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Robust Optimization Model for Multi-Objective Emergency Logistics Center Location Selection

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ABSTRACT

This paper is concerned with emergency material relief in response to major emergencies, concentrating on the difficulties in locating emergency logistics facilities and deploying emergency supplies. Using discrete scenarios, we describe the uncertainty of the demand for emergency supplies at the catastrophe site as well as the uncertainty of the cost and timing of the shipment of such supplies. Meanwhile, we consider two key objectives, i.e., emergency relief cost and emergency relief time, and build a multi-objective emergency logistics center siting model, including both deterministic and robust optimization models. In the construction of the siting model, due to the time urgency of emergency logistics, we adopt a bi-objective function, including transportation cost and transportation time, and consider the construction cost and inventory cost of the emergency logistics center. We also introduced a generalized hybrid frog-hopping algorithm to encode facilities that provide emergency material relief services. To verify the effectiveness of the models and algorithms, we design a multi-scenario simulation experiment, and the results show that the two models and algorithms we propose have good feasibility and effectiveness, and the robust optimization model performs well in handling various uncertainties.

KEYWORDS: Emergency logistics system; robust optimization; site selection; multi-objective; hybrid frog jump algorithm

1 Introduction

In real life, all kinds of natural disasters, man-made disasters and other major emergencies have occurred repeatedly, causing serious disruptions to the social order and leading to huge casualties and economic losses (Maharjan, R, et al, 2020). Therefore, the research and management of disaster emergency response and disaster emergency response system engineering have extremely important value and significance. When major emergencies, especially disaster events, occur suddenly, the emergency response system needs to be activated quickly in order to provide sufficient supplies to the affected areas and people to cope with the crisis. However, since emergencies are usually difficult to predict in advance and the extent of damage from disasters is difficult to assess accurately, once a serious emergency occurs, especially a natural disaster, it has a wide range of impacts and a long duration of impacts, which poses a great challenge to emergency rescue.

One of the common emergency response strategies is to pre-position relief supplies in emergency relief facilities close to the potential disaster site. This can help to reduce the time it takes to deliver the supplies, keep the cost of the relief under control, and increase the effectiveness of the relief. Since post-disaster rescue efforts depend on the effective deployment and delivery of emergency relief supplies, this is also the main purpose of the emergency logistics system. Emergency rescue network planning is a key link in emergency rescue and emergency response, and reasonable planning can significantly improve the deployment efficiency and effectiveness of emergency supplies (Karatas, M, et al, 2021), (Eshghi, A. A, et al, 2022). This typically entails researching two distinct issues, namely the placement of emergency facilities and the distribution of emergency supplies.

The research on emergency facilities can be traced back to the P-center of gravity and P-center problem proposed by Hakimi (Caglayan, N, et al, 2021), (Ji, X, et al, 2023). In the area of emergency facilities location and emergency logistics, studies (Shariat Mohaymany, A, et al, 2020), (Pourghader Chobar, A, et al, 2022). explored the emergency logistics and emergency materials allocation after natural disasters, to reduce the time it takes to deliver supplies and treat casualties, study (Men, J, et al, 2019) established a deterministic emergency logistics location model; study (Pourghader Chobar, A, et al, 2022) introduced the minimum and maximum critical distance and coverage level function, built a multi-quantity and multi-quality coverage model, and enhanced the genetic algorithm solution; In a study (Beiki, H, et al, 2020), the position of the emergency logistics system was examined in the immediate aftermath of the earthquake, and the genetic algorithm solution was enhanced. The concept, characteristics, system, model design, and solution algorithm of emergency logistics site selection have all been usefully explored in these studies. However, the problem itself and the uncertainty of data acquisition have not been taken into account, and all of the studies discuss and solve the problem using a single-objective model. In terms of multi-objective modeling, (Khanchehzarrin, S, et al, 2022) integrates several traditional facility siting models and verifies the correctness of the models through examples based on the fairness and efficiency of emergency rescue facilities; (de Veluz, M. R. D, et al, 2023) constructs a multi-objective emergency facility siting problem considering total cost, fairness and efficiency. These academic works present the emergency problem as a deterministic issue without taking into account the emergency problem's different uncertainties.

In dealing with uncertainty in a problem, two approaches, stochastic optimization and robust optimization, are commonly used. Stochastic optimization is one of the more commonly used classical methods, and its goal is often to maximise the expected gain under all circumstances or minimise the expected expense under all circumstances. In the research of the maximum coverage siting problem, for instance, study (Arshad, M. A, et al, 2022) proposed the idea of scenarios, and its goal was to maximise the number of demand served in all situations; a scenario-based facility siting model was developed by study (Zahedi, A, et al, 2020) with the aim of reducing estimated costs across all scenarios and time periods. In addition, some scholars have used fuzzy number of intervals or interval gray number to describe and solve the uncertainty of emergency logistics problems. The robust optimisation approach, which can be seen as a complimentary substitute for stochastic optimisation and sensitivity analysis, is characterised by the requirement to understand the probability distribution of uncertain parameters. It is derived from robust control theory. This minimax type of robust optimisation has captured the interest of many scholars. Minimax cost (minimax cost) or regret (minimax regret) form of robust model. For example, (Zafari, F, et al, 2019) used robust optimization method to study the single-objective emergency facility siting model with deadline requirements; (Liu, K, 2020) constructed a relative robust model for the siting of emergency logistics and distribution centers; For the location of the emergency material reserve store, (Ma, Y, et al, 2022) built a single-objective robust optimisation model and a stochastic optimisation model. All of the aforementioned research use the robust optimisation approach to examine the topic of where to locate emergency facilities in a context with a single purpose, and the majority of them use a simplified model that only takes into account one emergency resource.

To summarize, although some notable research results have been achieved in siting emergency facilities, there are still some information uncertainties and deficiencies in the handling of uncertainties in siting emergency logistics and mobilizing emergency supplies. Few research have addressed the issue of various types of emergency materials; the majority of previous studies have concentrated on single emergency material situations. The methods of reducing many objectives to a single objective are typically used in multi-objective emergency logistics siting studies, but these methods do not effectively address the unit and order-of-magnitude disparities among multiple objectives. In addition, existing studies mainly focus on the uncertainty of the problem parameters and ignore the different rescue stages in the emergency rescue process that may lead to decision uncertainty. In fact, the two objectives of emergency rescue cost and emergency rescue time may not be equally important, and they may be related to the rescue phase or the requirements of the decision maker.

To address these issues, this study introduces uncertainty scenarios to describe various uncertainty situations for emergency logistics facilities (e.g., material collection points and emergency logistics centers). We developed a multi-objective emergency logistics center site selection deterministic model and a robust optimization model, and introduced cost preference weights to take into account different rescue stage divisions or different decision-making needs of decision makers. By converting the objective values to dimensionless values, the multi-objective problem is reduced to a single-objective problem, and then an optimisation solution is developed using a generic hybrid frog leap method.

2 Related Work

In an uncertain environment, there are usually three approaches to solving the problem of siting an emergency logistics center: stochastic planning, fuzzy planning, and robust optimization. Stochastic planning requires knowledge of the probability distribution of the desired uncertain parameters, which is often difficult to obtain in reality. Fuzzy planning requires a certain amount of sample data and the personal experience of the decision maker to determine the fuzzy affiliation function of the uncertain parameters, which is very dependent on the subjective judgment of the decision maker. Compared with the former two, robust optimization can effectively reduce the interference of the uncertainty of data parameters on the final solution, especially for the field of emergency logistics, the adaptability of the optimal solution obtained by robust optimization is often better.

