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Research Article

Discrete Robustness Optimization on Emergency Transportation Network Based on Prospect Theory

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This paper focuses on the discrete robustness optimization of emergency transportation network with the consideration of timeliness and decision behavior of decision-maker under the limited rationality. Based on a situation that the nearer to disaster area, the higher probability of time delay, prospect theory is specially introduced to reflect the subjective decision behavior of decision-maker. Then, a discrete robustness optimization model is proposed with the purpose of the better timeliness and robustness. The model is based on the emergency transportation network with multistorage centers and multidisaster points. In order to obtain the optimal solution, an improved genetic algorithm is designed by introducing a bidirectional search strategy based on a newfangled path cluster to obtain specific paths that connect each storage centers and each disaster points. Finally, a case study is exhibited to demonstrate the reasonability of the model, theory, and algorithm. The result shows that the path cluster with the better timeliness and robustness can be well obtained by using the prospect theory and improved genetic algorithm. The analysis especially reveals that the robustness is correspondent to the risk aversion in prospect theory.

1. Introduction

As mentioned at the Copenhagen conference in 2009, the frequency and strength of natural disaster are trending higher than ever because of the damage on ecosystem getting serious. According to the disaster generation mechanism, natural disaster can be generally divided into geological disaster, meteorological disaster, environmental pollution disaster, fire disaster, marine disaster, and biological disaster [1]. Usually, those disasters have serious destruction on social and economic development in different degree. Especially, for some destructive disasters, such as earthquake, hail, and flood, they may cause unthinkable outcomes and leave us no time to respond. In most instances, destructive disaster usually leads to secondary disaster, which may enhance the destruction and incur some additional difficulties to rescuing. However, no matter how serious the situation is, some rescue decisions and measures must be taken immediately.

In order to reduce losses and improve rescue effectiveness, emergency response and guarantee system is scientifically constructed during the normal condition. Roughly, emergency response and guarantee system includes policies and regulations, institutions and organization, emergency prearranged planning, and emergency planning system. Obviously, emergency planning system is the precondition to enact emergency prearranged planning, and, also, it is supported by policies and regulations. Therefore, emergency planning system plays a fundamental and essential role in emergency response and guarantee system. The main content of emergency planning system is shown in Figure 1.

As shown in Figure 1, transportation network planning of emergency materials (TNPES) is a vital step in emergency planning system. The significance of TNPES is to prearrange suitable paths from existing transportation network, and emergency materials will be dispatched immediately to the disaster area through those paths, once unexpected disaster

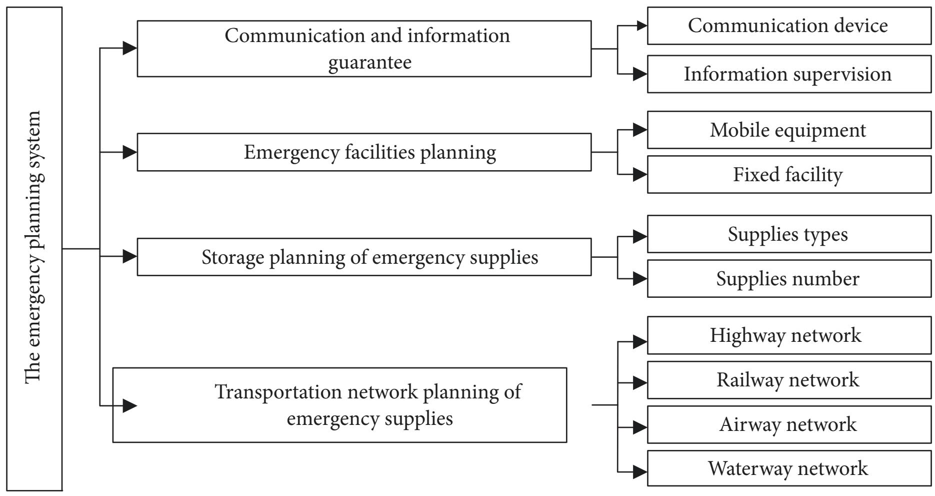

Figure 1: The main content of emergency planning system.

takes place. Unquestionably, if the suitable path is not preplanned, emergency materials may be delayed, which may have a bad effect on rescuing and lead to additional loss.

Obviously, the problem of TNPES belongs to the category of decision-making under uncertainty and risk. Supported by the policies and regulations, the selected path will be specialized for transporting emergency materials [2]. Without the interruption of other traffic during the emergency period, the transportation of emergency materials can be guaranteed in a great degree. However, the interruption caused by other uncertainty factors, like secondary disaster, cannot be predicted and averted. Especially, if the unexpected interruption is serious enough, the preplanned path may lose the value of use. Therefore, how to select out a suitable path from existing transportation network under complicated and uncertain environment is a difficulty and hot topic.

2. Literature Reviews and Discussions

According to the significance of TNPES, related specialists and scholars have made excellent researches from different viewpoints.

2.1. Emergency Materials Chain (ESC). Based on the substance of ESC, the problem of facility location and vehicle routing is effectively researched by literatures [3, 4]. The more comprehensive reviews about this problem are neatened and analyzed in [5, 6]. In recent years, research on management and response is a new and hot topic about ESC. With respect to the management, some literatures provide the further study, such as [7–9]. Thereinto, Othman et al. [7] concentrate on the study of decision support system for resources scheduling. Gaonkar and Viswanadham [8] incline to the framework of management. The risk management of ESC especially is lucubrated by [9]. For the response, Rawls and Turnquist [10] reveal that the response can be improved by scientifically arranging and planning the locations and demands of emergency materials. Based on the case of Nepal earthquakes in 2015, the internal response mechanism of ESC is analyzed and identified by [11]. Besides, some studies focusing on strategy and assessment about this problem, such as scientific and technical rescue work [12], integrated effect caused by disaster are analyzed in [13].

The research about ESC belongs to the field of emergency planning system. Those researches provide the foundation of TNPES to further study this problem. Beyond doubt, TNPES must obey operation mechanism of ESC. The excellent framework, management, and planning especially should be referenced during the research of TNPES.

2.2. Emergency Transportation Network (ETN). Research on optimization of ETN is another main content in the field of emergency planning system. Generally, those researches can be roughly divided as uncertainty research, indicators evaluation, and scheduling path planning

For uncertainty of ETN, vulnerability is lucubrated in [14–16]. Thereinto, Sheu, and Pan [14] construct three subnetworks to presupport the operation of ETN. According to the property of ETN, postdisaster vulnerability of ETN is analyzed by [15]. Diversely, vulnerability based spatial spreading degradations in road network is systematically revealed by [16]. In addition, Berger and Lo [17], Mišković et al. [18], and Coco et al. [19] pay their attentions on robustness of ETN. Based on the deficiency of estimating optimality in most researches, Berger and Lo [17] formulate a mixed-interlinear programming model by considering robust bound. Mišković et al. [18] specially focus on the search strategy, and Coco et al. [19] focus on the formulation and algorithm. Together with the uncertainty research, related indicators of ETN are also elaborately evaluated in [20–22]. Obviously, those researches are meaningful and give us insight to further study ETN.

Regarding researches on scheduling and planning, Alem et al. [23] concentrate on the postdisaster relief problem based emergency network. In addition, Duque et al. [24] study the problem of optimal route by repairing the rural road network. The study implies that multipath is necessary to emergency materials dispatch scheduling. Based on the timeliness, Bahaabadi et al. [25] present a model with multiobjective to find an optimal path from road network, in which the time-dependent stochastic travel time is taken into account. Inversely, Nikoo et al. [2] propose a three-objective interprogramming model to seek the path with best robustness by sacrificing the timeliness. Regarding the algorithm, genetic algorithm is frequently used in related researches, such as [26–28].

The common attitudes held by those literatures are that timeliness is vital to emergency rescue, and stochastic factors caused by unexpected disturbance make the environment of ETN more complex and uncertain. The conclusions especially resulting from the researches can improve the tolerance and sensitivity of ETN to complex environment. However, the decision behavior under uncertainty and risk is not considered in those researches.

2.3. Researches from Other Viewpoints. In recent years, more and more scholars focus on the study of emergency problems from other viewpoints. Thereinto, researches like Kahneman and Tversky [29], Geroliminis et al. [27], and Córdova and Vásquez [30] optimize ETN from the viewpoint of gridding unit. With the consideration of dependencies of emergency transportation network, supernetwork theory is used to describe information transaction in [31]. Besides, motivated by a fact that different travelers usually have different path-choice preferences, a multiobjective path-finding model with time-dependent stochastic travel time is proposed in [32], and the similar theory is also involved in [25]. Slightly different, focus on the emergency path planning, decision tree is used in [33]. One of newfangled contributions in [33] is that human factors are analyzed meticulously. Moreover, based on the scenario of postdisaster, planning of rescue supporting route is also lucubrated in [34].

Generally speaking, research on optimization of ETN, especially path planning, belongs to the category of decision-making. Those literatures give us some new insights to analyze the problem. Above all, the introduction of decision preference and scenario planning makes the research closer to the real world.

2.4. Literature Discussion and Contributions in This Paper

2.4.1. Literature Discussion. According to the classified analysis of aforementioned researches, the problem of ETN is a main body of ESC, and emergency path planning is a detailed one for ETN. Without a doubt, existing researches have provided some significant references. However, some shortcomings are still conspicuous.

For ETN, the complex and uncertainty of environment are considered, and optimization measures are also used to improve the tolerance and sensitivity of ETN to the complex environment, such as [14, 16, 18, 19]. But, the uncertainty scale and degree of ETN in related researches are uncontrollable. Therefore, the probability given stochastically does not reflect the disturbance mechanism in real world. For emergency path planning, performance metrics, especially the timeliness, are adopted by related literatures, like [2, 17, 27]. However, the time delay is given at random, which may lead to misconception for planner during making the decision. Moreover, some researches, like [25, 32], take the preference of route-choice into consideration, but the decision risk is not attached adequately. Although this shortcoming is made up by [33], the insufficient is still left over, because the decision behavior is analyzed just under the rational condition, which obviously violates the decision behavior under limited rationality when decision-maker faces an uncertainty situation.

