xi = \mathbb{R}^{|\mathscr{I}|}$, and the closed convex set $\mathscr{P}$ contains all probability distribution functions with second-order moments as P, which are defined as: $\mathscr{P} := \{P: P\{\varepsilon \in \Xi\} = 1, E_P[\varepsilon] = \mu_0\}$ and $\mathscr{P} := \{P: E_P[(\varepsilon - \mu_0)(\varepsilon - \mu_0)^T] = \Sigma_0\}$.

$$\min\left\{\sum_{j\in\mathscr{J}} x_j c_f + \max E\left[C_2\left(\widetilde{D}_j: c\right)\right]\right\}, \tag{1}$$

$$\text{s.t. } x_j \in \{0,1\}, \quad \forall i \in \mathscr{I}. \tag{2}$$

The first of the objective functions (1) is fixed cost, which is the investment cost of infrastructure, including office equipment consumption cost and basic hydropower cost. Fixed cost is not related to vehicle routing. The second cost is affected by the uncertain parameters of the second stage. Constraint (2) represents a 0-1 variable and participates in the corresponding logistics operation only if and only if $x_j = 1$. In the second phase of the TS-SCC model, demand is maximized with uncertain parameters:

$$C_2\left(\widetilde{D}_j: c\right), \tag{3}$$

$$\text{s.t. } c_t^2 \sum_{i\in\mathscr{I}}\sum_{j\in\mathscr{J}} x_i\left(\frac{d_{ij}}{\overline{v}_i} - t_0^j\right) + \max\left\{c_v^2 \sum_{i\in\mathscr{I}}\sum_{j\in\mathscr{J}} \frac{y_{ij}\widetilde{D}_j d_{ij}}{h_j} + \sum_{i\in\mathscr{I}}\sum_{j\in\mathscr{J}} x_j c_h y_{ij}\widetilde{D}_j\right\} \le C_2\left(\widetilde{D}_j: c\right), \tag{4}$$

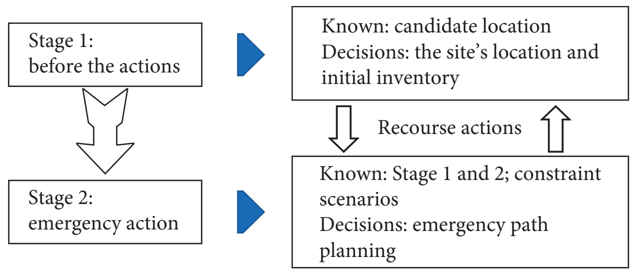

Figure 1: Schematic of the TS-SCC model.

Table 1: Description of relevant parameters.

Symbol	Description
D_j	Demand
c_f	Fixed operating cost
H_j^{Max}	Maximum inventory
h_j	Maximum load capacity
c_v	Fuel consumption cost per vehicle transit
E_c	Unit oil consumption of the vehicle
c_t	Unit delay penalty cost
d_{ij}	Origin and distance between initial requirement site
$\overline{v}_i$	Vehicle average speed
t_j	Baseline arrival time
T_j^{Max}	Maximum arrival time
x_i	$x_j \in \{0,1\}$, if $x_j = 0$, select site j; otherwise, unselected
y_{ij}	$y_{ij} \in [0,1]$, continuous variable, if $y_{ij} \neq 0$, path y_{ij} is selected
I	The set of i
J	The set of j

$$\sum_{j\in\mathcal{J}} y_{ij} \leq 1, \quad \forall j \in \mathcal{J}, \tag{5}$$

$$y_{ij} \leq x_j, \quad \forall i \in \mathcal{I}, \forall j \in \mathcal{J}, \tag{6}$$

$$\sum_{j\in\mathcal{J}} y_{ij}\widetilde{D}_j \leq H_j^{\text{Max}}, \quad \forall i \in \mathcal{I}, \tag{7}$$

$$\lceil y_{ij} \rceil \left(\frac{d_{ij}}{\overline{v}_j}\right) \leq T_{ij}^{\text{Max}}, \quad \forall j \in \mathcal{J}, \tag{8}$$

$$\begin{aligned} &P\left\{\varepsilon | \varepsilon \notin \Xi_j\right\} \leq \alpha_j, \\ &\widetilde{D}_j = D_j^0 + \varepsilon D_j^0, \quad \forall j \in \mathcal{J}, \end{aligned} \tag{9}$$

$$0 \leq y_{ij}, x_i \in \{0,1\}, \quad \forall i \in \mathcal{I}, \forall j \in \mathcal{J}. \tag{10}$$

The total cost when the objective function maximizes demand. Specific constraints: constraint (4) includes vehicle transportation costs, time costs, and handling costs; constraint (5) means that the total loading and unloading capacity cannot be higher than the total demand of the product, and there is no other outflow part; constraint (6) indicates that only the selected initial node will participate in the corresponding logistics operation; constraint (7) represents maximum capacity; constraint (8) represents maximum time constraints; constraint (9) represents random probability constraints, ε is a random influence factor, $\alpha_j \in (0,1)$ is a confidence level parameter, and $P\{\cdot\}$ represents the probability distribution function of random demand. Constraint (10) is a dependent variable. In solving problems (1)–(9), the following difficulties are encountered: on the one hand, in practical applications, the probability distribution of random parameters is unknown. Even if it is assumed to obey a known probability distribution and if ε is a continuous random variable, the objective function contains expectations and involves the calculation of multiple integrals, which is extremely difficult to calculate. On the other hand, in the second-stage optimization problem, there are multiple opportunity constraints because the probability distribution of random demand is unknown, the opportunity constraint is nonconvex, which is also very difficult to compute.

3. Establishment of TS-RC Model

Due to the diversity and irregularity of the real world, the TS-SCC model is not feasible. Specifically, the external market environment is full of uncertainties, and it is often difficult to obtain the law of key parameters development, especially the probability distribution of demand parameters [30]. The scope of application of an idealized random probability model is very limited. Therefore, we introduce the concept of robust optimization. Robust models provide an effective measure of uncertainty. Robust optimization studies are more applicable and stable than others. In this section, the above deterministic TS-SCC models transformed into a robust counterpart model by applying robust optimization theory. In robust models, the uncertain parameters change within an uncertain set, so that the probability distribution independent of the model can also be used to study inventory routing problems. Based on the random model, the initial node demand is defined as the random demand parameter $\widetilde{D}_j = D_j^0 + \widehat{D}_j$, where D_j^0 is the nominal demand, the fluctuation of demand is $\widehat{D}_j = \varepsilon D_j^0$, and the disturbance proportion is ε [31]. On this basis, three two-stage robust counterpart models are established.

3.1. TS-BRC Model. In the two-stage robust counterpart model for box sets (TS-BRC model), the uncertain demand is $\widetilde{D}j$ and the uncertain set is the box set [32]. Based on the robust optimization theory, the TS-SCC models are further transformed into a TS-BRC model. The domain of the uncertainty parameter is $\mathbb{U}_B = \left\{\{\varepsilon\}: \|\varepsilon\|_\infty \le \Psi_j\right\} = \{\varepsilon\}: |\varepsilon_j| \le \Psi_j\}$, where Ψj is the uncertainty level parameter (i.e., the security parameter) and Ψj indicates at most one parameter deviates from the nominal value.