Study (Ghasemi, P, et al, 2019) combed through the literature on the location of logistics and distribution centers for large-scale emergency rescue, and found that there are problems in the current research as well as put forward a future research trend, i.e., it is necessary to focus on solving the problem of multi-party coordination, and to optimize the layout of distribution center location through scientific planning. Study (Yenice, Z. D, et al, 2020) considers the uncertainty of emergency cost, establishes a robust siting path optimization model for multi-emergency resources, and solves it through CPLEX and GAMS programming, thus providing decision support for relevant departments. Study (Jamali, A, et al, 2021) proposes an emergency site selection and scheduling model based on robust optimization, which takes into account the facility failure problem as well as storage and transportation costs. In response to the uncertainty of material demand and vehicle transportation time, study (He, L, et al, 2022) took into account the risk of transportation time overrun and the risk of logistics facility point failure. It then established a robust optimisation model for emergency logistics time minimization by using combined vehicle and helicopter transportation, and it demonstrated the risk resistance of the robust optimisation method. Study (Zheng, F, et al, 2023) established an uncertain emergency facility siting model with deadline requirements, and compared and analyzed the solution obtained from robust optimization and the optimal solution in the deterministic case, and proved that the deviation of the robust solution is relatively small, and it can effectively avoid the risk. In (Jingchun Zhou, et al, 2023), the effect of random network failure on the location of emergency facilities is proposed, and a heuristic algorithm is used to maximize the coverage for post-disaster relief work. To control the position of commodities and fatalities in earthquake reaction, study (Jingchun Zhou, et al, 2023) suggested a multi-objective, multi-model, multi-commodity, multi-period robust optimisation model.Study (Sicuaio, T, et al, 2022) proposes a decision making model in the field of Artificial Intelligence and designs a coherent network which ensures the operation of certain infrastructures and potential resources even after they have been damaged due to disasters.

In summary, the previous studies in the literature have achieved some results in the emergency logistics center siting problem, but there are some shortcomings: 1) Insufficient handling of information uncertainty. Most of the studies used different methods to deal with information uncertainty, such as stochastic planning, fuzzy planning and robust optimization. However, these methods still have limitations in dealing with uncertainty. For example, stochastic planning requires knowledge of the probability distribution, while fuzzy planning is highly dependent on subjective judgment. Therefore, better methods are needed to cope with uncertainty, especially in emergency situations where uncertain parameters cannot be accurately estimated.2) Inadequate treatment of multi-objective problems. Most studies have addressed the multi-objective emergency logistics center siting problem, but the multi-objective problem is usually transformed into a single-objective problem, which may result in the trade-off between objectives not being properly addressed. A better approach is to develop optimization algorithms applicable to multi-objective problems to effectively handle conflicts and trade-offs among multiple objectives.

3 Mathematical Modeling

3.1 Problem description

We believe it is essential to quickly establish a number of emergency material collection points and emergency logistics centres in the disaster area or nearby areas after the occurrence of major emergencies (such as earthquakes, typhoons, and other natural disasters), considerations for space and resources, uncertainty regarding the material requirements of the impacted places (also known as emergency demand points), minimization of the emergency rescue time and emergency rescue expenses are all taken into account. We will address the issue of how to rationally choose the location for the emergency logistics centre, the appropriate material transfer route, and the amount of transfer while taking into account the uncertainty of the material demand at the disaster point (referred to as the demand point) and the two objectives of minimising the emergency relief time and the emergency relief cost.

The emergency logistics system under consideration consists of an emergency materials collection point, an emergency logistics centre, and an emergency demand point. Emergency materials are first transported from the collection point to the emergency logistics centre, where they are then distributed to the emergency demand point based on the current situation; The emergency supplies can also be delivered straight from the collection point to the emergency demand location because emergencies may result in the failure or blockage of rescue highways as well as other conditions. Emergency supplies can also be delivered directly from the collection site to the emergency demand location, taking into account the possibility that emergencies could result in situations like the obstruction of rescue routes or the failure of rescue roads. (1) Every emergency demand location does not require more emergency supplies than a single emergency logistics centre can store, and all emergency supplies can be transported uniformly by vehicles; (2) Don't assume that multiple emergency materials can't be delivered at the same time because the various types of emergency materials are compatible with transportation; (3) assuming that each emergency material collection point and the emergency logistics centre have an adequate number of transport vehicles and an adequate vehicle carrying capacity, do not consider the limitations on the working hours of the transport vehicles and the limitations on the capacity of the vehicles.

3.2 Explanation of Symbols

(1) Collection

U :the set of emergency material collection points u.

G :the set of emergency supplies type g;

I :set of alternative emergency material centers i;

J :set of emergency material demand points j.

(2) Variables

f_i :the fixed cost of opening i alternative emergency logistics centers;

c_{ui}^{g} : the unit transportation cost of transporting the g th emergency material from the material collection point u to the alternative logistics center i;

c_{ij}^{g} : the unit transportation cost of the g th emergency material from the alternative logistics center i to the emergency demand point j;

c_{uj}^{g} :the unit transportation cost of the g th contingency material transported from the material collection point u to the contingency demand point j.

t_{ui}^{g} : transport time of the g th emergency material from collection point u to the alternative logistics center so that it is transported;

t_{ij}^{g} : transportation time of the g th emergency material from the alternative logistics center i to the emergency demand point j;

t_{uj}^{g} :transportation time of the g th emergency material from material collection point u to emergency demand point j;

t_{i}^{g} :turnaround time of the g th emergency material at the alternative emergency logistics center i;

a_i^t :the unit storage cost of the g th emergency material at the alternative emergency logistics center i .

$h_u^{g,\max}$:the maximum quantity of the g th emergency material to be collected at material collection point u .

h_j^g :the quantity of the g th emergency material demanded at emergency demand point j .

θ_j^g :the quantity of the g th emergency material at the unsatisfied emergency demand point j .

λ_j^g :the unit penalty coefficient of unmet emergency demand point j for the g th kind of emergency supplies.

(3) Decision variables

$z_i \in \{0,1\}$:decision variable of whether or not to site in alternative emergency logistics center i , $z_i = 1$ means to site in emergency logistics center i , otherwise $z_i = 0$;

y_i^g : the storage capacity of the g th emergency material in the alternative emergency logistics center i ;

$w_{ui}^g \in \{0,1\}$:whether or not to transport the g th emergency material from collection point u to logistics center i ;

$w_{uj}^g \in \{0,1\}$:whether the g th emergency material is transported from collection point u to emergency demand point j ;

$w_{ij}^g \in \{0,1\}$: whether to transport the g th emergency material from logistics center i to emergency demand point j ;

x_{ui}^g :the quantity of the g th emergency material to be transported from collection point u to logistics center i ;

x_{uj}^g :quantity of type g contingency transported from collection point u to emergency demand point j ;

x_{ij}^{g} :the quantity of emergency goods of type g transported from logistics center i to emergency demand point j.

