Retraction

Retracted: Robust Two-Stage Location Allocation for Emergency Temporary Blood Supply in Postdisaster

Discrete Dynamics in Nature and Society

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope

(2) Discrepancies in the description of the research reported

(3) Discrepancies between the availability of data and the research described

(4) Inappropriate citations

(5) Incoherent, meaningless and/or irrelevant content included in the article

(6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] D. Luan, A. Liu, X. Wang, Y. Xie, and Z. Wu, "Robust Two-Stage Location Allocation for Emergency Temporary Blood Supply in Postdisaster," *Discrete Dynamics in Nature and Society*, vol. 2022, Article ID 6184170, 20 pages, 2022.

Research Article

Robust Two-Stage Location Allocation for Emergency Temporary Blood Supply in Postdisaster

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Disaster medical rescue in China mainly adopts the "on-site rescue" model. Whether the location of emergency temporary blood supply sites is reasonable or not directly affects the rescue efficiency. The paper studies the robust location-allocation for emergency temporary blood supply after disaster. First, the factors of several candidate sites were quantified by the entropy-based TOPSIS method, and 12 candidate blood supply sites with higher priority were selected according to the evaluation indicators. At the same time, the uncertainty of blood demand at each disaster site increased the difficulty of decision-making, and then, a robust location model (MIRP) was constructed with minimum cost with time window constraints. It is also constrained by the uncertain demand for blood in three scenarios. Second, the survival probability function was introduced, and the time window limit was given at the minimum cost to maximize the survival probability of the suffered people. Finally, the numerical example experiments demonstrate that the increase in demand uncertainty and survival probability cause the MIRP model to generate more costs. Compared with the three MIRP models, the MIRP-ellipsoid set model gained better robustness. Also, given the necessary restrictions on the time window, the cost can be reduced by about 13% with the highest survival probability. Decision-makers can select different combinations of uncertainty levels and demand disturbance ratios and necessary time constraints to obtain the optimal location-allocation solution according to risk preference and actual conditions.

1. Introduction

The frequent occurrence of public health emergencies, their unpredictable, wide-ranging, and extremely devastating characteristics have attracted the attention of many scholars, and related theoretical and practical research has become increasingly complete [1]. Public health emergencies not only threaten our health but also undermine social stability and hinder economic development [2]. After disasters, the first step of rapid emergency response is to activate the emergency response network, reasonably configure emergency response resources, and improve rescue efficiency [3]. One of the most important tasks of disaster relief is to rapidly meet the emergent needs of victims, such as food, clothing, water, shelter, and medical care [4, 5]. Among them, blood

transfusion is very important in disaster relief management, and blood is directly related to people's lives. The establishment of temporary blood supply stations at various disaster-stricken locations can effectively guarantee the blood needs of the affected people. The difference between the blood supply station and other basic medical facilities is as follows: the blood supply station is equipped with basic medical equipment and a variety of material accidents, can provide a stable blood transfusion environment, and is equipped with sufficient red blood cell blood to meet the needs of the seriously injured. However, when disasters occur, the geography of each area is severely affected, and the construction of blood supply stations is also affected by subjective and objective factors, such as the cost of building blood supply stations; subjective factors include supply

capacity, demand capacity, and coordination capacity; objective factors include the uncertainty of blood demand at each disaster site and time window constraints. Therefore, not all sites are suitable for the establishment of temporary blood supply stations. A systematic approach is required to solve the problem of the location of blood supply stations and blood distribution.

Recent disasters have shown the fact that insufficient blood supply led to an increase in mortality, such as the 2011 Japanese earthquake and subsequent tsunami interrupted blood supply [6]. In the 2008 Wenchuan earthquake, there were quality and wastage problems in the blood supply [7]. After the 2004 tsunami, it was difficult for Sri Lanka's national authorities to coordinate blood supply [8]. These examples have contributed to the fact that the mortality rate has increased to varying degrees, which shows that the timely supply of blood is vitally important after disasters.

Many scholars have studied the rescue of earthquake disasters and the problem of blood supply when disasters occur. For example, Şahin et al. [9] proposed a deterministic model to solve the location-allocation problem of the Turkish Red Crescent Society blood service area. Ghand-foroush et al. [10] transformed the nonconvex integer programming model into a 0-1 linear problem under deterministic demand to optimize the transportation of platelets from the production center to the blood transfusion center. However, when a disaster occurs, because the extent of the disaster in each area is unknown, the number of people affected is also unknown, and each disaster is unique, so the actual blood demand and various supplies are uncertain. Under certain conditions, the research problem is not in line with reality. Therefore, some scholars have introduced stochastic optimization theory into the research. Wang et al. [11, 12] hypothesized that based on stochastic programming, accurate distributions can be obtained from historical data. However, earthquakes do not occur frequently in a certain area, and historical data of blood supply are limited, and the known distribution assumptions are somewhat incorrect. René et al. [13] proposed a stochastic planning and simulation method to optimize the inventory problem of perishable blood products. Some other research works of literature are using stochastic optimization theory [14–16]. Although the introduction of stochastic optimization makes the research more realistic, the premise of stochastic optimization is that the demand needs to obey a certain probability distribution. Usually, the probability distribution of this demand is not accurately known when a disaster occurs, and then, stochastic optimization cannot fully reflect the actual situation to a certain extent. From the literature review, it can be found that there is little research founding on such problems based on the robust optimization method of the uncertain set.

There are many advantages of robust optimization. First of all, it does not need to know the probability distribution of the target audience's needs [17]. Even in the worst case, it can perform well [18]. The key to robust optimization is how to measure uncertainty, that is, how to construct an uncertainty set, which considers the risk preference and conservativeness of decision-makers to a certain extent, and makes up for the

shortcomings of stochastic optimization theory [19, 20]. Therefore, based on previous studies, the article adopts robust optimization to construct a MIRP model that is closer to the actual situation. The demand of the disaster site does not follow a single probability distribution but changes within a certain set of uncertainties. This makes the model constructed in this article more general and more in line with the actual situation.

In [21], considering the randomness and time urgency caused by the geographic location and terrain of the disaster relief point, a multiobjective fuzzy LRP optimization model based on chance-constrained planning is constructed to realize the joint decision-making of the emergency logistics center positioning and emergency vehicle path planning after the earthquake. In [22], considering the dynamic changes in the capacity of ambulance vehicles and medical facilities, the dynamic changes in the survival probability of various wounded with time, and the changes in the psychological status of the wounded, a medical facility with a secondary evacuation model for the wounded after the earthquake that maximizes the survival of the wounded and minimizes the psychological cost has been constructed. The dual-objective dynamic planning model for location selection and casualty transfer is more effective than increasing the number of temporary hospitals or capacity and the number of ambulances than increasing the number of rear hospitals or the capacity and the number of helicopters. The above research is decision-making for earthquake disasters under the multiobjective situation, which is considered. There are many factors such as capacity changes, the number of hospitals. However, we believe that the first factor to be considered when an earthquake disaster occurs is the survival probability of the victims, but there are currently few studies on this type. A similar approach has been taken in other areas, including the investment portfolio [23].

In addition, when disasters like earthquakes occur, the topography of various regions may be severely affected. Considering that the construction of blood supply stations is affected by subjective and objective factors, not all sites are suitable for building temporary blood supply stations. Therefore, a systematic approach is proposed in the article. The entropy-based TOPSIS method is employed to quantify the subjective factors of several candidate sites to select initial blood sites, by evaluating the construction cost, supply capacity, demand factors, and coordination capabilities. Due to objective factors including construction cost, time window constraints, and survival probability, it is impossible to select all alternative locations. Therefore, a robust optimization model with minimum cost and time window constraints is constructed to perform secondary location and distribution.

Based on the actual situation, the study uses the entropy TOPSIS method to initially screen the candidate sites, selects a better initial blood supply site, and then applies the robust optimization theory to the blood supply problem in disaster management. The main contributions are as follows:

(1) The site selection process of emergency facilities is redefined, combined with multicriteria decision-

making and robust optimization methods, which were not involved in previous studies. The reason for this is that we feel that whether it is traditional site selection using multiattribute methods or robust optimization methods, it is impossible to fully consider the comprehensive factors affecting site selection. The combination of the two methods is a very good idea.

(2) A mixed-integer programming model of the blood supply problem in disaster areas is established with time window constraints. In the site selection problem, especially the site selection problem in emergency management, the time constraint is a very important factor in emergency management issues. In previous studies, time constraints were rarely considered. We think this is wrong.

(3) Robust optimization theory to measure the uncertainty of blood demand is applied by setting the level of uncertainty parameters. Robust optimization is a good method to deal with uncertain situations. Compared with stochastic programming, robust optimization does not need to know the probability distribution function of uncertain information.

(4) According to the robust optimization method, a blood supply site selection model corresponding to the three situations of uncertain demand is established, and the three models are compared, and the robustness of the three models is analyzed. To measure demand uncertainty in the form of uncertainty sets, this method is more realistic, and the comparison of multiple methods can give decision-makers more choices.

(5) Introducing the survival time probability function, decision-makers can make corresponding decisions according to the emergency time of disaster events and meet the blood supply demand with the minimum time and cost while maximizing the survival probability of disaster victims. Survival probability is rarely mentioned in previous studies. We combine survival probability with time window constraints. This is in line with the reality. A higher survival probability must correspond to a tighter time window. Therefore, decision-makers can make better decisions with reference to time and survival probability.

The rest of the organization of this article is organized as follows: Section 2 describes the subjective influencing factors of site selection and introduces the entropy weight-TOPSIS method. Section 3 describes the problem of emergency temporary blood supply sites, constructs a deterministic model and a robust optimization model, Section 4 uses the Wenchuan earthquake to carry out case simulations and select the location of secondary emergency temporary blood supply sites, and Section 5 summarizes and prospects. The research framework of this study is shown in Figure 1.

2. Alternative Location Selection Based on the Entropy-TOPSIS Method

Wenchuan earthquake on May 12, 2008, which caused more than 400,000 casualties, was the most destructive earthquake since the establishment of China [24]. It is quite necessary to conduct the site selection and construction of emergency temporary blood supply stations owing to China's large population, complex geographical environment, and the use of the mode of "on-site treatment." Since the earthquake caused severe damage, the location of the emergency temporary blood supply station should be in a place with flat terrain, unobstructed roads, a certain area of open space, and other suitable relief factors. Based on the above requirements, the entropy-TOPSIS method was adopted to analyze several candidate locations in Wenchuan County, Sichuan Province, and screen out the qualified candidate locations.

2.1. Influencing Factors of Location

2.1.1. Construction Costs. During the process of selecting the site for blood supply stations, it is necessary to consider the cost factors and reasonably calculate the construction land and labor costs in the region and to ensure scientific and reasonable planning and construction costs and maximize the utilization of limited resources. This primarily includes land construction costs and labor costs and other factors.

