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Three-Stage Mixed Integer Robust Optimization Model Applied to Humanitarian Emergency Logistics by Considering Secondary Disasters

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ABSTRACT In recent years, natural disasters occur frequently, and secondary disasters induced by major disasters will also cause huge losses. The diversity of secondary disasters makes humanitarian emergency logistics (HEL) more challenging but often overlooked by researchers. In order to solve the comprehensive HEL problem of major and secondary disasters, a three-stage mixed integer linear optimization (TS-MILO) model is proposed. Among them, the uncertainty of the demand for relief supplies is also extremely difficult to deal with. In order to resist the interference of uncertainty, based on robust optimization, the TS-MILO model is further transformed into a three-stage mixed integer robust optimization (TS-MIRO) model, which are respectively BTS-MIRO (Box set), PTS-MIRO (Polyhedral set), and ETS-MIRO (Ellipsoid set). The experimental results show that the TS-MILO model can provide the lowest cost but cannot solve the uncertainty problem. The improved TS-MIRO model will pay a robust price (increase by at least 10.05%), but maintains supply stability even in the worst-case scenario. Specifically, ETS-MIRO model has strong robustness, and its cost increase only accounts for 44.66% of BTS-MIRO model in the worst case. The service level of the three TS-MIRO models increases with the safety parameters, among which the service level in the ETS-MIRO model increases significantly from 88.53% to 96.44%. The research results can provide a strong support for the decision making of disaster relief management department.

INDEX TERMS Secondary disasters, robust optimization, humanitarian emergency logistics.

I. INTRODUCTION

In recent years, large-scale natural disasters have frequently occurred, which resulted in a large number of casualties and property losses. In addition to the great damage caused by major disasters, the enormous losses brought about by subsequent secondary disasters cannot be ignored. The Hua-xian earthquake (M = 8[1]; Jan., 1556) is the largest earth-quake recorded in Shanxi, CHN, in which secondary disa-sters such as landslides and floods are induced by major disasters. According to historical records, 830,000 people were killed [1]. The Xingtai earthquake (M = 6.8; Mar., 1966) occurred in Heibei, CHN. Secondary disasters such as landslides, collapses, flood and water spraying occurred, which submerged large quantities of farmland and water conservancy facilities [2]. The San Francisco earthquake (M = 8.3; Apr., 1906) led to fire and other secondary disasters [3], [4]. The Kobe earthquake happened in JPN (M = 7.2; Jan., 1995), which resulted in the cracking of natural gas pipelines and further triggered secondary disasters such as fires [5], [6]. Besides, an earthquake (M = 6.8; Jul., 2006) occurred in the southwest of Java, IDN, causing a secondary disaster tsuna-mi [7]. The earthquake in Nepal killed 8,790 people, injured 22,300 people and damaged millions of buildings [8]. Secondary disasters refer to a series of disasters that followed strong earthquakes, such as fire and tsunami. Those events indicate that the losses caused by secondary disasters may even exceed those of major disasters. Con-sequently, we must pay high attention to secondary disa-sters.

HEL plays an indispensable role in post-disaster rescue. At present, scholars usually concentrate on the major disasters but neglect the secondary disasters. As an

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[1]M indicates the magnitude of the earthquake, with destructive and seismic intensity increasing progressively from I to XII.

extraordinary specialized emergency logistics, HEL can satisfy the de-mands of emergency materials like food and medicine in the post-disaster rescue, and play a very important part in reducing casualties and property losses [9]. Bussieres *et al.* (2017) believe that the implementation of the distribution system can achieve the target of large-scale material supply after major disasters [10]. Benini *et al.* (2003) used geo-graphic information system to analyze rescue data in major disasters and concluded that the benefits are considerable, but the costs are also high, especially the hidden costs [11]. Olness *et al.* (2005) consider training programs for rescue personnel to be an effective tool to improve rescue capa-bilities [12]. Chen *et al.* (2008) used artificial immune algori-thm to confirm the effectiveness of the HEL vehicle path planning model in major disasters [13]. According to the actual situation, there are some challenges in HEL management. Potential secondary disasters can easily inter-fere with the rescue plan, which makes the rescue in the disaster areas more difficult. The previous research often focused on the rescue work after a single stage of major disasters, whereas few scholars paid attention to secondary disasters. Therefore, this paper attempts to meet the rescue demands of major disasters, further planning to satisfy the rescue needs of secondary disasters, and to improve comprehensive rescue capacity of HEL. Considering the impact of secondary disa-sters and the limitations of current research, the purpose of this study is to explore the relationship between major and secondary disasters, and to develop models to respond to uncertain disasters.

In the research of HEL, the previous literature often focused on certain scenarios, while few scholars carried out research on its uncertainty. The uncertainty of the HEL process has a great impact on the rescue plan. It is not only reflected in the uncertainty of transportation demands, but also in that of the supply of relief materials. Because of the uncertainty, it is difficult to obtain accurate information. Secondary disasters are mainly caused by major disasters. Besides, the formers are more difficult to predict in advance and will undoubtedly be more laborious. Some scholars have analyzed and modeled the uncertainty in the actual operation management. Li *et al.* (2019) proposed an opportunity con-strained programming model to settle the energy storage problem under uncertainty [14]. Balcik and YanıKoğLu (2020) studied the uncertain routing problem by constructing a robust duration constraint model [15]. These studies have proved that compared with the certainty model, the uncertainty model method is more suitable for the actual situation and has more practical application value.

In view of the uncertainty in the HEL, scholars and experts have carried out research by using heuristics, fuzzy program-ming and stochastic programming. As for heuristics, some scholars have established models to figure out the total costs of all possible factors in HEL. However, these studies ignored the influence of possible secondary disasters. Xu *et al.* (2011), using ant algorithm under the condition of determined demand, verified the effectiveness of the model with the objective of minimizing supply imbalance [16]. Liu *et al.* (2016) studied the disruption management issue of post-earthquake HEL system, and worked out the problem via employing hybrid heuristic algorithm [17]. Zhang *et al.* (2013) proposed a new biome-metic method for the path selection of emergency logistics under the condition of known demand [18]. Zeng *et al.* (2014) proposed a neighborhood descent algorithm to resolve the problem of cumulative multi warehouse vehicle routing in emergency logistics under the condition of inventory determination [19]. Wang *et al.* (2015) established a mini-mum objective mathematical model in HEL, and used two-stage heuristics to figure out the problem [20]. And with regard to fuzzy programming and stochastic programming, there are still few scholars who have studied the HEL under uncertain conditions. For the sake of solving the issue of uncertainty, Xu *et al.* (2016) proposed an ambiguous two-level model and verified the practicability of the model [21]. Yang *et al.* (2008) proposed a new two-stage stochastic programming model to solve the problem of relief allocation [22]. Dai and Ma (2008) proposed hybrid clustering optimization model for large-scale disaster relief with the aim of minimizing the total number of deaths in major disasters [23]. Shen *et al.* (2019) proposed a triangle model to meet the demand of emergency logistics, and made use of a hybrid two-stage algorithm to solve it [24]. On the whole, the above scholars have studied the uncertainty decision-making problem of HEL from various dimensions. Heuristic algorithm, fuzzy programming and stochastic programming have developed more syste-matically, but there are still some limitations.

- The deterministic linear optimization model only focuses on the single stage decision-making problem.
- It is tough to offer a theoretical exact solution through the heuristic algorithm model, which depends on the selection of termination criteria.
- It is difficult to describe the actual situation by means of the linear chance constrained model. Besides, the solution easily leads to NP-hard problem, is complex.
- It is also hard to describe the membership function via stochastic fuzzy model, which results in lower feasibility of the results.
- Due to the lack of sufficient historical data in stochastic programming model, the blind assumption of probability distribution has high risk.

Therefore, it is necessary for us to conduct in-depth research on the uncertainty of HEL and seek a more compati-ble and more practical research methodology.

With the rapid development of theory, robust optimization has been proved to be able to overcome the limitations of stochastic optimization in uncertain problems [25]. Although the research on robust optimization theory is relatively ma-ture, its application still needs to be further enriched, espe-cially in the field of HEL. The advantage of robust optimi-zation is that the model performs reasonably well, even if we estimate the cost at the worst case, and that a robust solution can be acquired. Robust optimization

theory was first put forward by Bertsimas et al [26]. As a tool for optimization under uncertain conditions, robust optimization does not depend on probability distribution or membership function, but represents uncertainty through a specific set [27]. Some scholars have used its theory to study decision making problem of path planning. In the case of uncertainty, Zhang proposed a two objective robust optimization model to re-solve the emergency medical service problem [28]. Chen *et al.* constructed the two-stage robust security-constrained unit commitment model and applied it to a number of research areas [29]–[32]. Through actual cases, it has been proved that it can effectively reduce the conservatism of uncertain sets and ensure the economy of optimization results. Robust optimization can take the uncertainty of parameters and the heterogeneity of risk preference of decision makers into consideration, which will undoubtedly provide valuable empirical suggestions for the research of HEL. Some school-ars have applied the robust optimization to the research of supply chain management [33], [34] and decision planning [35]. Jadidbonab *et al.* (2020) adopted the non-probability information interval method to optimize the self-scheduling problem under the uncertainty with the goal of maximizing the benefits under the circumstance of uncertainty of renew-able resources [36]. Gholinejad *et al.* (2019) proposed an energy management system for multiple home energy hubs in a community, and the simulation results have displayed the effectiveness [37]. Nazari-Heris *et al.* (2019) proposed a multi-objective two-stage random unit model, which was applied to a new flexible energy gas electric networking system [38]. In terms of new energy applications, Mirzaei *et al.* proposed a great many robust optimization models for uncertain energy demand and variable wind direction, and verified the performance of the robust optimization model [39]–[41]. Al-Sumaiti *et al.* (2019) proposed a more pro-mising approach to meet the demands of power supply by considering the impact of the probability uncertainty nature of weather [42]. As is mentioned above, robust optimization has been applied to the fields of supply chain management, decision planning and new energy by experts and scholars from all walks of life. However, in the research of HEL, few people use the robust optimization. Therefore, it is innovative to apply the robust optimization theory to researching HEL.