3.3 Multi-objective deterministic model construction

The first emergency relief time target takes into account the turnaround and deployment times of emergency materials in the logistics centre as well as the transportation times of emergency materials between the material collection point, the emergency logistics centre, and the emergency demand point; the second emergency relief cost target is primarily made up of the construction costs. The construction and operation (storage) costs of the emergency logistics centre as well as the cost of transporting emergency supplies between the material collecting site, the emergency logistics centre, and the emergency demand point make up the bulk of the second emergency relief cost target.

$$\min \text{Time} = \sum_{g,i} t_i^g y_i^g + \sum_{g,u,i,j} \left(\omega_{ui}^g x_{ui}^g t_{ui}^g + \omega_{uj}^g x_{uj}^g t_{uj}^g + \omega_{ij}^g x_{ij}^g t_{ij}^g \right) + \sum_{j,g} \lambda_j^g \theta_j^g \tag{1}$$

$$\min \ \text{Cos}t = \sum_i f_i z_i + \sum_{g,i} a_i^g y_i^g + \sum_{g,u,i,j} \left(\omega_{ui}^g x_{ui}^g c\omega_{ui}^g + \omega_{uj}^g x_{uj}^g c_{uj}^g + \omega_{ij}^g x \omega_{ij}^g c_{ij}^g \right) + \sum_{j,g} \lambda_j^g \theta_j^g \tag{2}$$

$$s.t. \ \sum_u x_{ui}^g \omega_{ui}^g = y_i^g z_i, \forall i \in I, g \in G \tag{3}$$

$$\sum_j x_{ij}^g \omega_{ij}^g = y_i^g z_i, \forall i \in I, g \in G \tag{4}$$

$$\sum_u x_{uj}^g \omega_{uj}^g + \sum_j x_{ij}^g \omega_{ij}^g z_i = h_j^g, \forall j \in J, g \in G \tag{5}$$

$$\sum_i x_{ui}^g \omega_{ui}^g z_i + \sum_j x_{uj}^g \omega_{uj}^g \le h_u^{g,\max}, \forall u \in U, g \in G \tag{6}$$

$$\sum_u \omega_{uj}^g + \sum_i \omega_{ij}^g z_i = 1, \forall j \in J, g \in G \tag{7}$$

$$\max_{u,j} \left\{ \omega_{ui}^g, \omega_{ij}^g \right\} \le z_i, \forall i \in I, g \in G \tag{8}$$

$$\sum_j h_j^g \le \sum_u h_u^{g,\max}, \forall g \in G \tag{9}$$

$$\omega_{ui}^g, \omega_{uj}^g, \omega_{ij}^g \in \{0,1\}, \forall u \in U, i \in I, j \in J, g \in G \tag{10}$$

$$z_i \in \{0,1\}, \forall i \in I \tag{11}$$

$$y_i^g, x_{ui}^g, x_{ui}^g, x_{ij}^g \ge 0, \forall u \in U, i \in I, j \in J, g \in G \tag{12}$$

Eqs. (1) and (2) in the model are the objective functions, and Eq. (2) is to minimise the cost of emergency rescue, which includes the cost of building the emergency logistics centre, the cost of storing emergency materials there, and the cost of transporting emergency materials. Eq. (1) is to minimise the emergency rescue time, which includes transport time and turnaround time.

Eq. (3) for the emergency logistics system of the material flow conservation conditions, where Eqs. (3) and (4) show the emergency logistics centre at the flow conservation conditions, Formula (5) shows the emergency demand point at the flow conservation or the demand is satisfied, and Eq. (6) shows the flow at the point of collection of materials conservation or the collection of materials at the point of collection of the transport out; Eq. (7) indicates that Eq. (7) means that only one logistics center or collection point can provide material relief for a certain material at each emergency demand point; Eq. (8) means that only selected logistics centers can transport the material; Eq. (9) guarantees the supply capacity of each emergency material; the limits on decision variables are shown in equations (10) and (12).

3.4 Multi-objective robust optimization model construction

The demand for different types of materials at each emergency demand point is difficult to estimate accurately due to the suddenness of emergencies and the difficulty of accurate prediction, and the transportation costs and times of emergency materials may change due to the possibility of an untimely supply of emergency materials. Considering these uncertainties, the set of problem scenarios and robust constraint coefficients are introduced, and scenario $s \in S$ is added to the symbols of the existing variables and decision variables to denote the variables or decision variables corresponding to scenario $s \in S$. In this way, the model is based on the above modeling model. To this end, the following multi-objective robust optimization model is constructed based on the model identified above:

$$\min \max_{s\in S} \ \text{Time}_s \tag{13}$$

$$\min \max_{s\in S} \ \text{Cost} \tag{14}$$

$$\text{Time}_s = \sum_{g,i} t_i^{g^s} y_i^{gs} + \sum_{g,u,i,j} \left(\omega_{ui}^{g^s} x_{ui}^{g^s} t_{ui}^{g^s} + \omega_{uj}^{gs} x_{uj}^{g^s} t_{uj}^{g^s} + \omega_{ij}^{g^s} x_{ij}^{gs} c_{ij}^{gs} \right) + \sum_{j,g} \lambda_j^{g^s} \theta_j^{g^s}, s \in S \tag{15}$$

$$\text{Cost}_s = \sum_i f_i^s z_i^s + \sum_{g,i} a_i^{g^s} y_i^{g^s} + \sum_{g,u,i,j} \left(\omega_{ui}^{g^s} x_{ui}^{g^s} c_{ui}^{g^s} + \omega_{uj}^{g^s} x_{uj}^{gs} c_{uj}^{g^s} + \omega_{ij}^{g^s} x_{ij}^{g^s} c_{ij}^{g^s} \right) + \sum_{j,g} \lambda_j^{g^s} \theta_j^{g^s}, s \in S \tag{16}$$

$$\text{s. t. } \sum_u x_{ui}^{gs} \omega_{ui}^{gs} = y_i^{gs} z_i^s, \forall s \in S, i \in I, g \in G \tag{17}$$

$$\sum_j x_{ij}^{gs} \omega_{ij}^{gs} = y_i^{gs} z_i^s, \forall s \in S, i \in I, g \in G \tag{18}$$

$$\sum_u x_{uj}^{gs} \omega_{uj}^{gs} + \sum_i x_{ij}^{gs} \omega_{ij}^{gs} z_i^s = h_j^{gs}, \forall s \in S, j \in J, g \in G \tag{19}$$

$$\sum_i x_{ui}^{gs} \omega_{ui}^{gs} z_i^s + \sum_i x_{uj}^{gs} \omega_{uj}^{gs} \le h_u^{g,\max}, \forall s \in S, u \in U, g \in G \tag{20}$$

$$\text{Time}_s \le \left(1 + p_s\right) \text{Time}_s^{**}, \forall s \in S \tag{21}$$

$$\text{Cost}_s \le \left(1 + p_s\right) \text{Cost}_s^{**}, \forall s \in S \tag{22}$$

$$\sum_u \omega_{uj}^{gs} + \sum_i \omega_{uj}^{gs} z_i^s = 1, \forall s \in S, j \in J, g \in G \tag{23}$$

$$\max_{uj} \left\{ \omega_{ui}^{g^s}, \omega_{ij}^{g^s} \right\} \le z_i^s, \forall s \in S, i \in I, g \in G \tag{24}$$

$$\sum_j^{u,j} h_j^{g^s} \le \sum_u h_u^{g,\max}, \forall s \in S, g \in G \tag{25}$$

$$\omega_{ui}^{gs}, \omega_{uj}^{gs}, \omega_{ij}^{gs} \in \{0,1\}, \forall s \in S, u \in U, i \in I, j \in J, g \in G \tag{26}$$

$$z_i^s \in \{0,1\}, \forall s \in S, i \in I \tag{27}$$

$$y_i^{gs}, x_{ui}^{gs}, x_{uj}^{gs}, x_{ij}^{gs} \ge 0, \forall s \in S, u \in U, i \in I, j \in J, g \in G \tag{28}$$

Where $Time_s^{**}, Cost_s^{**}$ are the optimal time and optimal cost values of the multi-objective deterministic problem under scenario s, Eqs. (13)-(16) are the objective functions, which represent the minimization of the time and cost values under all scenarios, and the constraints Eqs. (21) and (22) represent the robustness constraints on the time and cost values under each scenario.