2.4.2. Contributions in This Paper. Based on the aforementioned analysis, this paper focuses on the discrete robustness optimization of ETN with the consideration of transportation timeliness and decision behavior of decision-maker under limited rationality. The main contributions about this paper are the following:

(a) With the consideration of uncertainty of secondary disaster that may lead to the time delay, prospect theory is introduced, based on the required arrival time of emergency materials, to reflect the subjective decision of decision-maker under limited rationality.

(b) A discrete robustness optimization model is proposed based on an ETN with multistorage center and multidisaster point. The purpose of this model is to find several paths with the better timeliness and better robustness to transport emergency materials.

(c) An improved genetic algorithm is specially designed to obtain the optimal solution. Technically, bidirectional search strategy is designed based on a newfangled path cluster that integrates the specific paths to connecting each storage centers and disaster points.

The subsequent structure of the paper is arranged as follows. Section 3 is the description of discrete optimization model of ETN, and prospect theory is also introduced in this section. Section 4 is the algorithm design. A series of rationalities are analyzed based on a case study in Section 5. Section 6 is some conclusions.

3. Optimization Model of ETN

3.1. Problem Description and Analysis. With contrast to the traditional transportation network, ETN belongs to a rescue system that emergency materials are transported from storage centers to the disaster points. In addition, the timeliness is more important than economical efficiency, and the environment is also more complex. Without loss of generality, we make an appointment that ETN is a connected network with multistorage centers and multidisaster points. Then, let $N = (V, E)$ be an ETN, where V and E are the sets of point v_i and oriented edge $e_{i,j}$, respectively. Besides,

$V_s = \{v_s \mid v_s \in V\}$, set of storage center points.

$V_c = \{v_c \mid v_c \in V\}$, set of crossover points.

$V_d = \{v_d \mid v_d \in V\}$, set of disaster points.

Especially, $V_s \cap V_c = \varnothing$, $V_c \cap V_d = \varnothing$, $V_s \cap V_d = \varnothing$, and $V_s \cup V_c \cup V_d = V$. Let $x_{i,j}$ be a 0-1 binary variable to describe ETN.

$$x_{i,j} = \begin{cases} 1, & \text{if } e_{i,j} \in \mathrm{E} \\ 0, & \text{Ohters} \end{cases} \quad (1)$$

Based on the description, know that at least one path is valid for disaster point $v_d \in V_d$ to obtain emergency materials from storage center $v_s \in V_s$. As a preliminary vision with a hopeful attitude, let $P^{s,d}$ be a path that is selected to transport emergency materials from v_s to v_d. Then, it can be described by a binary decision variable $x_{i,j}^{s,d}$ that

$$x_{i,j}^{s,d} = \begin{cases} 1, & \text{if } e_{i,j} \in p^{s,d} \\ 0, & \text{Ohters} \end{cases} \quad (2)$$

Obviously, $x_{i,j}^{s,d}$ resulted from the planning finally determined. As having analyzed previously, timeliness is the most prominent factor to emergency materials because of the emergency rescue period within 72 hours, after which the chance of survival population may decrease dramatically [35]. Because of the importance of timeliness to emergency materials, we use timeliness as a main factor for decision-maker to make decision during the path preplanning.

With respect to the transportation time, there are nominal transportation time $t_{i,j}$ on $e_{i,j}$ and potential transportation time $\widetilde{t}_{i,j}^{s,d}$ on $e_{i,j} \in p^{s,d}$. The relationship between $t_{i,j}$ and $\widetilde{t}_{i,j}^{s,d}$ is that

$$\widetilde{t}_{i,j}^{s,d} = t_{i,j} + \Delta t_{i,j}^{s,d} \quad (3)$$

where $\Delta t_{i,j}^{s,d}$ is the potential time delay on $e_{i,j} \in p^{s,d}$.

Obviously, for an experienced decision-maker, $\widetilde{t}_{i,j}^{s,d}$ is more reasonable than $t_{i,j}$ during the decision-making. In fact, $t_{i,j}$ is easy to be obtained according to the design criterion of $e_{i,j}$ or empirical value. However, $\Delta t_{i,j}^{s,d}$ is nearly impossible to be precaptured and premastered precisely, because the reason of time delay is over tens of thousands, and it is nearly impossible to take all of them into consideration. In order to facilitate the research, $\Delta t_{i,j}^{s,d}$ is given stochastically in some related researches, like [36]. However it may not well reflect the real situation.

As we all known, emergency events, like macroquake, usually lead to the secondary disasters, majority of which may provoke traffic congestion during the emergency materials transportation. Therefore, we can make a feasible assumption that $\Delta t_{i,j}^{s,d}$ is mainly caused by secondary disaster, like earthquake, landslide, or debris flow. Based on the assumption, we can intuitively image that the higher probability of those secondary disasters on the edge $e_{i,j}$, the more potential to time delay. With respect to the probability of secondary disaster, some simulation models are proposed by related researches, like [37]. However, the decision-maker, despite capturing the probability of secondary disasters, is still under limited rationality of when and where the time delay potentially will take place. In addition, the scale of time delay still cannot be captured. Therefore, how to predict the time delay on each $e_{i,j}$ is extremely important for a decision-maker during the decision-making.

3.2. Time Delay Prediction Based on Prospect Theory. As having researched by [37], let us turn now to the situation that the nearer to the disaster area, the higher probability the secondary disasters will occur, which also means the higher probability the time delay will be. In order to facilitate the research and without loss of generality, we make an appointment that the secondary disaster just indicates earthquake, landslide, or debris flow. Xu and Li [37] reveal that the occurrence number of secondary disaster at point v_i obeys the following.

$$f\left(r_{i,d}\right) = -A \lg r_{i,d} + B \quad (4)$$

where $r_{i,d}$ is the distance from v_i to disaster point v_d. A and B are the parameters that can be simulated by matching the variance of number of secondary disasters.

In order to get the total number of secondary disasters on $e_{i,j}$, $e_{i,j}$ can be roughly divided into τ small sections. For edge $e_{i,j}$, let $m_{i,j}^{d}$ be the potential number of predicted secondary disasters caused by disaster point v_d; then, $m_{i,j}^{d}$ is approximately equal to

$$m_{i,j}^{d} = \sum_{k=1}^{\tau} d_{i,j}^{k} f\left(r_{k,d}\right) \quad (5)$$

where $d_{i,j}^{k}$ is the length of the *k-th* section and $r_{k,d}$ is the middle distance from the *k-th* section to v_d.

According to (5), the probability $p_{i,j}$ of predicted secondary disasters on each edge $e_{i,j}$ can be further conjectured by

$$p_{i,j} = \frac{\sum_{v_d \in V_d} m_{i,j}^{d}}{\sum_{v_d \in V_d} \sum_{v_p \in V} \sum_{v_q \in V} \left(m_{p,q}^{d} \cdot x_{p,q}\right)} \quad (6)$$

Equations (5) and (6) show that $p_{i,j}$ is just an approximate value that reflects the probability of predicted secondary disasters. However, the time delay, which is mainly caused by those predicted secondary disasters, still cannot be predicted precisely by decision-maker because of limited rationality. In fact, in the behavior theory, prospect theory reveals that no matter how precise the probability is, the decision result is finally made based on the subjective reflection of probability, not the probability directly. Just as the weight function in prospect theory [29], it reflects that decision-maker usually overweight the smaller probability and underestimates the higher one. Therefore, we can use the weight function to mimic the decision behavior of decision-maker under limited rationality. That is we have the following.

When decision-maker faces gains,

$$\omega^{+}\left(p_{i,j}\right) = \frac{{p_{i,j}}^{\gamma}}{\left[{p_{i,j}}^{\gamma} + \left(1 - p_{i,j}\right)^{\gamma}\right]^{1/\gamma}} \quad (7)$$

When decision-maker faces losses,

$$\omega^{-}\left(p_{i,j}\right) = \frac{{p_{i,j}}^{\delta}}{\left[{p_{i,j}}^{\delta} + \left(1 - p_{i,j}\right)^{\delta}\right]^{1/\delta}} \quad (8)$$

where γ and δ are the parameters of decision weight.

With respect to the gains and losses, they are based on the reference point, which is the neutral attitude of decision-maker. As behavior theory showed, decision-maker usually focuses on the deviation between impersonal outcome and subjective outcome, not the impersonal outcome itself [29]. Based on this reason, we now give a reasonable explanation of gains and losses of time delay on each edge $e_{i,j} \in p^{s,d}$.

