Research on Evolutionary Game of Emergency Material Allocation under Bounded Rationality

Bin Ma, Changfeng Zhu, Yubo Zhang, and Qingrong Wang

Abstract—**In order to ensure the efficiency and rationality of Emergency Materials Allocation (EMA) and make the allocation scheme more realistic, the impact of secondary disasters on material demand and transportation time as well as the disaster victims' competitive psychology of materials under bounded rationality are comprehensively considered. Prospect Theory (PT) was introduced to construct the payment function of material allocation scheme in disaster locations, and Evolutionary Game (EG) model under bounded rationality was established. The evolutionary equilibrium scheme was obtained through the model, and the effects of risk attitude coefficient, perceived probability coefficient and attribute decision preference coefficient on the prospect value of the scheme and the evolutionary equilibrium scheme were analyzed. The results show that the EG model of EMA under bounded rationality can give consideration to the dynamics of disaster situation and the bounded rationality game psychology of disaster location, which makes the decision result more in line with the reality. The risk attitude, probability perception ability and the degree of preference for the allocation and delivery time of emergency materials of disaster locations will have an impact on the game results within a certain range.**

Index Terms—**Dynamic material demand, Evolutionary Game (EG), Emergency Materials Allocation (EMA), Prospect Theory (PT), Secondary disasters**

I. INTRODUCTION

Sudden disasters are affected by many uncertain factors such as secondary disasters. The occurrence of disaster events seriously damages the stability of the society and threatens the safety of people's lives and property. As an important part of emergency resource management, emergency materials allocation (EMA) has a significant impact on the effectiveness of emergency rescue. The supply of emergency materials after a disaster is often limited and generally in a state of short supply. There is an obvious competitive in the allocation of materials among disaster locations. Meanwhile, due to the occurrence of secondary disasters, the demand and transportation time of emergency materials are dynamic. How to allocate emergency materials reasonably and efficiently to minimize the possible losses caused by disasters is an urgent problem to be solved at present, which has important practical significance.

At present, many scholars have studied the EMA problems from different perspectives and have achieved fruitful results. [1][2][3][4][5][6][7][8][9][10] considered factors such as utility and allocation costs of EMA, and took timeliness, economy, fairness and satisfaction as the goals to established an optimal dispatch model for emergency materials. Among them, a utility maximization model for resource allocation have been established, and a resource allocation algorithm based on particle swarm optimization algorithm (PSO) have been proposed in [5][6]; single (deployment center) to several (disaster location) and several to several EMA problems have been studied respectively in [7][8]. [9][10] was no longer limited to the single-cycle emergency resource allocation, and considered the non-utility loss caused by material shortage and the coverage rate of resource allocation respectively, and a multi-cycle EMA model established in it. However, the actual disaster development is affected by many uncertain factors and is highly dynamic. The above researches did not consider dynamic disaster situation and material demand. [11][12][13][14][15] established a dynamic allocation model of EMA considering the dynamic demand, aiming at the dynamic change of casualties, time-varying supply and demand, initial rescue and remediation and so on. Among them, a dual-objective robust optimization model aiming at the minimum number of casualties and rescue centers has been established in [12]. [13] constructed the material dynamic demand function in the initial rescue and recovery stages, and assumed that the material demand showed a linear downward trend in the initial rescue stage, but this was not consistent with the non-uniform decrease of the actual material demand over time. The above researches all considered the dynamic demand, but do not consider the dynamic transport time and the impact of secondary disasters on the material demand.

In addition, all of the above researches assumed that the decision maker is completely rational, ignoring the bounded rationality of them in the actual decision. In response to the above deficiencies, an optimal scheduling model for emergency supplies with the goal of minimizing the public's psychological risk perception degree and material unsatisfaction degree has been established in [16] by introducing PT to quantify the risk perception of the public. Path attributes and risk attitudes of decision makers have

Manuscript received June 30, 2021; revised September 23, 2021. This work was supported in part by the National Natural Science Foundation of China (No. 71961016, 72161024), the Natural Science Foundation of Gansu Province (No. 20JR10RA212, 20JR10R10RA214), and "Double-First Class" Major Research Programs, Educational Department of Gansu Province (No. GSSYLXM-04).