2.1.2. Supply Capacity. After the temporary blood supply station is built, it can not only meet the demand of blood transportation but also may involve site expansion or new distribution lines. Therefore, both the existing supply capacity and the requirements for spatial development should be emphasized in the site selection.

2.1.3. Demand Factors. In the construction of temporary blood supply stations, the severity of surrounding natural disasters should be considered to guarantee the blood demand of more demand points under the temporary blood supply stations.

2.1.4. Coordination Ability. The layout planning of temporary blood supply stations should focus on the connection with other modes of transportation. It is better to combine the layout of urban and rural transportation hubs for site selection.

For decision-makers, these four factors are appropriate for the location of emergency temporary blood supply stations. First of all, decision-makers do not want to invest too much and have the greatest benefits. In addition, because the construction of emergency temporary blood supply stations is greatly affected by topographical factors, factors must be considered when coordinating capabilities.

2.2. Location Method.
There are many methods for multi-attribute decision-making, such as the WSM method, VIKOR method, and ELECTRE method. The WSM method
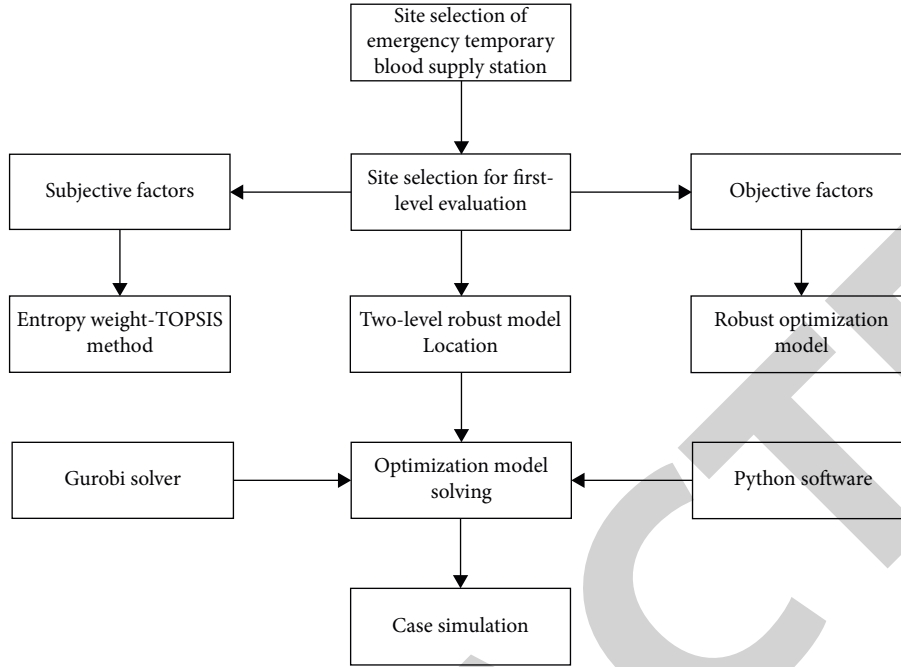
FIGURE 1: Research framework.

is simple and is the most widely used method. The VIKOR method is a better method to resolve conflicting factors. The calculation of the ELECTRE method is complicated. In this study, the entropy weight-TOPSI method is selected to select the first-level location of the emergency temporary blood supply station. The main reason is that it is sorted by calculating the distance between the evaluation plan and the ideal solution and the negative ideal solution. Compared with traditional methods, it has the characteristics of intuitive analysis principle, simple calculation, and low sample demand, which is more suitable for the site selection requirements of blood supply sites.

Step 1: build an index system. According to the main factors affecting the site selection of blood supply stations, four index systems were selected to construct the evaluation index system of node location.

Step 2: construct the original evaluation index matrix. There are m options to be selected and n evaluation indicators affecting each option. Then, the original decision matrix composed of the indicator data of each option is as follows:

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix} = \begin{bmatrix} a_{ij} \end{bmatrix}_{m \times n}, \quad (1)$$

where a_{ij} represents the data of the jth indicator of scheme i.

Step 3: generate the standard matrix. By standardizing the data in the matrix, the standard matrix R after data normalization can be obtained:

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix}. \quad (2)$$

Step 4: calculate the weight by using the entropy weight method

(1) Standardize the decision matrix:

$$p_{ij} = \frac{r_{ij}}{\sum_{i=1}^{m} r_{ij}}, \quad i = 1, 2, \ldots, m. \quad (3)$$

(2) Calculate the entropy value of the jth index:

$$e_j = -K \sum_{i=1}^{m} p_{ij} \ln p_{ij}, \quad j = 1, 2, \ldots, n, \quad (4)$$

where $K > 0, K = 1/\ln m$.

(3) Calculate the difference coefficient of the jth index:

$$g_i = 1 - e_j, \quad (5)$$

If the value difference of an index is larger, it has a greater impact on the evaluation of the scheme. Correspondingly, there will be a smaller entropy value and a larger difference coefficient. As a result, the difference coefficient can indirectly reflect the importance of the index.

(4) The weight of each index can be calculated by the difference coefficient as follows:

$$w_j = \frac{g_j}{\sum_{j=1}^{n} g_j}. \quad (6)$$

Step 5: generate the evaluation matrix:

$$V = \left(v_{ij}\right)_{m \times n} = \left(w_r r_{ij}\right)_{m \times n} = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1n} \\ v_{21} & v_{22} & \cdots & v_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ v_{m1} & v_{m2} & \cdots & v_{mn} \end{bmatrix}. \quad (7)$$

Step 6: determine the positive ideal solution and negative ideal solution:

$$\text{positive ideal solution: } v_j^+ = \max\left(v_{ij}\right),$$
$$\text{negative ideal solution: } v_j^- = \min\left(v_{ij}\right). \quad (8)$$

Step 7: calculate the distance:

$$S_i^* = \sqrt{\sum_{j=1}^n \left(v_{ij} - v_j^*\right)^2}, \quad i = 1, 2, \ldots, m,$$

$$S_i^- = \sqrt{\sum_{j=1}^n \left(v_{ij} - v_j^-\right)^2}, \quad i = 1, 2, \ldots, m. \quad (9)$$

Step 8: calculate the fit degree for ranking:

$$C_i^* = \frac{S_i^-}{S_i^* + S_i^-}, \quad 0 < C_i^* < 1, i = 1, 2, \ldots, m, \quad (10)$$

where C_i^* represents the relative proximity between the evaluation object i and the ideal solution. The greater the value of C_i^*, the better the evaluation object.

3. Robust Location-Allocation Optimization Modeling

In this study, the location and distribution of emergency temporary blood supply stations under uncertain conditions were explored. In this problem, two types of sites were considered, namely, emergency temporary blood supply sites and disaster area blood demand sites, as illustrated in Figure 2. Given cost minimization and demand responsiveness, the goal was to consider the number of emergency blood supply stations and to minimize the operating and management costs of emergency blood supply stations while meeting the blood demand in the disaster area and determining the proportion of blood demand points in the disaster area allocated to emergency temporary blood supply stations. Besides, the construction costs of emergency blood supply stations, transportation costs, and penalty costs for failure to arrive within the time window were considered.

3.1. Hypotheses

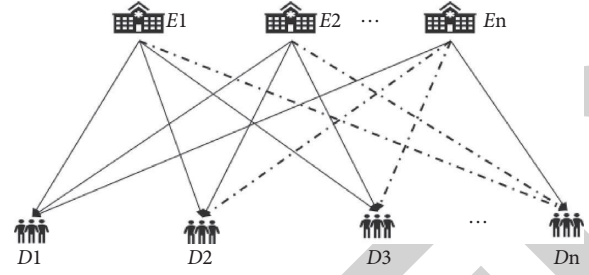(1) Nodes in the network represent a demand point or emergency temporary blood supply site

Figure 2: Distribution network of emergency temporary sites.

(2) The vehicle is set to keep uniform speed in the driving process, to make the model easy to solve

(3) Assume that the vehicle is not affected by road congestion during driving

(4) Assume that the operation of the entire system neglects device interrupt

3.2. Symbol Description

i is the blood demand point in the disaster area, $i \in \{1, 2, \ldots, m\}$

j is the emergency blood supply station to be selected, $j \in \{1, 2, \ldots, n\}$

f_j is the fixed cost of building an emergency blood supply station

g_j is the maximum blood storage capacity of each emergency blood supply station

C_{ij} is the unit transportation cost of vehicles from point j to point i

D_i is the blood demand of blood demand point i in the disaster area

d_{ij} is the distance from the emergency blood supply station j to the blood demand point i in the disaster area

$\bar{v}_j$ is the average speed of the vehicle leaving the emergency blood supply station j

O_a is the earliest time allowed to reach the demand point

O_b is the latest time allowed to reach the demand point, varying according to the survival probability

ε is the penalty cost that does not arrive within the time window

x_j is the 0-1 decision variable (if it is 1, the first emergency temporary blood supply station is selected; otherwise, it is 0)

y_{ij} is the proportion that blood demand point i in the disaster is allocated to emergency temporary blood supply station j

q_{ij} is the 0-1 decision variable (if y_{ij} is not 0, it will be 1; otherwise, it is 0)

α_{ij} is the 0-1decision variable (if $O_a \le q_{ij} \cdot (d_{ij}/\overline{v}_j) \le O_b$, it is 1; otherwise, it is 0)

3.3. Deterministic Model (MILP). When the demand of blood demand points in disaster areas is known, the nominal model (i.e., the deterministic model) is usually expressed as follows [25–28]:

$$\min Z_1 = \sum_{j=1}^{n} f_j \cdot x_j + \sum_{i=1}^{m} \sum_{j=1}^{n} C_{ij} \cdot d_{ij} \cdot y_{ij}$$

$$\cdot D_i + \varepsilon \sum_{i=1}^{m} \sum_{j=1}^{n} (1 - \alpha_{ij}), \tag{11}$$

$$\text{s.t. } \sum_{j=1}^{n} y_{ij} = 1, \quad \forall i \in I, \tag{12}$$

$$\sum_{i=1}^{m} D_i y_{ij} \le g_j, \quad \forall j \in J, \tag{13}$$

$$y_{ij} \le x_j, \quad \forall i \in I, \forall j \in J, \tag{14}$$

$$0 \le y_{ij} \le 1, \quad \forall i \in I, \forall j \in J, \tag{15}$$

$$O_a \le q_{ij} \cdot \frac{d_{ij}}{\overline{v}_j} \le O_b, \tag{16}$$

$$x_j, q_{ij}, \alpha_{ij} \in \{0, 1\}, \tag{17}$$

where objective function (11) aims to minimize the sum of the costs of site-allocation problems of emergency blood supply stations. The costs include fixed cost, vehicle transportation cost, and time window penalty cost. Formula (12) indicates that the amount of blood sent to the blood demand point of the disaster area must meet its demand. Formula (13) suggests that the amount of blood transported by the emergency blood supply site does not exceed its maximum stock capacity. Formula (14) reflects that vehicles can only be assigned to selected emergency blood supply stations. Formula (15) reveals that the proportion on any allocated route should not exceed 1. Formula (16) represents the time window constraint. Different from the simple time constraint in the past, time and survival probability are closely combined to emphasize the survival probability and restrict time simultaneously. Formula (17) designates the 0-1 variable.