During the emergency materials path planning, the value of $\Delta t_{i,j}^{s,d}$ cannot be predicted. However, in order to without losing the rescue value of emergency materials, each category of emergency materials has its own required arrival time, and it is also the latest arrival time, beyond which the value may decrease abruptly. Just like a scarce medicine, if the medicine from manufacturer arrives at the hospital beyond the required arrival time, it will lose its value in that the patient has died. Therefore, let each category of emergency materials i have its required arrival time T_i. Based on preplanning, decision-maker pins his hope on the prediction that the expected transportation time T from storage center to disaster point is without beyond the required arrival time T_i. That is,

$$T = \min \{T_1, T_2, T_3, \ldots, T_n\} \tag{9}$$

In other words, for the decision-maker with positive attitude, the maximal tolerated time delay $\overline{t}^{s,d}$ on $p^{s,d}$ is expected as

$$\overline{t}^{s,d} = T - t^{s,d} \tag{10}$$

where $t^{s,d}$ is the nominal transportation time on $p^{s,d}$; that is,

$$t^{s,d} = \sum_{v_i} \sum_{v_j} \left(t_{i,j} \cdot x_{i,j}^{s,d} \right) \tag{11}$$

Let $\overline{t}_0^{s,d}$ be the neutral maximal tolerant time delay per hour on path $p^{s,d}$. Then, $\overline{t}_0^{s,d}$ can be formulated by

$$\overline{t}_0^{s,d} = \frac{\overline{t}^{s,d}}{t^{s,d}} \tag{12}$$

Obviously, $\overline{t}_0^{s,d}$ is average time delay per hour on path $p^{s,d}$, which can be regarded as the neutral reference point or impersonal outcome under complete rationality on each edge $e_{i,j} \in p^{s,d}$. As mentioned that the nearer to the disaster point, the higher probability the time delay on each $e_{i,j} \in p^{s,d}$, therefore, if we let $\overline{t}_{i,j}^{s,d}$ be the potential time delay on $e_{i,j} \in p^{s,d}$, then, $\overline{t}_{i,j}^{s,d}$ can be formulated by

$$\overline{t}_{i,j}^{s,d} = \frac{\overline{t}^{s,d} \cdot h_{i,j}^{s,d}}{t_{i,j}} \tag{13}$$

where

$$h_{i,j}^{s,d} = \frac{p_{i,j}}{\sum_{v_i} \sum_{v_j} \left(p_{i,j} \cdot x_{i,j}^{s,d} \right)} \tag{14}$$

Then, $\overline{t}_{i,j}^{s,d}$ can be regarded as the potential reference point or subjective outcome under the limited rationality on $e_{i,j}$. Obviously, if $\overline{t}_0^{s,d} > \overline{t}_{i,j}^{s,d}$, the result means gains for decision-maker or, otherwise, means losses. In fact, value function in prospect theory reveals that decision-maker usually holds the attitude of risk aversion in positive domain and risk seeking in negative domain, especially that the attitude is more sensitive to losses than gains. The affection caused by this attitude can be described as the following value function.

$$g\left(t_{i,j}^{s,d}\right) = \begin{cases} \left(\overline{t}_0^{s,d} - \overline{t}_{i,j}^{s,d}\right)^{\alpha}, & \text{if } t_0^{s,d} \geq t_{i,j}^{s,d} \\ -\lambda \left(\overline{t}_{i,j}^{s,d} - \overline{t}_0^{s,d}\right)^{\beta}, & \text{if } t_{i,j}^{s,d} > t_0^{s,d} \end{cases} \tag{15}$$

where α is the parameter of risk aversion. β is the parameter of risk seeking. λ is the parameter of sensitive to loss.

Then, we can give subjective reflection between neutral tine delay and predicted time delay on edge $e_{i,j} \in p^{s,d}$. The prospect value of each edge $e_{i,j}$ can be obtained by

$$V\left(t_{i,j}^{s,d}\right) = \begin{cases} g\left(t_{i,j}^{s,d}\right) \cdot \omega^{+}\left(p_{i,j}\right), & \text{if } g\left(t_{i,j}^{s,d}\right) \geq 0 \\ g\left(t_{i,j}^{s,d}\right) \cdot \omega^{-}\left(p_{i,j}\right), & \text{if } g\left(t_{i,j}^{s,d}\right) < 0 \end{cases} \tag{16}$$

Based on the descriptions and analysis above, we now turn back to (3), and the predicted transportation time can be replaced by (17).

$$\widehat{t}_{i,j}^{s,d} = t_{i,j} + \Delta \overline{t}_{i,j}^{s,d} \tag{17}$$

$$\Delta \overline{t}_{i,j}^{s,d} = t_{i,j} \cdot \left(\overline{t}_0^{s,d} - r \cdot V\left(t_{i,j}^{s,d}\right) \right) \tag{18}$$

where r is the weight factor of prospect valve in time delay, and it can be stipulated as

$$r = \frac{t^{s,d}}{\overline{t}^{s,d}} \tag{19}$$

There is no doubt that $\Delta \overline{t}_{i,j}^{s,d}$ is not the genuine time delay on edge $e_{i,j} \in p^{s,d}$, but the predicted one after subjective reflection of decision-maker under limited rationality. Similarly, $\widehat{t}_{i,j}^{s,d}$ is the predicted transportation time with the consideration of time delay under limited rationality.

3.3. Discrete Robustness Optimization Model. The transportation time on each edge $e_{i,j}$ is analyzed explicitly in Section 3.2. The introduction of predicted time delay especially based on prospect theory can give an expression to the subjective reflection of decision-maker under limited rationality, by which the result is more reasonable for decision behavior in real word. However, as shown in (17), the timeliness is apparently yielded with the consideration of predicted time delay, for which the selected path is more adaptable to its complex environment. In fact, it is not necessary to take all of the time delay into consideration, because it is nearly impossible that all the edges $e_{i,j} \in p^{s,d}$ are interrupted.

Therefore, during the decision-making, this weakness can be avoided by controlling the number of interrupted edges and the corresponding optimal decision will be made.

Therefore, let U be a controllable uncertainty set of edges, where $U \subseteq E$. The edge especially in set U can be selected from ETN with probability $P_{i,j}$ to mimic the disturbance caused by the secondary disaster in real world. Let $|U|$ be the number of edges in U, and Γ is an integer to denote the uncertainty controllable variable to the ETN. Then, the objective function based on the decision variable $x_{i,j}^{s,d}$ can be given as follows.

$$\min \quad Z=\sum_{v_s\in V_s}\sum_{v_d\in V_d}\left(\sum_{e_{i,j}\in E}\left(t_{i,j}\cdot x_{i,j}^{s,d}\right)+\max_{\{U\mid U\subseteq E,|U|\le\Gamma\}}\sum_{e_{i,j}\in U}\left(\Delta\hat{t}_{i,j}^{s,d}\cdot x_{i,j}^{s,d}\right)\right) \tag{20}$$

$$\text{S.T.} \quad \sum_{v_d\in V_d}\left(\sum_{v_j\in V}x_{s,j}^{s,d}-\sum_{v_i\in V}x_{i,s}^{s,d}\right)=\left|V_d\right|,\quad \forall v_s \tag{21}$$

$$\sum_{v_s\in V_s}\left(\sum_{v_i\in V}x_{i,d}^{s,d}-\sum_{v_j\in V}x_{d,j}^{s,d}\right)=\left|V_s\right|,\quad \forall v_d \tag{22}$$

$$\sum_{v_s\in V_s}\sum_{v_d\in V_d}\left(\sum_{v_i\in V}x_{i,c}^{s,d}-\sum_{v_j\in V}x_{c,j}^{s,d}\right)=0,\quad \forall v_c \tag{23}$$

$$x_{i,j}^{s,d}\le x_{i,j},\quad \forall s,d,i,j \tag{24}$$

Evidently, the purpose of objective function is to obtain several paths with the best robustness and better timeliness. Hence, the robustness and adaption of each path to complexity environment are improved. In order to solve the problem easily, the objective function, especially the robustness function, must be transformed into an equivalent linear function. According to the property of the objective function and the transformation rule proposed by [38], let $\Gamma^{s,d}$ be an integer to denote uncertainty controllable variable of edge $e_{i,j}$ on the $p^{s,d}$. Obviously, $\Gamma^{s,d}$ resulted based on Γ, and both of them are accordant. Then, the equivalent transformation of the objective function can be given as follows.

$$\min \quad Z=\sum_{v_s\in V_s}\sum_{v_d\in V_d}\left(\sum_{e_{i,j}\in E}\left(t_{i,j}\cdot x_{i,j}^{s,d}\right)+z^{s,d}\Gamma^{s,d}+\sum_{e_{i,j}\in U}q_{i,j}^{s,d}\right) \tag{25}$$

$$\text{S.T.} \quad \sum_{v_d\in V_d}\left(\sum_{v_j\in V}x_{s,j}^{s,d}-\sum_{v_i\in V}x_{i,s}^{s,d}\right)=\left|V_d\right|,\quad \forall v_s \tag{26}$$

$$\sum_{v_s\in V_s}\left(\sum_{v_i\in V}x_{i,d}^{s,d}-\sum_{v_j\in V}x_{d,j}^{s,d}\right)=\left|V_s\right|,\quad \forall v_d \tag{27}$$

$$\sum_{v_s\in V_s}\sum_{v_d\in V_d}\left(\sum_{v_i\in V}x_{i,c}^{s,d}-\sum_{v_j\in V}x_{c,j}^{s,d}\right)=0,\quad \forall v_c \tag{28}$$

$$z^{s,d}+q_{i,j}^{s,d}\ge\Delta\hat{t}_{i,j}^{s,d}\cdot x_{i,j}^{s,d},\ e_{i,j}\in U,\ \forall s,d \tag{29}$$

$$z^{s,d}\ge 0,\ \forall s,d \tag{30}$$

$$q_{i,j}^{s,d}\ge 0,\ \forall s,d \tag{31}$$

$$x_{i,j}^{s,d}\le x_{i,j},\ \forall s,d,i,j \tag{32}$$

4. Algorithm Design

4.1. Problem Analysis. The problem of obtaining an optimal path from start point to terminal point in a network belongs to the shortest path problem, which is also an NP problem. In addition, the obvious differences in this paper are as follows.

(1) The predicted time delay $\Delta\hat{t}_{i,j}^{s,d}$ is calculated based on the $t^{s,d}$ on $p^{s,d}$, not on the edge $e_{i,j}$ directly. That is, only the path is confirmed and can $\Delta\hat{t}_{i,j}^{s,d}$ be loaded on the $e_{i,j}$ to reflect the limited rationality of decision-maker.

(2) The ETN in this paper is a multisource and multiterminal network. Therefore, at least $|V_s|\times|V_d|$ paths are needed to realize the emergency materials transportation from v_s to v_d.

(3) Based on the objective function, the optimal solution with the smallest objective value entails that the path in optimal solution must be the shortest path from v_s to v_d. Otherwise, it will be replaced by the better one.

From the analysis, when the scale of ENT is bigger enough, the optimal solution can hardly be obtained by traditional classical algorithm because of the parallelism and complexity.