Theorem 1. *Under the condition of uncertainty, when the uncertain parameter is not 0, the key constraints in the TS-BRC model* $\min_{+}\{\sum_{j\in\mathcal{J}} x_j c_f + \max E[C_2(\widetilde{D}_j: c)]\}$ *is equivalent to them in the TS-SCC model* $\left\{\inf Z_B: \sum_{j\in\mathcal{J}} x_j c_f + \sup_{\mathbb{U}_B} E[C_2(\widetilde{D}_j: c)] \le Z_B\right\}$. *When the uncertain parameter is 0, the TS-BRC model degenerates into a two-stage linear optimization model.*

The first stage of the TS-BRC model is (11)–(13), which aims to minimize the total cost under uncertain conditions:

$$\inf Z_B, \tag{11}$$

$$\text{s.t.} \sum_{j\in\mathcal{J}} x_j c_f + \sup_{\mathbb{U}_B} E\left[C_2\left(\widetilde{D}_j: c\right)\right] \le Z_B, \tag{12}$$

$$x_j \in \{0,1\}, \quad \forall i \in \mathcal{J}. \tag{13}$$

The second stage of the TS-BRC model is (14)–(21), which aims to minimize the initial distribution cost while maximizing the satisfaction of demand:

$$\inf C_2\left(\widetilde{D}_j: c\right), \tag{14}$$

$$\text{s.t. } C\left(D_j^0\right) + \sup_{\mathbb{U}_B}\left[\Psi_j\left(c_v^2 \sum_{i\in\mathcal{J}}\sum_{j\in\mathcal{J}} \frac{y_{ij}\widehat{D}_j d_{ij}}{h_j} + \sum_{i\in\mathcal{J}}\sum_{j\in\mathcal{J}} x_j c_h y_{ij}\widehat{D}_j\right)\right] \le C_2, \tag{15}$$

$$\sum_{i\in\mathcal{J}}\sum_{j\in\mathcal{J}} x_i c_t^2\left(\frac{d_{ij}}{\overline{v}_i} - t_0^j\right) + D_j^0\left(\sum_{i\in\mathcal{J}}\sum_{j\in\mathcal{J}} x_j c_h^2 y_{ij} + \sum_{i\in\mathcal{J}}\sum_{j\in\mathcal{J}} \frac{c_v^2 y_{ij} d_{ij}}{h_j}\right) \le C\left(D_j^0\right), \tag{16}$$

$$\sum_{i\in I} y_{ij} \le 1, \quad \forall j \in \mathcal{J}, \tag{17}$$

$$\sup\left(\sum_{j\in\mathcal{J}} y_{ij} D_j^0 + \Psi_j' \sum_{j\in\mathcal{J}} y_{ij}\hat{D}_j\right) \le H_j^{\text{Max}}, \quad \forall i \in \mathcal{J}, \tag{18}$$

$$\lceil y_{ij} \rceil \left(\frac{d_{ij}}{\overline{v}_j}\right) \le T_{ij}^{\text{Max}}, \quad \forall j \in \mathcal{J}, \tag{19}$$

$$\mathbb{P}\{\varepsilon | \varepsilon \notin \mathbb{U}_B\} \le \alpha_j, \quad \forall j \in \mathcal{J}, \tag{20}$$

$$0 \le y_{ij} \le x_i, \quad x_i \in \{0,1\}, \forall i \in \mathcal{J}, \forall j \in \mathcal{J}. \tag{21}$$

Proof. The constraints of the uncertain linear programming (LP) in question are "hard," and the decision-maker cannot tolerate violations of constraints when the data are in $\mathbb{U}$. General linear programming (LP) problem is $\{\max C^T X | AX \leq B, L \leq X \leq U\}$. Under uncertain conditions, the uncertain LP problem can be expressed as $\{\min_{\mathbb{U}_{\mathbb{B}}} \{C^T X + D\colon AX \leq B\}\}$. Among them, the cost function is $C^T X + D$, the basic constraint is $AX \leq B$, and the support set is $\mathbb{U}_B$. Consider the matrix A, assume that element $\hat{a}_{ij}$ in A is uncertain, and then define that $\tilde{a}_{ij} = a_{ij} + \hat{a}_{ij}\xi_{ij}$, where $\tilde{a}_{ij}$ is the really value, a_{ij} is nominal value, while $\hat{a}_{ij}$ is fluctuation and ξ_{ij} is factor $(\xi \in \mathbb{U}_B)$. So, they can be replaced equivalently. Then, uncertain sets and their corresponding robust equivalences are as follows: $\sum_j a_{ij} x_j + \max_{\xi \in \mathbb{U}} \sum_j \hat{a}_{ij} x_j \xi_{ij} \leq B$. And, it is equivalent to $\sum_{\mathcal{J}} a_{ij} X + \Psi \sum_{\mathcal{J}} \hat{a}_{ij} |X| \leq B$. Set $\mathbb{P}_\infty = [\mathcal{J}_{L\times L}; \mathbb{O}_{1\times L}]$, $+_\infty = [\mathcal{O}_{L\times 1}; \Psi]$, $\mathbb{K}_\infty = \{[\theta_{L\times 1}; t]\colon \|\theta\|_\infty = t\}$, where L is the number of uncertain parameters. Therefore, the inner layer maximization in it can be rephrased as $\max_{\xi \in \mathbb{U}^B} \{\sum_j \hat{a}_{ij} X \xi_{ij}\colon \mathbb{P}_\infty \xi + +_\infty \in \mathbb{K}_\infty \Psi\}$. Define the dual variable as w_i and λ_i, according to dual cone theory $\mathbb{K}_\infty^* = \{[\theta_{L\times 1}; t]\colon \|\theta\|_l \leq t\}$. Then, we can get $\min_{w,\lambda} \{\Psi \lambda_i\colon w_{ij} = \hat{a}_{ij} X, \forall j, \sum_{\mathcal{J}} |w_{ij}| \leq \lambda_i\}$, and $\min_{w,\lambda} \{\Psi \sum_{\mathcal{J}} |w_{ij}|\colon w_{ij} \leq \hat{a}_{ij} X, \forall_j\}$ is equivalent. Thus, it can be reformed as in the second stage $\Psi \sum_{\mathcal{J}} \hat{a}_{ij} X$, and $\inf Z_B\colon \sum_{j\in\mathcal{J}} x_j c_f + \sup_{\mathbb{U}_B} E[C_2(\tilde{D}_j\colon c)] \leq Z_B$. So, Theorem 1 was proved. □

3.2. TS-ERC Model. In the TS-RC model for ellipsoid sets (TS-ERC model), when the uncertain parameter is defined by l_2 norm and made it float in the range of ellipsoid set,

$$\mathbb{U}_E = \left\{ \varsigma \in \mathbb{R}^{|I|}\colon \|\varepsilon\|_2 \leq \Omega_j = \varepsilon \sqrt{\sum_J \left|\varepsilon_j\right|^2}, \quad \varepsilon \in \mathbb{R}^{|I|\times|I|}, \Omega_j \in \mathbb{R} \right\}. \tag{22}$$