3.4. Robust Counterpart. Considering the following linear programming problems with uncertain coefficients,

$$\left\{ \min_x c^T x + d : Ax \le b \right\}_{(c,d,A,b) \in U}, \tag{18}$$

where $c^T x + d$ indicates the objective function; $Ax \le b$ is the constraint, considering the ith row of matrix A. It is assumed that only one element $\tilde{a}_{ij}$ in the coefficient matrix is uncertain, $\tilde{a}_{ij} = a_{ij} + \hat{a}_{ij}\xi_j$. Among them, $\tilde{a}_{ij}$ represents the actual value of the parameter, a_{ij} denotes the determined value of the parameter, $\hat{a}_{ij}$ refers to the fluctuation of the parameter, ξ_j designates the uncertainty factor (is the uncertainty set), and ξ can take any value in the set. Then, the original constraint can be written as follows:

$$\sum_j a_{ij}x_j + \max_{\xi \in U} \sum_j \hat{a}_{ij}x_j\xi_j \le b. \tag{19}$$

Its robust equivalents will be discussed in the next section.

3.4.1. Uncertain Set of Boxes. If the uncertainty set is box-like, it can be defined by an infinite norm l_∞. $U^B = U_\infty = \{\xi : \|\xi\|_\infty \le \psi\} = \{\xi : |\xi_j| \le \psi\}$, where ψ denotes the uncertainty level parameter, suggesting that the deviation coefficient from the initial value on the first-row vector does not exceed ψ. Meanwhile, it is used to measure the conservatism of constraint conditions and reflect the risk preference degree of decision-makers. The smaller the value of ψ, the higher the risk preference degree of decision-makers.

Theorem 1. *Formula (19) can be equivalently written as*

$$\sum_j a_{ij}x_j + \psi \sum_j \hat{a}_{ij}|x_j| \le b. \tag{20}$$

3.4.2. Polyhedron Uncertain Set. If the uncertain set is a polyhedron, it can be defined by the 1-norm l_1. $U^P = U_1 = \{\xi : \|\xi\|_1 \le \Lambda\} = \{\xi \cdot \sum |\xi_j| \le \Lambda\}$, where Λ represents the uncertain parameter.

Theorem 2. *Formula (19) can be equivalently written as*

$$\sum_j a_{ij}x_j + \Lambda p_i \le b, \quad p_i \ge \hat{a}_{ij}|x_j|. \tag{21}$$

3.4.3. Ellipsoidal Uncertain Set. If the uncertainty set is an ellipsoid, it can be defined by the 2-norm l_2. $U^E = U_2 = \{\xi : \|\xi\|_2 \le \Omega\} = \{\xi \cdot \sqrt{\sum_j \xi_j^2} \le \Omega\}$, where Ω indicates both the uncertain horizontal parameter and the radius of the uncertain set.

Theorem 3. *Formula (19) can be equivalently written as*

$$\sum_j a_{ij}x_j + \Omega \sqrt{\hat{a}_{ij}^2 x_j^2} \le b. \tag{22}$$

3.5. Robust Optimization Model (MIRP). In this section, the MILP model is transformed into three different MIRP models, and the uncertainty set is used to replace the

uncertainty constraint. Compared with the deterministic model, three uncertain robust optimization models are all nonconvex optimization problems. The difficulty of solving becomes greater, and the complexity of the problem increases, and as the degree of uncertainty increases, the difficulty of solving gradually increases. The blood demand in the disaster area is uncertain and defined as a random variable $\widetilde{D}$; $\widehat{D}$ is defined as the fluctuation of the demand; thus, $\widetilde{D} = D + \widehat{D}$. According to the theoretical knowledge of robust optimization [28–30], the MILP model can be transformed into three MIRP models.

3.5.1. MIRP-Box Set Model.
If the initial blood demand of the disaster area is $\widetilde{D}$, the uncertain set is a box. ψ denotes the level of uncertainty. The box uncertainty set model can be expressed as equations (23)–(30).

$$\min Z_b, \tag{23}$$

$$\text{s.t.} \ \sum_{j=1}^{n} f_j \cdot x_j + \sum_{i=1}^{m} \sum_{j=1}^{n} C_{ij} \cdot d_{ij} \cdot y_{ij} D_i$$
$$+ \varepsilon \sum_{i=1}^{m} \sum_{j=1}^{n} \left(1 - \alpha_{ij}\right) + \psi \cdot \sum_{i=1}^{m} \sum_{j=1}^{n} C \cdot d_{ij} \cdot y_{ij} \cdot \widehat{D}_i \leq Z_b, \tag{24}$$

$$\sum_{j=1}^{n} y_{ij} = 1, \quad \forall i \in I, \tag{25}$$

$$\sum_{i=1}^{m} D_i y_{ij} + \psi \cdot \sum_{i=1}^{m} \widehat{D}_i y_{ij} \leq g_j, \quad \forall j \in J, \tag{26}$$

$$y_{ij} \leq x_j, \quad \forall i \in I, \forall j \in J, \tag{27}$$

$$0 \leq y_{ij} \leq 1, \quad \forall i \in I, \forall j \in J, \tag{28}$$

$$O_a \leq q_{ij} \cdot \frac{d_{ij}}{\overline{v}_j} \leq O_b, \tag{29}$$

$$x_j, q_{ij}, \quad \alpha_{ij} \in \{0, 1\}. \tag{30}$$

3.5.2. MIRP-Polyhedron Set Model.
If the initial blood demand of the disaster area is $\widetilde{D}$, the uncertain set is a polyhedron. Λ, Λ' represent the uncertainties in the objective function and constraint, respectively; μ, μ' indicate their corresponding dual variables, respectively. Then, the polyhedral uncertainty set model can be expressed as equations (31)–(38).

$$\min Z_p, \tag{31}$$

$$\text{s.t.} \ \sum_{j=1}^{n} f_j \cdot x_j + \sum_{i=1}^{m} \sum_{j=1}^{n} C_{ij} \cdot d_{ij} \cdot y_{ij} D_i$$
$$+ \varepsilon \sum_{i=1}^{m} \sum_{j=1}^{n} \left(1 - \alpha_{ij}\right) + \Lambda \mu \leq Z_p, \tag{32}$$

$$\sum_{j=1}^{n} y_{ij} = 1, \quad \forall i \in I, \tag{33}$$

$$\sum_{i=1}^{m} D_i y_{ij} + \Lambda' \mu' \leq g_j, \quad \forall j \in J, \tag{34}$$

$$y_{ij} \leq x_j, \quad \forall i \in I, \forall j \in J, \tag{35}$$

$$0 \leq y_{ij} \leq 1, \quad \forall i \in I, \forall j \in J, \tag{36}$$

$$O_a \leq q_{ij} \cdot \frac{d_{ij}}{\overline{v}_j} \leq O_b, \tag{37}$$

$$x_j, q_{ij}, \alpha_{ij} \in \{0, 1\}. \tag{38}$$

3.5.3. MIRP-Ellipsoid Set Model.
If the initial blood demand of the disaster area is $\widetilde{D}$, the uncertain set is an ellipsoid. Considering that the demand $\widetilde{D}$ is uncertain, $U_E^1 = \left\{ \widetilde{D} \in R, \sum_{i=1}^{m} [(\widetilde{D}_i - D_i)/\widehat{D}_i]^2 \leq \Omega^2 \right\}$ represents the set of ellipsoids. Since the problem is a nonlinear constraint problem, $\widetilde{D}_i = \gamma_i D_i$, we set $U_E^1 = U_E^2 = \left\{ \widetilde{D} \in R, (\widetilde{D}_i - D_i)^T C^{-1} (\widetilde{D}_i - D_i) \leq \Omega^2 \right\}$, where matrix C is an n-order diagonal matrix of element $\widehat{D}_i^2$ (nonzero). It can be verified that $\sum_{j=1}^{n} f_j \cdot x_j + \sum_{i=1}^{m} \sum_{j=1}^{n} C_{ij} \cdot d_{ij} \cdot y_{ij} \cdot D_i + \varepsilon \sum_{i=1}^{m} \sum_{j=1}^{n} (1 - \alpha_{ij}) + \Omega_1 \sqrt{\sum_{i=1}^{m} (\widehat{D}_i^2 y_{ij} d_{ij} C_{ij})} \leq Z_e$, let $\beta_i = \sum_{j=1}^{n} y_{ij} d_{ij} C_{ij}$, $F = \sqrt{\sum_{i=1}^{m} \widehat{D}_i^2 \beta_i^2}$, as it aims to solve the minimum cost, so $\beta_i \geq \sum_{j=1}^{n} y_{ij} d_{ij} C_{ij}$, $F \geq \sqrt{\sum_{i=1}^{m} \widehat{D}_i^2 \beta_i^2}$. Similarly, $\sum_{j=1}^{n} D_i y_{ij} + \Omega_2 \sqrt{\sum_{i=1}^{m} (\widehat{D}_i^2 y_{ij})} \leq g_j$, $Q = \sqrt{\sum_{i=1}^{m} y_{ij}^2 \widehat{D}_i^2}$, relaxation constraint $Q \geq \sqrt{\sum_{i=1}^{m} y_{ij}^2 \widehat{D}_i^2}$ is added.