In addition to the application of robust optimization, this paper further extends the single-stage HEL path planning to three-stage. Through careful observation of the actual activities, we can find that in the rescue process, the relief materials are not only transported from the origin to the disaster relief point, but there are also logistics operations of multiple transshipment. However, the single stage model is too idealistic to reflect the reality. Thus, it is necessary to explore and study the multi-stage model. Most of the related researches only involve the design of one or two of the three sub-stages. There is no research on integrating these three sub stages to systematically solve the path planning problem of HEL. In addition, the relationship among the three sub-stages is interdependent, since some inputs of the first stage planning model are the outputs of the second stage model and some inputs of the second stage model are obtained from the third stage. Therefore, the sub-stages must be designed simultaneously with the overall planning model. This method can be used to design a seamless emergency rescue supply network integrating three disaster ma-nagement sub-stages. In the field of application, especially in the HEL, it has not been found whether the two-stage or even multi-stage problem model can be solved by robust optimization.

In summary, the contributions and innovations of this research are as follows. In general, this research can play a guiding role in the construction of the model for HEL, and help decision makers to formulate an appropriate emergency relief strategy to respond to natural disasters.

- This paper not only focuses on the impact of major disasters, but also further analyses the impact of secondary disasters and the internal relationship between them.
- Based on the comprehensive consideration of three sub-stages of disaster management, a three-stage mixed integer linear optimization (TS-MILO) model is proposed.
- Robust optimization theory is applied to the research of three-stage HEL problem. TS-MILO model is further transformed into TS-MIRO model.
- According to the real location data of HEL, computer simulation analysis is carried out. This model provides valuable decision support for government relief departments.

The rest of this paper is organized as follows. In Section II, the description of the problems and TS-MILO model are given. In Section III, the TS-MILO model is constructed and it is further transformed into TS-MIRO model in Section IV. The contents in Section V and VI are about the numerical analysis. In Section VII, the conclusion and future research are put forward.

II. PROBLEM DESCRIPTION

Fire, tsunami and other secondary disasters are mainly brought about by major disasters such as earthquakes, and the occurrence of major disasters is the premise of their generation. HEL planning can be divided into three stages. The HEL rescue process of major disasters includes emer-gency preparation stage (the first stage) and rescue stage (the second and third stage). At the same time, on the basis of meeting the rescue requirements, reasonable planning and allocation of resources can reduce the loss caused by unnecessary operation. Decision making in the first stage is influenced by the results of the second stage. Similarly, the decision making in the second stage is affected by the third stage (Fig. 1).

In HEL emergency rescue network, there are I original warehouses, J major disaster sites and K secondary disaster sites (Fig. 2). First of all, TS-MILO model is established. The purpose of the model is to explore how to reduce the total costs as many as possible on the basis of meeting the demand to the maximum extent. The first stage is the post-disaster preparation stage. In this stage, under the circumstance of only knowing the location of the disaster, it is necessary to

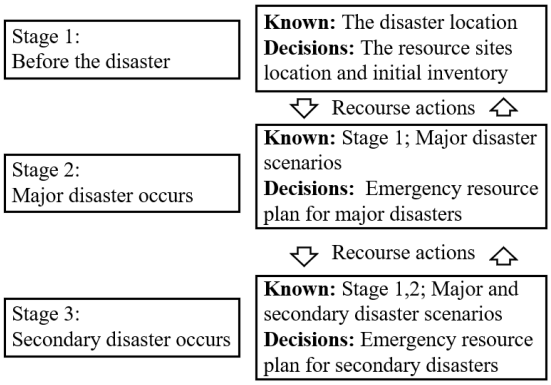

FIGURE 1. Description of the internal relationship of three stage HEL.

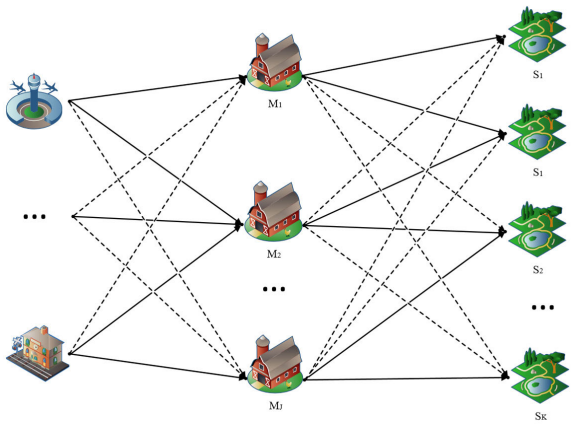

FIGURE 2. Description of HEL vehicle routing plan.

estimate the demand of disaster relief materials, and then select the location of disaster relief sites. The selection of rescue nodes should meet the demand of the maximum service and the feasibility of practical operation. The second stage is the material distribution stage of the main disaster areas. The goal of this stage is to solve the initial path planning problem of emergency supplies. On the basis of comprehensive consideration of the practical feasibility (cost and capacity), the rescue materials are transported from the original warehouses to the main disaster affected areas, in which the demands of emergency materials are not only affected by their own demands, but also by the demands of the third stage of secondary disaster. The third stage is the material distribution stage of the secondary disaster area. The goal of this stage is to solve the problem of vehicle routing in secondary disaster areas. Considering the potential demand of the secondary disaster areas, the surplus materials should be allocated to the secondary disaster areas after meeting the demand of major disaster.

The three-stage HEL rescue network has the following two functions. On the one hand, overall planning needs to ensure that humanitarian relief needs are satisfied to the maximum extent. It includes not only the demands of the main disaster areas, but also the material demands of the secondary disaster sites. On the other hand, it is also necessary to reduce the costs of operation management through reasonably plan-ning path. The costs are divided into three types: fixed operating costs, vehicle transportation costs and time costs [43], [44].

A. ABBREVIATIONS AND ACRONYMS

The specific parameters are shown in Table 1.

TABLE 1. Parameters and variables.

Type	Description
D_j	Demand for major disaster relief sites.
D_k	Demand of secondary disaster relief sites.
c_f	Fixed operating costs.
H_j^{Max}	Maximum inventory of major sites.
h_2	Maximum load of large vehicle.
h_3	Maximum load of small vehicle.
c_v	Fuel consumption cost.
c_t	Unit delay penalty cost.
d_{ij}	Distance between starting and major sites.
d_{jk}	Distance between major and secondary sites.
$\overline{v}_i$	Average vehicle speed.
t_j	Baseline arrival time for second stage.
t_k	Baseline arrival time for third stage.
T_j^{Max}	Maximum time of second stage.
T_k^{Max}	Maximum time of third stage.
ε	Coefficients of parameters for second stage
ξ	Coefficients of parameters for third stage.
I	The set of original sites consists of i.
J	The set of major sites, consists of j.
K	The set of secondary sites, consists of k.
x_j	0-1 variable, choose j when $x_j = 1$; or, not.
y_{ij}	Continuous variable, choose ij when $y_{ij} \neq 0$.
z_{jk}	Continuous variable.

B. ASSUMPTION

Combined with the above analysis, following assumptions are made for the three-stage HEL problems.

- It is assumed that in addition to meeting their own needs, the major sites can also supply materials to multiple second-ary disaster relief sites.
- The rescue demands of all sites must be met. And any rescue demand site has at least a supply site to supply.
- The vehicles used at the same stage are of the same type with the same fuel consumption and load capacity.
- The geographical location and time window of candidate initial disaster relief sites are known.

- The average speed of vehicles in different regions are different, which depends on road conditions and time period in the area.

III. MODEL CONSTRUCTION

In this section, the basic three-stage mixed integer linear optimization (TS-MILO) model is constructed to analyze the three-stage HEL problem deeply.

A. TS-MILO MODEL

According to the actual situation of HEL, the specific costs involved include: the fixed cost, handling cost, transportation cost and path time cost [45], [46]. TS-MILO model is constructed, which aims to meet the demands of human-itarian relief, achieve the goal of selecting material storage sites and calculating the minimization of overall costs. According to the real situation, the first stage of TS-MILO is shown below.

$$\min \left\{ \sum_{J} x_j c_f + \sum_{I}\sum_{J} c_h y_{ij} D_j + \sum_{I}\sum_{J} y_{ij}[E(D_j : c_m^2)] \right\} \tag{1}$$

$$s.t. \sum_{J} y_{ij} \le 1, \quad \forall i \in I \tag{2}$$

$$\sum_{J} y_{ij} D_j \le H_j^{Max}, \quad \forall i \in I \tag{3}$$

$$y_{ij} \le x_j, \quad \forall i \in I,\ \forall j \in J \tag{4}$$

$$x_j \in \{0,1\}, \quad y_{ij} \ge 0,\ \forall i \in I,\ \forall j \in J \tag{5}$$

Among them, the first item of (1) is fixed cost, which is infrastructure investment cost, including office equipment loss cost and basic water and electricity cost. Fixed cost has nothing to do with vehicle routing planning. The second is the handling cost, which is affected by the demand. The third cost is affected by the second stage of vehicle routing planning.