In this model, $\mathbb{R}$ is a closed convex set. Ω_j is an adjustable safety parameter and the ball diameter of the uncertain set [33]. The matrix $\varepsilon = \Sigma^{1/2}$ can be obtained and Σ is the covariance matrix。

Theorem 2. *Under the condition of uncertainty, when the uncertain parameter is not 0, the key constraints in the TS-ERC model* $\min_+ \{\sum_{j\in\mathcal{J}} x_j c_f + \max E[C_2(\tilde{D}_j\colon c)]\}$ *is equivalent to them in the TS-SCC model* $\{\inf Z_E\colon \sum_{j\in\mathcal{J}} x_j c_f + \sup_{\mathbb{U}_B} E[C_2(\tilde{D}_j\colon c)] \leq Z_E\}$. *When the uncertain parameter is 0, the TS-ERC model degenerates into a two-stage linear optimization model.*

The first stage of the TS-ERC model is (23)–(25), which aim to minimize the total cost under uncertain conditions:

$$\inf Z_E, \tag{23}$$

$$\text{s.t.} \sum_{j\in\mathcal{J}} x_j c_f + \sup_{\mathbb{U}_E} E\left[C_2\left(\tilde{D}_j\colon c_m^2\right)\right] \leq Z_E, \tag{24}$$

$$x_j \in \{0,1\}, \quad \forall j \in \mathcal{J}. \tag{25}$$

The second stage of the TS-ERC model is (26)–(35), which aims to minimize the initial distribution cost based on maximizing satisfaction.

$$\inf C_2\left(\tilde{D}_j\colon c\right), \tag{26}$$

$$\text{s.t. } C_2\left(D_j^0\right) + \Omega_j \Upsilon_j + \sup_{\mathbb{U}_E} E\left[C_3\left(\tilde{D}_k\colon c_n^3\right)\right] \leq C_2, \tag{27}$$

$$\sum_{i\in I}\sum_{j\in J} x_j c_t^2 \left(\frac{d_{ij}}{\overline{v}_i} - t_0^j\right) + \sup_{\mathbb{U}_E}\left(\sum_{i\in\mathcal{J}}\sum_{j\in\mathcal{J}} x_j c_h^2 y_{ij} D_j^0 + \sum_{i\in I}\sum_{j\in J} \frac{c_v^2 y_{ij} D_j^0 d_{ij}}{h_j}\right) \leq C\left(D_j^0\right), \tag{28}$$

$$\Upsilon_j \geq \sqrt{\sum_{j\in J} \hat{D}_j^2 r_i'^2}, \quad \forall i \in \mathcal{J}, \forall j \in \mathcal{J}, \tag{29}$$

$$r_i' \geq \sum_{i\in I}\sum_{j\in J}\left(x_j c_h^2 y_{ij} + \frac{c_v^2 y_{ij} d_{ij}}{h_j}\right), \quad \forall i \in \mathcal{J}, \forall j \in \mathcal{J}, \tag{30}$$

$$\sum_{j\in J} y_{ij} D_j^0 + \Omega_j \Upsilon_j \leq H_j^{\text{Max}}, \quad \forall i \in \mathcal{J}, \tag{31}$$

$$\sum_{i\in I} y_{ij} \leq 1, \quad \forall j \in \mathcal{J}, \tag{32}$$

$$\lceil y_{ij} \rceil \left(\frac{d_{ij}}{\overline{v}_j} \right) \leq T_{ij}^{\text{Max}}, \quad \forall j \in \mathcal{J}, \tag{33}$$

$$\mathbb{P}\{\varepsilon | \varepsilon \notin \mathbb{U}_E\} \leq \alpha_j, \quad \forall j \in \mathcal{J}, \tag{34}$$

$$0 \leq y_{ij} \leq x_j, \qquad x_j \in \{0,1\}, \forall i \in \mathcal{I}, \forall j \in \mathcal{J}. \tag{35}$$

Proof. The ellipsoid uncertainty set is $U^E = \{a_i \in R^n: a_i = \overline{a}_i + \Delta\xi, \xi \leq \Omega\}$, where $\Delta = \sum^{1/2}$. The constraints $\max a_i^T X \leq B$ of it can be translated as $\max\{a_i^T X: (a_i - \overline{a}_i)^T \Sigma^{-1} (a_i - \overline{a}_i) \in \Omega^2\}$. As for Σ is positive, so it is a convex problem. Therefore, LP can be solved by Karush–Kuhn–Tucher condition. $\min \mathcal{F}(a_i^*) = -a_i^{*T} X$ and s.t. $g(a_i^*) = (a_i^* - \overline{a}_i)^T \Sigma^{-1} (a_i^* - \overline{a}_i) - \Omega^2 \leq 0$. Thus, in our decision-making environment, meaningful solutions to an uncertain problem are exactly its robust feasible solutions. It remains to decide how to interpret the value of the objective (which can also be uncertain) at such a solution. As applied to the objective, the "worst-case-oriented" philosophy makes it natural to quantify the quality of a robust feasible solution x by the guaranteed value of the original objective, that is, by its largest value $\sup \mathbb{U}_E E[C_2(\widetilde{D}_j: c)]$. Thus, the best possible robust feasible solution is the one which solves the optimization problem $\min_+ \{\sum_{j\in\mathcal{J}} x_j c_f + \max E[C_2(\widetilde{D}_j: c)]\}$ in the TS-SCC model or which is the same to $\{\inf Z_E: \sum_{j\in\mathcal{J}} x_j c_f + \sup_{\mathbb{U}_E} E[C_2(\widetilde{D}_j: c)] \leq Z_E\}$ in the TS-ERC model. The latter problem is called the robust counterpart of the original uncertain problem. Above all, Theorem 2 can be proved. □

3.3. TS-BPRC Model. In the TS-RC model for mixed set of box and polyhedron (TS-BPRC model), the set of uncertain requirements is mixed of a box and a polyhedron set, where the box set is defined by the l_∞ norm and the polyhedron set by the l_1. Based on robust optimization theory, the TS-SCC model is further transformed into a TS-BPRC model with the domain of uncertainty parameters defined as

$$\begin{aligned} \mathbb{U}_{\text{BP}} &= \{\mathbb{U}_\infty \cap \mathbb{U}_1\} = \{\mathbb{U}_{Bj} \cap \mathbb{U}_{Pj}\} \\ &= \{\{\varepsilon\}: \|\varepsilon\|_\infty \leq \Psi_j, \|\varepsilon\|_1 \leq \Gamma_j\} \\ &= \left\{\{\varepsilon\}: \left|\varepsilon_j\right| \leq \Psi_j, \{\varepsilon\} \cdot \sum \left|\varepsilon_j\right| \leq \Gamma_j\right\}. \end{aligned} \tag{36}$$

Here, Ψ_j and Γ_j are uncertain parameters. To simplify the tedious expression, $\Lambda_j = \min\{\Psi_j, \Gamma_j\}$, where Λ_j is set as security parameters in the mixed intersection robust counterpart model.