4.2. Improved Genetic Algorithm. Genetic algorithm (GA) is proposed based on the evolutionary theory and genetic mechanism. With contrast to other intelligence algorithms, GA has advantage in solving the problem with property of parallelism because of its better robustness, flexibility, and, especially, the adaption without constraints from the problem [39, 40]. In GA, crossover operator, mutation operator, and selection operator are the cores of search strategy of the algorithm. Generally, majority of existing researches use GA to search path from network with single-source and single-terminal. Therefore, the GA is improved in this paper to search the optimal solution from ETN with multistorage centers and multiterminal points. Besides, the search strategy is also improved.

4.2.1. Chromosome. Chromosome is coded as the role that combining the problem solution domain with search domain that GA can deal with. Since there are several paths in a path cluster, we present a notion of chromosome cluster. Then, chromosome in cluster represents path.

For chromosome, the loca of gene represents the starting point of edge $e_{i,j}$, and the gene represents the end point of

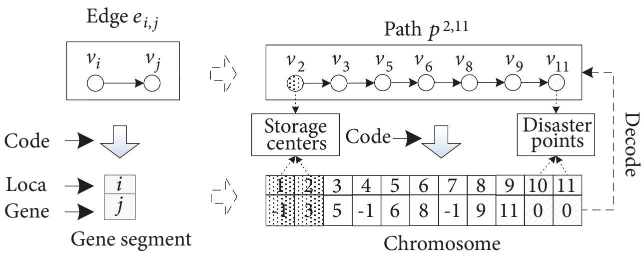

Figure 2: A description of chromosome.

$e_{i,j}$. If $e_{i,j} \notin p^{s,d}$, the corresponding gene is appointed as -1. Especially, if $v_j \in V_d$, the corresponding gene is appointed as 0.

Based on decision variable $x_{i,j}^{s,d}$, if the chromosome represents the path $p^{s,d}$, and the value of gene i is j, $x_{i,j}^{s,d} = 1$, otherwise, $x_{i,j}^{s,d} = 0$. A description of chromosome is given in Figure 2.

As there are several paths obtained as the optimal solution to realize the emergency materials transportation from v_s to v_d, chromosome cluster can be introduced, and it can be recorded in a two-dimensional matrix. Specifically, the column subscript of this matrix has same means of loca in chromosome. The rower of matrix is consistent with the subsequence of obtained chromosome. Now, we give an example to illustrate the chromosome cluster as Figure 3 shown.

Obviously, in order to ensure the constraint that each disaster point can obtain emergency materials from each storage center, the chromosomes in the optimal cluster is $|V_s| \times |V_d|$ at least.

4.2.2. Search Strategy. In terms of the objective function, chromosome can be generated with the search mechanism that the edge with the smaller nominal time $t_{i,j}$ has the higher probability to be selected. The advantage of this searching mechanism can guarantee the convergence of the algorithm and avoid the result falling into local optimum. However, for monodirectional search, the ergodicity of each storage center or disaster point cannot be satisfied. In order to make up this weakness, we improve the strategy with bidirectional search, respectively, named father search with forward search strategy and mother search with backward search strategy.

(1) Father Search Strategy. Father search direction is consistent with the direction of edge. We appoint different v_s as starting point for each search. Once all v_s are traversed, the father search will be over, and the chromosomes are recorded in a chromosome cluster, which can be called father chromosome cluster. As the stochastic search mechanism, the terminal point of each search is uncertainty. The flow chart of father search is shown in Figure 4.

(2) Mother Search Strategy. The direction of mother search is the reverse of edge direction. For each search, v_d is appointed as starting point, and the total search time is $|V_d|$. The search will be over when the search meets terminal point v_s. As the selected path is converse to the real path, therefore, it needs to be reverted before coding as a chromosome. This chromosome can also be recorded in a cluster and called mother chromosome cluster. The flow chart of mother search is shown in Figure 5.

Obviously, after each father search and mother search, all the storage centers and disaster points are traversed. The proportionality and availability of solution resulting from two searches can also be guaranteed.

4.2.3. Crossover Operator. Crossover operator is proposed to find a better offspring during the interaction. Since the path in the father cluster is optimal in terms of starting point of each edge $e_{i,j}$ and for the mother cluster, the optimal one is in terms of the ending point of each $e_{i,j}$; therefore, we are incline to find offspring with optimal property in terms of both staring point and ending point. In order to make it possible, we give the following description.

(1) Crossover Point. We appoint a gene (except disaster point), which is contained both in father chromosome and in mother chromosome, as a crossover point. Especially, if there is no crossover point, we grant those parent chromosomes are irreproducible. If there are several crossover points in parent chromosomes, we can select one stochastically as a real crossover point.

(2) Crossover Mechanism. For each chromosome in father cluster, it will be taken out to match each chromosome in mother cluster. Once matched successfully, they will take part in the crossover with the mechanism that the crossover point together with the subsequent genes replaced each other both in father chromosome and in mother chromosome. This process can be denoted as $\otimes$.

Based on the description of crossover point and crossover mechanism, an example of crossover operator is shown in Figure 6.

After the crossover operator, all the chromosomes in father cluster, mother cluster, and offspring cluster will become a new population.

4.2.4. Selection Operator. Selection operator is introduced to find a chromosome with the best evaluation indicator from the existing population. In this paper, we give a stable optimal cluster to contain the exclusive chromosome. Obviously, the scale of this cluster is $|V_s| \times |V_d|$. For each selection, all the chromosomes in population will be compared with the corresponding one in the optimal cluster. Once a better one is found, the corresponding one will be replaced. The terminal condition of selection operator is when each chromosome in optimal cluster is compared. Based on the objective function, the evaluation indicator of each chromosome can be given as

$$F^{s,d} = \min \left\{ \sum_{e_{i,j} \in E} \left(t_{i,j} \cdot x_{i,j}^{s,d} \right) + z^{s,d} \Gamma^{s,d} + \sum_{e_{i,j} \in U} q_{i,j}^{s,d} \right\} \tag{33}$$

Now, we give the max cycle time T_e as the terminal condition of the algorithm. According to the description

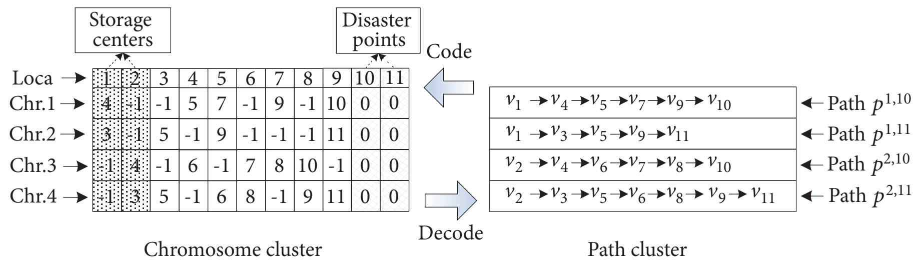

Figure 3: An example to illustrate chromosome cluster.

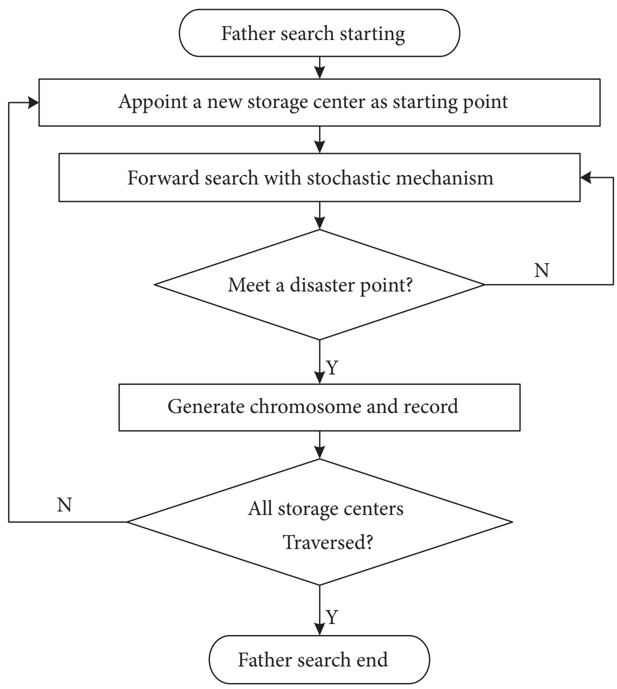

Figure 4: Flow chart of father search.

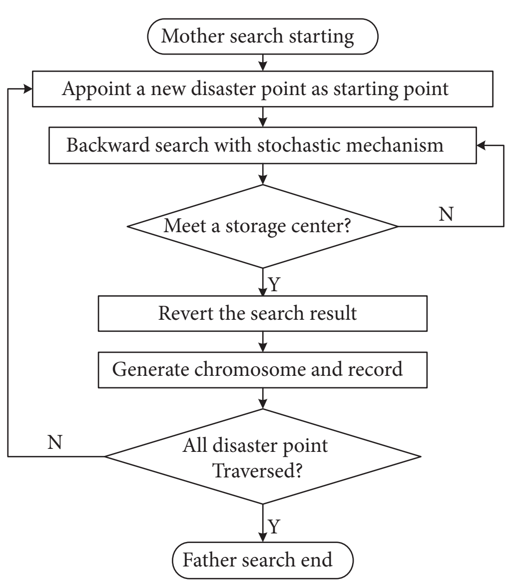

Figure 5: Flow chart of mother search.

above, the flow chart of improved genetic algorithm is given as Figure 7.

An improved genetic algorithm is designed in this section. The main improvement is that a bidirectional search strategy is proposed based on the ETN with multisource and multiterminal. Besides, chromosome cluster is also newfangled one. Additional illustration is that mutation operator is omitted in that the weakness of falling into local optimum is avoided by introduction of father search and mother search.

5. Case Study

An ETN with 19 points is introduced in this section, where v_1, v_2, and v_3 are the storage centers, v_{18} and v_{19} are the disaster points, and others are the crossover points. The ETN in case study is shown in Figure 8.

Based on the ETN shown in Figure 8, values of related parameters are presented in Table 1.