Specific constraints: (2) represents that the total handling capacity cannot be higher than the total demand, and there is no other outflow part; (3) shows that the maximum handling capacity is less than its maximum capacity; (4) only the selected initial sites participate in the corresponding logistics operation; constraint (5) is related variable constraint, in which only participates in the corresponding emergency material distribution when $x_j = 1$.

$$C_2(D_j : c_m^2) = \min \left\{ \begin{array}{l} \sum_{I}\sum_{J} (c_v^2 y_{ij} D_j d_{ij}) \big/ h_2 \\ + \sum_{I}\sum_{J} c_t^2 x_i (d_{ij} \big/ \bar{v}_i - t_0^j) \\ + \sum_{J}\sum_{K} z_{jk} E[C_3(D_k : c_n^3)] \end{array} \right\} \tag{6}$$

$$s.t. \sum_{J} y_{ij} \le 1, \quad \forall i \in I \tag{7}$$

$$\sum_{J} y_{ij} D_j \le H_j^{Max}, \quad \forall i \in I \tag{8}$$

$$\lceil y_{ij} \rceil \cdot (d_{ij} \big/ \bar{v}_j) \le T_{ij}^{Max}, \quad \forall j \in J,\ \forall k \in K \tag{9}$$

$$y_{ij} \le x_i, \quad \forall i \in I,\ \forall j \in J \tag{10}$$

$$x_i \in \{0,1\}, \quad y_{ij} \ge 0, z_{jk} \ge 0,\ \forall i \in I,\ \forall j \in J,\ \forall k \in K \tag{11}$$

In the second stage of TS-MILO, the transportation cost is minimized on the basis of meeting the demand of initial sites. Among them, the first item of (6) is the vehicle transportation cost of the second stage. The second is the time cost, and the third one is related to the path planning in the third stage. Specific constraints: (7) represents that the total distribution volume cannot be higher than the total demand; (8) represents the maximum storage capacity; (9) represents time constraint; (10) only the selected initial node participates in the corresponding emergency logistics operation; (11) is related variable constraint.

$$C_3(D_k : c_n^3) = \max \left\{ \begin{array}{l} c_t^3 \sum_{J}\sum_{K} \lceil z_{jk} \rceil (d_{jk} \big/ \bar{v}_j - t_0^k) \\ + c_v^3 \sum_{J}\sum_{K} (z_{jk} D_k d_{jk}) \big/ h_3 \end{array} \right\} \tag{12}$$

$$s.t. \sum_{J} z_{jk} \le 1, \quad \forall k \in K \tag{13}$$

$$\sum_{j \in J} z_{jk} D_k \le H_k^{Max}, \quad \forall k \in K \tag{14}$$

$$\lceil z_{jk} \rceil \cdot (d_{jk} \big/ \bar{v}_j) \le T_{jk}^{Max}, \quad \forall j \in J,\ \forall k \in K \tag{15}$$

$$y_{ij} \ge 0, \quad z_{jk} \ge 0,\ \forall j \in J,\ \forall k \in K \tag{16}$$

In the third stage of TS-MILO, the purpose is to minimize the total cost on the basis of meeting the needs of secondary disaster relief sites to the maximum extent. The first term of (12) is the time penalty cost of the third stage, and the second term is the vehicle transportation cost. Specific constraints: (13) represents the total distribution volume unable to be higher than the total material supply; (14) represents the maximum storage capacity; (15) represents time constraint; (16) is related variable constraint.

IV. CONSTRUCTING TS-MIRO MODEL

Based on the TS-MILO model, this section further constructs three robust optimization models under uncertain conditions, which are three-stage mixed integer robust optimization model based on box set (BTS-MIRO model), three-stage mixed integer robust optimization model based on polyhedron set (PTS-MIRO model), and three-stage mixed integer robust optimization model based on ellipsoid set (ETS-MIRO model).

A. UNCERTAINTY SCENARIOS

In the process of post disaster rescue, there is no ideal model. On the contrary, the external environment is full of complexity and uncertainty. It is very difficult to obtain the precise value or probability distribution of key parameters, especially the demand parameters [47]. The idealization of theoretical

research may lead to low degree of feasibility in reality, in other words, the stability of deterministic model under uncertain conditions is infeasible. Therefore, we intro-duce the concept of robust optimization. In reality, the problem to be solved is uncertain, which is reflected in the uncertainty of parameters. Robust model can provide an effective uncertainty measurement method, so the research of robust optimization has high applicability. Applying the theory of robust optimization [48], the TS-MILO model is transformed into TS-MIRO model. The uncertain parameters change in uncertain sets, so it can be studied without depending on the probability distribution. The greater the volatility of the first type of initial rescue sites demand is, the greater the uncertainty and uncontrollability will be. The uncertain parameter $\tilde{D}j^0 = Dj + \hat{D}j$, where, Dj^0 is nominal value, $\hat{D}j = \varepsilon Dj^0$ is fluctuation demand and ε is disturbance proportion. The demand fluctuation of secondary disaster stations is high and uncontrollable. It is defined as a random demand parameter $\tilde{D}_k = D_k^0 + \hat{D}_k$, D_k^0 is nominal value, $\hat{D}_k = \xi D_k^0$ is demand fluctuation and ξ is disturbance proportion. Therefore, BTS-MIRO, PTS-MIRO and ETS-MIRO models are established, respectively [49].

B. BTS-MIRO MODEL

In BTS-MIRO model, the uncertain demand is $\tilde{D}_j, \tilde{D}_k$ and the uncertainty set is box. BTS-MIRO. According to robust optimization, TS-MILO model is further transformed into BTS-MIRO equivalent model [50], [51]. The set is defined as $D : U^{B1,B2} = \{\{\varsigma, \zeta\} \| \varepsilon, \xi \|_\infty \le \Psi_{j,k}\} = \{\{\varsigma, \zeta\} : |\varepsilon_j, \xi_k| \le \Psi_{j,k}\}$, where, $\Psi_{j,k}$ is uncertain parameter (i.e. Safety Parameter, SP), which means that at most $|\Psi|$ parameters deviate from the nominal value.

Theorem 1: Under uncertain situation, when the box uncertainty set is empty, the BTS-MIRO model will degrade to TS-MILO model. When the box uncertainty parameter set is non-empty, (1) - (16) robust equivalent model is (17) - (34).

The first stage of BTS-MIRO is (17) - (22), and its goal is to minimize the total cost under uncertain conditions.

$$\min\ Z_B \tag{17}$$

$$s.t.\ \max\left\{\begin{array}{l}\sum_J x_j c_f + \sum_I \sum_J y_{ij}[C_2(D_j^0, c_m^2)] \\ +\sum_I \sum_J x_j c_h y_{ij} D_j^0 + \sum_I \sum_J x_i c_h y_{ij} \hat{D}_j \\ +\Psi_j \sum_I \sum_J y_{ij}[C_2(\hat{D}_j, c_m^2)]\end{array}\right\} \le Z_B \tag{18}$$

$$\sum_J y_{ij} \le 1, \quad \forall i \in I \tag{19}$$

$$\sum_J y_{ij} D_j^0 + \Psi_j \sum_J y_{ij} \hat{D}_j \le H_j^{Max}, \quad \forall i \in I \tag{20}$$

$$y_{ij} \le x_j, \quad \forall i \in I,\ \forall j \in J \tag{21}$$

$$x_j \in \{0, 1\}, \quad y_{ij} \ge 0,\ \forall i \in I,\ \forall j \in J \tag{22}$$

The second stage of BTS-MIRO is (23) - (28), and its goal is to minimize the distribution cost of emergency materials on the basis of maximizing the demand of major disaster relief sites.

$$\min\ C_2(\tilde{D}_j : c_m^2) \tag{23}$$

$$s.t.\ \max\left\{\begin{array}{l}c_v^2 \sum_I \sum_J \frac{y_{ij} D_j^0 d_{ij}}{h_2} + c_t^2 \sum_I \sum_J x_i (\frac{d_{ij}}{\bar{v}_i} - t_0^j) \\ +\Psi_j (c_v^2 \sum_I \sum_J y_{ij} \hat{D}_j d_{ij} \big/ h_2) \\ +\Psi_j [c_t^2 \sum_I \sum_J x_i (d_{ij} \big/ \bar{v}_i - t_0^j)] \\ +\sum_J \sum_K z_{jk} C_3(\tilde{D}_k, c_m^3)\end{array}\right\}$$

$$\le C_2 \tag{24}$$

$$\sum_J y_{ij} \le 1, \quad \forall i \in I \tag{25}$$

$$\sum_J y_{ij} D_j^0 + \Psi_j \sum_J y_{ij} \hat{D}_j \le H_j^{Max}, \quad \forall i \in I \tag{26}$$

$$\lceil y_{ij} \rceil \cdot (d_{ij} \big/ \bar{v}_j) \le T_{ij}^{Max}, \quad \forall j \in J,\ \forall k \in K \tag{27}$$

$$x_j \in \{0, 1\}, \quad y_{ij} \ge 0, z_{jk} \ge 0,\ \forall j \in J,\ \forall k \in K \tag{28}$$

The third stage of BTS-MIRO is (29) - (34), and its goal is to minimize the cost of secondary disaster rescue on the basis of maximizing the demand of secondary disaster sites.

$$\min\ C_3(\tilde{D}_k : c_n^3) \tag{29}$$

$$s.t.\ \max\left\{\begin{array}{l}\sum_J \sum_K c_t^3 z_{jk} (\frac{d_{jk}}{\bar{v}_j} - t_0^k) + \sum_J \sum_K \frac{c_v^3 z_{jk} D_k^0 d_{jk}}{h_3} \\ +\Psi_k [c_v^3 \sum_J \sum_K (z_{jk} \hat{D}_k d_{jk}) \big/ h_3]\end{array}\right\}$$

$$\le C_3 \tag{30}$$

$$\sum_J z_{jk} \le 1, \quad \forall k \in K \tag{31}$$

$$\sum_J z_{jk} D_k^0 + \Psi_k \sum_J z_{jk} \hat{D}_k \le H_k^{Max}, \quad \forall k \in K \tag{32}$$

$$\lceil z_{jk} \rceil \cdot (d_{jk} \big/ \bar{v}_j) \le T_{jk}^{Max}, \quad \forall j \in J,\ \forall k \in K \tag{33}$$

$$y_{ij} \ge 0, \quad z_{jk} \ge 0,\ \forall j \in J,\ \forall k \in K \tag{34}$$

C. PTS-MIRO MODEL

In the PTS-MIRO model, the uncertain set of demand sites is polyhedron set, which is defined by l_1 norm: $D : U^{P1,P2} = \{\{\varsigma, \zeta\} : \|\varepsilon, \xi\|_1 \le \Gamma_{j,k}\} = \{\{\varepsilon, \xi\} \cdot \sum |\varepsilon_{j,k}| \le \Gamma_{j,k}\}$, in which $\Gamma_{j,k}$ is the uncertain parameter [52]–[55].