4 Model Solving

4.1 *Multi-objective treatment*

In the model of this paper, it is difficult to harmonize the time and cost objectives, and in the actual emergency logistics rescue process, the requirements on cost and time are different, so the importance of the two may be different. In addition, the measurement units of time and cost are different, so the traditional linear weighting method is not feasible. Although (Hong, J. D, et al, 2019). has used the percentage dimensionless method (using a fixed value of 100 divided by the target value) to eliminate the difference in the units of measurement of the two sub-objectives, there are two shortcomings in this approach: one is that it does not truly reflect the difference in the units of measurement of the two objectives and their order of magnitude, and the other is that it cannot adapt to the changes in the problem data. For this reason, we first eliminated the two target units for each scenario, using the following formula:

$$\text{Time}_s^R = \frac{\text{Time}_s}{\text{Time}_s^*}, \quad \text{Cost}_s^R = \frac{\text{Cost}_s}{\text{Cost}_s^*} \tag{29}$$

Where $Time_s^*, Cost_s^*$ denote the optimal objective values obtained by modifying the objective function of the multi-objective deterministic model under scenario s to a single minimization of rescue time (without considering the objective Eq. (2)) and a single minimization of rescue cost (without considering the objective Eq. (1)). It is easy to see that Eq. (29) not only eliminates the unit of measurement between the two objectives, but also eliminates the order-of-magnitude difference between the two objective values, and automatically adapts to changes in the problem data. Secondly, we consider the degree of importance assigned to the two objectives by the decision maker, and let W be the value of the importance assigned to the cost objective by the decision maker according to the actual situation, which is called the cost preference weight, and satisfies $0 \le w \le 1$. Then the objective functions (1)-(2) of the multi-objective deterministic model can be transformed into the following Eq.s:

$$\min(1-w)\cdot \mathrm{Time}_s^R + w\cdot \mathrm{Cost}_s^R = (1-w)\cdot \frac{\mathrm{Time}_s}{\mathrm{Time}_s^*} + w\cdot \frac{\mathrm{Cost}_s}{\mathrm{Cost}_s^*} \quad (30)$$

The objective function of the multi-objective deterministic model is modified to Eq. (30), and the time and cost values corresponding to the optimal solution obtained under scenario s are set to be $Time_s^{**}, Cost_s^{**}$, respectively, so that we can deal with the objective functions (13)-(14) of the multi-objective robust optimization model as follows:

$$\min \max_{s\in S}(1-w)\cdot \frac{\mathrm{Time}_s}{\mathrm{Time}_s^{**}} + w\cdot \frac{\mathrm{Cost}_s}{\mathrm{Cost}_s^{**}} \quad (31)$$

Noting that the main purpose of Eq. (29) is to eliminate the unit of measurement and its order of magnitude difference between the two objectives, for all the scenarios of the problem, small changes in the data can also cause changes in the values of optimal time and optimal cost under the single objective, which are usually not too large; based on this consideration, if the solution time of the algorithm is to be saved, it is also possible to use the values of optimal time $Time_0^*$ and optimal cost $Cost_0^*$ under the single objective of the benchmark scenario in place of the values of optimal time $Time_s^*$ and optimal cost $Cost_s^*$ under the scenarios with a single objective, respectively, in Eqs. (29) to (30).

4.2 Design of Hybrid Frog Leading Algorithm

Shuffled Frog Leading Algorithm (SFLA) is a new type of biomimetic intelligent optimization algorithm that imitates frog groups searching for food, which is proposed by (Wan, M, et al, 2023) to solve the combinatorial optimization problem. Its main feature is to divide the group of frogs into multiple subgroups, and each subgroup executes its own local search strategy, repeatedly merging and splitting frog groups during the search process, and exchanging information among the subgroups. Because the algorithm uses the concept of subgroups, it increases the flexibility and effectiveness of the search process and avoids falling into local optima more effectively than other intelligent optimization methods.

For any intelligent algorithm, the coding of the problem is the most important part. We encode the rescue service facilities (emergency material collection points and alternative emergency logistics centers) that each kind of material at the emergency material demand points receives, i.e., we use the rescue services provided by the emergency material collection points and the alternative emergency logistics centers for each kind of material at all the emergency material demand points as the encoding. Specifically, assuming that there are m emergency material demand points, each of which has n types of material demands, an $m \times n$ dimensional vector (called a frog or chromosome) is constructed using symbolic coding:

$$X = \left(x_1, \ldots, x_n, x_{n+1}, \ldots, x_{2n}, \ldots, x_{mn}\right) \quad (32)$$

The value of $x_k (1 \le k \le mn)$ indicates the number of the collection point or alternative emergency logistics center that provides a certain type of emergency material to the corresponding demand point, and position $k = (i-1) \cdot n + j$ corresponds to the j th type of emergency material for the i th demand point.

For example, assuming that there are two demand points, each of which has three types of emergency material requirements, and that there are three material collection points (numbered I, 2, 3) and three alternative emergency logistics centers (numbered 4, 5, 6) in the rescue system, the frogs are (1, 4, 2, 5, 4, 1), indicating that the rescue services provided to the three types of emergency materials at the first demand point are Collection Point 1, Emergency Logistics Center 4, and Collection Point 2, and the rescue services provided to the three types of emergency materials at the second demand point are Emergency Logistics Center 5, Emergency Logistics Center 4, and Collection Point l, respectively. collection point 1, emergency logistics center 4 and collection point 2 for the first demand point, and emergency logistics center 5, emergency logistics center 4 and collection point l for the second demand point.

Initialization of the total frog population: According to the number of demand points for emergency supplies and the number of emergency supplies, a character will be randomly generated for each locus of individual frogs to represent the facility that will provide services to the corresponding demand point and emergency supplies for that locus (it may be an alternative emergency logistics center or a collection point for emergency supplies).

The first frog is assigned to the first subpopulation, the second frog is assigned to the second subpopulation, and so on. All frogs are sorted from smallest to largest in terms of suitability, and so on, with the m th frog assigned to the mth subpopulation, and the $m+1$ th frog assigned to the $m+1$ th subpopulation, and so on, until all frogs have been processed.

Local search strategy: Assuming that the optimal and worst individuals of each group are F_l^b, F_l^w respectively, and the global optimal individual of the frog group is F_g^b, each subgroup performs a local search in the following way:

$$F_i = \begin{cases} F_i^b & F_{i,l}^w = F_i^b \\ \text{rand} & F_{i,l}^w \ne F_i^b \end{cases} \quad (33)$$

Where F_i^b is the i th component of the locally optimal individual F_i^b (or the globally optimal individual F_g^b), $F_{i,l}^w$ is the i th component of the locally worst individual F_l^w , and $rand$ denotes the random selection of a service facility (emergency material collection point or emergency logistics center).

Adaptation function: For the multi-objective deterministic model, we directly use Eq. (30); for the multi-objective robust optimization model, we use Eq. (31), if the current individual does not satisfy the robust constraints under a certain scenario S, a large penalty term is applied to the adaptability of the individual.

In this paper, the flowchart of the generalized hybrid frog jumping algorithm for solving the multi-objective deterministic model and the multi-objective robust optimization model is shown in Figure 1.