Theorem 3. *Under the condition of uncertainty, when the uncertain parameter is not 0, the key constraints in the TS-BRC model* $\min_+ \{\sum_{j\in\mathcal{J}} x_j c_f + \max E[C_2(\widetilde{D}_j: c)]\}$ *is equivalent to them in the TS-SCC model* $\{\inf Z_{BP}: \sum_{j\in\mathcal{J}} x_j c_f + \sup_{\mathbb{U}_{BP}} E[C_2(\widetilde{D}_j: c)] \leq Z_{BP}\}$. *When the uncertain parameter is 0, the TS-BPRC model degenerates into a two-stage linear optimization model.*

The first stage of the TS-BPRC model is (37)–(39), which aims to minimize the total cost under uncertain conditions:

$$\inf Z_{\text{BP}}, \tag{37}$$

$$\text{s.t.} \sum_{j\in\mathcal{J}} x_j c_f + \sup_{\mathbb{U}_{\text{BP}}} E\left[C_2\left(\widetilde{D}_j: c\right)\right] \leq Z_{\text{BP}}, \tag{38}$$

$$x_j \in \{0,1\}, \quad \forall j \in \mathcal{J}. \tag{39}$$

The second stage of the TS-BPRC model is (40)–(47), which aims to minimize the distribution cost while maximizing the satisfaction of demands:

$$\inf C_2\left(\widetilde{D}_j: c\right), \tag{40}$$

$$\text{s.t.}\ C\left(D_j^0\right) + \sup_{\mathbb{U}_{\text{BP}}} \Lambda_j \left(c_v^2 \sum_{i\in\mathcal{I}} \sum_{j\in\mathcal{J}} \frac{y_{ij}\hat{D}_j d_{ij}}{h_j} + \sum_{i\in\mathcal{I}} \sum_{j\in\mathcal{J}} x_j c_h y_{ij} \hat{D}_j \right) \leq C_2, \tag{41}$$

$$\sum_{i\in\mathcal{I}} \sum_{j\in\mathcal{J}} x_j c_h^2 y_{ij} D_j^0 + c_v^2 \sum_{i\in\mathcal{I}} \sum_{j\in\mathcal{J}} \frac{y_{ij} D_j^0 d_{ij}}{h_j} + c_t^2 \sum_{i\in\mathcal{I}} \sum_{j\in\mathcal{J}} x_i \left(\frac{d_{ij}}{\overline{v}_i} - t_0^j \right) \leq C\left(D_j^0\right), \tag{42}$$

$$\sum_{i\in I} y_{ij} \leq 1, \quad \forall j \in \mathcal{J}, \tag{43}$$

$$\sum_{j\in\mathcal{J}} y_{ij} D_j^0 + \Lambda_j' \sum_{j\in\mathcal{J}} y_{ij} \widehat{D}_j \leq H_j^{\text{Max}}, \quad \forall i \in \mathcal{I}, \tag{44}$$

$$\lceil y_{ij} \rceil \left(\frac{d_{ij}}{\bar{v}_j} \right) \leq T_{ij}^{\text{Max}}, \quad \forall j \in \mathcal{J}, \tag{45}$$

$$\mathbb{P}\{\varepsilon | \varepsilon \notin (\mathbb{U}_B \cap \mathbb{U}_P)\} \leq \alpha_j, \quad \forall j \in \mathcal{J}, \tag{46}$$

$$0 \leq y_{ij} \leq x_j, \quad x_i \in \{0, 1\}, \forall i \in \mathcal{I}, \forall j \in \mathcal{J}. \tag{47}$$

Proof. General linear programming (LP) is $\{\max C^T X | AX \leq B,\ L \leq X \leq U\}$. And $\sum_j a_{ij} x_j + \Gamma_i p_i \leq B_i$, $p_i \geq \hat{a}_{ij} |x_j|$. Defining $\mathbb{P}_1 = [\mathcal{J}_{L\times L};\ \mathbb{O}_{1\times L}], +_1 = [\mathcal{O}_{L\times 1}; \Gamma]$, $\mathbb{K}_1 = \{[\theta_{L\times 1}; t]\colon \|\theta\|_1 = t\}$, $\mathbb{P}_\infty = [\mathcal{J}_{L\times L}; \mathbb{O}_{1\times L}]$, $+_\infty = [\mathcal{O}_{L\times 1}; \Psi], \mathbb{K}_\infty = \{[\theta_{L\times 1}; t]\colon \|\theta\|_\infty = t\}$, where L is the number of uncertain parameters . In the TS-BPRC model, the set is defined as $\mathbb{U}_{\text{BP}} = \{\mathbb{U}_\infty \cap \mathbb{U}_1\}$. Therefore, the problem of inner layer maximization can be rephrased as $\max_{\xi\in U^P} \{\sum_{\mathcal{J}} \hat{a}_{ij} X\xi_{ij}\colon \mathbb{P}_{1,\infty}\xi + +_{1,\infty} \in \mathbb{K}_{1,\infty}\Gamma, \Psi\}$. Then, we can get the problem $\min_+ \{\max E[C_2(\tilde{D}_j\colon c)]\}$, and the problem $\{\inf Z_{\text{BP}}\colon \sup_{\mathbb{U}_{\text{BP}}} E[C_2(\tilde{D}_j\colon c)] \leq Z_{\text{BP}}\}$ is equivalent. Thus, it can be reformed as $\{\inf Z_{\text{BP}}\colon \sum_{j\in\mathcal{J}} x_j c_f + \sup_{\mathbb{U}_{\text{BP}}} E[C_2 (\tilde{D}_j\colon c)] \leq Z_{\text{BP}}\}$ in the first stage and $\sup_{\mathbb{U}_{\text{BP}}} \Lambda_j (C^T X)$ in the second stage. In summary, Theorem 3 can be proved. □

4. Simulation

In the case of emergency management, how to allocate emergency relief materials reasonably and effectively is a very important and difficult problem. According to the actual situation, this section takes the material dispatching system of Aba Prefecture earthquake in Sichuan Province as the research object and carries out indepth analysis (Figure 2). The earthquake has brought a huge impact on the lives of local people, under the auspices of the government part of the emergency rescue work. Among them, how to protect people's livelihood has become the primary issue. Specifically, the affected areas received a variety of vegetables and other materials from all over the country. The distribution of these materials is very complicated. The reasons are as follows: on the one hand, the category of donated relief materials is single, which cannot be directly distributed to the affected people. It cannot directly distribute the demand to retail investors and needs professional personnel to sort, pack, and deliver. It is almost impossible to operate in the emergency state, and it cannot be completed. On the other hand, the donated materials must be distributed within the fresh-keeping period, and the remaining disposable distribution time is very short without long-distance transportation time. The most effective way to solve these problems is to establish a temporary transit center. In the temporary center sorting and distribution, the efficiency is relatively high.

In this paper, a TS-SCC model is established to solve the problem of material supply in emergency, considering the material classification and variable supply. In the actual rescue process, the Rescue Department is faced with the two-stage vehicle path planning problem. The first stage is the location problem of temporary storage station, and the goal is to determine the location node and calculate the total cost. According to the actual situation of the disaster area, after comprehensive analysis, the flat and wide sites in the disaster area are selected as candidate temporary sites, which are represented by S_1, S_2, S_3, S_4, and S_5. These temporary storage centers have dual functions: one is responsible for the screening and sorting of materials and the other is to provide material reserve services for subsequent scheduling. On the basis of comprehensive consideration of various location factors, the origin of rescue materials is determined as the transfer yard of the bus station. The second stage is path planning. The goal of the second stage is to minimize the initial distribution cost, including material handling cost, transportation cost, and time cost.