According to the values in Table 1, uncertainty probability $p_{i,j}$ can be obtained. Based on serious of matching, when $A = 8.23$ and $B = 20.38$ in (4) and $\tau = 1000$ in (5), the uncertainty probability of each edge under controllable variable $\Gamma = 47$ is given as Figure 9.

From Figure 9, we can see that the probability becomes different along with the edge gets close to corresponding disaster point. However, the situation that the nearer it is to disaster point, the higher the probability of time delay is not reflected vividly, the reason is that the result takes the length of each edge into consideration additionally. If we eliminate this factor, the probability of unit length on each edge is shown as in Figure 10.

Obviously, Figure 10 can well reflect the phenomenon we appointed. Especially, for three conditions in Figure 10, the value of the edge that is nearest to the disaster point is beyond triple to the farthest one. In addition, both in Figure 9 and in Figure 10, the synthesis probability is caused by disaster points v_{18} and v_{19} commonly, and the result is also in accordance with the real word.

5.1. Optimal Solutions. Based on the essential information given above, we acquiescently appoint that the minimum expected arrive time $T = 8$ in (9) and let the max cycle of algorithm $T_e = 250$. When the C++ runs for 0.274s, the path cluster with the best predicted transportation time can be obtained. The results of the best path cluster under $\Gamma = 47$ are shown in Table 2.

Table 1: Values of related parameters.

No.	$e_{i,j}$	$d_{i,j}$ (km)	$t_{i,j}$ (h)	Distance to v_{18} (km)		Distance to v_{19} (km)	
				$r_{i,18}$	$r_{j,18}$	$r_{i,19}$	$r_{j,19}$
1	(1,4)	34.42	0.95	145.33	113.12	154.63	119.35
2	(1,5)	47.27	1.21	145.33	117.03	154.63	114.71
3	(1,7)	51.04	1.52	145.33	96.63	154.63	112.28
4	(2,4)	33.23	0.78	150.23	113.12	146.18	119.35
5	(2,5)	32.78	0.84	150.23	117.03	146.18	114.71
6	(3,4)	41.86	1.04	140.54	113.12	133.74	119.35
7	(3,5)	25.19	0.62	140.54	117.03	133.74	114.71
8	(3,6)	35.13	1.12	140.54	113.79	133.74	102.39
9	(4,7)	28	0.63	113.12	96.63	119.35	112.28
10	(4,8)	25.14	0.75	113.12	94.73	119.35	95.13
11	(4,10)	50.09	1.21	113.12	64.48	119.35	81.61
12	(5,6)	25.36	0.67	117.03	113.79	114.71	102.39
13	(5,8)	23.58	0.65	117.03	94.73	114.71	95.13
14	(5,9)	41.05	1.05	117.03	88.58	114.71	76.47
15	(6,8)	33.38	0.73	113.79	94.73	102.39	95.13
16	(6,9)	26.92	0.84	113.79	88.58	102.39	76.47
17	(6,11)	49.1	1.36	113.79	65.12	102.39	65.23
18	(7,8)	32.12	0.79	96.63	94.73	112.28	95.13
19	(7,10)	31.66	0.81	96.63	64.48	112.28	81.61
20	(7,11)	50.12	1.23	96.63	65.12	112.28	65.23
21	(7,14)	59.35	1.77	96.63	37.56	112.28	67.67
22	(8,9)	31.78	0.71	94.73	88.58	95.13	76.47
23	(8,10)	33.72	0.97	94.73	64.48	95.13	81.61
24	(8,11)	32.22	0.85	94.73	65.12	95.13	65.23
25	(9,11)	27.55	0.63	88.58	65.12	76.47	65.23
26	(9,12)	29.92	0.86	88.58	65.32	76.47	46.48
27	(9,15)	48.27	1.09	88.58	42.06	76.47	34.67
28	(10,11)	26.76	0.58	64.48	65.12	81.61	65.23
29	(10,13)	25.66	0.74	64.48	42.7	81.61	57.08
30	(10,14)	29.97	0.90	64.48	37.56	81.61	67.67
31	(11,12)	31.25	0.87	65.12	65.32	65.23	46.48
32	(11,13)	23.26	0.6	65.12	42.7	65.23	57.08
33	(11,15)	30.96	0.69	65.12	42.06	65.23	34.67
34	(12,15)	25.36	0.77	65.32	42.06	46.48	34.67
35	(12,17)	30.05	0.9	65.32	46.43	46.48	18.97
36	(13,14)	19.73	0.45	42.7	37.56	57.08	67.67
37	(13,15)	24.43	0.59	42.7	42.06	57.08	34.67
38	(13,16)	28.86	0.74	42.7	24.61	57.08	32.99
39	(13,18)	44.21	0.98	42.7	2	57.08	45.7
40	(14,16)	34.67	0.77	37.56	24.61	67.67	32.99
41	(14,18)	38.18	1.06	37.56	2	67.67	45.7
42	(15,16)	17.43	0.48	42.06	24.61	34.67	32.99
43	(15,17)	20.13	0.52	42.06	46.43	34.67	18.97
44	(16,17)	25.39	0.60	24.61	46.43	32.99	18.97
45	(16,18)	25.1	0.56	24.61	2	32.99	45.7
46	(16,19)	32.68	0.88	24.61	45.14	32.99	2
47	(17,19)	18.03	0.45	46.43	45.14	18.97	2

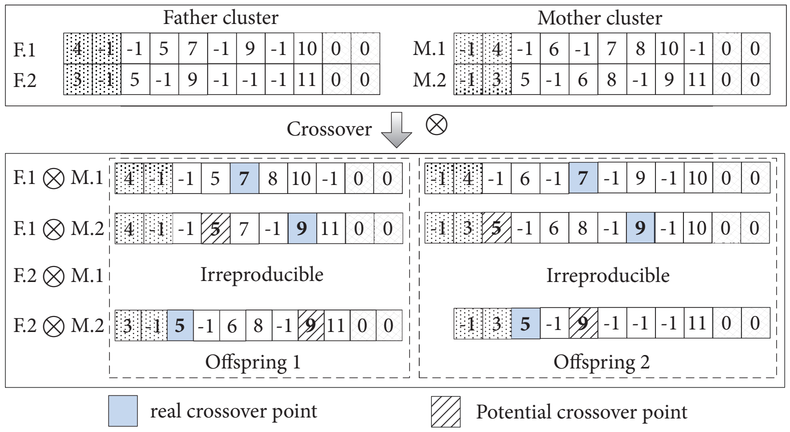

Figure 6: An example of crossover operator.

Table 2: The results of the best path cluster under $\Gamma = 47$.

No.	Path	Details	Nominal time	Time delay	Predicted time
1	$P^{1,18}$	1⟶4⟶10⟶13⟶18	3.88	4.12	8
2	$P^{1,19}$	1⟶4⟶7⟶8⟶9⟶12⟶17⟶19	5.29	2.85	8.14
3	$P^{2,18}$	2⟶4⟶10⟶13⟶18	3.71	4.29	8
4	$P^{2,19}$	2⟶5⟶9⟶15⟶17⟶19	3.95	4.05	8
5	$P^{3,18}$	3⟶5⟶8⟶10⟶13⟶18	3.96	4.04	8
6	$P^{3,19}$	3⟶5⟶8⟶11⟶15⟶17⟶19	3.78	4.22	8

Note: time/hour.

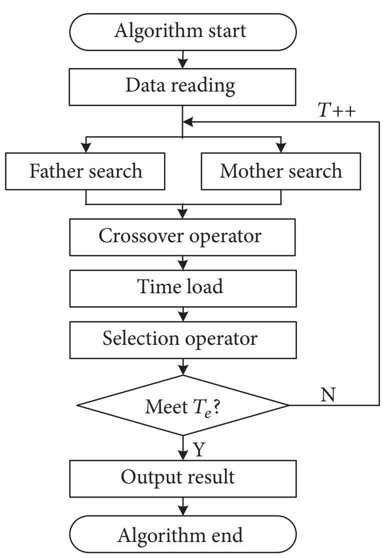

Figure 7: Flow chart of improved genetic algorithm.

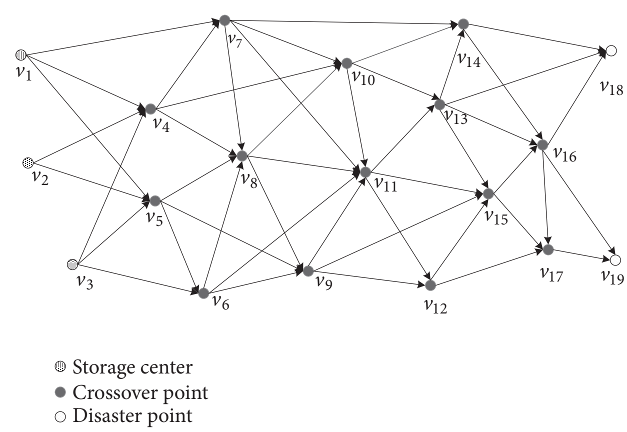

Figure 8: The ETN in case study.

As the result in Table 2, the nominal time, time delay, and expected time of the optimal path cluster are 24.57, 23.57, and 48.14 hours, respectively. The path (10⟶13⟶18) especially is commonly shared by $P^{1,18}$, $P^{2,18}$, and $P^{3,18}$; the main reason is that it has the better timeliness and robustness, and it is significant to disaster point p_{18}. The same reason can also go for path (15⟶17⟶19) to $P^{2,19}$ and $P^{3,19}$. In addition, the predicted time of $P^{1,19}$ is beyond the required time, which means that this path has the higher probability to time delay, and the decision-maker should pay much attention to this path during the emergency materials transportation.

In terms of the optimal path cluster, the convergence procedure based on predicted time, time delay, and nominal time are shown in Figures 11 and 12, respectively.