The model can be expressed as equations (39)–(49).

$$\min Z_e, \tag{39}$$

$$\text{s.t.} \ \sum_{j=1}^{n} f_j \cdot x_j + \sum_{i=1}^{m} \sum_{j=1}^{n} C_{ij} \cdot d_{ij} \cdot y_{ij} \cdot D_i$$
$$+ \varepsilon \sum_{i=1}^{m} \sum_{j=1}^{n} \left(1 - \alpha_{ij}\right) + \Omega_1 F \leq Z_e, \tag{40}$$

$$\sum_{j=1}^{n} y_{ij} = 1, \quad \forall i \in I, \tag{41}$$

$$F \geq \sqrt{\sum_{i=1}^{m} \widehat{D}_i^2 r_i^2}, \tag{42}$$

$$\beta_i \geq \sum_{j=1}^{n} y_{ij} d_{ij} C_{ij}, \quad \forall i \in I, \tag{43}$$

$$\sum_{j=1}^{n} D_i y_{ij} + \Omega_2 Q \leq g_j, \tag{44}$$

$$Q \geq \sqrt{\sum_{i=1}^{m} y_{ij}^2 \widehat{D}_i^2}, \quad \forall j \in J, \tag{45}$$

$$y_{ij} \leq x_j, \quad \forall i \in I, \forall j \in J, \tag{46}$$

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

$$O_a \leq q_{ij} \cdot \frac{d_{ij}}{\overline{v}_j} \leq O_b, \tag{48}$$

$$x_j, q_{ij}, \quad \alpha_{ij} \in \{0, 1\}. \tag{49}$$

4. Case Simulation

4.1. Site Selection Analysis. During the earthquake disaster, various terrains are destroyed, and roads are severely blocked. Therefore, it is imperative to select suitable alternative blood supply stations since the proper geographical location can provide convenient and efficient treatment conditions. The construction cost, blood supply capacity, demand factors, and coordination ability of blood supply stations constitute the screening conditions of alternative locations. Thus, 30 locations were selected as candidate locations, and the entropy-TOPSIS method was employed to compare and select the final 12 alternative locations.

4.1.1. Collecting Original Data. The original index data of 30 candidate locations are listed in Table 1.

4.1.2. Generating the Standardized Matrix. Standardized matrix is generated as follows:

$$R = \begin{pmatrix}
0.333333 & 0.177778 & 0.394737 & 0.263158 \\
0.466667 & 0.6 & 0.815789 & 0.552632 \\
0.433333 & 0 & 0.263158 & 0.078947 \\
0.533333 & 0.444444 & 0.289474 & 0.447368 \\
0.633333 & 0.933333 & 0.578947 & 0.789474 \\
0.3 & 0.422222 & 0.210526 & 0.447368 \\
0.366667 & 0.577778 & 0.026316 & 0.315789 \\
0.4 & 0.822222 & 0.947368 & 0.947368 \\
0.133333 & 1 & 0.815789 & 0.921053 \\
0.166667 & 0.444444 & 0.5 & 0.052632 \\
0.6 & 0.844444 & 0.921053 & 0.868421 \\
0.633333 & 0.444444 & 0.289474 & 0.078947 \\
0.566667 & 0.6 & 0.447368 & 0.447368 \\
0 & 0.622222 & 0.684211 & 0.052632 \\
0.466667 & 0.888889 & 0.947368 & 0.789474 \\
1 & 0.866667 & 0.815789 & 1 \\
0.866667 & 0.466667 & 0 & 0.289474 \\
0.833333 & 0.6 & 0.315789 & 0.578947 \\
0.4 & 0.711111 & 0.052632 & 0.736842 \\
0.233333 & 0.377778 & 0.394737 & 0.342105 \\
0.066667 & 0.933333 & 0.921053 & 0.736842 \\
1 & 0.911111 & 0.789474 & 1 \\
0.7 & 0.422222 & 0 & 0 \\
0.666667 & 0.555556 & 0.184211 & 0.684211 \\
0.6 & 1 & 1 & 0.736842 \\
0.733333 & 0.244444 & 0.263158 & 0.447368 \\
0.766667 & 0.288889 & 0.526316 & 0.289474 \\
0.333333 & 0.577778 & 0.263158 & 0.447368 \\
0.4 & 0.755556 & 0.710526 & 0.815789 \\
0.166667 & 0.377778 & 0 & 0.315789
\end{pmatrix}. \tag{50}$$

4.1.3. Calculating the Weight. According to formulas (4) and (6), the entropy value and weight of each indicator can be calculated. The calculation results are provided in Table 2.

4.1.4. Calculating the Distance and the Fitting Degree. According to formulas (9) and (10), the distance and the fitting degree of each evaluation vector to positive and

TABLE 1: Original data of candidate location indexes.

Candidate sites	Construction costs	Supply capacity	Demanding factors	Coordination ability
J_1	5000	5.5	7.2	6.5
J_2	5200	7.4	8.8	7.6
J_3	5150	4.7	6.7	5.8
J_4	5300	6.7	6.8	7.2
J_5	5450	8.9	7.9	8.5
J_6	4950	6.6	6.5	7.2
J_7	5050	7.3	5.8	6.7
J_8	5100	8.4	9.3	9.1
J_9	4700	9.2	8.8	9.0
J_{10}	4750	6.7	7.6	5.7
J_{11}	5400	8.5	9.2	8.8
J_{12}	5450	6.7	6.8	5.8
J_{13}	5350	7.4	7.4	7.2
J_{14}	4500	7.5	8.3	5.7
J_{15}	5200	8.7	9.3	8.5
J_{16}	6000	8.6	8.8	9.3
J_{17}	5800	6.8	5.7	6.6
J_{18}	5750	7.4	6.9	7.7
J_{19}	5100	7.9	5.9	8.3
J_{20}	4850	6.4	7.2	6.8
J_{21}	4600	8.9	9.2	8.3
J_{22}	6000	8.8	8.7	9.3
J_{23}	5550	6.6	5.7	5.5
J_{24}	5500	7.2	6.4	8.1
J_{25}	5400	9.2	9.5	8.3
J_{26}	5600	5.8	6.7	7.2
J_{27}	5650	6.0	7.7	6.6
J_{28}	5000	7.3	6.7	7.2
J_{29}	5100	8.1	8.4	8.6
J_{30}	4750	6.4	5.7	6.7

TABLE 2: Entropy and weight of each index.

Index	Entropy	Difference coefficient	Weight
Construction costs	0.953102	0.046898023	0.211284
Supply capacity	0.967956	0.032043539	0.144362
Demand factors	0.917829	0.082171034	0.370196
Coordination ability	0.939146	0.06085385	0.274158

negative ideal solutions can be calculated. The calculation results are exhibited in Table 3.

4.2. Determining Alternate Locations.
According to the ranking of the fitting degree in Table 3, the top 12 candidate locations are selected as the alternative locations of blood supply sites, namely, J_7, J_4, J_{22}, J_{16}, J_{26}, J_9, J_3, J_{12}, J_{18}, J_{30}, J_{27}, J_5.

4.3. Data Set.
After the alternative locations of the 12 blood supply stations obtained above were determined, they were set as $j_1, j_2, \ldots, j_{12}$, respectively. Meanwhile, 25 hard-hit villages were selected as disaster area blood demand points. The relative positions of each affected point and alternative location point are illustrated in Figure 3, in which the fixed cost of each alternative location point is f_j, capacity limit is g_j, and the average speed that vehicles left point j is $\bar{v}_j$, as shown in Table 4. The nominal demands D_i of blood demand

points in each area are presented in Table 5. The nominal transport costs between various nodes are provided in Table 6.

4.4. Comparison of MILP and MIRP Models.
In this section, Gurobi 9.0 was adopted to solve the MIRP model under the above different uncertain sets (box, polyhedron, and ellipsoid). The results of MIRP and MILP models were compared. Besides, the minimum cost was obtained by solving the MILP model under the condition that the nominal demand was determined. Six emergency temporary blood supply stations were selected from the alternative locations, namely, E_2, E_4, E_5, E_6, E_8, and E_{10}. The specific results are illustrated in Figure 4.

4.4.1. MIRP-Box Set Model.
In the MIRP-box set model, the impact of ψ on total cost is uncertain. The specific results are exhibited in Table 7. When $\psi = 0$, the result is the same as that of the MILP model, that is, 3.36×10^5, and the selected emergency temporary blood supply sites are E_2, E_4, E_5, E_6, E_8, and E_{10}. With the increasing level of uncertainty, the number of emergency temporary blood supply stations and the total cost gradually increase. The cost increases slowly, indicating that the model is conservative. Particularly, 10 emergency temporary blood supply stations are needed for blood supply

Table 3: Distance between evaluation vectors and positive and negative ideal solutions and the fitting degree.

Candidate site	S_i^*	S_i^-	C_i^*	Ranking
J_1	0.160363	0.136661	0.460102	20
J_2	0.332282	0.225266	0.40403	29
J_3	0.12356	0.135432	0.522919	7
J_4	0.06132	0.087319	0.587458	2
J_5	0.11622	0.115369	0.498164	12
J_6	0.09653	0.064038	0.39882	30
J_7	0.077437	0.126165	0.619666	1
J_8	0.36465	0.320515	0.467793	17
J_9	0.319816	0.372576	0.5381	6
J_{10}	0.25733	0.178978	0.41021	27
J_{11}	0.323196	0.248012	0.434189	23
J_{12}	0.134699	0.147319	0.522375	8
J_{13}	0.100955	0.092925	0.479292	15
J_{14}	0.384621	0.269135	0.411675	26
J_{15}	0.362004	0.279876	0.436026	22
J_{16}	0.200734	0.246838	0.551504	4
J_{17}	0.24019	0.210635	0.467221	18
J_{18}	0.108644	0.118821	0.522371	9
J_{19}	0.238732	0.210862	0.469006	16
J_{20}	0.143195	0.106691	0.426959	24
J_{21}	0.410724	0.395887	0.490803	13
J_{22}	0.180883	0.229211	0.558922	3
J_{23}	0.226512	0.159967	0.413908	25
J_{24}	0.167234	0.140276	0.456167	21
J_{25}	0.372213	0.255395	0.406933	28
J_{26}	0.136633	0.160652	0.540399	5
J_{27}	0.19459	0.198332	0.504763	11
J_{28}	0.070024	0.060201	0.462283	19
J_{29}	0.239006	0.227668	0.487853	14
J_{30}	0.105641	0.108211	0.50601	10

when the level of uncertainty is at its maximum ($3.36 \times 10^5 = 26$).

4.4.2. MIRP-Polyhedron Set Model. In the MIRP model under the polyhedron set, the impact of Λ on the total cost is exhibited in Table 8. When Λ is 0, the MIRP model is equivalent to the MILP model, with the same cost. The total cost shows an upward trend as the value increases. Compared with the box model, the increasing speed is general, suggesting that the model has general robustness. When Λ is 23, the supply reaches saturation, and 12 blood supply stations need to be established to guarantee the demand.

4.4.3. MIRP-Ellipsoid Set Model. In the MIRP model under the ellipsoid set, the impact of Ω on the total cost is provided in Table 9. When Ω is 0, the MIRP model is equivalent to the MILP model, with the same cost. The total cost increases as the value of Ω increases. Compared with the first two models, its upward speed is relatively slow, reflecting that the model has good robustness.

4.4.4. Impact of Uncertainty Level on Total Costs. In this section, the three uncertainty set models obtained by the robust optimization theory were compared with our nominal model. Each set of uncertainty levels was implemented in the corresponding uncertainty set model. Figure 5 suggests that different MIRP models present different robustness when uncertainty levels are different. The three MIRP models are equivalent to the MILP nominal model when the uncertainty level is 0. Additionally, the cost of the three MIRP models increases as the uncertainty level increases. When the uncertainty level is less than 18, the total cost of the three MIRP models is low while the convergence is too slow. The three models tend to be stable when the level of uncertainty is 23. Among them, the MIRP-ellipsoid set model has a lower total cost and faster convergence speed compared to the other two models, demonstrating its stronger robustness.