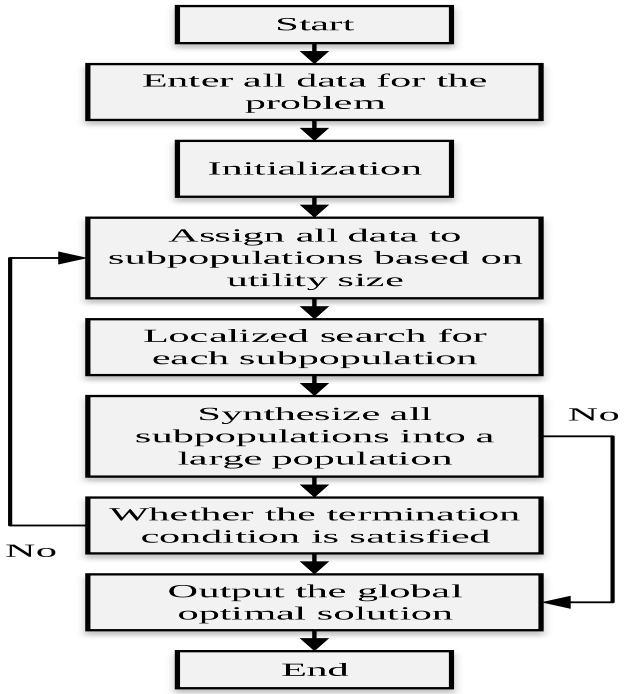

Figure 1 Flowchart of the hybrid frog jump algorithm SFLA (main flow on the left, local search flow on the right)

5 Algorithm Analysis

5.1 Data description

It is known that an emergency logistics system has three emergency material collection points (numbered 1, 2, 3), three optional emergency logistics in a tb alternative points (numbered 4, 5, 6), as well as three emergency material demand points (numbered 7, 8, 9) and three kinds of emergency material (numbered G_1, G_2, G_3), the baseline scenario of the problem data in Table 1-3, and in addition to set the demand point of the shortage of emergency material unit penalty factor of 280. On the basis of the baseline scenario data, the demand for materials at the demand point, unit transportation cost and transportation time will be subject to the share of uniformly distributed random numbers on [0, 0.2], and a total of five scenarios of problem data will be generated.

Table 1 Alternative emergency logistics center information

No.	Construction Costs	Unit storage cost			Material turnaround time			Unit transportation cost			Transportation time		
		G_1	G_2	G_3	G_1	G_2	G_3	7	8	9	7	8	9
4	300	20	35	30	1	2	3	140	110	190	6	4	7
5	200	20	35	30	3	3	4	140	100	200	3	3	4
6	200	20	35	30	2	2	1	150	100	200	5	8	3

Table 2 Information on material collection points

No.	Unit storage cost			Material turnaround time			Unit transportation cost			Transportation time		
	4	5	6	4	5	6	7	8	9	7	8	9
1	50	60	80	5	6	2	150	180	240	12	12	10
2	50	50	60	2	4	6	150	150	180	4	8	13
3	50	65	70	8	3	4	150	200	210	10	9	15

Table 3 Information on emergency supplies

Maximum collection volume	G_1	G_2	G_3	Requirements	G_1	G_2	G_3
1	400	500	400	7	400	400	400
2	400	300	300	8	300	300	300
3	200	200	300	9	200	200	200

5.2 Results and analysis

The following settings are used to solve the multi-objective model using the hybrid frog hopping algorithm in this study: There can be up to 100 hybrid iterations, 40 local searches per frog subpopulation, a maximum of 4 subpopulations, and a maximum of 20 individuals in each subpopulation.In addition, this paper sets the robustness constraint coefficient to be the same for all the scenarios, i.e., $p_s = p, \forall_s = S$.

5.2.1 Cost preference weights

First, the baseline scenario data are taken into account to confirm the reliability of the multi-objective deterministic model. The hybrid frog jump algorithm is used to optimise and solve the cost preference weights, which are taken at intervals of 0.05 from 0 to 1. Table 4 displays the ideal rescue allocation plan for all types of materials at all demand points. According to the optimal rescue allocation programme 2-4-6-6-2-2-5-6-5, Collection Point 2, Emergency Logistics Centre 4 and Emergency Logistics 6 are responsible for allocating the three different types of emergency supplies at the first demand point, while Emergency Logistics Centre 6, Collection Point 2 and Collection Point 2 are responsible for providing the three different types of emergency supplies at the second demand point and Emergency Logistics Centre 6 is responsible for providing the rescue services at the third demand point. The findings in Table 4 demonstrate that initially, the decision-maker prioritises the emergency response time when performing the rescue, and as a result, all three emergency logistics centres are opened to meet the initial rescue's time urgency requirements. However, as the cost preference weights gradually rise (from 0.35 to 0.6), the number of emergency logistics centres is reduced to two (i.e., the locations of Emergency Logistic Centres 5 and 6); when the cost preference weights further increase, the decision maker prioritizes the emergency response cost (i.e., the locations of Emergency Logistic Centers 5 and 6). As the cost preference weight increases further, the decision maker prioritizes contingency costs (from 0.65 to 1), and the number of emergency logistics centers decreases to one (i.e., site selection for Emergency Logistics Center 4).

Table 4 Optimal relief allocation scenarios with different cost preference weights

Cost preference weights	Optimal Rescue Allocation Program
[0.05,0.3]	2-4-6-6-2-2-5-6-5
[0.35,0.4]	2-1-6-5-2-1-5-5-6
[0.45,0.5]	2-2-1-6-2-2-5-2-6
[0.55,0.6]	2-1-1-1-2-1-5-5-6
[0.65,0.8]	2-1-1-1-2-2-5-5-2
0.85	1-1-1-2-2-2-5-6-3
[0.9,1]	1-2-1-1-1-2-4-5-3

Table 5 Optimal Rescue Paths and Rescue Material Movement under Three Cost Preference Weights

w=0.35			w=0.55			w=0.8		
Rescue Costs 557100			Rescue Costs 470021			Rescue Costs 453900		
Rescue Time 21700			Rescue Time 25000			Rescue Time 26400		
G_1	G_2	G_3	G_1	G_2	G_3	G_1	G_2	G_3
$2\to7$	$1\to7$	$1\to6\to7$	$2\to7$	$1\to7$	$1\to7$	$2\to7$	$1\to7$	$1\to7$
400	400	400，400	400	400	400	400	400	400

$1\to6\to8$	$2\to8$	$2\to8$	$1\to8$	$2\to8$	$2\to8$	$1\to8$	$2\to8$	$2\to8$
300,300	300	300	300	300	300	300	300	300
$3\to5\to9$	$3\to5\to9$	$3\to6\to9$	$3\to5\to9$	$3\to5\to9$	$3\to6\to9$	$3\to5\to9$	$3\to5\to9$	$3\to9$
200,200	200,200	200,200	200,200	200,200	200,200	200,200	200,200	200

Table 5 gives the results of rescue routes and rescue material transportation under three cost preference weights in the baseline scenario. When the cost preference weights are 0.35, 0.55, and 0.8, the emergency rescue costs are 557,100, 47,100, and 45,390, and the emergency rescue times are 21,700, 25,000, and 26,400, respectively. Obviously, when the decision maker assigns different weights to the rescue costs, the emergency rescue costs and times have different optimal values, and it is not possible to achieve the possibility of decreasing both the costs and times of the emergency rescue. Obviously, when the decision maker assigns different weights to rescue costs, the cost and time of emergency rescue have different optimal values, and it is impossible to achieve the possibility that the cost and time of emergency rescue decrease at the same time.