Theorem 2: Under uncertain situation, when the polyhedron uncertainty set is empty, the PTS-MIRO model will degrade to TS-MILO model. When the box uncertainty parameter set is non-empty, (1) - (16) robust equivalent model is (35) - (52).

The first stage of PTS-MIRO is (35) - (40), and its goal is to minimize the overall rescue cost.

$$\min\ Z_P \tag{35}$$

$$s.t.\ \sum_J y_{ij} \le 1, \quad \forall i \in I \tag{36}$$

$$\sum_J y_{ij} D_j^0 + \Gamma_j \sum_J y_{ij} \hat{D}_j \le H_j^{Max}, \quad \forall i \in I \tag{37}$$

$$y_{ij} \le x_j, \quad \forall i \in I,\ \forall j \in J \tag{38}$$

$$\max \left\{ \begin{array}{l} \sum_J x_j c_f + \sum_I \sum_J x_j c_h y_{ij} D_j^0 \\ + \sum_I \sum_J y_{ij} [C_2(D_j^0, c_m^2)] + \sum_I \sum_J x_i c_h y_{ij} \hat{D}_j \\ + \Gamma_j \sum_I \sum_J y_{ij} [C_2(\hat{D}_j, c_m^2)] \end{array} \right\} \le Z_P \tag{39}$$

$$x_j \in \{0,1\}, \quad y_{ij} \ge 0,\ \forall i \in I,\ \forall j \in J \tag{40}$$

The second stage of PTS-MIRO Model is (41) - (46), and its goal is to minimize the initial rescue cost.

$$\min\ C_2(\tilde{D}_j : c_m^2) \tag{41}$$

$$s.t.\ \max \left\{ \begin{array}{l} \sum_I \sum_J \frac{c_v^2 y_{ij} D_j^0 d_{ij}}{h_2} + c_t^2 \sum_I \sum_J x_i (\frac{d_{ij}}{\bar{v}_i} - t_0^j) \\ + \sum_J \sum_K z_{jk} C_3(\tilde{D}_k, c_m^2) \\ + \Gamma_j (c_v^2 \sum_I \sum_J y_{ij} \hat{D}_j d_{ij} \big/ h_2) \\ + \Gamma_j [c_t^2 \sum_I \sum_J x_i (d_{ij} \big/ \bar{v}_i - t_0^j)] \end{array} \right\} \le C_2 \tag{42}$$

$$\sum_J y_{ij} \le 1, \quad \forall i \in I \tag{43}$$

$$\sum_J y_{ij} D_j^0 + \Gamma_j \sum_J y_{ij} \hat{D}_j \le H_j^{Max}, \quad \forall i \in I \tag{44}$$

$$\lceil y_{ij} \rceil \cdot (d_{ij} \big/ \bar{v}_j) \le T_{ij}^{Max}, \quad \forall j \in J,\ \forall k \in K \tag{45}$$

$$x_j \in \{0,1\}, \quad y_{ij} \ge 0,\ z_{jk} \ge 0,\ \forall j \in J,\ \forall k \in K \tag{46}$$

The third stage of PTS-MIRO is (47) - (52), and its goal is to minimize the cost of secondary disaster relief.

$$\min\ C_3(\tilde{D}_k : c_n^3) \tag{47}$$

$$s.t.\ \max \left\{ \begin{array}{l} c_t^3 \sum_J \sum_K \lceil z_{jk} \rceil (\frac{d_{jk}}{\bar{v}_j} - t_0^k) \\ + c_v^3 \sum_J \sum_K \frac{z_{jk} D_k^0 d_{jk}}{h_3} + \Gamma_k (c_v^3 \sum_{J,K} \frac{z_{jk} \hat{D}_k d_{jk}}{h_3}) \end{array} \right\} \le C_3 \tag{48}$$

$$\sum_J z_{jk} \le 1, \quad \forall k \in K \tag{49}$$

$$\sum_J z_{jk} D_k^0 + \Gamma_k \sum_J z_{jk} \hat{D}_k \le H_k^{Max}, \quad \forall k \in K \tag{50}$$

$$\lceil z_{jk} \rceil \cdot (d_{jk} \big/ \bar{v}_j) \le T_{jk}^{Max}, \quad \forall j \in J,\ \forall k \in K \tag{51}$$

$$y_{ij} \ge 0, \quad z_{jk} \ge 0,\ \forall j \in J,\ \forall k \in K \tag{52}$$

D. ETS-MIRO MODEL

In ETS-MIRO model, the uncertain parameters float in the ellipsoid set. Through the l_2 norm, $U^{E1,E2}$ are defined as: $\{\{\varsigma, \zeta\} : \|\varepsilon\|_2, \|\xi\|_2 \le \Omega_{j,k}\} = \left\{\varepsilon \sqrt{\sum_J \varepsilon_j^2}, \xi \sqrt{\sum_K \xi_k^2} \le \Omega_{j,k}\right\}$, in which $\Omega_{j,k}$ is the adjustable SP and also the spherical diameter of uncertain set [56]. The set $\{U^{E1,E2}\}$ of uncertain $\tilde{D}_{j,k}$ is $\{\tilde{D} \in R, \sum_{J,K} [(\tilde{D}_{j,k} - D_{j,k}^0) \big/ \hat{D}_{j,k}]^2 \le \Omega_{j,k}^2\}$. Since the model is a nonlinear problem, set $U^{E1,E2}$ is equivalent to $\{(\tilde{D}_{j,k} - D_{j,k})^T C^{-1} (\tilde{D}_{j,k} - D_{j,k}) \le \Omega_{j,k}^2\}$, where C is an n-order diagonal matrix with $\hat{D}_{j,k}^2$ (nonzero) elements, then get $C(D_{j,k}^0) + \Omega_{j,k} \sqrt{\sum_{J,K} (\hat{D}_{j,k}^2)[\sum_{I,J} (y_{ij}, z_{jk}) c_{v,t,c}]^2} \le Z_E$. Set $r_{j,k} = \sum_J \sum_K c_{v,t,c}(y_{ij}, z_{jk})$, $P_{j,k} = \sqrt{\sum_J \sum_K \hat{D}_{j,k}^2 r_{j,k}^2}$. Then, the above formula is converted to $C(D_{j,k}^0) + \Omega_{j,k} P_{j,k} \le Z_E$. Since the goal is to minimize the cost, relaxation constraint $P'_{j,k} \ge \sqrt{\sum_{J,K} \hat{D}_{j,k}^2 r_i^2}$, $r'_{j,k} \ge \sum_J \sum_K c_{v,t,c}(y_{ij}, z_{jk})$ are added.

Theorem 3: Under uncertain situation, when the ellipsoid uncertainty is empty, the ETS-MIRO model will degrade to TS-MILO model. When the box uncertainty parameter set is non-empty, (1)-(16) robust equivalent model is (53) - (76).

The first stage of ETS-MIRO is (53) - (60), and its goal is to minimize the total cost under uncertain conditions.

$$\min\ Z_E \tag{53}$$

$$s.t.\ \max \left\{ \begin{array}{l} \sum_J x_i c_f + \sum_I \sum_J x_i c_h y_{ij} D_j^0 \\ + \Omega_j (\sum_I \sum_J x_i c_h y_{ij} \hat{D}_j \\ + \Omega_j [\sum_I \sum_J y_{ij} C_2(\hat{D}_j, c_m^2)] \end{array} \right\} \le Z_E \tag{54}$$

$$\sum_J y_{ij} \le 1, \quad \forall i \in I \tag{55}$$

$$\sum_J y_{ij} D_j^0 + \Omega_j P' \le H_j^{Max}, \quad \forall i \in I \tag{56}$$

$$P_j \ge \sqrt{\sum_J \hat{D}_j^2 r_i'^2} \tag{57}$$

$$r'_j \ge \sum_I \sum_J c_{v,t,c}(y_{ij}, z_{jk}) \tag{58}$$

$$y_{ij} \le x_j, \quad \forall i \in I,\ \forall j \in J \tag{59}$$

$$x_j \in \{0,1\}, \quad y_{ij} \ge 0,\ \forall i \in I,\ \forall j \in J \tag{60}$$

The second stage of ETS-MIRO is (61) - (69), and its goal is to minimize the cost of major disaster relief.