There are 5 temporary storage sites in total, which are the candidate temporary storage sites determined in the first stage. There are 8 demand sites, which are represented by $D_1, D_2, \ldots, D_8$. In the complex humanitarian logistics system, there are 1 material origin, 5 temporary storage stations, 8 demand points, and any alternative path corresponds to different transportation costs. In the process of simulation, in addition to the comprehensive calculation cost of real-time oil price and actual distance, traffic congestion and time constraints are also involved.

4.1. Related Basic Parameter Data. Basic data information [34] includes fixed operating costs, demand, and average vehicle speed of storage stations (Table 2). The actual distance between nodes directly obtained through Google Map is shown in Table 3.

4.2. Results of TS-SCC Model and RC Model. In this section, we use MATLAB as the programming platform and Gurobi as the solvers to solve the above models, respectively. The results of the TS-SCC model are shown in Table 4. The results of the model are affected by the probability distribution. In this section, the common probability distribution is selected for simulation experiments. With increasing the mean value of parameters $(0.05 \longrightarrow 0.15)$, the total cost of the model shows an upward trend. Under different distribution functions, the total cost of emergency management is also very different. This means that, in the TS-SCC model, changing the parameters will directly affect the total cost. However, in the actual emergency environment, the development of events is uncertainty, and it is difficult to obtain sufficient historical data to calculate the specific distribution function or even to accurately estimate the

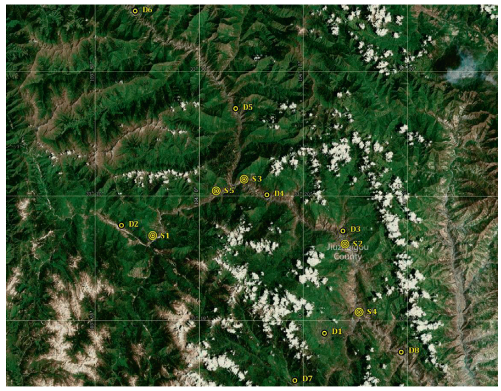

Figure 2: Location of emergency management.

Table 2: Basic information of temporary inventory site.

Storage sites	S_1	S_2	S_3	S_4	S_5
Distance	41.5	7.1	23.6	9.3	28
Maximum Inventory	1750	1600	1400	1350	1400
Average speed	45	40	40	45	35
Fixed cost	7500	6500	5500	4500	4200
Oil consumption	14.4	14.4	14.4	14.4	14.4
Load capacity	4–6	4–6	4–6	4–6	4–6
Demand sites	$M1$	$M2$	$M3$	$M4$	$M5$
Nominal demand	700	900	500	400	300
Demand sites	M_6	M_7	M_8	—	—
Nominal demand	600	800	750	—	—

Table 3: Distance between sites.

	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8
S_1	39.7	6.3	38.2	23.6	30.3	56.4	71.7	60.8
S_2	1.1	47.2	3.1	16.4	33.6	60.5	33.9	22.4
S_3	21.5	27.7	19.6	4.7	13.8	41.8	53.2	42.3
S_4	12.1	58.2	14.7	27.2	45.9	72.7	21.8	10.7
S_5	26.1	22.6	24.7	9.3	15.4	43.2	58.1	46.4

Table 4: Results of TS-SCC model.

Distribution	Mean	Cost	Time	Mean	Cost	Time	Mean	Cost	Time
Normal	0.05	$8.8933E+04$	851.2	0.1	$8.8912E+04$	816.5	0.15	$8.8931E+04$	961.9
Poisson	0.05	$8.8929E+04$	813.1	0.1	$8.8928E+04$	909.4	0.15	$8.8929E+04$	893.4
Uniformity	0.05	$8.8939E+04$	903.1	0.1	$8.8938E+04$	896.9	0.15	$8.8936E+04$	865.3
Bernoulli	0.05	$8.8901E\ +0\ 4$	906.5	0.1	$8.8924E+04$	796.6	0.15	$8.8930E+04$	996.1
Index	0.05	$8.8926E+04$	897.6	0.1	$8.8929E+04$	897.4	0.15	$8.8926E+04$	988.4
Gamma	0.05	$8.8912E+04$	602.1	0.1	$8.8918E+04$	906.7	0.15	$8.8936E+04$	978.6
Weber	0.05	$8.8937E+04$	912.4	0.1	$8.8929E+04$	903.4	0.15	$8.8933E+04$	985.3

mean value and variance. So, the TS-SCC model in emergency management has a very low feasibility.

Through MATLAB programming, the following results are obtained. It can be seen from Table 5 that, with the increase of safety parameters, the three total costs show a gradual upward trend. When the $SP=0$ (mean value is 0), the TS-RC is equivalent to the TS-SCC model. In the two-stage box set TC model, when the security parameters increase from 1 to 8, the total cost increases from $3.71E+04$ to $3.78e+04$, with an increase of 1.887%. In the TS-ERC model, when the security parameters increase from 1 to 8, the total cost increases with an increase of 2.695%. In the TS-RC model for mixed set of box and polyhedron, when the security parameters increase from 1 to 8, the total cost increases with an increase of 1.617%. The TS-BPRC model is more robust.

Table 5: Results of TS-RC model.

SP	ε	TS-BRC model		TS-ERC model		TS-BPRC model	
		Cost	Time	Cost	Time	Cost	Time
0	0.05	$8.8933E+04$	419.2	$8.8933E+04$	419.2	$8.8933E+04$	419.2
1	0.05	$8.8933E+04$	420.0	$8.8933E+04$	433.4	$8.8933E+04$	469.7
2	0.05	$8.8934E+04$	413.8	$8.8934E+04$	431.8	$8.8934E+04$	459.1
3	0.05	$8.8935E+04$	409.2	$8.8935E+04$	426.9	$8.8937E+04$	453.0
4	0.05	$8.8937E+04$	418.1	$8.8937E+04$	436.5	$8.8939E+04$	455.5
5	0.05	$8.8939E+04$	419.6	$8.8939E+04$	440.3	$8.8940E+04$	455.5
6	0.05	$8.8939E+04$	424.6	$8.8941E+04$	422.4	$8.8941E+04$	470.3
7	0.05	$8.8941E+04$	426.2	$8.8944E+04$	438.7	$8.8943E+04$	471.9
8	0.05	$8.8943E+04$	416.6	$8.8946E+04$	445.2	$8.8944E+04$	475.0
1	0.10	$8.8933E+04$	432.5	$8.8933E+04$	448.8	$8.8933E+04$	489.0
2	0.10	$8.8934E+04$	420.5	$8.8934E+04$	467.4	$8.8935E+04$	464.8
3	0.10	$8.8935E+04$	423.6	$8.8936E+04$	446.8	$8.8938E+04$	475.1
4	0.10	$8.8937E+04$	422.1	$8.8939E+04$	453.3	$8.8939E+04$	474.9
5	0.10	$8.8944E+04$	423.4	$8.8942E+04$	467.2	$8.8940E+04$	475.5
6	0.10	$8.8945E+04$	426.6	$8.8945E+04$	446.8	$8.8942E+04$	490.0
7	0.10	$8.8946E+04$	428.9	$8.8946E+04$	456.4	$8.8942E+04$	473.1
8	0.10	$8.8948E+04$	430.0	$8.8947E+04$	466.7	$8.8943E+04$	474.5