Second, in order to further analyze the relationship between cost preference weights and emergency response, especially how to set cost preference weights in different emergency response phases. Figure 2 shows the trend of the mean and standard deviation of cost and time for all scenarios as a function of cost preference weights. Table 5 and Figure 2 show that when the decision maker assigns larger and larger values to the cost preference weights, the optimal value of rescue cost decreases gradually, but the emergency rescue time increases gradually, which is consistent with the real rescue situation; on the other hand, different values of the cost preference weights can correspond to different stages of the emergency rescue, and in the initial stage of the emergency rescue, the main consideration is the high timeliness, and it is acceptable to have a higher emergency rescue cost, which can be regarded as corresponding to a smaller cost preference weight. In the early stage of emergency rescue, the main consideration is high timeliness, and it is acceptable to have higher emergency rescue cost, which can be regarded as corresponding to smaller cost preference weights (e.g., 0.35 in Table 5); in the middle stage of emergency rescue, both timeliness and cost have to be taken into account, which can be regarded as corresponding to moderate cost preference weights (e.g., 0.55 in Table 5); in the later stage of emergency rescue, timeliness takes a back seat, and the main consideration is the cost, which can be regarded as corresponding to larger cost preference weights (e.g., 0.8 in Table 5).
Analyzing the trends of rescue cost and rescue time in Figure 2, the corresponding weights can be roughly divided into three intervals, with the first interval being [0, 0.45], the second [0.45, 0.75], and the third [0.75, 1], which can be regarded as corresponding to the early, middle, late, and final stages of rescue, respectively. The first stage is characterized by low cost preference weights, the optimal rescue time is small, but the rescue cost remains high, which is in line with

the time urgency requirement of activating the emergency rescue system after a disaster occurs; the second stage is characterized by moderate cost preference weights, which takes into account the urgency requirement of the rescue time, but also considers the cost limitation that can be afforded by the emergency rescue system, and the cost of the rescue decreases rapidly with the slow increase of weights, but the required rescue time increases rapidly; the third interval segment is [0.75, 1], and the three cost preference weights can be seen as corresponding to the early, middle, late or final stage respectively. The third stage is characterized by a large cost preference weight, which mainly considers the cost limitations of the emergency rescue system and is in line with the characteristics of the late stage or the end stage of emergency rescue, in which the cost decreases slowly and the time increases a little faster.

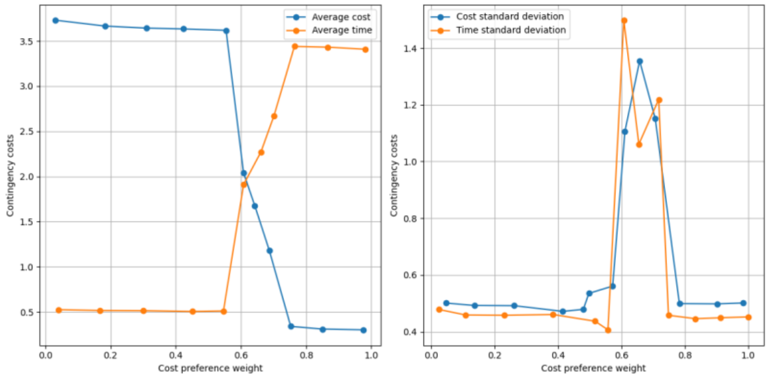

Figure 2 Trends in the mean and standard deviation of the deterministic model

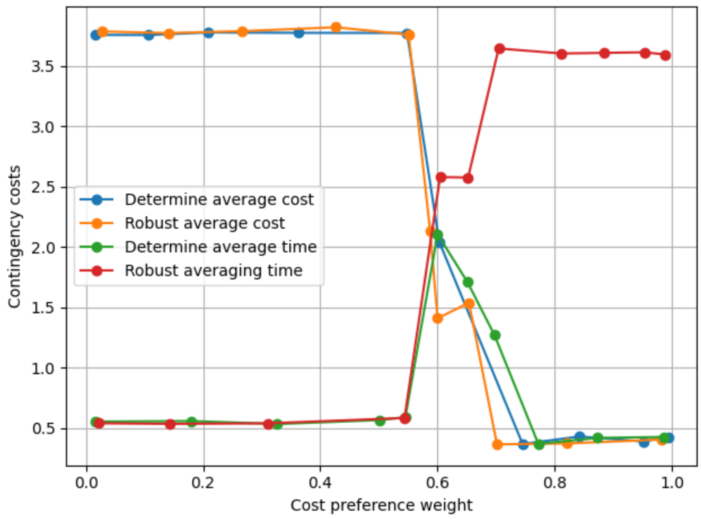

Figure 3 Trends in the mean values of the two models

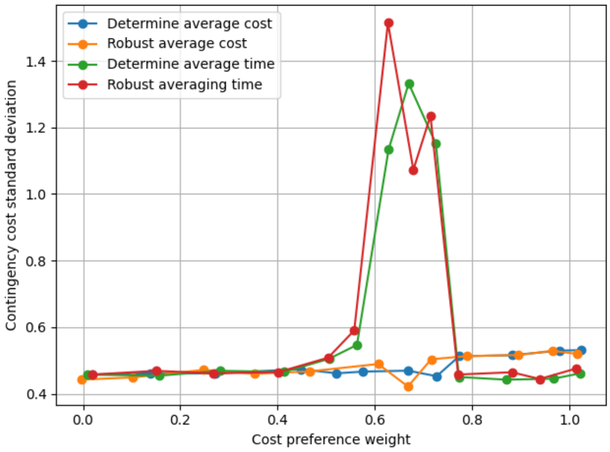

Figure 4 Trend of standard deviation of the two models

Again, in this research, the robust constraint coefficients of all the scenarios are assumed to be 0.2 in order to examine the benefits and drawbacks of the multi-objective robust optimisation model and the deterministic model. Figures 3 and 4 show the trend of the mean (time and cost) and standard deviation (time and cost) of the two models with the variation of cost preference weights, respectively. The average results in Figure 3 only give an initial indication that there is not much difference between the two models when the cost preference weights are taken at [0, 0.55] and [0.75, 1], but the average cost of the deterministic model is significantly higher than the average cost of the robust optimization model when the cost preference weights are taken at [0.6, 0.7]. However, when we focus on the standard deviations (time and cost) of the two models given in Figure 4, We can see that both of the deterministic model's standard deviations are higher than those of the robust optimisation model; in particular, when the cost preference weights are taken as [0.55, 0.7], the deterministic model's standard deviation is about twice as high as that of the robust optimisation model. This suggests that the robust optimization model is more resistant to various uncertainties. Specifically, in terms of the general trend, the corresponding cost preference weights of the robust model can be divided into three bands, the first band is [0, 0.45], the second band is roughly [0.45, 0.75], and the third band is roughly [0.75, 1], and the three cost preference weight bands can be regarded as corresponding to the early, middle, and late stages of the rescue, respectively.

According to the results of the chart and the previous discussion, we can consider the emergency rescue is divided into three types, the rescue of the early stage of the time urgency, the rescue of the rescue of the middle stage of the rescue of the rescue of the cost and the rescue of the rescue of the late stage of the rescue of the rescue of the cost, decision-making or modeling optimization of the solution can be chosen to choose a different cost preference weight, and here, according to the discussion of the above will be the cost of the weight of the range of values of the weight of preference for the distinction as [0, 0.45], [0.45, 0.75], [0.45, 0.75], [0.75]. Here, based on the above discussion, the range of cost preference weights is distinguished as [0, 0.45], [0.45, 0.75] and [0.75, 1], or a single value, such as 0.35, 0.55 and 0.8.

5.2.2 Impact analysis of robust constraint coefficients

In order to examine the impact of different robust constraint coefficients, we consider five different values of robust constraint coefficients, i.e., 0.1, 0.15, 0.2, 0.25, and 0.3. Figure 5 gives the robust objective values obtained by the multi-objective robust optimization model with different robust constraint coefficients (left) and the average objective values of all scenarios under the current robust optimal solution (right). The average objective value here means that the optimal robust solution can be obtained for a given robust constraint coefficient, which corresponds to the objective value of each scenario, and the average of these objective values is calculated. As can be seen from Figure 5, when the cost preference weights are taken in [0, 0.45] and [0.75, 1], the robust objective value and the average objective value under different robust constraint coefficients are very stable; in addition, it is noted that when the cost preference weights are taken in [0.75, 1] and all the robust constraint coefficients are taken in 0.1, the robust objective value and the average objective value have large fluctuations, which indicates that the robust coefficients are small (i.e., given the robust constraint coefficient), and the average objective value of the cost preference weights are not very stable. This shows that when the robustness coefficient is small (i.e., the given robustness requirements are more stringent), it is more difficult to find a robust optimal solution, and even in extreme cases, it may not be possible to find a feasible solution that satisfies all the scenarios. When the cost preference weights are within [0.5, 0.75], different robust constraint coefficients have different impacts. When the robust requirements are more stringent (robust coefficient of 0.1), the robust objective value increases rapidly with the increase of the cost preference weights; when the robust requirements are more lenient (robust coefficient of 0.3), the robust objective value fluctuates upward and downward; and when the robust requirements are general (0.15 to 0.25), the robust objective value is relatively high and the robust objective value is relatively low. When the robustness requirement is moderate (0.15 to 0.25), the robustness target value is relatively flat. Based on the above analysis, we recommend that the robust constraint coefficients in robust optimization should be taken in the range of [0.15, 0.25], or take the middle value of 0.2.