$$\min\ C_2(\tilde{D}_j : c_m^2) \tag{61}$$

$$\max\ \{C(D_j^0) + \Omega_j P_j\} \le C_2 \tag{62}$$

$$\sum_I \sum_J \frac{c_v^2 y_{ij} D_j^0 d_{ij}}{h_2} + c_t^2 \sum_I \sum_J x_i (\frac{d_{ij}}{\bar{v}_i} - t_0^j) \le C(D_j) \tag{63}$$

$$\sum_J y_{ij} D_j^0 + \Omega_j \sum_J y_{ij} \hat{D}_j \le H_j^{Max}, \quad \forall i \in I \tag{64}$$

$$\sum_J y_{ij} \le 1, \quad \forall i \in I \tag{65}$$

$$\lceil y_{ij} \rceil \cdot (d_{ij}/\bar{v}_j) \le T_{ij}^{Max}, \quad \forall j \in J, \ \forall k \in K \tag{66}$$

$$x_j \in \{0,1\}, y_{ij} \ge 0, z_{jk} \ge 0, \quad \forall j \in J, \ \forall k \in K \tag{67}$$

The third stage of ETS-MIRO is (68) - (76).

$$\min \ C_3(\tilde{D}_k : c_n^3) \tag{68}$$

$$s.t. \ \max\left\{C(D_k^0) + \Omega_k P_k'\right\} \le C_3 \tag{69}$$

$$r_k' \ge \sum_I \sum_J c_{v,t} z_{jk}, \quad \forall k \in K \tag{70}$$

$$c_t \sum_J \sum_K \left(\frac{\lceil z_{jk} \rceil d_{jk}}{\bar{v}_j} - t_0^k\right) + \sum_J \sum_K \frac{z_{jk} c_v^2 D_k^0 d_{jk}}{h_3} \le C(D_k^0) \tag{71}$$

$$P_k' \ge \sqrt{\sum_J \hat{D}_k^2 r_i'^2} \tag{72}$$

$$\sum_J z_{jk} D_k^0 + \Omega_k \sum_J z_{jk} \hat{D}_k \le H_k^{Max}, \quad \forall k \in K \tag{73}$$

$$\sum\nolimits_{j \in J} z_{jk} \le 1, \quad \forall k \in K \tag{74}$$

$$\lceil z_{jk} \rceil \cdot (d_{jk}/\bar{v}_j) \le T_{jk}^{Max}, \quad \forall j \in J, \ \forall k \in K \tag{75}$$

$$y_{ij} \ge 0, \quad z_{jk} \ge 0, \ \forall j \in J, \ \forall k \in K \tag{76}$$

E. ALGORITHM DESIGN

Through MATLAB (R2016a) as programming platform, the algorithm process of model is shown (Table 2). All data analysis is carried out on the same PC, which has 2.44 GHz 4-core CPU (Inter Core), 256GB SSD and 8GB RAM.

TABLE 2. Three-stage HEL algorithm based on gurobi.

1	The initial values and related parameters were input, and the constraint variables were directly input into TS-MILO model. BTS-MIRO Model setting: $Dom: U^{B1,B2} = \{\varepsilon, \xi\} : \mid \varepsilon_j, \xi_k \mid \le \Psi_{j,k}$ BTS-MIRO Model setting: $Dom: U^{P1,P2} = \left\{\{\varepsilon, \xi\} \cdot \sum \mid \varepsilon_{j,k} \mid \le \Gamma_{j,k}\right\}$ BTS-MIRO Model setting: $Dom: U^{E1,E2} = \left\{\sum_J \sum_K [\frac{\tilde{D}_{j,k} - D_{j,k}^0}{\hat{D}_{j,k}}]^2 \le \Omega_{j,k}^2\right\}$
2	Input constraints, vehicle constraints, storage capacity constraints and time window constraints, etc. #1. BTS-MIRO and PTS-MIRO models direct input constraints. #2, the ETS-MIRO model will further relax before input.
3	Set solution environment and solved by GUROBI (9-1-0);
4	If step 2 is satisfied, terminate; other, return step 1 again;
5	If the model converges or iterates to the maximum times, the optimal solution is output.

V. NUMERICAL EXPERIMENT

In this section, a real case is used to verify the effectiveness of the models in HEL. The model selects Yushu Earthquake (M = 7.1, Apr., 2010) as an example (Fig. 3).

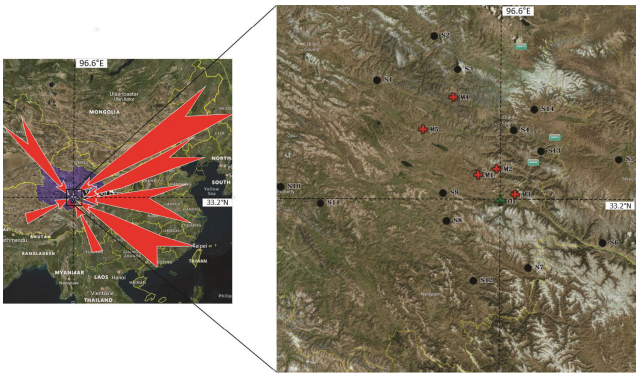

FIGURE 3. Accurate geographic location of yushu earthquake.

In actual rescue process, the Rescue Department is faced with the HEL problem. The first stage is to determine the location of major disaster relief sites, which are determined according to the disaster situation. Taking Jiegu street as the center, the location of the main disaster relief sites is determined first. The goal is to determine the location and minimize the overall total cost. These major sites offer dual functions. One is to provide materials for their own disaster areas, and the other is to provide materials for the secondary disaster areas. The original center of relief materials is determined as O_1 of Batang Airport (Cargo mark), and Jiegu, *et al.*[2] towns are selected as the major disaster relief sites (Red Cross), which are $M_1, M_2, \cdots, M_5$. The second stage is the path planning from the original center to the major sites. There are five major sites, which are selected among the alternative sites in the first stage. The aim of the second stage is to minimize the initial distribution costs. The third stage is the path planning from the major sites to the secondary sites. Secondary disasters are often caused by the follow-up effects of major disasters, such as small-scale aftershocks, landslides, dammed lakes, floods and so on. There are 14 secondary sites (Black solid), namely as Lixin, *et al.*,[3] which are represented by $S_1, S_2, \cdots, S_{14}$. The aim of the third stage is to minimize the costs from major sites to the second sites.

In the process of route planning, we remove the interference factors and get the relative position of the sites (Fig. 4). On the basis of maximizing the satisfaction of demand, the minimum costs are pursued. In the HEL system, there is one original center, 5 major sites and 14 secondary sites. Any alternative path corresponds to different costs. The transportation costs are determined by the comprehensive calculation of real-time oil price, actual distance, and traffic congestion and time limit. On the basis of comprehensive consideration of relevant costs, the following case simulation is carried out.

[2]The 5 major sites are Jiegu, Zhongda, Batang, Anchong and Longbao. Data sources: http://news.ceic.ac.cn

[3]The 14 secondary sites are Lixin, Bagan, Gaduo, Labu, Derongma, Zhenke, Xiaosumang, Xialaxiu, Shanglaxiu, Sahuteng, Anggsai, Maozhuang, Xiewu and Zhenqi. Data sources: http://news.ceic.ac.cn

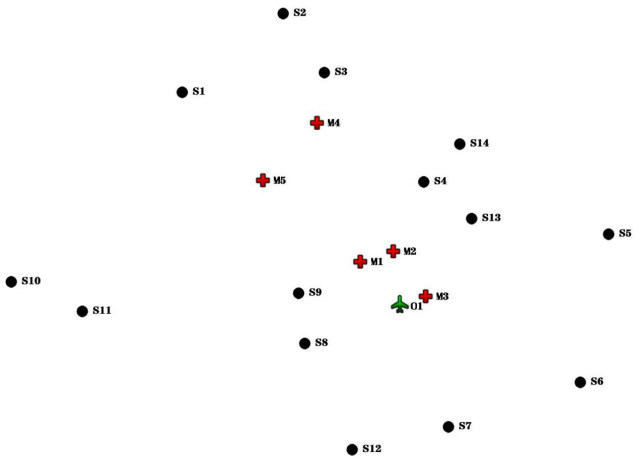

FIGURE 4. The relative location of the site, including the airport, the major and secondary disaster area.

A. RELATED DATA

The data are mainly from China Seismological Bureau and National Bureau of Statistics. In this paper, the input parameters are estimated using historical data of a disaster-prone area (Yushu, Qinghai Province). The basic information includes information of vehicle (Table 3).

TABLE 3. Vehicle information.

Types	Length	Loading	Transportation	Fuel
Large	5.6 m	7-8 ton	20 CNY/km	25.5 L
Small	3.6 m	4-6 ton	12 CNY/km	14.4 L

The fixed operating costs, demand for major sites, demand for secondary sites, and vehicle speed (Table 4). The distance between sites can be obtained through Google map [57], [58] as is shown in Table 5.

TABLE 4. Basic parameters of HEL.

	M_1	M_2	M_3	M_4	M_5
D_j	17250	3560	14520	6200	13400
d_{ij}	25.9	191.4	16.1	143.2	90.5
H	25500	21700	23900	31800	37100
$\overline{v}$	65	70	60	55	50
f	60000	62000	74000	79000	83000
	S_1	S_2	S_3	S_4	S_5
D_k	8590	2720	2250	1980	1910
	S_6	S_7	S_8	S_9	S_{10}
D_k	1350	5720	4500	5910	4040
	S_{11}	S_{12}	S_{13}	S_{14}	-
D_k	1350	23400	1800	3150	-

B. TS-MILO MODEL RESULTS

The minimum costs (Optimal solution) of TS-MILO model are 8.5274 E+05 CNY, and the model operating efficiency (Time) is 2570.736 ms. The path planning for the

TABLE 5. Distance betweem major to secondary sites.