4.3. Path Planning for TS-SCC and TS-RC Model. According to the operation results of the TS-SCC model, the path planning scheme can be obtained. Materials donated are gathered from all over the country and transported to stations by transport vehicles. Due to the implementation of traffic control, the routes of rescue materials transportation vehicles are distributed in a radial pattern, and they rush to the rescue site at the fastest speed. At the same time, in addition to redistribution of materials, station also serves as a temporary warehouse to store materials. Under the TS-SCC model, S_2, S_3, S_4, and S_5 was selected as the initial sites location to undertake the main relief material supply service, but $S1$ temporary storage node was not activated. The second stage is distribution service, which is represented by dotted lines. Distribution routes go through almost all feasible routes while meeting the needs of all designated hospitals. Careful analysis reveals the following conclusions.

As shown in Figure 3, under the TS-SCC model, the cost of distribution routing accounts for a large proportion of the total cost. Although this planning method can ensure stable supply of materials and meet rescue needs, it still faces some problems in the specific service path planning. For example, the cost increases associated with long-distance transportation; circuitous transportation resulting from cross-distribution routes, which increases costs; unreasonable use of major temporary storage sites, which increases the cost of retransshipment; and once uncertainties arise in the actual rescue process, such as increased demand fluctuations, the stability and sustainability of the TS-SCC model cannot be guaranteed. Certification, which makes the logistics service of relief materials, faces some challenges and difficulties. Therefore, in the process of rescue, it is necessary to plan rationally and explore more optimized improvement strategies, i.e., to optimize the distribution route.

As a whole, three TS-RC models are quite different from TS-SCC models. In the TS-RC model, $S2$ is selected. As can be seen from Figures 4–6, selection of S_2 will greatly shorten the transportation distance of logistics, thus improving the

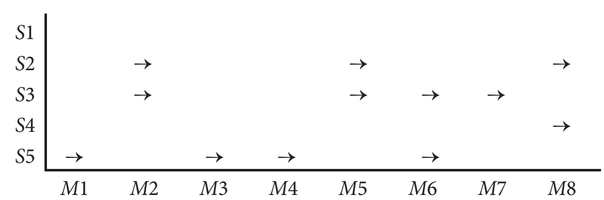

Figure 3: Distribution route of the TS-SCC model.

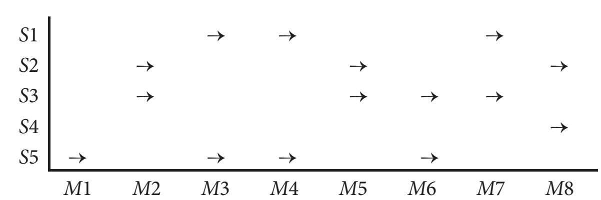

Figure 4: Distribution route of the TS-BRC model.

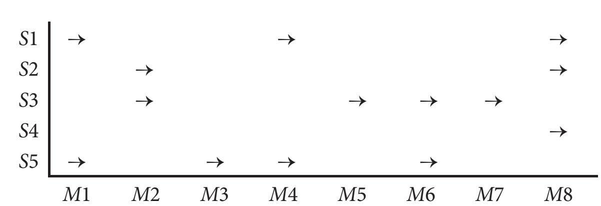

Figure 5: Distribution route of the TS-ERC model.

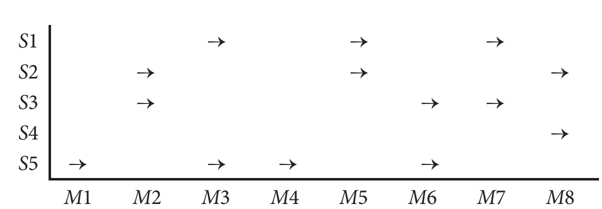

Figure 6: Distribution route of the TS-BPRC model.

operation efficiency. In detail, the TS-BPRC model is compared with the other three models. In the initial route planning of the first stage, the transit proportion is relatively balanced among the major transfer centers, and the transit capacity and load pressure of each temporary storage station are relatively balanced. As can be clearly seen in Figure 6, the nodes have been deeper into the hinterland of the disaster area and closer to the demand points, which also make the path planning more reasonable. In the second-stage planning, compared with the other two robust corresponding models, the proportion of long-distance line transportation is further reduced and the proportion of short-distance transportation is increased, especially after fully utilizing this node deep inside the hinterland. Comparatively speaking, the service proportion in each path tends to be short-haul route, which bears less cost and therefore increases the proportion of material supply. As a result, onboard mileage is more efficient, and delivery routes are more accurate and fast, showing better optimization performance.

5. Model Sensitivity Analysis

This section compares and analyses the performance of each model, including operational efficiency, uncertainty, and degree of demand fluctuation.

5.1. Model Run-Time Performance Comparison. This section analyses the operating efficiency of the four models. To facilitate comparison and run in the same computer environment, the security parameters are set as unique variables, and the running time of the models is observed.

Figure 7 shows the operational efficiency of three TS-RC models and TS-SCC model. It can be seen that the TS-SCC model has the highest operational efficiency, and the overall running time is much lower than the TS-RC model (green line). The effect of volatility on time is significant. On the whole, there is a clear boundary, and the running time of the model with low volatility is short. The main reason is that the demand parameters can converge quickly. In the comparison of RC models, it is found that when the volatility is high, the time performance of the TS-BRC model and the TS-ERC model fluctuates violently, while TS-BPRC model is relatively robust. Therefore, when solving practical problems, we can build an appropriate model according to the size of real data.

5.2. Comparative Analysis of Temporary Node Storage Ratio. Figure 8 shows the utilization ratio of each temporary logistics storage site. In the TS-SCC model, S_1 and S_4 accounts for a large proportion, and S_1 is not used (the proportion of S_1 is 0). In the TS-RC models, due to the difference of uncertain parameters, the proportion of transshipment is also variable. In terms of details, the transport ratio of S_1 showed an increasing trend. In particular, in the TS-BPRC model, the proportion of S_1 is more than 20%. The enabling of site S_1 is the biggest difference between the TS-RC model and the TS-SCC model. As site S_1 is deeply rooted in the hinterland of the target area, it will play a very important role in adjusting the transportation plan.

From Figure 9, it can be concluded that the temporary stations S_1 and S_3 has a downward trend among all stations compared with the TS-SCC model and the TS-RC model. The decrease in the proportion of transshipment in transit stations indicates that the importance of the stations is reduced, which in turn reduces the influence in the distribution path of the second stage. Among other sites, S_4 has the lowest fluctuation range and remains basically unchanged. It is worth noting that the proportion of S_2 and S_5 transshipment shows an upward trend, and the change of inventory proportion directly affects the fluctuation of cost and logistics service level. S_2 and S_5 will play a greater role in the TS-RC model.