From this part of the experiment, we can see that robust optimization can well solve the problem of the secondary location of emergency temporary blood supply sites. Different MIRP models can get different results. The uncertainty is measured by the uncertainty set. Uncertainty can also get different results, which is fully consistent with reality.

4.5. Location and Blood Supply Route Optimization. First, the MILP model was solved under certain requirements. The results after comprehensively considering all aspects of cost are exhibited in Figure 3. In the MILP model, 6 emergency blood supply sites were selected from 12 candidates. This
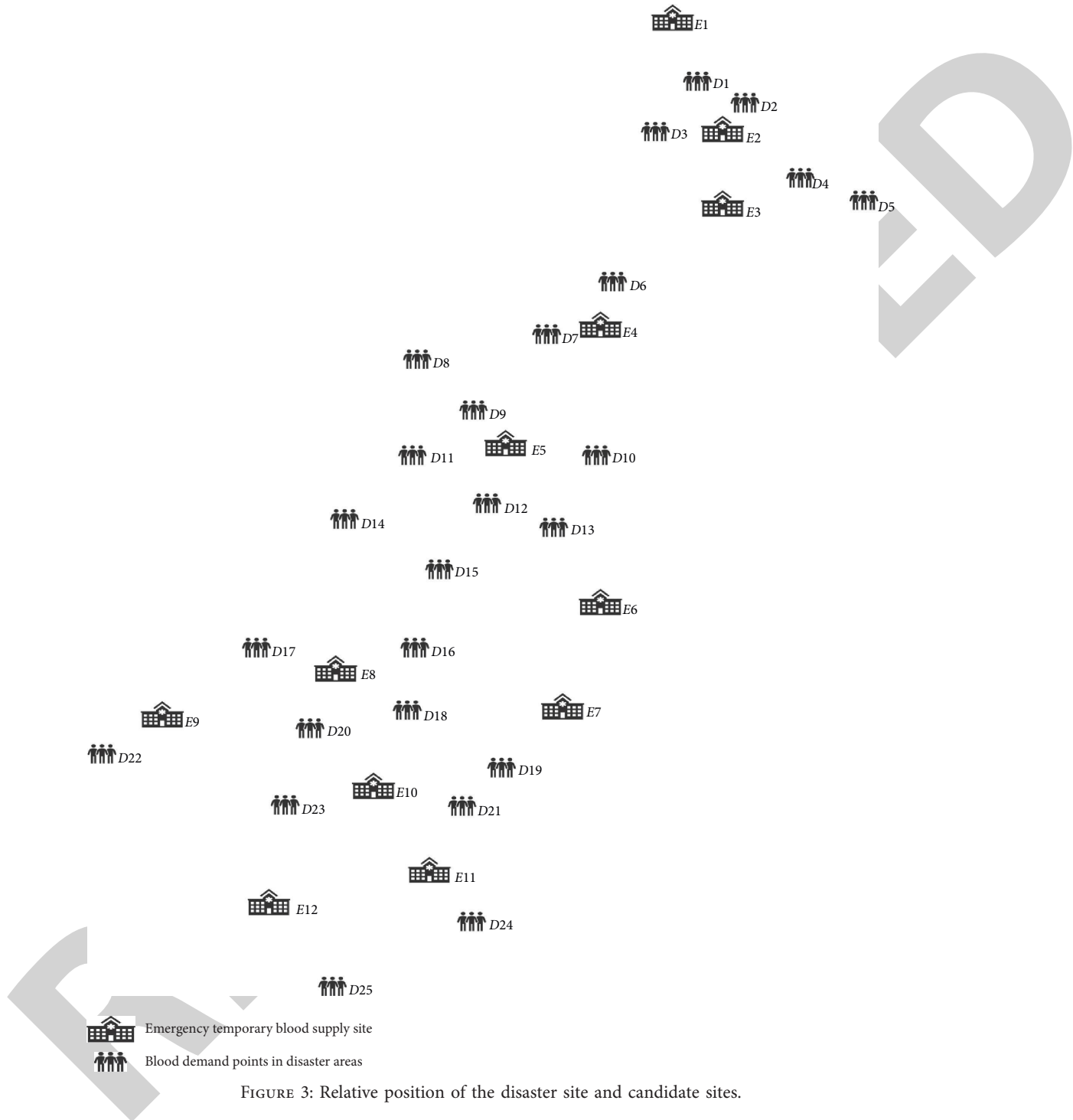
FIGURE 3: Relative position of the disaster site and candidate sites.

TABLE 4: Basic parameters of emergency temporary blood supply stations.

j	1	2	3	4	5	6	7	8	9	10	11	12
f_j	5050	5300	6000	6000	5600	4700	5150	5450	5750	4750	5650	5450
g_j	856	1100	880	788	1000	950	920	1200	980	1150	800	1000
$\overline{v}_j$	30	35	42	37	42	38	41	29	34	29	36	41

TABLE 5: Nominal demand of blood demand points in disaster areas.

i	1	2	3	4	5	6	7	8	9	10	11	12
D_i	200	250	181	170	235	195	210	170	250	205	220	200
13	14	15	16	17	18	19	20	21	22	23	24	25
185	180	216	186	197	235	180	190	225	215	185	176	160

TABLE 6: Unit transportation cost between various nodes.

C_{ij}	E_1	E_2	E_3	E_4	E_5	E_6	E_7	E_8	E_9	E_{10}	E_{11}	E_{12}
D_1	9.1	2.9	11.2	25.9	43.0	58.6	70.0	71.8	93.2	81.3	90.4	97.1
D_2	10.7	1.3	9.6	25.0	42.2	57.3	68.7	71.0	79.3	80.3	89.3	96.1
D_3	12.9	1.7	7.5	22.2	39.3	54.5	66.0	68.0	76.3	77.5	86.5	93.3
D_4	20.3	8.8	10.0	21.7	38.9	51.5	62.4	67.8	76.9	75.9	84.1	92.0
D_5	20.3	10.0	12.0	24.2	41.4	53.5	64.4	70.2	79.3	78.2	86.2	94.2
D_6	33.4	22.9	16.6	1.2	17.9	33.8	45.6	46.9	55.5	56.1	65.1	71.8
D_7	36.1	27.1	21.0	4.4	13.8	30.9	42.0	42.5	51.1	52.1	61.4	67.8
D_8	45.1	37.4	33.0	18.0	12.7	31.7	42.5	34.9	41.7	46.5	56.9	61.0
D_9	46.1	37.2	31.7	15.2	7.0	26.3	37.6	32.9	40.8	43.6	53.5	58.6
D_{10}	49.5	38.5	31.1	15.1	7.5	17.6	29.4	33.3	43.0	40.9	49.3	56.9
D_{11}	52.3	43.3	37.8	21.1	7.0	23.7	34.2	27.1	34.6	38.0	48.3	52.8
D_{12}	57.1	47.3	40.8	23.8	6.3	16.0	26.5	22.5	31.7	32.1	41.8	47.6
D_{13}	57.9	47.2	40.0	23.5	8.6	10.7	22.1	24.9	34.9	31.9	40.6	48.0
D_{14}	63.1	54.7	49.1	32.4	16.0	24.1	31.5	17.1	23.5	29.4	40.4	42.9
D_{15}	65.2	55.5	48.8	31.8	14.4	13.9	21.4	14.7	24.5	23.9	34.0	39.3
D_{16}	73.8	63.9	57.1	40.2	23.0	15.9	18.2	7.6	18.2	15.4	25.7	30.9
D_{17}	78.2	69.5	63.6	46.7	29.5	32.2	30.1	6.4	8.4	18.4	29.3	29.0
D_{18}	82.5	72.3	65.2	48.5	31.5	100.4	16.7	8.8	16.4	6.7	16.8	22.6
D_{19}	85.0	74.2	53.7	50.7	34.9	18.7	10.0	18.2	25.5	10.6	14.2	24.6
D_{20}	86.8	77.3	70.7	53.7	36.2	28.3	25.5	7.6	8.4	8.0	18.2	18.3
D_{21}	92.0	81.3	73.8	57.6	41.3	26.1	17.0	19.8	24.2	7.8	6.7	17.8
D_{22}	103.1	86.9	81.3	64.4	47.3	44.0	42.2	12.2	10.0	15.5	30.1	22.1
D_{23}	94.9	85.3	78.6	61.6	44.2	34.1	28.6	16.0	13.5	8.3	12.8	9.8
D_{24}	103.2	92.2	84.6	68.8	52.9	37.0	25.8	30.7	32.8	8.0	9.8	14.0
D_{25}	115.9	101.6	94.2	77.8	61.0	46.8	37.4	34.6	32.4	11.0	10.0	12.0

scheme was the optimal and ideal one with the lowest cost. However, the demand for blood in each disaster area is uncertain when the disaster occurs. Thus, the candidate sites and blood supply routes were selected by solving the three MIRP models when the uncertainty level was neutral ($\psi = \Lambda = \Omega = 13$) to conform to the actual situation, as presented in Figures 6–8. It can be observed that the model can also generate a good solution when the demand and the decision-maker's risk preferences are uncertain.

4.5.1. Survival Probability and Total Cost. The rescue efficiency of disaster-stricken points depends on two aspects: one is the time when the relief materials arrive, and the other is the quantity of relief materials. It is a very natural choice to use the survival probability of the trapped person over time to measure the arrival time of rescue materials to maximize the rescue effect. Therefore, when a disaster occurs, the survival probability of the wounded is closely related to time. In the event of a disaster, the survival probability of the wounded is directly related to time. Regarding the survival probability of the wounded, Fiedrich et al. [31] obtained the general form of survival probability and time function based on the actual

data of multiple earthquake disasters. On this basis, Yu [32] assumed that the time T corresponding to the average survival probability of the wounded could be estimated to be 0.5 and then constructed the function of survival probability and time. In this study, this function was adopted to describe the relationship between survival probability and time. Figure 9 illustrates the graphs of survival probability function corresponding to T of 60, 120, 180, and 240 (min), respectively.