	S_1	S_2	S_3	S_4	S_5	S_6	S_7
O_1	128.3	312.5	201.5	161.3	120.6	410.6	98.2
O_2	300.2	484.4	194.4	33.9	202.3	491.2	271.3
O_3	158.9	343.1	235.5	194.2	150.4	434.1	69.6
O_4	113.9	297.5	49.2	277.1	243.1	528.3	215.6
O_5	63.5	247.6	266.1	232.2	185.3	475.8	163.1
	S_8	S_9	S_{10}	S_{11}	S_{12}	S_{13}	S_{14}
O_1	90.2	74.6	169.5	197.5	257.7	52.4	101.7
O_2	265.1	247.8	334.9	363.3	423.1	128.4	87.5
O_3	82.5	65.1	160.2	188.1	248.3	76.5	125.8
O_4	209.4	191.8	286.9	314.9	375.1	164.6	208.9
O_5	156.9	139.5	234.4	262.4	322.6	116.7	156.4

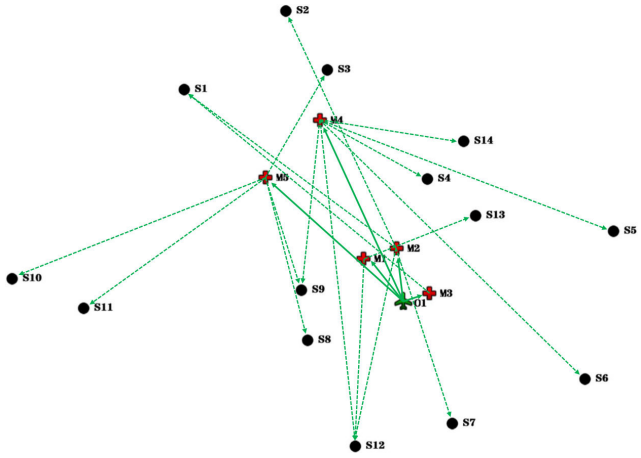

FIGURE 5. The distribution planning of TS-MILO model. Notes: the solid and dotted line for the major and secondary disaster.

TS-MILO model is shown in Fig. 5. We can find that the all the sites are selected as storage warehouses for major relief materials. In the second stage, materials will be distributed in the main disaster relief areas, i.e. from the initial center (Airport) to major disaster relief sites planned according to the material transportation. The transportation of relief materials mainly involves major site M_4 and M_5, which respectively account for 32.91% and 32.52% of the total demands. Both of them are responsible for providing major relief supplies. The third stage is aimed at offering the material distribution services of the secondary disaster sites. On the premise of meeting the demands of each node, the distribution path of TS-MILO model almost traverses all feasible paths. Through careful analysis, we can find that although the distribution path can guarantee the supply of basic materials via the TS-MILO model, there are still some problems in the specific service process. For example, the long-distance transportation in the route planning will increase the fuel cost. The time costs caused by circuitous transportation in route planning will increase the suffering of the rescued. The unreasonable use of major disaster relief sites will lead to the increase of costs of subsequent re transportation. Once

there is uncertainty in the actual rescue process, for example, the fluctuation of demands in the target area will increase. These uncertainties will make the stability and sustainability of TS-MILO model unable to be guaranteed, which makes the relief material logistics service face some challenges and difficulties. As a result, in the rescue process, we must plan reasonably, explore more optimized improvement strategies, and seek more robust path planning scheme. According to the above analysis, we must optimize the distribution path.

C. BTS-MIRO Model

In the BTS-MIRO model, the effect of $\Psi_{j,k}$ on the total costs is constantly changing. The results of the BTS-MIRO model are shown in Table 6 below. The total costs of HEL increase with the increasing of SP. According to the Theorem 1, when $\Psi_{j,k} = 0$, the BTS-MIRO model corresponds to the TS-MILO model and the total costs are 8.5274 E+05 CNY. In BTS-MIRO model, the rate rises from 8.5274 E+05 to 9.3323 E+05, with an increase of 9.44%.

TABLE 6. Cost, site selection and operation efficiency of BTS-MIRO model.

SP	Cost/CNY	Nos	Sites	Time /ms
0	8.5274 E+05	5	1,2,3,4,5	2562.62
1	8.5380 E+05	5	1,2,3,4,5	2509.07
2	8.5566 E+05	5	1,2,3,4,5	2550.11
3	8.5731 E+05	5	1,2,3,4,5	2522.68
4	8.5800 E+05	5	1,2,3,4,5	2782.67
5	8.6041 E+05	5	1,2,3,4,5	2718.11
6	8.6415 E+05	5	1,2,3,4,5	2735.88
7	8.6464 E+05	5	1,2,3,4,5	2708.15
8	8.7485 E+05	5	1,2,3,4,5	2834.76
10	8.9323 E+05	5	1,2,3,4,5	2868.60
11	9.0323 E+05	5	1,2,3,4,5	2846.22
12	9.1174 E+05	5	1,2,3,4,5	2946.96
13	9.2323 E+05	5	1,2,3,4,5	2986.76
14	9.3323 E+05	5	1,2,3,4,5	2994.95

As is shown in Fig. 6, the BTS-MIRO model is compared with the TS-MILO model: In the first two stages, three major sites M_3, M_4, M_5 bear more than 81.31% of the material supply of secondary disaster relief services. In the third stage of secondary disaster relief logistics planning, the main disaster relief site M_3 undertakes a larger distribution service than before, with the transshipment proportion increasing from 11.8% to 28.57%. The transshipment proportion involving M_4, M_5 declined, but they still account for 27.51% and 29.87% of the main relief sites respectively. Although the distribution line is centralized to M_3, and the route planning is relatively reasonable, there are still some circuitous transportation problems in other lines, so there is still room to optimize the BTS-MIRO model.

D. PTS-MIRO MODEL

In the PTS-MIRO model, the total costs vary with SP. The results of PTS-MIRO model are shown in Table 7. The total costs of emergency relief logistics increase with the increase of SP. According to the Theorem 2, when $\Gamma_{j,k} = 0$, the PTS-MIRO model is equivalent to the TS-MILO model.

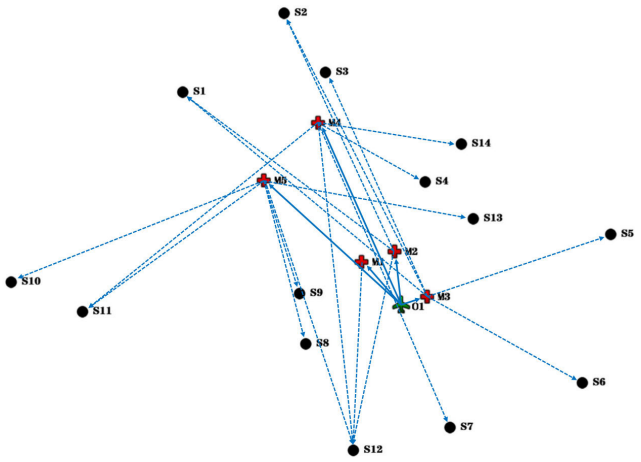

FIGURE 6. The distribution planning of BTS-MIRO model. Notes: the solid and dotted line for the major and secondary disaster.

TABLE 7. Cost, site selection and operation efficiency of PTS-MIRO model.

SP	Cost /CNY	Nos	Sites	Time/ms
0	8.5274 E+05	5	1,2,3,4,5	2562.62
1	8.5331 E+05	5	1,2,3,4,5	2614.45
2	8.5569 E+05	5	1,2,3,4,5	2629.51
3	8.5793 E+05	5	1,2,3,4,5	2679.18
4	8.6109 E+05	5	1,2,3,4,5	2645.04
5	8.7099 E+05	5	1,2,3,4,5	2614.16
7	8.8633 E+05	5	1,2,3,4,5	2673.40
8	8.7661 E+05	5	1,2,3,4,5	2722.00
9	9.4563 E+05	5	1,2,3,4,5	2842.07
10	9.9226 E+05	5	1,2,3,4,5	2969.15
11	9.8768 E+05	5	1,2,3,4,5	2974.58
12	1.0252 E+06	5	1,2,3,4,5	2935.17
13	1.0094 E+06	5	1,2,3,4,5	2988.87
14	1.0205 E+06	5	1,2,3,4,5	2997.86

In BTS-MIRO model, the rate rises from 8.5274 E+05 to 1.0205 E+06CNY, with an increase of 19.67%. It can be seen that compared with BTS-MILO model, PTS-MILO model requires higher costs.

As is shown in Fig. 7, the PTS-MIRO model is compared with the BTS-MIRO and TS-MILO models: In the initial route planning of first two stages, M_3, M_4, M_5 are still the main material transfer centers. From the comparison of relative location sites, it can be found that the transfer of transport transfer center makes the route planning more reasonable and reduces the circuitous transportation in secondary stage. Compared with BTS-MIRO model and TS-MILO model, PTS-MIRO model reduces the proportion of long-distance line transportation and increases the proportion of short-distance line transportation in the third stage of secondary disaster relief path planning, which can provide specific reference for quickly reaching destination, which has a positive role in promoting path optimization.

E. ETS-MIRO MODEL

The results of the ETS-MIRO model are shown in Table 8. Similarly, the total costs increase with the increase of SP of

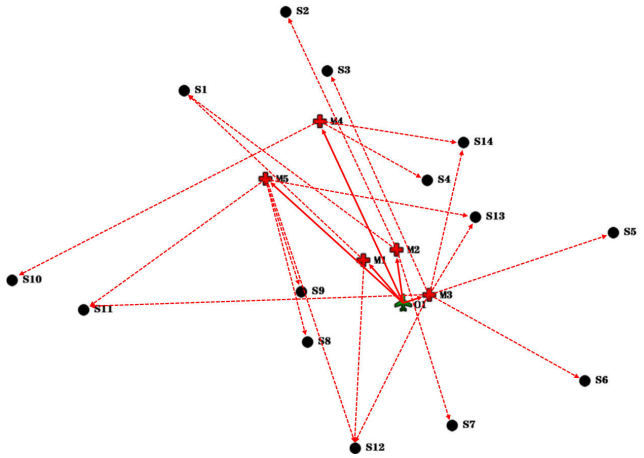

FIGURE 7. The distribution planning of PTS-MIRO model. Notes: the solid and dotted line for the major and secondary disaster.