5.3. The Impact of Demand Fluctuation on Total Cost. In this section, we compare and analyze the impact of demand volatility on the total cost in the four models and explore the impact of the fluctuation of random parameters on the total cost under the condition of fixed security parameters ($\Psi_j = \Omega_j = 3$ or $\Psi_j \cap \Gamma_j = 3$). The calculation results are shown in Figure 10. The total cost of the TS-SCC model is higher than that of the two-stage robust corresponding model. In the robust counterpart model, the increasing trend is quite different. The TS-BRC model and the TS-ERC model have greater randomness, and the TS-BPRC model has strong ability to resist uncertainty. Careful observation shows that the growth rate is slightly different. The cost of the TS-SCC model increases sharply, while that of the TS-BPRC model increases slowly.

5.4. Impact of Security Parameters on Service Level. In this section, the performance of the model is analyzed through the level of service (SL). Due to the high demand for timeliness of material scheduling in humanitarian logistics management, this section compares the service level of models through time difference and analyzes the advantages and disadvantages of different models. The calculation formula of service level is as follows:

$$\mathrm{SL} = \left[1 - \frac{\sum_J \left(y_{ij} \widetilde{D}_j d_{ij} / \overline{v}_{ij} \right) - t_j \sum_J \widetilde{D}_j}{t_j \sum_J \widetilde{D}_j} \right] \times 100\%, \tag{48}$$

where I and J are the number of arcs in the model. The simulation results under different parameters are shown in Figure 11.

Figure 11 illustrates the effect of SP on the SL of the model under the condition of fixed stochastic demand volatility ($\varepsilon = 0.15$). Fortunately, it can be seen that the service level tends to increase with the increase of security level. Safety parameters have good performance. This partly compensates for the cost of robustness (increased total cost) due to uncertainty and also mitigates the loss of reduced service levels due to demand volatility. Careful comparison shows that, in TS-BRC model, when SP increases from 1 to 8, logistics service level increases from 89.83% to 93.21% in the

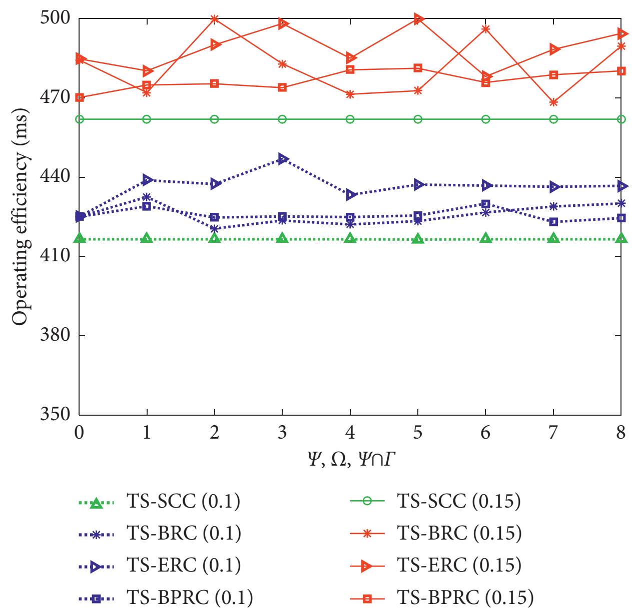

Figure 7: Model operation efficiency comparison.

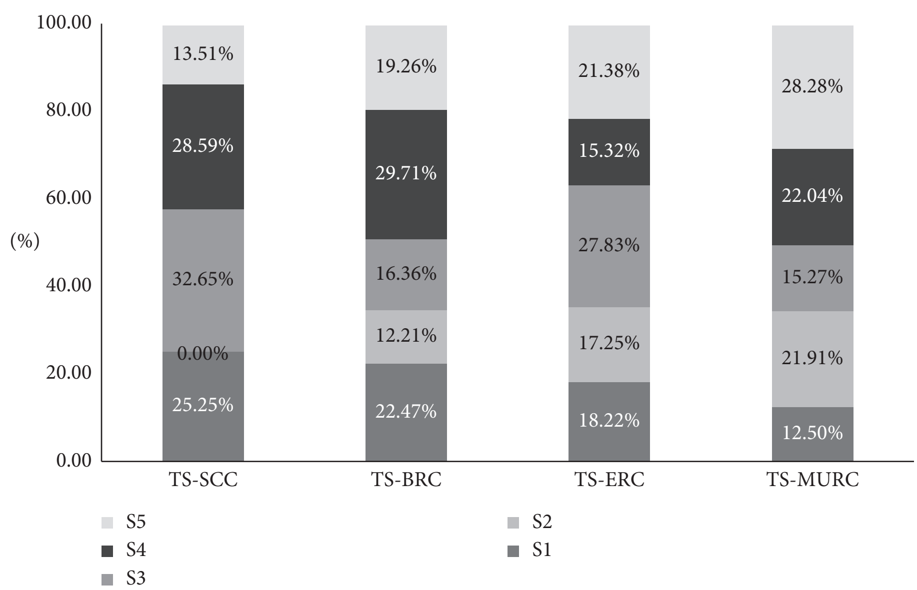

Figure 8: Inventory proportion of the temporary storage site.

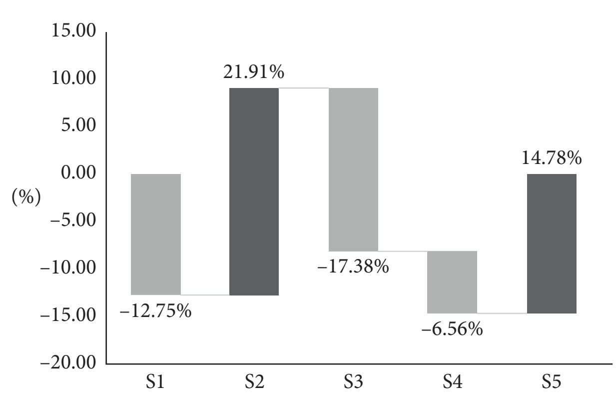

Figure 9: Inventory change range of the temporary storage site.

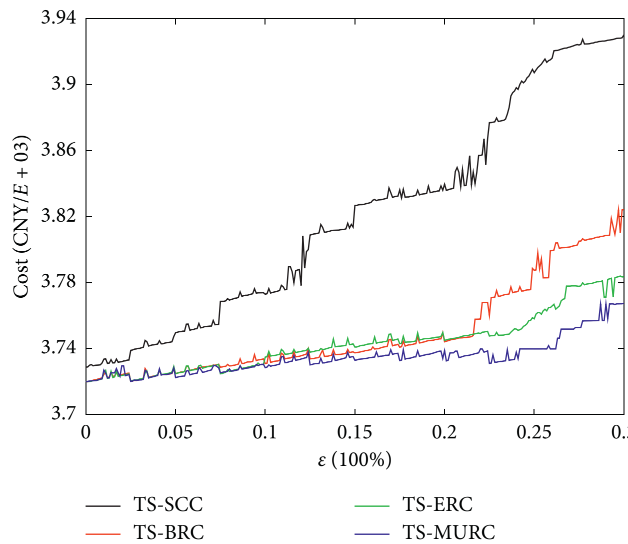

Figure 10: The influence of demand fluctuation on total cost.