The function image at $T = 60$ was selected as the research object when the disaster of the Wenchuan earthquake is relatively severe. In practice, the latest time allowed to reach the disaster area (O_b) was changed to observe the impact of time on the total cost. Table 10 lists the actual time between $T = 60$ and survival probability of 0.5–0.95 and the change of total cost under different time constraints. As revealed from the table, the total costs of the three models all increase with the increase of survival probability when $T = 60$ since the improvement of survival probability makes the time window tighter. Therefore, it is necessary to adjust a more appropriate scheme to perform the distribution. Moreover, multiple routes or opening more emergency blood supply stations will undoubtedly increase the total cost. Compared with the three models, the MIRP-ellipsoid set model has the lowest cost,
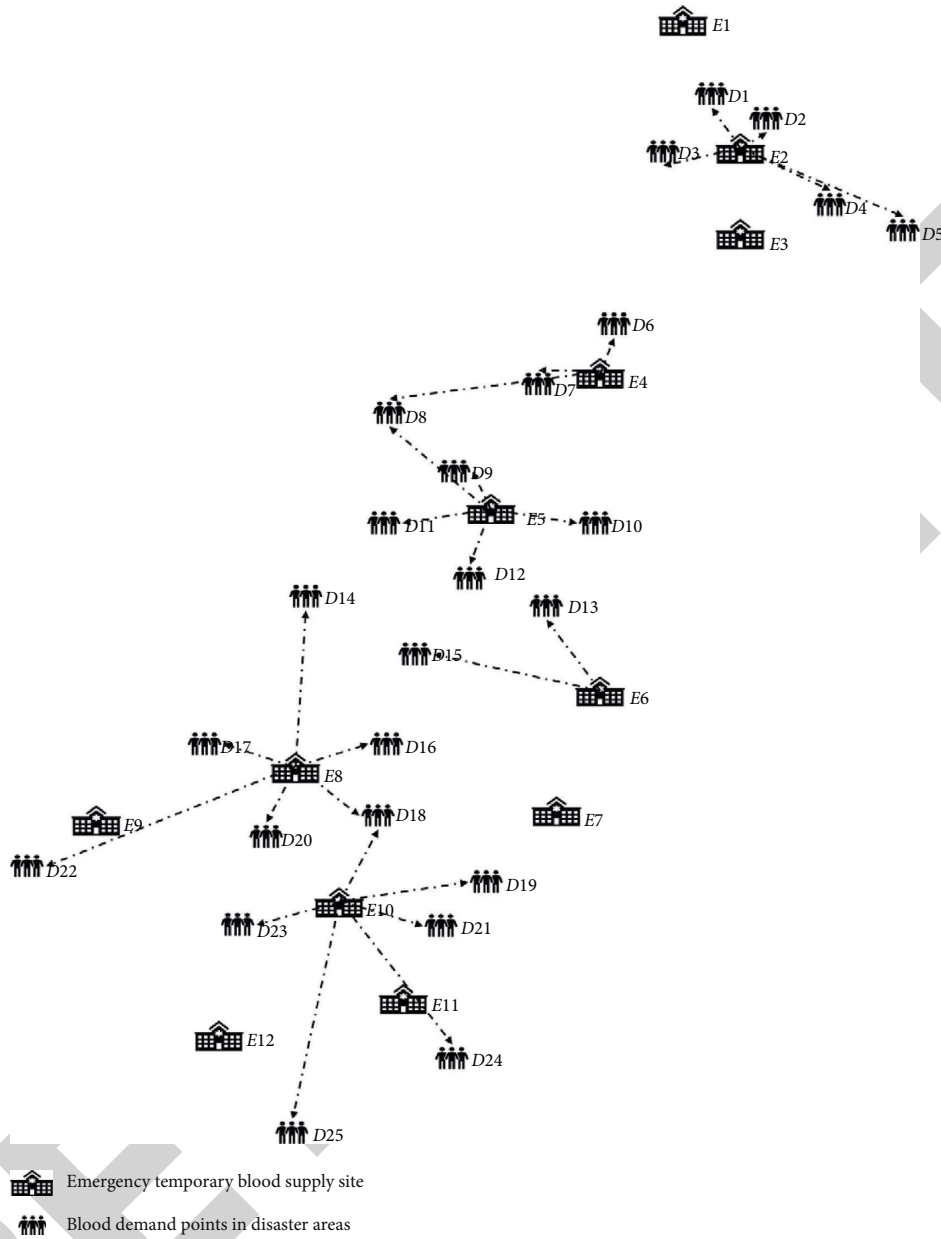
Figure 4: MILP model.

Table 7: Optimal scheme under MIRP-box set.

ψ	Costs (10^5)	Quantity	Selected sites
0	3.36	6	2, 4, 5, 6, 8, 10
3	3.79	6	2, 4, 5, 6, 8, 10
6	4.31	6	2, 4, 5, 6, 8, 10
9	4.47	8	2, 3, 4, 5, 6, 8, 10, 11
13	4.69	8	2, 3, 4, 5, 6, 8, 10, 11
15	4.86	8	2, 3, 4, 5, 6, 8, 10, 11
18	5.21	9	2, 3, 4, 5, 6, 7, 8, 10, 11
21	5.41	9	2, 3, 4, 5, 6, 7, 8, 10, 11
23	5.44	10	2, 3, 4, 5, 6, 7, 8, 9, 10, 11
26	5.53	10	2, 3, 4, 5, 6, 7, 8, 9, 10, 11

Table 8: Optimal scheme in MIRP-polyhedron set.

Λ	Costs (10^5)	Quantity	Selected sites
0	3.36	6	2, 4, 5, 6, 8, 10
3	3.78	7	2, 3, 4, 5, 6, 8, 10
6	3.85	8	2, 3, 4, 5, 6, 8, 10, 11
9	4.01	9	1, 2, 3, 4, 5, 6, 8, 10, 11
13	4.21	10	1, 2, 3, 4, 5, 6, 7, 8, 10, 11
15	4.67	10	1, 2, 3, 4, 5, 6, 7, 8, 10, 11
18	4.95	10	1, 2, 3, 4, 5, 6, 7, 8, 10, 11
21	5.39	11	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11
23	5.59	12	1, 2, 3, 4, 5, 6, 7, 8, 10, 11, 12
26	5.61	12	1, 2, 3, 4, 5, 6, 7, 8, 10, 11, 12

Table 9: Optimal scheme under MIRP-ellipsoid set.

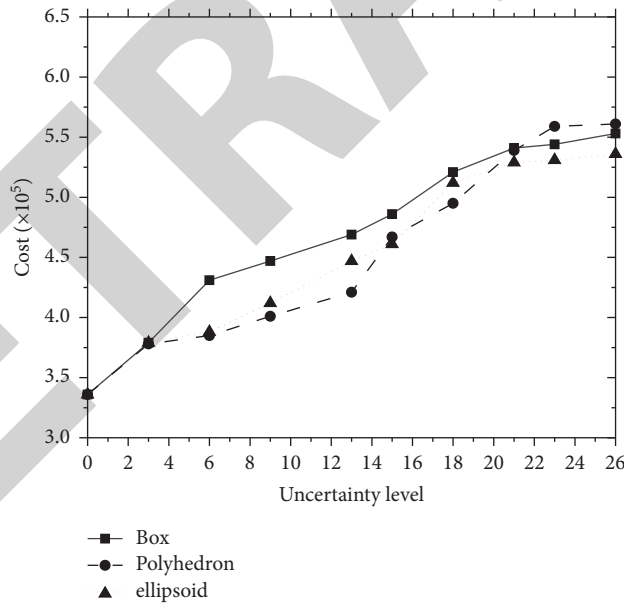| Ω	Costs (10^5)	Quantity	Selected sites
0	3.36	6	2, 4, 5, 6, 8, 10
3	3.79	7	2, 3, 4, 5, 6, 8, 10
6	3.88	8	2, 3, 4, 5, 6, 8, 10, 11
9	4.12	9	1, 2, 3, 4, 5, 6, 8, 10, 11
13	4.47	9	1, 2, 3, 4, 5, 6, 8, 10, 11
15	4.61	10	1, 2, 3, 4, 5, 6, 7, 8, 10, 11
18	5.12	10	1, 2, 3, 4, 5, 6, 7, 8, 10, 11
21	5.29	11	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11
23	5.31	12	1, 2, 3, 4, 5, 6, 7, 8, 10, 11, 12
26	5.36	12	1, 2, 3, 4, 5, 6, 7, 8, 10, 11, 12

Figure 5: Impact of uncertainty level on total costs.

suggesting that the model has the smallest robustness. Since time is an imperative factor influencing the survival probability in the event of a disaster, decision-makers can set the necessary time limit according to the actual situation of the disaster at an appropriate cost, to achieve a higher survival rate.

4.5.2. Impact of Demand Disturbance on the Total Cost. The change in total cost when the demand disturbance varies is presented in Table 11. The impact of the disturbance ratio

($\xi = 0.05, 0.10, 0.15, 0.20, 0.25, 0.30$) on the target cost was mainly studied. As exhibited in the table, the total cost of the three MIRP models gradually increases when the disturbance ratio increases from 0.05 to 0.3. The greater the disturbance ratio, the greater the total cost. It can be revealed by comparing these three models that the MIRP-polyhedron set model has the highest cost, the MIRP-box model has the middle cost, and the MIRP-ellipsoid set model has the lowest cost. This demonstrates the good robustness of the ellipsoid set model. However, the MIRP-ellipsoid model generally
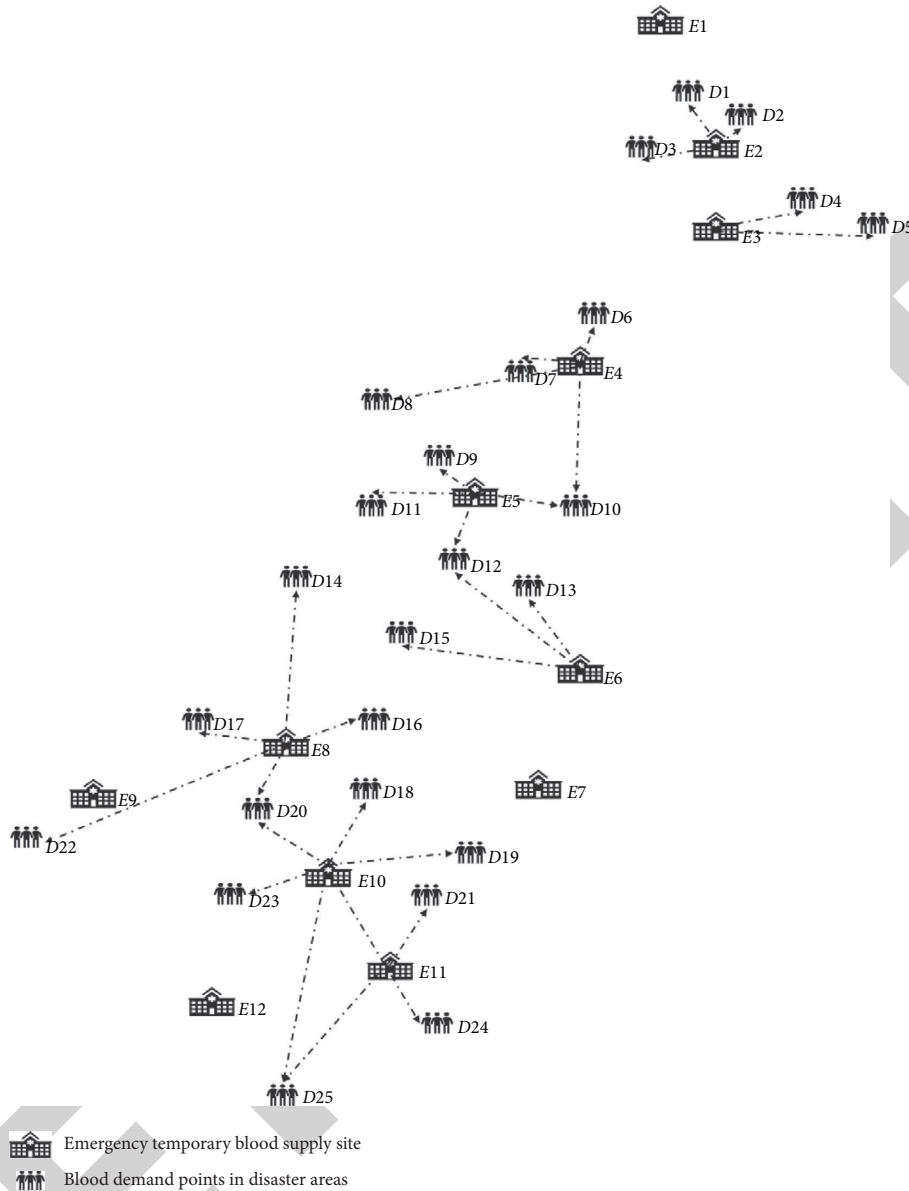
Figure 6: MIRP-box set.