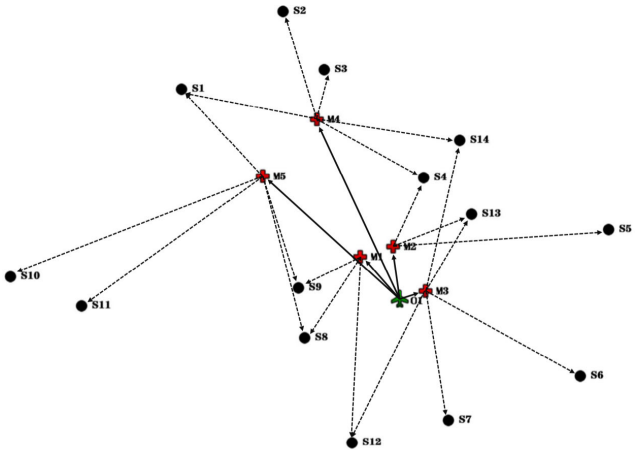

FIGURE 8. The distribution planning of ETS-MIRO model. Notes: the solid and dotted line for the major and secondary disaster.

TABLE 8. Cost, site selection and operation efficiency of ETS-MIRO model.

SP	Cost /CNY	Nos	Sites	Time/ms
0	8.5274 E+05	5	1, 2, 3, 4, 5	2562.62
1	8.5331 E+05	5	1, 2, 3, 4, 5	2602.72
2	8.5474 E+05	5	1, 2, 3, 4, 5	2616.60
3	8.5536 E+05	5	1, 2, 3, 4, 5	2622.40
4	8.5917 E+05	5	1, 2, 3, 4, 5	2743.13
6	8.6367 E+05	5	1, 2, 3, 4, 5	2769.17
7	8.6404 E+05	5	1, 2, 3, 4, 5	2741.11
8	8.6891 E+05	5	1, 2, 3, 4, 5	2778.48
10	8.7622 E+05	5	1, 2, 3, 4, 5	2721.96
11	8.8109 E+05	5	1, 2, 3, 4, 5	2726.96
12	8.8286 E+05	5	1, 2, 3, 4, 5	2882.83
13	8.8386 E+05	5	1, 2, 3, 4, 5	2832.34
14	8.8568 E+05	5	1, 2, 3, 4, 5	2940.63

the model. According to Theorem 3, when $\Omega_{j,k} = 0$, ETS-MIRO model is equivalent to TS-MILO model, and the cost is 8.5274 E+05CNY. In ETS-MIRO model, the rate rises from 8.5274 E+05 to 8.8568 E+05CNY, only with an increase of 3.87%. It can be seen that compared with BTS-MILO and PTS-MILO model, ETS-MIRO shows higher robustness.

As is shown in Fig. 8, the ETS-MIRO model is compared with the PTS-MIRO, BTS-MIRO and TS-MILO models: In the initial planning of the first two stages, the proportion of transport transfer is relatively evenly distributed in the major transport centers. The transit capacity and load pressure of each major disaster relief point are relatively balanced. The sites have penetrated into the hinterland of the disaster area and is closer to the affected people. In consequence, increasing the storage ratio of M_2 makes the path planning more reasonable. In the third stage of planning, the ratio of PTS-MIRO, BTS-MIRO and TS-MILO models is relatively higher. The proportion of long-distance transportation is further reduced, while the proportion of short-distance transportation is increased in the ETS-MIRO model.

Especially after making full use of this node which goes deep into the disaster area, the performance is more obvious. In comparison, the proportion of services in each path tends to be short path. The costs of short distance route are fewer, and its proportion in the supply of materials shows an upward trend. Due to the higher efficiency of vehicle mileage and more accurate and quick distribution route, TS-MIRO has shown better optimization performance.

VI. MODEL SENSITIVITY ANALYSIS

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

A. OPERATING PERFORMANCE COMPARION

This section compares the operation efficiency of each model by observing the operation time of the models. In order to ensure the effectiveness of the results, the following settings are made: running in the same computer environment, setting the SP as the only variable. We use MATLAB as the platform. The solvers GUROBI and CPLEX are used to solve the above models respectively, and the results are shown in Table 9.

TABLE 9. Performance comparison of models.

TS Model	Cost(G) /E+05	Cost(C) /E+05	Gap /%	Time(G) /ms	Time(C) /ms	Ratio /%
LO	8.5274	8.5256	<0.01	2562.62	6578.73	38.95
BTS	8.6464	8.6472	<0.01	2708.15	6067.92	44.63
PTS	8.8633	8.8699	<0.01	2673.00	5778.41	46.26
ETS	8.6404	8.6398	<0.01	2741.11	6173.34	44.40

Note 1: ***G, C represent the cost solved by GUROBI, CPLEX.***

In the total costs comparison of the model, the costs in the calculation results of the model is not affected by the algorithm. Gap%<0.1 is found in the error comparison of the calculation, which indicates that the model is effective without significant difference in different solvers. From com-parison of the calculation performance of the model, it can be seen that those two solvers are used to solve the models. GUROBI can save at least 38% of the time consumption compared with

the solvers CPLEX. Obviously, the algorithm of GUROBI is better than that based on CPLEX.

Fig. 9 show that, the TS-MILO model has the highest running efficiency and the overall operation time is much shorter than that of MIRO model ($\leq$2600 *ms*). Detailed comparison of the four models shows that, when $SP \leq 3$, BTS-MIRO>ETS-MIRO>PTS-MIRO, which means that the BTS-MIRO model is the most efficient. When $3 \leq SP \leq 8$, PTS-MIRO>ETS-MIRO>BTS-MIRO, which means that the PTS-MIRO model is the most efficient. When $9 \leq SP$, ETS-MIRO>PTS-MIRO>BTS-MIRO, which means that the ETS-MIRO model is the most efficient with a large number of uncertain parameters. Due to small scale of this HEL problem, there is little difference in time. However, when the constraints and variables in the model increase to tens of thousands or even tens of millions, the operational efficiency of the model solution will be significantly different. There-fore, when solving practical problems, we can build an ap-propriate model according to real data.

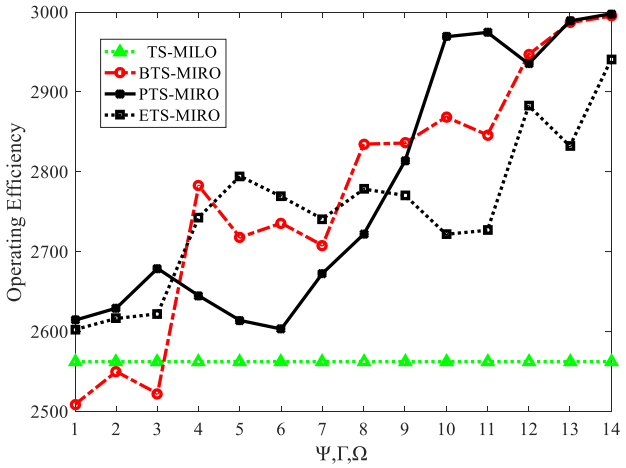

FIGURE 9. Operation efficiency comparison between models.

B. IMPACT OF DEMAND VOLATILITY AND SAFETY PARAMETERS

In this section, we analyze the impact of demand volatility on the total cost. The control variable method is used to analyze the effect of the fluctuation of random parameters on the total cost, where ($\Psi_j, \Gamma_j, \Omega_j = 3$; $\Psi_k, \Gamma_k, \Omega_k = 7$). The calculation results are shown in Figure 10. Although TS-MIRO model will pay a certain cost, that is, the total cost is higher than TS-MILO model, it can still give path planning scheme even if in uncertain situation. The growth rate of costs is slightly different. The costs of PTS-MIRO model increase sharply, while that of ETS-MIRO model increases slowly. In the PTS-MIRO model, when the demand volatility increases from 0 to 30%, the total costs increase from 8.5512 E+05CNY to 9.6885 E+05CNY, with an increase of 13.6%. In the ETS-MIRO model, when the demand volatility increases from 0.00% to 30%, the total costs increase from 8.5512 E+05CNY to 8.8907 E+05CNY, with an increase

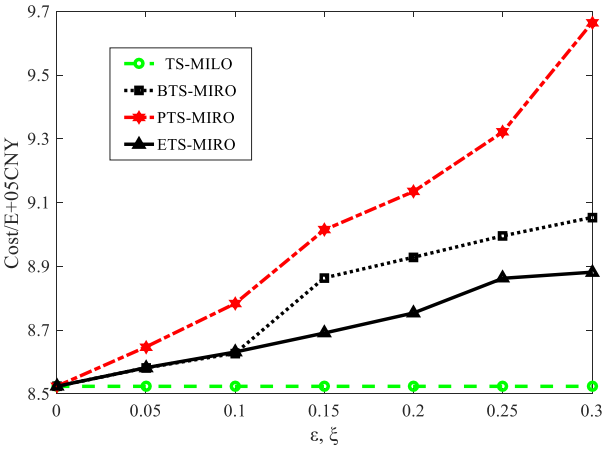

FIGURE 10. The effect of demand volatility on total costs.