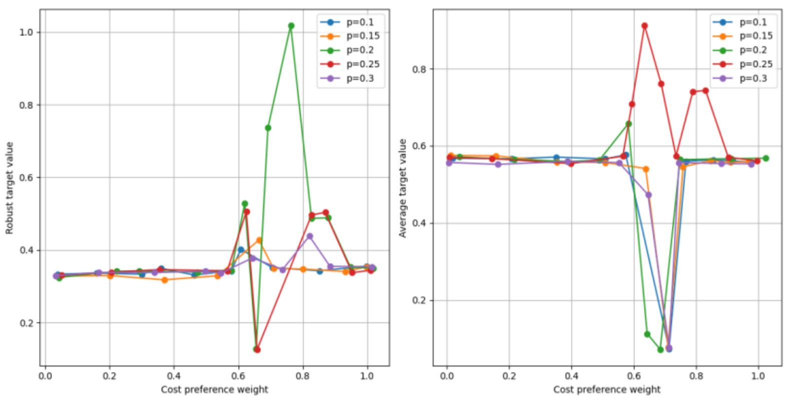

Figure 5 Impact analysis of robust constraint coefficients

5.3 Real Scenario

Since many earthquakes have occurred in Sichuan Province in recent years, the calculation examples in this chapter will take Sichuan Province as the object of analysis. A total of 15 emergency material demand points are set up, including Wenchuan, Mianzhu, Beichuan and other places, and 4 alternative points are proposed to establish emergency logistics centers, including Chengdu, Mianyang and other places. The emergency material demand of each region is determined according to population data, etc., as shown in Table 6.

Table 6 Emergency material demand in disaster-stricken regions

Demand Points I	Demand (million pieces)	Demand Points i	Demand (million pieces)
1 Wenchuan	6-14	9 Pengzhou	74-83
2 Mianzhu	45-53	10 Jiangyou	81-92
3 Beichuan	15-23	11 Deyang	58-66
4 Qingchuan	16-25	12 Ya'an	58-66
5 Mao County	5-12	13 Leshan	108-116
6 Dujiangyan	64-72	14 Baoxing	0-9
7 Anxian	39-45	15 Ziyang	105-113
8 Pingwu	12-21		

The construction cost of the emergency logistics center, capacity based on the construction standards of the disaster relief supplies reserve depot and related policies, as shown in Table 7-8.

Table 7 Basic parameters of alternative points of emergency logistics center

Alternative Points J	Logistics Center Capacity (10,000 pieces)	Construction cost (million yuan)
1 Chengdu	330	300
2 Mianyang	300	230
3 Guangyuan	280	210
4 Meishan	260	180

Table 8 Other costs

Transportation costs (million yuan per 10,000 units. kilometers)	Delayed transportation cost (million yuan/million pieces-hours)	Storage cost (million yuan/million pieces)
0.0125	5	2

The distance between the affected area and the alternative point of the emergency logistics center is calculated according to the road distance between the two cities given by Baidu map, as shown in Table 9.

Table 9 Distance between the affected area and the alternative points of the emergency logistics center Unit: km

Alternative Points J / Disaster area I	1 Chengdu	2 Mianyang	3 Guangyuan	4 Leshan
1 Wenchuan	135	215	382	202
2 Mianzhu	92	52	225	18
3 Beichuan	200	92	255	292
4 Qingchuan	288	176	94	375
5 Mao County	175	255	422	242
6 Dujiangyan	66	144	313	135
7 Anxian	122	18	178	210
8 Pingwu	276	160	202	365
9 Pengzhou	44	95	262	133
10 Jiangyou	158	43	148	252
11 Deyang	73	52	222	162
12 Ya'an	138	152	419	101
13 Leshan	175	292	459	72
14 Baoxing	200	317	478	168
15 Ziyang	107	199	366	108

Emergency supplies transport vehicle speed change range of 30 km / h a 50 km / h, road speed under normal circumstances for 50 km / d, when the emergency supplies transport penalty time for 3 hours, that is, the transport time of more than 3 hours will produce delayed transportation costs.

5.3.1 Deterministic model solution

Based on the parameter setting in 5.1, in the deterministic siting model, the deterministic demand of emergency materials in the affected area and the transportation time between the affected area and the emergency logistics center can be calculated as shown in Table 10-11.

Table 10 Demand for emergency materials in the affected area (deterministic)

Demand Points I	Demand (million pieces)	Demand Points i	Demand (million pieces)
1 Wenchuan	9	9 Pengzhou	79
2 Mianzhu	49	10 Jiangyou	85
3 Beichuan	21	11 Deyang	62
4 Qingchuan	18	12 Ya'an	62
5 Mao County	9	13 Leshan	110
6 Dujiangyan	68	14 Baoxing	5
7 Anxian	41	15 Ziyang	107
8 Pingwu	15		

Table 11 Transportation time between the affected region and the alternative points of the emergency logistics center Unit: hours

Alternative Points J / Disaster area I	1 Chengdu	2 Mianyang	3 Guangyuan	4 Leshan
1 Wenchuan	2.69	4.29	7.61	6.19
2 Mianzhu	1.85	1.03	4.49	5.55
3 Beichuan	4	1.85	5.11	7.45
4 Qingchuan	5.71	3.49	1.85	9.3
5 Mao County	3.49	5.09	8.43	6.97
6 Dujiangyan	1.2	2.85	6.25	4.7
7 Anxian	2.45	0.33	3.57	5.93
8 Pingwu	5.6	3.3	4.05	8.95
9 Pengzhou	0.8	1.89	5.21	4.5
10 Jiangyou	3.13	0.85	2.95	6.73
11 Deyang	1.45	1.05	4.5	4.8
12 Ya'an	2.77	5.01	8.35	2.05
13 Leshan	3.53	5.81	9.17	1.43
14 Baoxing	4	6.33	9.59	3.33
15 Ziyang	2.2	3.95	7.2	2.19

The weighting of transportation time and cost in the model can be adjusted by adjusting the parameter input, i.e., whether transportation time or transportation cost is more important to the site selection results in the site selection model. Now, we take $\lambda = 0.5$ and carry out the calculation.

The solution will be done with the help of a toolbox in Matlab software called RSOME (Robust Stochastic Optimization Made Easy), which is a Matlab algebraic toolbox for general optimization modeling under uncertainty. After Matlab software calculations, the optimal objective function is 25,193,000 yuan, the total cost of deterministic model site selection The specific composition is shown in Table 12.

Table 12 Deterministic model site selection total cost composition Unit: 10,000 yuan

Construction Costs	Inventory Costs	Transportation Costs	Delay Penalty Cost	Objective Function
692	1488	689	22.1	2519.2

The optimal choice of emergency logistics center is shown in Table 13, where l indicates that the location is chosen to establish an emergency logistics center and 0 indicates that it is not chosen.