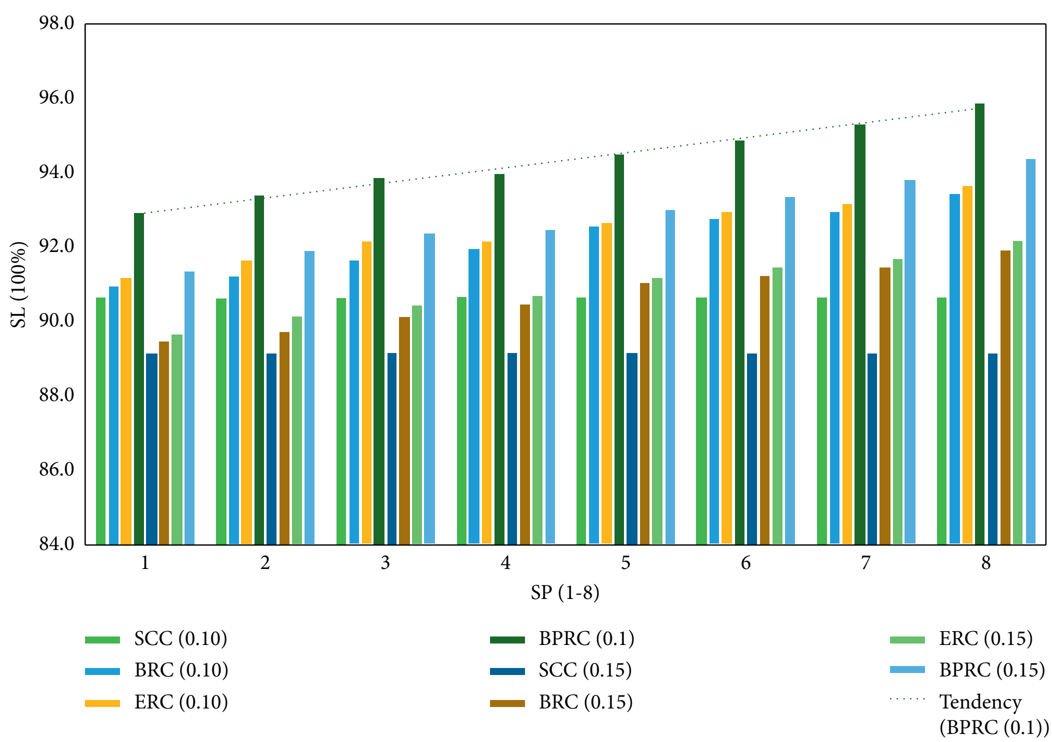

Figure 11: Service level affected by SP.

path planning stage. The TS-BPRC model has strong robustness. When SP is increased from 1 to 8, the logistics service level increased from 90.32% to 94.96% in the path planning stage. In the process of emergency management, rapid responsiveness must be paid attention to by managers. Considering uncertainties, although robust corresponding models in each two stages can give a more robust route planning scheme, the performance and application scope of each scheme is also different. Therefore, emergency rescue decision-makers must review the situation and work out the most reasonable path according to local conditions. This scheme can minimize the loss caused by delay and ensure the fairness of caring material distribution, but the logistics cost of this scheme is the highest among all schemes. Generally, in the process of public health emergencies, caring materials are relatively scarce, especially in the early period of public health emergencies, so it is necessary to control logistics costs properly. Decision-makers need to weigh the various

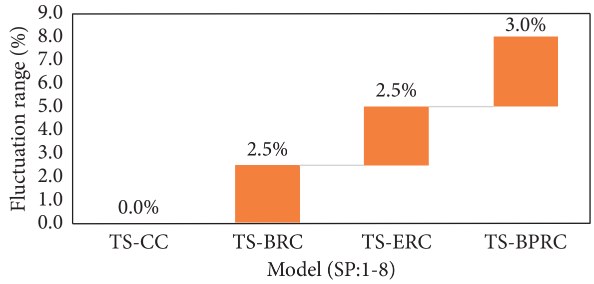

Figure 12: Service level fluctuation in different models.

objectives against the actual situation and trends of the epidemic and choose the ideal alternative for decision-making. Ideally, the limited resources of love should be fully utilized while minimizing all costs to achieve cost savings.

Figure 12 shows the change value of the growth rate of logistics service level. Based on TS-SCC model, the service level change trend of other models is compared. When the level of security parameters increases from 1 to 8, the service level of TS-BRC model and TS-ERC model increases by 2.5% relative to each other, while the increase of TS-BPRC model is 3.0%. The rise in service level demonstrates the advantages of robust optimization, and robust route planning can still be developed under uncertain conditions. This has a clear guiding significance for the emergency management department to formulate the rescue plan.

6. Conclusion

Due to the emergency, there is a serious shortage of living materials. In order to ensure the supply of materials in the incident area, we conducted a study on the issue of humanitarian logistics management. The research focuses on the material allocation problem with huge impact, which aims to carry out reasonable location and path planning for materials according to the actual situation, so as to minimize losses and save costs. In this paper, firstly, a two-stage stochastic chance constrained model is established and solved by using a solver. Due to the influence of uncertain demand, this paper further transforms the two-stage stochastic chance constrained model into a two-stage robust counterpart model. The validity and practicability of the model and the algorithm are validated by specific cases.

The following conclusions are drawn. When the volatility is high, the time performance of the two-stage box set robust counterpart model and the two-stage ellipsoid set robust counterpart model fluctuates violently, while the mixed set robust counterpart model is relatively robust. Furthermore, the two-stage mixed set robust counterpart model has strong ability to resist uncertainty. In the two-stage box set robust counterpart model, the logistics service level increases from 89.83% to 93.21% in the path planning stage when the safety parameters increase. The two-stage mixed set robust counterpart model does have the strong robustness. When gradually promoting, the level of logistics service increases from 90.32% to 94.96% in the path planning stage.

The innovation and contribution of this paper are mainly reflected in the following: how to construct a two-stage robust counterpart model to discuss uncertain optimization problems. To start with, in order to improve the satisfaction of logistics transportation service, a two-stage stochastic chance constrained model with opportunity constraints is considered, in which the uncertain set is composed of the first and second moment of stochastic demand. Unlike the classical two-stage stochastic problem, this model does not assume a preknown probability distribution of stochastic demand. Compared with the stochastic model, this model is unwillingly to suppose that uncertain demand belongs to a predetermined set. Moreover, the two-stage stochastic chance constrained model is equivalently transformed into a two-stage robust counterpart model. In addition, according to the universality of the model, we construct three robust counterpart models with different undefined sets. In the process of study, this paper considers that the storage node is fixed, while the actual location of the node may be mobile, which depends on the source and quantity of the caring material, as well as the type and quality difference of the material. This will also be the starting point or research direction of future research.

Data Availability

No data were used to support this study.

Conflicts of Interest

The author declares no conflicts of interest.

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