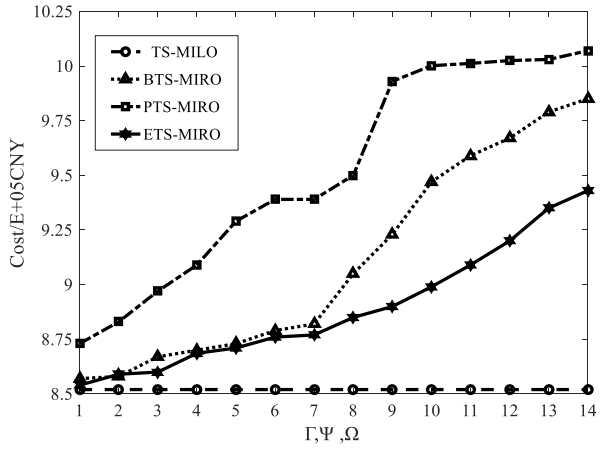

FIGURE 11. The effect of safety parameters on total cost.

of 4.6%. In addition, the rising trend of costs is quite different. Among them, BTS-MIRO model and PTS-MIRO model have greater randomness, ETS-MIRO model has a strong ability to resist uncertainty.

Fig. 11 analyses the effect of the changes of SP on total costs, under the condition of $\varepsilon = 0.10$. The costs show an upward trend with the increasing of SP. Different TS-MIRO models have different rising rates of costs, while TS-MILO models are not affected by safety parameters and maintain a low level, which can be used as reference standard. PTS-MIRO models have the highest increasing rate of costs and the highest robustness costs due to improving safety level. BTS-MIRO models are centered, while ETS-MIRO models are the most stable and require the lowest robustness costs. The analysis suggests that the costs increase by at least 10.05% (ETS-MIRO model). The growth rate of BTS-MIRO model is 18.16%. The growth rate of ETS-MIRO model only accounts for 44.66% of BTS-MIRO model. Therefore, the ETS-MIRO model has high robustness and strong ability to resist uncertainty.

C. SERVICE LEVEL AND ITS RESPONSIVENESS

The performance is analyzed through Level of Service (SL). Due to high requirement for timeliness in HEL, this section

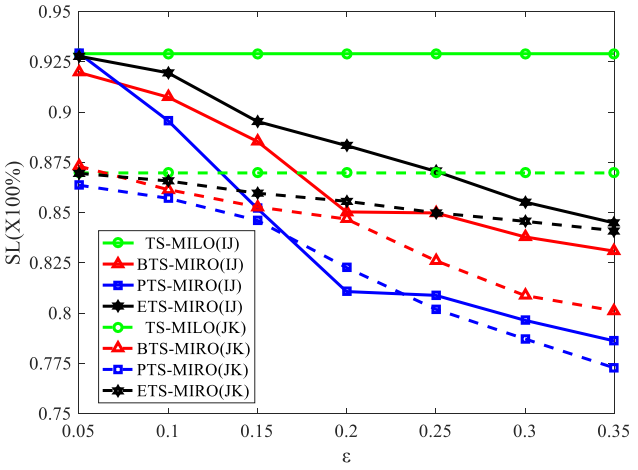

FIGURE 12. The impact of demand volatility on service level.

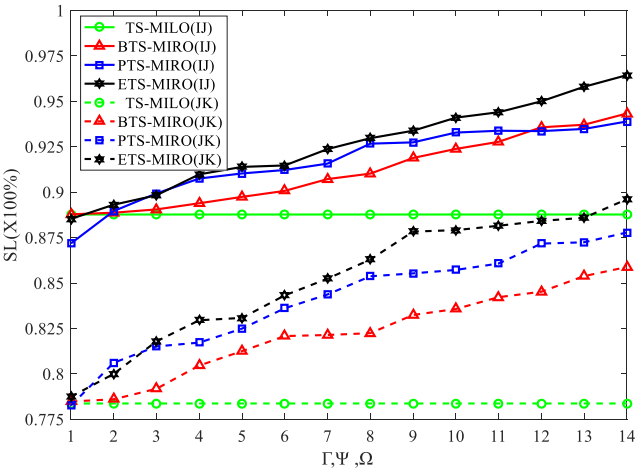

FIGURE 13. Service level is affected by safety parameters. Note: IJ and JK represent the major and secondary disaster.

compares the SL of models through time differences, and analyses the advantages and disadvantages of the different models. The SL is calculated by following formula. Com-puter simulation results under different parameters are shown in Fig. 12 and 13.

$$SL = \left[1 - \frac{\sum_{J}\sum_{K} \frac{(y_{ij}, z_{jk})\tilde{D}_{j,k} d_{ij,jk}}{\bar{v}_{ij,jk}} - t_{j,k} \sum_{J}\sum_{K} \tilde{D}_{j,k}}{t_{j,k} \sum_{J,K} \tilde{D}_{j,k}} \right] \times 100\%$$

where, I, J represents the number of arcs in the model.

Fig. 12 shows the influence of volatility on SL, under fixed SP ($\Psi_j, \Gamma_j, \Omega_j = 3$; $\Psi_k, \Gamma_k, \Omega_k = 7$). Through analysis of the influence of the volatility on the model, the following three conclusions can be drawn. The SL of TS-MILO model is not affected by fluctuation, and of course, the problem under uncertain conditions is unable to solve. Due to the determined data, the SL is also the highest (SL=92.87% of the second stage and 86.97% of the third stage). The SL of three TS-MIRO models shows downward trend with the increase of volatility. The greater the amplitude of volatility is, the lower SL is. The impact of demand volatility on SL in the second stage is greater than that in the third stage. The reason is that the uncontrollability of rescue work aggravates the uncertainty in the process of HEL. For the major disaster areas, the uncertainty of secondary disasters should be considered in addition to the impact of uncertainty fluctu-ation in their own regions. Due to the lack of information and low efficiency of resource turnover for secondary disaster areas, the cumulative uncertainty has a more significant influence on the second stage (SL downward). Volatility has a higher influence on SL in the second stage than that on the third stage. The reason is that in the planning of major disaster relief material dispatch, besides the impact of uncer-tainty itself, the influence of uncertainty on secondary disa-ster needs considering. It can be clearly seen from the com-parison that the ETS-MIRO model has strong robustness. The BTS-MIRO model is centered and the PTS-MIRO model is most affected by volatility, which means that PTS-MIRO model has the weakest ability to resist uncertainty, while ETS-MIRO model performs better.

Fortunately, Fig. 13 illustrates the impact of SP on the SL under the condition of fixed volatility ($\varepsilon = 0.15$). We can see that the SL tends to increase in SP. SP has a great effect on the improvement of service quality, and it performs well both in the second and the third stage. To a certain extent, this makes up for the robustness cost caused by uncertainty and also reduces the loss of SL owing to volatility. Careful comparison shows that ETS-MIRO model has strong robustness. When SP increases from 1 to 14, SL will increase from 88.53% to 96.44% in the second stage and from 78.74% to 89.61% in the third stage. In the process of disaster relief, managers must pay attention to the rapid responsiveness of rescue. Considering uncertainties, although each TS-MIRO model can give path planning plans, the performance and application scope of each plan are also different. HEL decision makers must review the situation and make the most reasonable plan according to local conditions.

VII. CONCLUDING REMARKS

Humanitarian emergency logistics (HEL) management is a major decision-making related to social economy and people's life safety, which is highly valued by the national government. Most of the previous studies focused on major disasters, but the impact of secondary disasters was easily ignored. On the basis of fully analyzing the internal relationship between primary and secondary disasters, this paper establishes a three-stage mixed integer linear optimization (TS-MILP) model based on inventory, vehicle load and time constraints. Under the condition that all parameters are determined, this paper compiles the algorithm based on GUROBI, and gives the basic feasible path planning scheme. In the previous research, it was often carried out under certain circumstances, while the actual rescue process is uncertain. Therefore, the management of HEL under uncertain conditions has higher research value. In order to

prevent the dissimilation effect of uncertainty, robust optimization is introduced. By constructing the corresponding uncertain set, the TS-MILO model is transformed into a three-stage mixed integer robust optimization (TS-MIRO) model. Finally, the practicability is verified by experiments.

The main contributions of this article are: First, the traditional HEL problem in major and secondary disasters is subdivided, and the single-stage problem is subdivided into three-stage problem. Secondly, the robust optimization theory is introduced, and the deterministic optimization model is further extended to the robust optimization model with uncertainty in mind. Finally, experiments are carried out with real data, and a feasible route planning scheme is given based on the model calculation results.

Through the study of this paper, we can draw the following conclusions. On account of the idealization of parameter data, the three-stage mixed integer linear optimization model can give the lowest total costs and the highest service level. However, in reality, such an ideal data set is extremely difficult to obtain, even unavailable, so its practical feasibility is not high. On the whole, the three-stage mixed integer robust optimization model will pay a certain robust cost, such as the increase of costs and the increase of complexity of calculation, due to the influence of stochastic demand fluctuation. But they can solve uncertain humanitarian logistics problems and maintain robustness. From the details, the service level of the improved robust model has been significantly improved. The ellipsoid set robust optimization model performs best, while the polyhedron set robust optimization model has the weakest ability to resist environmental changes. The robust optimization model proposed in this paper can better solve the uncertainty of relief work.

The proposed model can not only be used to solve the problem of HEL in the earthquake areas, but also has great expansibility. It can also be applied to other problems, such as supply chain management with secondary replenishment, vehicle routing planning with secondary transshipment, home medical service with personnel transfer, etc. These problems have similar characteristics, that is, in addition to the main demand or supply, there is also a demand for secondary. On the technical level, the programming algorithm used in this paper still has plenty of room for improvement. Through the application of new technology, the proposed model will be more accurate and more efficient. In the future, our research will explore the application mode of science and technology. It can be predicted that the informatization and intelligence of emergency rescue management is the future direction.

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