Table 13 Deterministic model emergency logistics center selection

Emergency Logistics Center	1 Chengdu	2 Mianyang	3 Guangyuan	4 Meishan
Whether to choose	1	1	0	1

The proportions of needs being met at each emergency material demand point are shown in Table 14.

Table 14 Proportion of needs met at the point of need for deterministic modeled emergency supplies

Alternative Points J / Disaster area I	1 Chengdu	2 Mianyang	3 Meishan
1 Wenchuan	1	0	1
2 Mianzhu	0	0	1
3 Beichuan	0	0	1
4 Qingchuan	0	1	0
5 Mao County	0	0	0
6 Dujiangyan	0	0	0
7 Anxian	1	0	0
8 Pingwu	0	1	0
9 Pengzhou	0	1	0
10 Jiangyou	1	0	0
11 Deyang	1	1	0
12 Ya'an	0	0	1
13 Leshan	0	0	1
14 Baoxing	0	1	0
15 Ziyang	1	0	0

This allows us to determine the volume of emergency supplies that the emergency logistics centre will transfer to each location where they are needed, as well as the volume of supplies that the emergency logistics centre will stock, as shown in Table 15.

Table 15 Deterministic model emergency logistics center to each demand point transport volume Unit: 10,000 pieces

Alternative Points J / Disaster area I	1 Chengdu	2 Mianyang	3 Meishan
1 Wenchuan	9	0	0
2 Mianzhu	0	47	0
3 Beichuan	0	21	0
4 Qingchuan	0	17	0
5 Mao County	9	0	0
6 Dujiangyan	66	0	0
7 Anxian	0	43	0
8 Pingwu	0	15	0
9 Pengzhou	79	0	0
10 Jiangyou	0	87	0
11 Deyang	0	60	0
12 Ya'an	0	0	62
13 Leshan	0	0	110
14 Baoxing	0	0	5
15 Ziyang	107	0	0
Total transportation volume	270	290	177
Warehouse utilization	81.9%	96.9%	68.2%

5.3.2 Robust optimization model solution

The parameters required by the model are given in 5.1 and 5.2.1, also solved by Matlab programming, by setting different r to adjust the degree of conservatism of the robust optimization model, so that $\Gamma=5$, the optimal objective function value of 2572.02, robust optimization model of the total cost of the site selection of the specific composition of the model as shown in Table 16.

Table 16 Robust optimization model site selection total cost composition Unit: million yuan

Control level	Construction Costs	Inventory Costs	Transportation Costs	Delay Penalty Cost	Objective Function
$\Gamma=5$	692	1519	705.1	22.9	2572.02

The optimal selection of the emergency logistics center in the robust optimization model is shown in Table 17, with 1 indicating that the location is selected to establish the emergency logistics center and O indicating that it is not selected.

Table 17 Robust optimization model of emergency logistics center selection

Emergency Logistics Center	1 Chengdu	2 Mianyang	3 Guangyuan	4 Meishan
Whether to choose	1	1	0	1

The percentage of demand being satisfied at each emergency material demand point is shown in Table 18.

Table 18 Proportion of emergency material demand point requirements satisfied by robust optimization model

Alternative Points J / Disaster area I	1 Chengdu	2 Mianyang	3 Meishan
1 Wenchuan	1	0	0
2 Mianzhu	0	0	0
3 Beichuan	0	0	0
4 Qingchuan	0	0	0
5 Mao County	0	0	1
6 Dujiangyan	1	1	0
7 Anxian	0	0	0
8 Pingwu	0	0	0
9 Pengzhou	0	0	1
10 Jiangyou	0	1	0
11 Deyang	1	0	0
12 Ya'an	0	0	1
13 Leshan	0	1	0
14 Baoxing	0	0	0
15 Ziyang	0	0	1

From this, the inventory quantity of the emergency logistics center can be calculated, as shown in Table 19.

Table 19 Robust optimization model emergency logistics center to each demand point transport volume Unit: 10,000 pieces

Alternative Points J / Disaster area I	1 Chengdu	2 Mianyang	3 Meishan
Total transportation/inventory	282	300	177
Warehouse utilization	85.9%	100%	68.1%

Robust Optimal Site Selection Model The optimal site selection scheme and transportation routes are shown in Figure 7.

5.4 Comparison between deterministic model and robust optimization model

According to the above can be derived from the two models of the total cost of site selection composition comparison, F = 0 indicates that there is no change in demand, all the demand is fixed, the model is equivalent to the deterministic site selection model, as shown in Table 20.

Table 20 Comparison of the total cost of site selection between the two models Unit: 10,000 yuan

Control level	Construction Costs	Inventory Costs	Transportation Costs	Delay Penalty Cost	Objective Function
$\Gamma=0$	690	1477	682	21.5	2518.8
$\Gamma=5$	690	1517	705.2	23.8	2573.02
$\Gamma=10$	690	1557	725.3122	23.8	2621.62
$\Gamma=15$	690	1597	759.411	28.9	2682.63

The cost of building the emergency logistics centre does not change with the increase in control level, as can be seen from the comparison of the results of the deterministic model and robust optimisation model. Both models use the same site selection scheme and choose Chengdu, Mianyang, and Meishan as the three locations for the construction of the emergency logistics centre. In contrast, the inventory cost, transportation cost, and delayed penalty cost keep increasing with the increase of the number of emergency material demand points with uncertain demand (Ershadi, M. M, et al, 2022), (Boonmee, C, et al, 2020).

Table 21 Comparison of warehouse utilization rate of two models

Control level	1 Chengdu	2 Mianyang	3 Meishan
$\Gamma=0$	82.2%	97.2%	67.8%
$\Gamma=5$	85.9%	100%	67.8%
$\Gamma=10$	89.2%	100%	70.2%
$\Gamma=15$	94.3%	100%	72.4%

As can be seen from Table 21, the utilization rate of Mianyang Emergency Logistics Center is the highest in both models. And when the storage capacity of emergency materials in Mianyang Emergency Logistics Center reaches the upper limit, the emergency materials are preferentially stored in Chengdu Emergency Logistics Center, i.e., the utilization rate of Chengdu Emergency Logistics Center-61N increases faster than the utilization rate of Meishan Emergency Logistics Center.

6 Conclusion

This paper considers how to activate the emergency rescue system to carry out emergency rescue operations after a special event, especially a natural disaster, and examines the problems of emergency logistics center site selection and the corresponding material transfer routes and transfer volumes, incorporating the uncertainties of material demand, transport costs and transport times at the disaster site (demand site), by developing a deterministic multi-objective emergency logistics centre site selection model as well as a strong optimisation model of multi-objective emergency logistics centre site selection, with the goals of reducing the overall rescue costs as well as the length of time it takes to save people. In order to transform the bi-objective into a single-objective and take into account factors like changes in the order of magnitude of the problem data, a method of transforming the bi-objective into a single-objective using the optimal value of a single-objective is constructed, which uses a robust optimisation model for multi-objective emergency logistics centre site selection. In order to solve the two models efficiently, a generalized hybrid frog jumping algorithm is designed, and the effectiveness of the model and the algorithm is verified with examples. Based on the results, we discuss the effects of different cost preference weights and different robust constraint coefficients, and give the rules for setting cost preference weights and the recommended values of robust constraint coefficients in different phases of emergency rescue. However, there are also shortcomings in this study, such as the differences in transportation modes, the road conditions or interruptions of rescue roads, the number and capacity constraints of material carriers, and the price factors of collecting emergency materials in different rescue phases, etc., Which approach to further research on the location of emergency logistics centres will be practical.

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Consent for publication

All authors reviewed the results, approved the final version of the manuscript and agreed to publish it.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declared that they have no conflicts of interest regarding this work.

Authors' Contributions:

Quan Gan, is responsible for designing the framework, analyzing the performance, validating the results, and writing the article.

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