chooses more emergency blood supply sites though the MIRP-ellipsoid model has good robustness, allowing decision-makers to make decisions on the basis of demand fluctuations and risk preferences. The MIRP-ellipsoid model is more suitable when there are many candidate sites and decision-makers are conservative. The impact of the demand disturbance ratio on the model cost is illustrated in Figure 10.
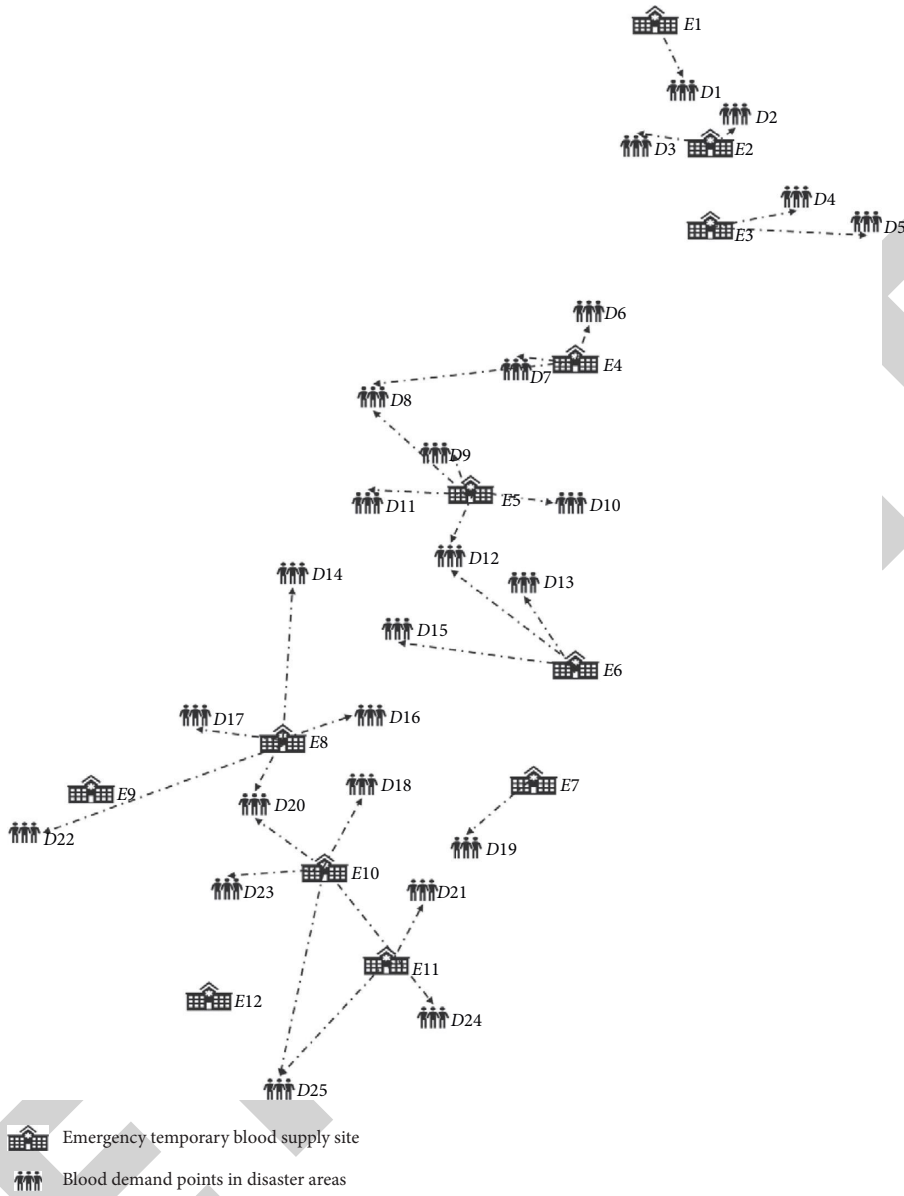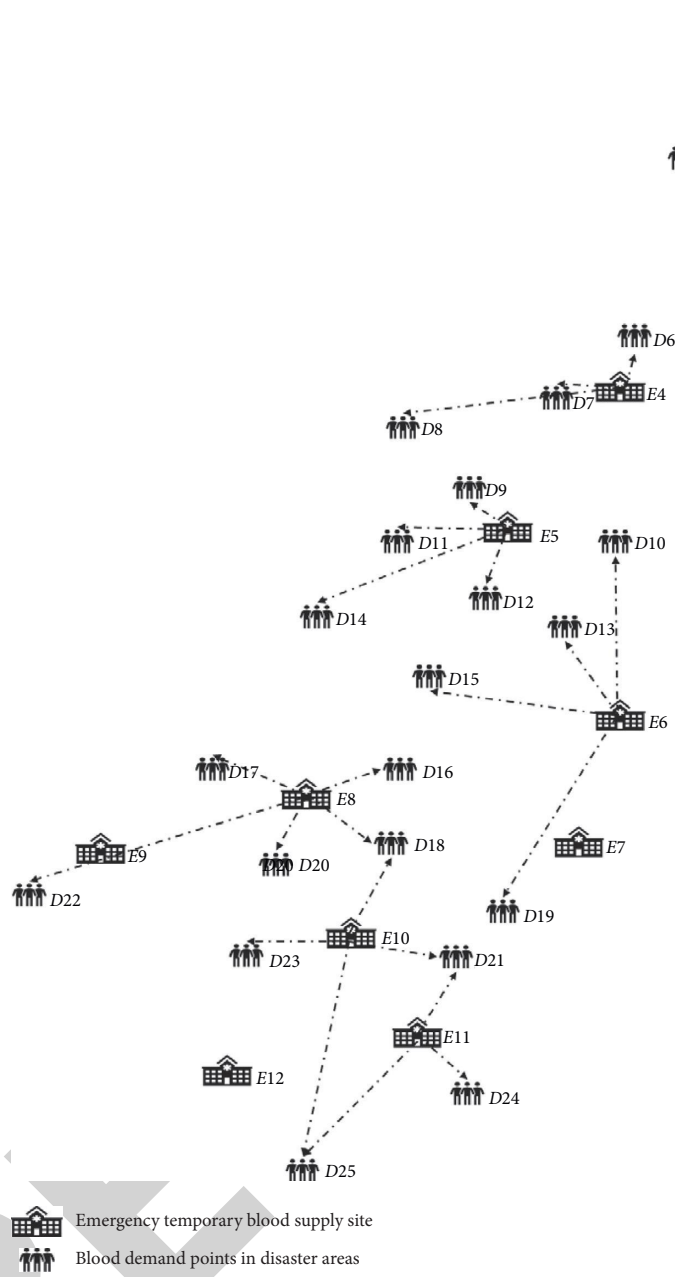
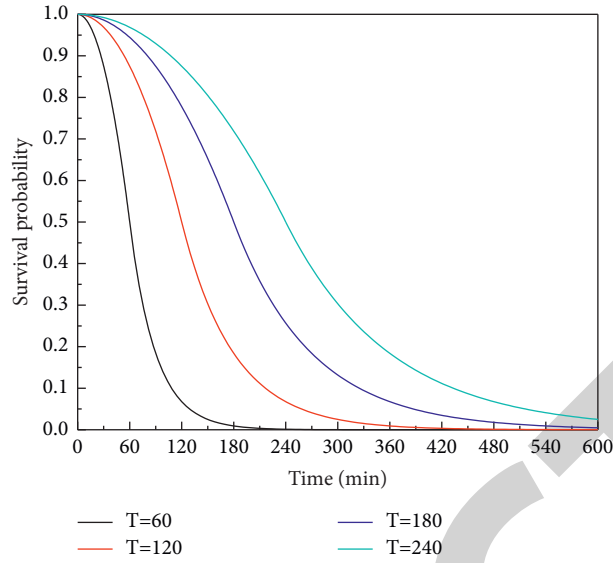Figure 7: MIRP-polyhedron set.

Figure 8: MIRP-ellipsoid set.

FIGURE 9: Function of survival probability and time.

TABLE 10: Total costs at different survival probability times.

Survival probability	$T = 60$	Total costs		
		MIRP-box set	MIRP-polyhedron set	MIRP-ellipsoid set
0.5	60	3.68	3.95	3.76
0.55	57	3.74	4.17	3.95
0.6	53	3.85	4.26	4.18
0.65	50	3.96	4.37	4.27
0.7	46	4.05	4.48	4.35
0.75	42	4.18	4.54	4.41
0.8	37	4.21	4.69	4.47
0.85	32	4.38	4.85	4.56
0.9	26	4.65	5.1	4.73
0.95	19	4.97	5.45	4.82

TABLE 11: Impact of demand disturbance ratio on the model.