According to Figures 11 and 12, the predicted time in Figure 11 tends to be stable when iteration is at 104. However, the nominal time and time delay in Figure 12 is stable when iteration is at 144. This means that a better path cluster, in which the increment of time delay is exactly equal to the

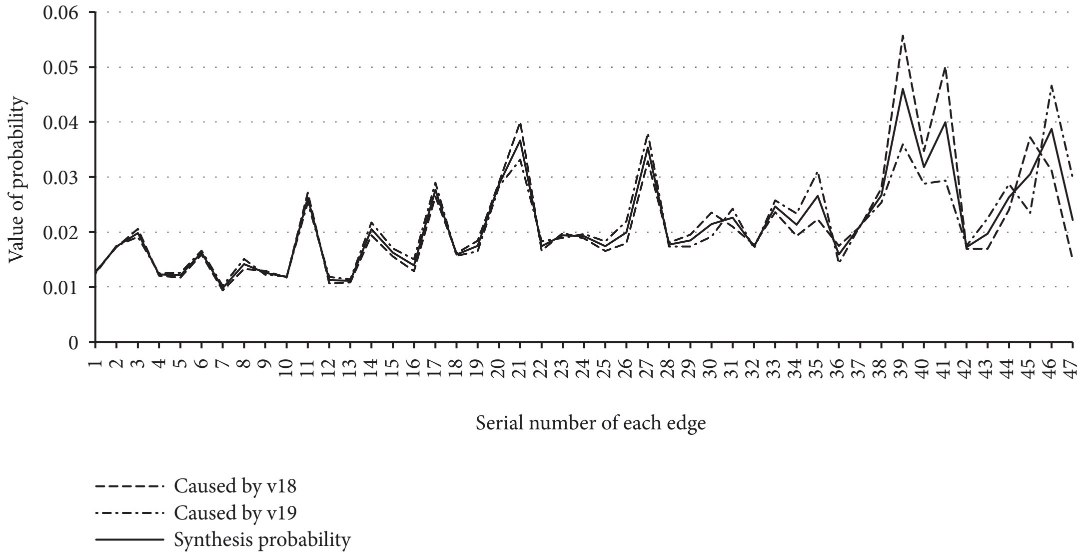

Figure 9: The uncertainty probability of each edge under controllable variable Γ = 47.

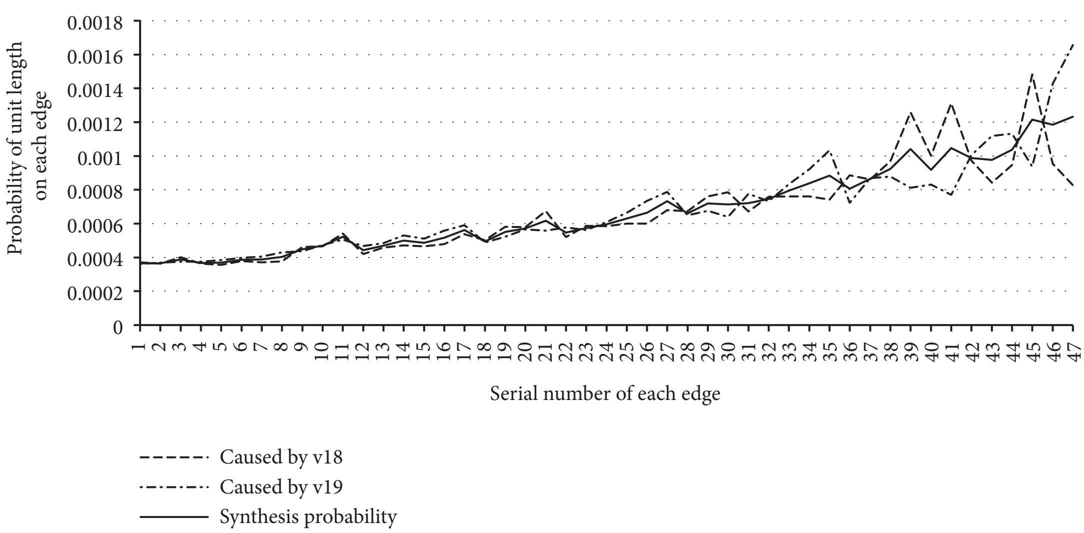

Figure 10: Probability of unit length on each edge.

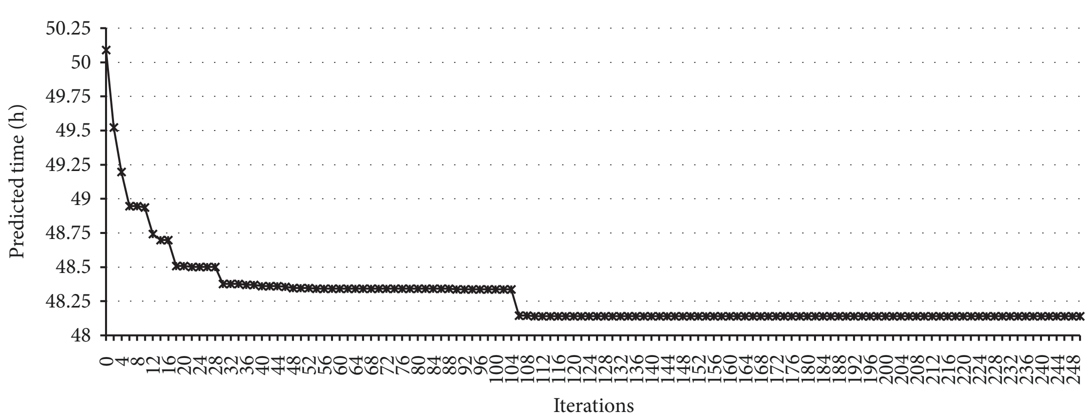

Figure 11: The convergence procedure based on predicted time.

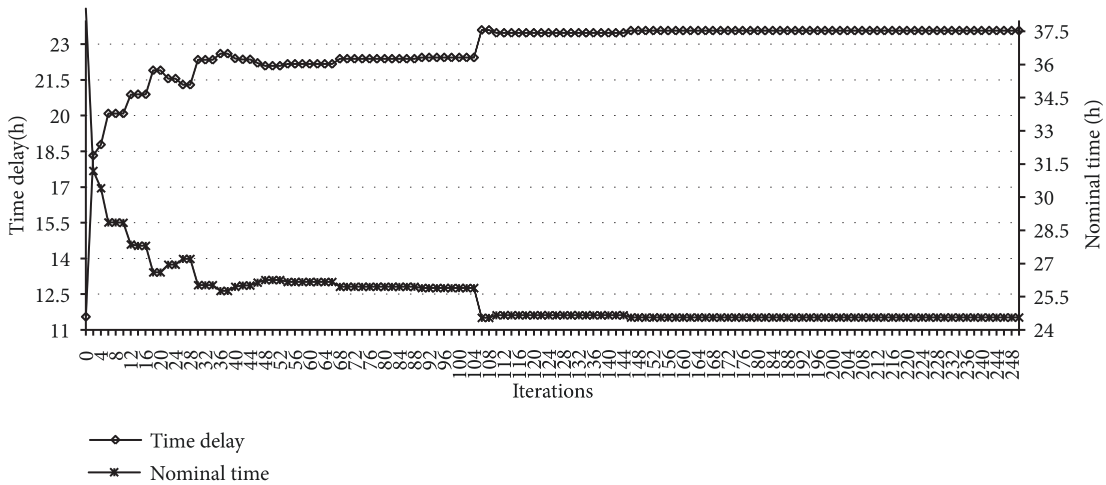

Figure 12: The convergence procedure based on time delay and nominal time.

decrement of nominal time, is found when iteration is at 144. Generally, the predicted time is the comprehensive reflection of time delay and nominal time. In addition, in order to meet the required arrival time, the convergence procedures in Figures 11 and 12 show that the path with the better robustness has the better timeliness in the condition of all the edges under the uncertainty; that is, $\Gamma = 47$. In order to analyze the convergence of each path in cluster, the convergence procedure of each path based predicted transportation time is shown in Figure 13.

From Figure 13, we can see the convergence procedures of each path are different, but the trends are strictly consistent with the convergence procedure in Figure 11. However, a peculiar phenomenon is that the predicted transportation time of $P^{1,19}$ is finally beyond the required arrival time, which is also mentioned in Table 1. Further analysis shows that the reason is that all the paths from v_1 to v_{19} are much great and comprehensively influenced; consequently, both the timeliness and robustness have to be yield as much as possible.

As mentioned in Section 4, the main improvement of genetic algorithm is that a bidirectional search strategy is proposed according to the ETN with multisource and multiterminal. In some of the other researches, the network is usually transformed as the one with single-source and single-terminal. In order to verify the effectiveness of the improved genetic algorithm in this paper, we transform the ETN as the one with single-source and single-terminal and solve it by the traditional genetic algorithm. Then, the comparison of convergence procedure based on two genetic algorithms is shown in Figure 14.

According to the comparison in Figure 14, the convergence of improved genetic algorithm tends to table when iteration is at 104; however, the table convergence of traditional genetic algorithm is at 184. Besides, the results of improved genetic algorithm are much more obvious than traditional genetic algorithm before the iteration at 30, which reflects that the bidirectional search strategy has higher search ability. Combined with analysis above, the results demonstrate the improved genetic algorithm is more reasonable and efficient to solve the path optimization problem in the network with multisource and multiterminal.

5.2. Influence Analysis of Subjective Decision

5.2.1. Influence Analysis Based Network Viewpoint. The advantage of discrete robustness optimization model is that the uncertainty scale is controllable. From the viewpoint of network, Γ is an important parameter to reflect the optimism or pessimism attitude of decision-maker. In order to analyze the influence caused by attitude of decision-maker, the value of optimal path cluster under different Γ are shown in Figure 15.

Obviously, with the uncertainty scale up, the predicted time tends to increase. It reflects that the attitude of decision-maker becomes more and more pessimistic. Generally, the attitude of decision-maker is insensitive when $\Gamma \leq 8$, and the attitude is in the hesitation when $8 < \Gamma \leq 22$. Especially, $\Gamma > 22$, attitude becomes pessimistic. Next, we take $p^{2,18}$ and $p^{2,19}$ as examples for further analysis. The related information of e $p^{1,18}$ and $p^{1,19}$ is shown in Table 3.

The result in Table 3 shows that the optimal paths are different with Γ taking different values. It entails that the paths in optimal cluster are amended to adapt the circumstance under different Γ. Especially, when Γ takes the value in median parts of the uncertainty scale, the optimal paths have the poorest timeliness of nominal time. Strangely, when $\Gamma = 47$, the optimal path is some as to the optimal path under $\Gamma = 0$. This phenomenon gives us a conclusion that the optimal solution under medium scale of uncertainty is the most difficult scenario for decision-maker to make decision, and the final result usually has higher sacrifice of the timeliness.

5.2.2. Influence Analysis Based Path Viewpoint. During the decision of optimal path cluster, prospect theory is introduced to reflect the subjective decision of decision-maker under limited rationality. Actually, the influence is embodied

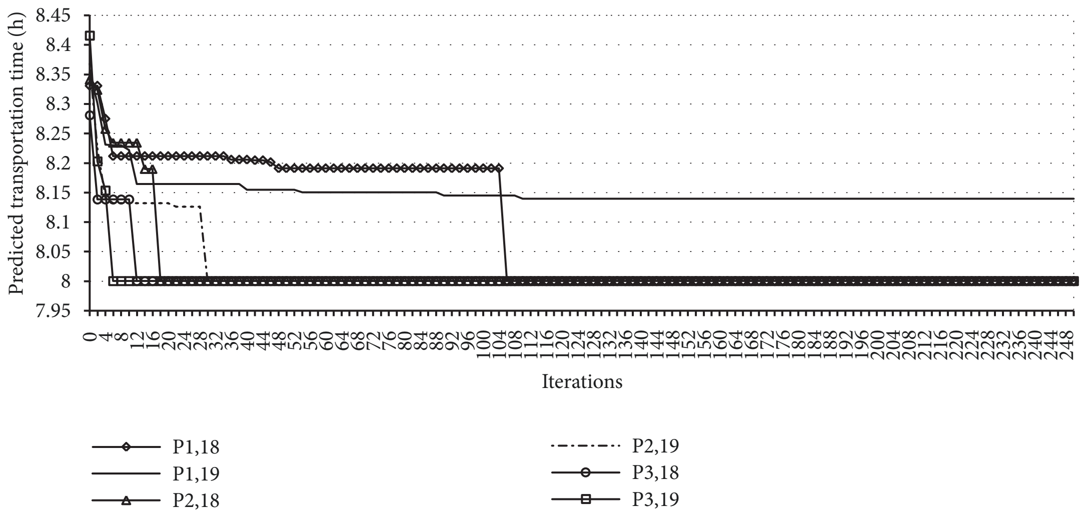

Figure 13: The convergence procedure of each path based on predicted transportation time.

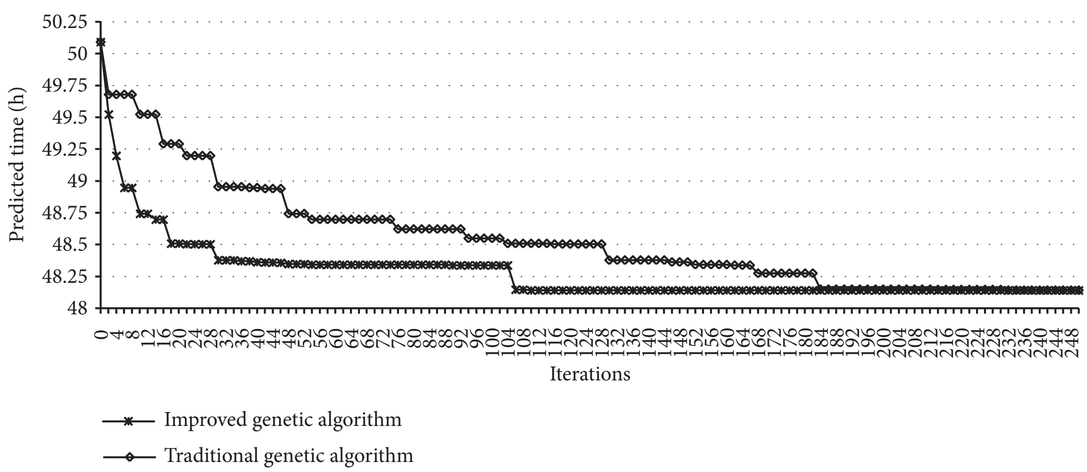

Figure 14: The comparison of convergence procedure based on two genetic algorithms.

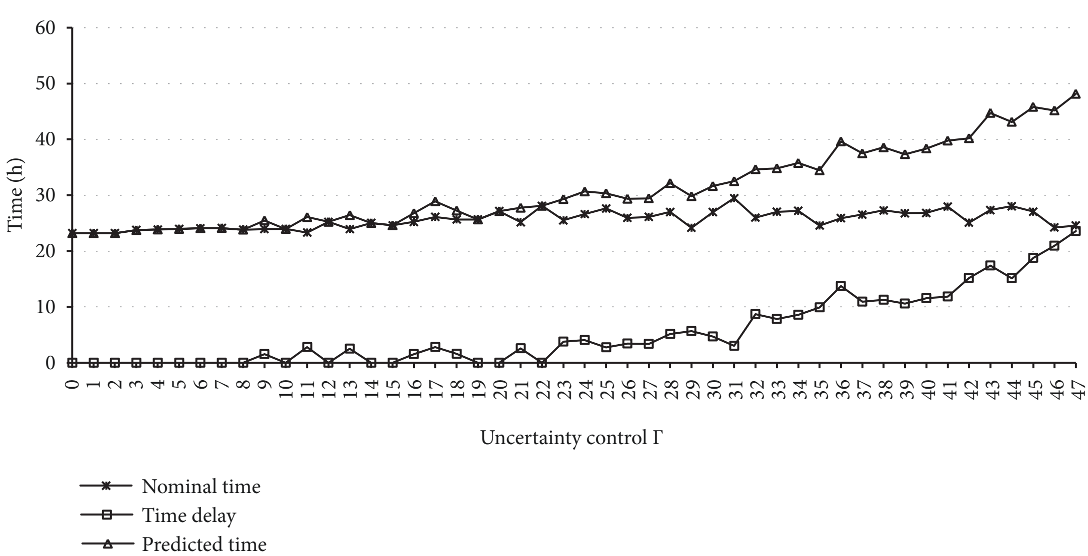

Figure 15: The value of optimal path cluster under different Γ.

Table 3: The related information of $p^{2,18}$ and $p^{2,19}$.

Γ	Path	Details	Nominal time	Time delay	Predicted time
0	$P^{2,18}$	2⟶4⟶10⟶13⟶18	3.71	0	3.71
	$P^{2,19}$	2⟶5⟶9⟶15⟶17⟶19	3.95	0	3.95
7	$P^{2,18}$	2⟶5⟶8⟶11⟶13⟶18	3.92	0	3.92
	$P^{2,19}$	2⟶5⟶9⟶12⟶17⟶19	4.10	0	4.10
17	$P^{2,18}$	2⟶5⟶8⟶10⟶13⟶16⟶18	4.50	0.76	5.26
	$P^{2,19}$	2⟶5⟶8⟶10⟶13⟶15⟶17⟶19	4.76	0.25	5.01
27	$P^{2,18}$	2⟶4⟶10⟶13⟶14⟶18	4.24	0.97	5.21
	$P^{2,19}$	2⟶4⟶10⟶13⟶15⟶17⟶19	4.29	1.11	5.40
37	$P^{2,18}$	2⟶4⟶8⟶11⟶13⟶18	3.96	1.87	5.83
	$P^{2,19}$	2⟶4⟶8⟶11⟶13⟶16⟶19	4.60	1.27	5.87
47	$P^{2,18}$	2⟶4⟶10⟶13⟶18	3.71	4.29	8
	$P^{2,19}$	2⟶5⟶9⟶15⟶17⟶19	3.95	4.05	8

Note: time/hour.

in the time delay. In order to analyze the influence caused by of subjective decision under limited rationality, the time delay of different $P^{1,18}$ based different viewpoints are listed in Tables 4, 5, and 6, respectively.

As Tables 4 and 6 showed, for each $e_{i,j}$, DSD is smaller than DND but bigger than DPD, when $h_{i,j}$ takes smaller values. It illustrates that decision-maker holds risk aversion attitudes when he faces the situation with smaller probability of time delay. On the contrary, DSD is bigger than DND but smaller than DPD, when $h_{i,j}$ takes bigger values; that is, the attitude is risk seeking when he faces the higher probability of time delay. From the viewpoint of each path, decision-maker holds attitude of risk aversion because of $\sum$DSD beyond both $\sum$DPD and $\sum$DND. Obviously, the more obvious the attitude of risk aversion holds, the better the robustness is.

DSD especially is all equal to DND in Table 5, but it does not violate the conclusion obtained above. The reason is mainly caused by the weight factor of prospect valve in time delay in equation (19). Further analysis shows that the tolerant time delay in Table 4 is so plenty that subjective reflection turns invalid. In fact, it is coincident with decision behavior in the real world.

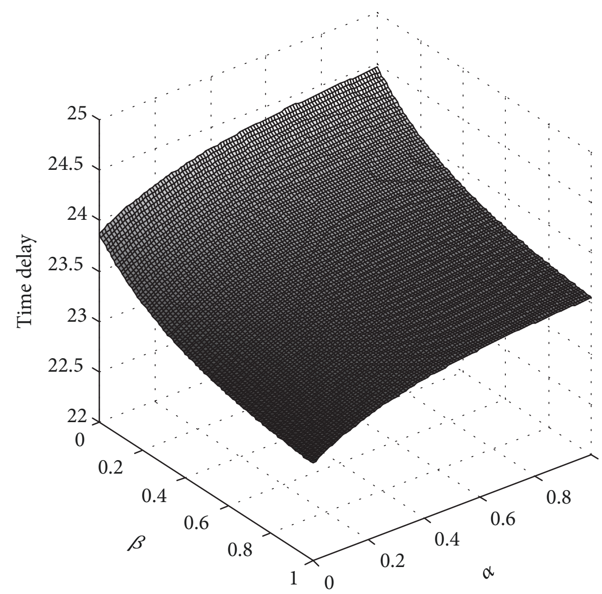

Figure 16: The influence of time delay caused by α and β.