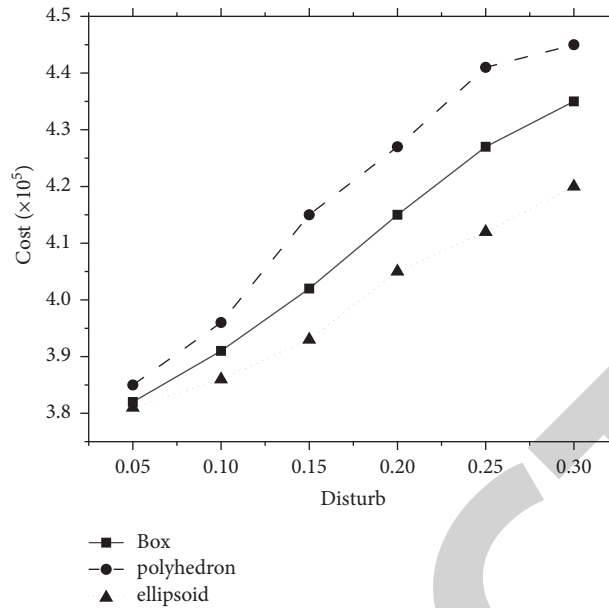| ξ	MIRP-box set		MIRP-polyhedron set		MIRP-ellipsoid set	
	Total costs	Number of selected sites	Total costs	Number of selected sites	Total costs	Number of selected sites
0.05	3.82	6	3.85	6	3.81	7
0.1	3.91	6	3.96	6	3.86	7
0.15	4.02	7	4.15	7	3.93	8
0.2	4.15	7	4.27	8	4.05	8
0.25	4.27	8	4.41	8	4.12	8
0.3	4.35	8	4.45	8	4.2	9

Figure 10: Impact of demand disturbance ratio on the model.

5. Conclusion

In this study, the entropy weight-TOPSIS method and robust optimization theory were applied to the site selection allocation of emergency temporary blood supply stations under uncertain time window constraints. Considering that the site selection of blood supply stations is affected by subjective factors, a systemic method was developed to solve the location-allocation problem of emergency temporary blood sites. First, the entropy weight-TOPSIS method was adopted to evaluate various subjective factors of the alternative locations. Then, the optimal one was chosen from several candidate temporary blood sites. Afterward, a minimum cost model (MILP model) determined by the nominal blood demand was proposed given the objective factors such as capital constraint, time window constraint, and survival probability constraint. An initial solution was obtained. However, decision-makers will cause waste of resources and loss of economic property when making site decisions as the demand for blood in disaster areas is uncertain after the disaster. Based on these objective factors, there is a certain deviation between the optimal solution obtained by using the deterministic method and that of practical problems. Hence, the robust optimization method was employed to transform the MILP model regarding the minimum cost for the three MIRP models based on the minimum cost of the uncertain set. Three MIRP models with uncertain demand were established. Finally, a Gurobi solver was adopted to solve the problem. In all possible cases, the maximum deviation between the solution obtained in this paper and the optimal solution was the smallest. In the uncertainty case, the risk can be avoided to the maximum extent. Although the MILP method can obtain high-quality solutions, the reliability of the results is significantly reduced due to its too ideal parameters. Among the MIRP models, the MIRP-box set model and the MIRP-polyhedron set model possess higher costs and more selected blood supply sites. Generally, the MIRP-ellipsoid set model has the smallest total cost, fewer selected candidate sites, and better robustness. Additionally, the sensitivity analysis of the demand disturbance was conducted. Besides, the time window and the survival probability are also combined in this study. With the increase in the given survival probability, the total cost increases accordingly. Furthermore, how to choose an appropriate distribution scheme within the given time to obtain the highest survival probability of victims should also be considered by decision-makers when the actual disaster occurs. The combination of the two decision-making methods in this article is a new idea, and relatively good research results have been obtained. Compared with a single decision-making method, we can consider more practical factors. This is also in line with the characteristics of emergency management decision-making because we often face the constraints of many factors in the actual decision-making process. In future research, we can also refer to this kind of thinking and take more factors into consideration. The decisions made in this way are more in line with the actual situation and more valuable.

In the location of emergency temporary blood supply sites, there are often more uncertain parameters, such as transportation cost, transportation time, and facility interruption. How to consider more uncertainties and establish related mathematical models to make the problem more in line with the actual situation is the direction that will continue to require in-depth research in the future.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this study.

References

[1] J. Suo, H. Yang, and K. Xiang, "The emergency management system for public health emergencies in China: reality, international experience and future vision," *Journal of UESTC (Social Sciences Edition)*, vol. 22, no. 3, pp. 17–29, 2020.

[2] H. X. Guo, X. Yao, J. Zhu, and J. D. Hou, "Study on making public health emergency reference plan with case-based reasoning," *Journal of UESTC (Social Sciences Edition)*, vol. 23, no. 3, pp. 39–47, 2021.

[3] L. Zhang, J. Wang, and M. Zhang, "Network planning model and algorithm for post-disaster emergency relief based on uncertain demand," *Operations Research and Management Science*, vol. 3, pp. 49–55, 2014.

[4] A. Kamyabniya, M. M. Lotfi, M. Naderpour, and Y. Yih, "Robust platelet logistics planning in disaster relief operations under uncertainty: a coordinated approach," *Information Systems Frontiers*, vol. 20, no. 4, pp. 759–782, 2018.

[5] G. Rodrigo, P. Lamas, and F. J. Pino, "A stochastic programming approach for floods emergency logistics," *Transportation Research Part E Logistics & Transportation Review*, vol. 75, pp. 18–31, 2015.

[6] K. E. Nollet, H. Ohto, H. Yasuda, and A. Hasegawa, "The great east Japan earthquake of March 11, 2011, from the vantage point of blood banking and transfusion medicine," *Transfusion Medicine Reviews*, vol. 27, no. 1, pp. 29–35, 2013.

[7] Y. Sha and J. Huang, "The multi-period location-allocation problem of engineering emergency blood supply systems," *Systems Engineering Procedia*, vol. 5, no. 1, pp. 21–28, 2012.

[8] K. K. S. Kuruppu, "Management of blood system in disasters," *Biologicals*, vol. 38, no. 1, pp. 87–90, 2010.

[9] G. Sahin, H. Sueral, and S. Meral, "Locational analysis for regionalization of Turkish red crescent blood services," *Computers & Operations Research*, vol. 34, no. 3, pp. 692–704, 2007.

[10] P. Ghandforoush and T. K. Sen, "A DSS to manage platelet production supply chain for regional blood centers," *Decision Support Systems*, vol. 50, no. 1, pp. 32–42, 2010.

[11] T. Wang, S. Wang, and Q. Meng, "Introduction to stochastic programming," in *Liner Ship Fleet Planning*, pp. 41–48, Elsevier, Amsterdam, Netherlands, 2017.

[12] A. J. King and S. W. Wallace, *Modeling with Stochastic Programming*, Springer, Berlin, Germany, 2012.

[13] R. Haijema, N. van Dijk, J. van der Wal, and C. S. Sibinga, "Blood platelet production with breaks: optimization by SDP and simulation," *International Journal of Production Economics*, vol. 121, no. 2, pp. 463–473, 2006.

[14] C. Kamp, M. Heiden, O. Henseler, and R. Seitz, "Management of blood supplies during an influenza pandemic," *Transfusion*, vol. 50, no. 1, pp. 231–239, 2010.

[15] K. Katsaliaki and S. C. Brailsford, "Using simulation to improve the blood supply chain," *Journal of the Operational Research Society*, vol. 58, no. 2, pp. 219–227, 2007.

[16] N. Mustafee, S. J. E. Taylor, K. Katsaliaki, and S. Brailsford, "Facilitating the analysis of a UK national blood service supply chain using distributed simulation," *Simulation*, vol. 85, no. 2, pp. 113–128, 2009.

[17] K. Gkiotsalitis and F. Alesiani, "Robust timetable optimization for bus lines subject to resource and regulatory constraints," *Transportation Research Part E: Logistics and Transportation Review*, vol. 128, pp. 30–51, 2019.

[18] M. Bougeret, A. A. Pessoa, and M. Poss, "Robust scheduling with budgeted uncertainty," *Discrete Applied Mathematics*, vol. 261, pp. 93–107, 2019.

[19] R. Huang, S. Qu, X. Yang, and Z. Liu, "Multi stage distributional robust optimization with risk aversion," *Journal of Industrial and Management Optimization*, vol. 13, no. 5, pp. 233–259, 2017.

[20] W. Zhou and Z. Xu, "Envelopment analysis, preference fusion, and membership improvement of intuitionistic fuzzy numbers," *IEEE Transactions on Fuzzy Systems*, vol. 28, no. 9, pp. 2119–2130, 2020.

[21] C. S. Liu, Y. Peng, and G. Kou, "Research on fuzzy location-routing problem in post-earthquake delivery of relief materials," *Chinese Journal of Management Science*, vol. 24, no. 5, p. 8, 2016.

[22] H. L. Sun, L. P. Chai, L. Zhang, and Z. Zhe, "Multi-objective dynamic facility location-transportation problem in emergency humanitarian logistics," *Chinese Journal of Management Science*, vol. 28, no. 3, p. 10, 2020.

[23] D. Luan, C. Wang, Z. Wu, and Z. Xia, "Two-stage robust optimization model for uncertainty investment portfolio problems," *Journal of Mathematics*, vol. 2021, Article ID 3087066, 19 pages, 2021.

[24] Codification Committee of Massive Wenchuan Earthquake Sichuan Earthquake Relief Chronicle, *Massive Wenchuan Earthquake Sichuan Earthquake Relief Work Chronicle of Events*, pp. 6–35, Sichuan People's Publishing House, Chengdu, China, 2017.

[25] Z.-H. Zhang and H. Jiang, "A robust counterpart approach to the bi-objective emergency medical service design problem," *Applied Mathematical Modelling*, vol. 38, no. 3, pp. 1033–1040, 2014.

[26] H. Jia, F. Ordóñez, and M. Dessouky, "A modeling framework for facility location of medical services for large-scale emergencies," *IIE Transactions*, vol. 39, no. 1, pp. 41–55, 2007.

[27] C. Revelle, "Review, extension and prediction in emergency service siting models," *European Journal of Operational Research*, vol. 40, no. 1, pp. 58–69, 1989.

[28] A. L. Soyster, "Technical note-convex programming with set-inclusive constraints and applications to inexact linear programming," *Operations Research*, vol. 21, no. 5, pp. 1154–1157, 1973.

[29] A. Ben-Tal and A. Nemirovski, "Robust solutions of uncertain linear programs," *Operations Research Letters*, vol. 25, no. 1, pp. 1–13, 1999.

[30] D. Bertsimas and M. Sim, "The price of robustness," *Operations Research*, vol. 52, no. 1, pp. 35–53, 2004.

[31] F. Fiedrich, F. Gehbauer, and U. Rickers, "Optimized resource allocation for emergency response after earthquake disasters," *Safety Science*, vol. 35, no. 1, pp. 41–57, 2000.

[32] W. Y. Yu, "Relief goods transport model based on survival probability function," *Statistics and Decision*, vol. 387, no. 15, pp. 73–75, 2013.