5.2.3. Parameters Analysis in Prospect Theory. The subjective reflection of decision-maker is mainly influenced by the value of parameters in prospect theory. Based on time delay, this section focuses on the analysis of influence caused by the value of parameters in prospect theory. The influence of time delay caused by α and β is shown in Figure 16.

α and β are the parameters in value function. From Figure 16 we can see that the bigger the value that α takes, the higher the time delay is. In other words, the decision attitude turns more risk aversion. On the contrary, the attitude turns more risk seeking when β turns bigger. Similarly, the influence of time delay caused by γ and δ is shown in Figure 17.

Compared with value function, Figure 17 shows that parameters in weight function have higher influence on time delay. Especially, when γ takes values in $[0.4, 0.8]$, the attitude of risk seeking is obvious, and the risk aversion is obvious when δ takes values in $[0.6, 1]$. Generally, δ has higher influence than γ.

In addition, prospect theory presents that both α and γ have comprehensive influence on gains, and so do β and δ on losses. Therefore, the influence of time delay caused by α and γ is shown in Figure 18.

Obviously, time delay is gradually increased with the value of α up. When $\alpha < 0.8$, the variation of γ has greater influence on time delay. However, when $\alpha \geq 0.8$, the influence is unconspicuous. Generally, the influence caused by variation of γ is greater than that of α. In other words, subjective reflection is more sensitive to weight function than value function. Similarly, the influence of time delay caused by β and δ is shown in Figure 19.

Table 4: The time delay of $P^{1,18}$ with the better robustness and the poorer timeliness.

Items	$P^{1,18}(1 \longrightarrow 7 \longrightarrow 10 \longrightarrow 13 \longrightarrow 18)$				$\sum$
$e_{i,j}$	(1,7)	(7,10)	(10,13)	(13,18)	—
$t_{i,j}$ (h)	1.520	0.810	0.740	0.980	4.050
$h_{i,j}$	0.195	0.172	0.181	0.452	1.000
DND	1.483	0.790	0.722	0.956	3.950
DPD	0.770	0.678	0.717	1.786	3.950
DSD	1.282	0.756	0.719	1.763	4.520

Note: DND is the time delay based neutral decision under complete rationality. DPD is the time delay based probabilistic decision under complete rationality. DSD is the time delay based subjective decision under limited rationality. $h_{i,j}$ is the relative probability in (14).

Table 5: The time delay of $P^{1,18}$ with the better timeliness and the poorer robustness.

Items	$P^{1,18}(1 \longrightarrow 4 \longrightarrow 10 \longrightarrow 13 \longrightarrow 18)$				$\sum$
$e_{i,j}$	(1,4)	(4,10)	(10,13)	(13,18)	—
$t_{i,j}$ (h)	0.950	1.210	0.740	0.980	3.880
$h_{i,j}$	0.122	0.254	0.179	0.445	1.000
DND	1.009	1.285	0.786	1.041	4.120
DPD	0.503	1.046	0.736	1.835	4.120
DSD	1.009	1.285	0.786	1.041	4.120

Table 6: The time delay of $P^{1,18}$ with the poorer timeliness and the poorer robustness.

Items	$P^{1,18}(1 \longrightarrow 7 \longrightarrow 11 \longrightarrow 15 \longrightarrow 16 \longrightarrow 18)$					$\sum$
$e_{i,j}$	(1,7)	(7,11)	(11,15)	(15,16)	(16,18)	—
$t_{i,j}$ (h)	1.520	1.230	0.690	0.480	0.560	4.480
$h_{i,j}$	0.164	0.237	0.204	0.142	0.252	1.000
DND	1.194	0.966	0.542	0.377	0.440	3.520
DPD	0.577	0.836	0.718	0.501	0.888	3.520
DSD	1.031	0.918	0.663	0.446	0.746	3.804

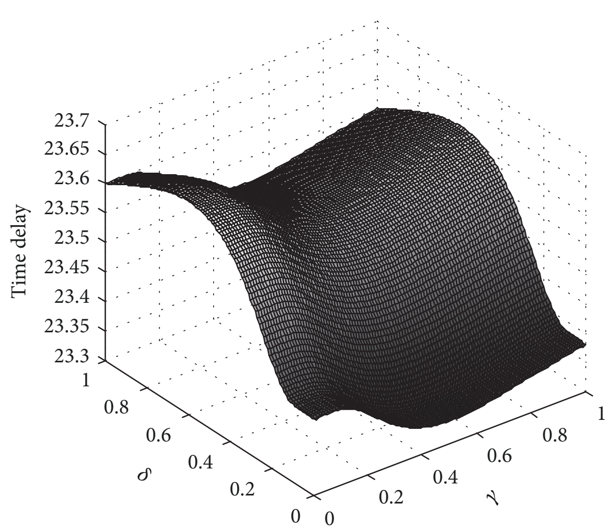

Figure 17: The influence of time delay caused by γ and δ.

As shown in Figure 19, the influence on time delay caused by variation of β is obvious when $\delta \geq 0.4$, and the influence caused by δ is obvious when $\beta \leq 0.7$. Similar to the reflection in Figure 18, Figure 19 also shows that the time delay is much more sensitive to weight function than value function. Combining with Figures 18 and 19, we can make conclusion that weight function has greater influence on subjective reflection than value function in this paper.

6. Conclusions

This paper focuses on the discrete robustness optimization of emergency logistic network based on a situation that the nearer to the disaster area, the higher probability the time delay. Thereinto, prospect theory is especially introduced to describe the subjective reflection of decision-maker under limited rationality. In addition, an improved genetic algorithm is also designed based on the optimization model to obtain the optimal path cluster with the better timeliness and robustness from ETN with multistorage centers and multidisaster points. According to the analysis of case study, some conclusions can be summarized as follows.

(1) With the required arrival time, prospect theory can well describe the subjective reflection of decision-maker under limited rationality. Generally, decision-maker who faces a path with more nominal transportation time and less

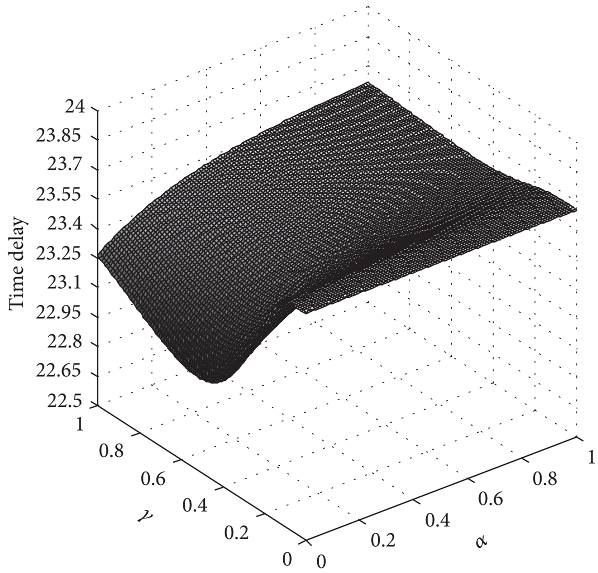

Figure 18: The influence of time delay caused by α and γ.

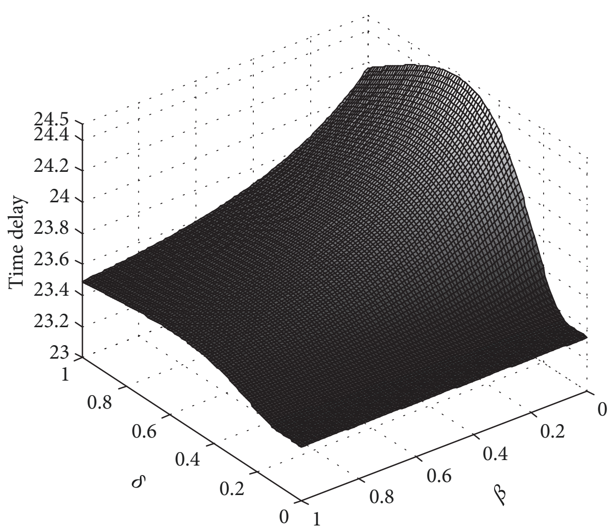

Figure 19: The influence of time delay caused by β and δ.

tolerant delay time holds an attitude of risk seeking, which can be described as a proverb that what is hopeless and bold is often successful. On the contrary, the attitude will turn to risk aversion when decision-maker faces a path with less nominal transportation time and more tolerant delay time, which also can be described as a proverb that caution is the mother of security.

(2) Based on the realistic situation that the nearer to the disaster area, the higher the probability of time delay, decision-maker who is under limited rationality, holds the attitude of risk aversion when he faces an edge with lower probability of time delay, and the attitude turns risk seeking when he faces an edge with higher probability.

(3) The advantage of discrete robustness optimization in this paper is that the uncertainty scale is controllable, by which the uncertainty environment of ETN can be vividly mimicked. Robustness especially in the model is correspondent to the attitude of risk aversion in prospect theory, and the optimal solution under different scale of uncertainty means the better risk aversion attitude of decision-maker with consideration of timeliness.

In addition, genetic algorithm has better advantage in obtaining path cluster from ETN with multistorage centers and multidisaster points. The shortage in this paper is that reference point is only just based on the timeliness. In fact, the optimization resulting from multireference point, such as capacity of each edge and path, is more practically significance. Besides, group decision can also be used in this paper, by which universality of optimal solution is more general. Those will be the next step to further study.

Data Availability

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

Conflicts of Interest

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

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