Bin Ma is a master degree candidate at School of Traffic and Transportation, Lanzhou Jiaotong University, Lanzhou 730070, China. (e-mail: BinMa0324@163. com).

Changfeng Zhu is a Professor at School of Traffic and Transportation, Lanzhou Jiaotong University, Lanzhou 730070, China. (Corresponding author, phone: +86 18919891566, e-mail: cfzhu003@163. com).

Yubo Zhang is a master degree candidate at School of Traffic and Transportation, Lanzhou Jiaotong University, Lanzhou 730070, China. (e-mail: YuboZhang0706@163. com).

Qingrong Wang is a Professor at School of Electronic and Information Engineering, Lanzhou Jiaotong University, Lanzhou 730070, China. (e-mail: wangqr003@163. com).

been considered comprehensively and an emergency logistics selection model based on cumulative prospect theory (CPT) has been established in [17]. The risk perception of disaster victims on the delivery time of materials has been analyzed in [18], and PT and unfair theory have been introduced to it to establish an EMA model with maximum satisfaction. Considering the high risk and uncertainty of emergency situations, PT was introduced to study the problem of emergency decision-making in emergency situations in [19][20].

In fact, there are a great deal of game phenomena in emergency, and introducing the game theory to study it is in line with the actual background of the problem. In order to deepen people's understanding of game phenomenon in emergency management, [21] on emergency game was reviewed and analyzed. The game phenomenon among the government, enterprises and residents in emergency management were analyzed in [22]. A game model of public-private emergency cooperation in emergency logistics has been established in [23] by analyzing the major participating forces in emergency logistics. [24] introduced PT to depict the psychology of victims in non-cooperative game environment, and an EMA game competition model under bounded rationality has been established. [25] considered the game of demand for rescue workers among multiple disaster locations with limited emergency rescue worker and the bounded rational behavior of victims in the game process, and a bi-level game scheduling model of emergency rescue workers under bounded rationality has been constructed. It is worth mentioning that [24][25] introduced PT to depict the psychology of victims in non-cooperative game environment, which made up the complete rationality defect of the model to a certain extent. The fly in the ointment is that the above-mentioned researches still failed to break out of the limitation of the traditional game theory itself, which is completely rational.

EG imitates the theory of biological evolution, takes the population as the object, and breaks through the limitation of the assumption of complete rationality in traditional game theory. It believes that the players are bounded rational and can more reasonably describe the game behaviors of the bounded rational players [26][27]. After continuous development and improvement, EG has been widely used in research fields with interactive multi-agents, such as energy and electric power [28][29][30][31][32]. In recent years, some researches have also started to apply EG to the emergency field. Considering the problem of material demand explosion and space mismatch of material supply, a tripartite EG model of advanced emergency management, local emergency management and emergency logistics enterprises have been established in [33]. Factors such as cooperation benefit, inaction penalty and coordination cost were considered in [34], and the interaction mechanism of the relationships among government, government-owned nonprofit organizations and grassroots nonprofit organizations was researched by using EG. However, the current application of EG in the field of emergency response mainly focuses on the analysis of the interaction between public and private entities. Few researches have applied EG to EMA. In EMA, victims with bounded rationality have obvious competition and game psychology for materials. Therefore, it is necessary to introduce EG to study the problem of EMA.

Based on the above researches, this paper intends to comprehensively consider the impact of secondary disasters on the emergency materials demand and transportation time and the competitive game psychology of the disaster victims with limited rationality on the basis of existing research, and introduce the PT to characterize the perceived payment of the victims with bounded rationality on the EMA scheme. Treat disaster locations as game populations, construct a multi-population EG model of EMA under bounded rationality, and conduct research on EMA.

The rest of this paper is summarized as follows: Section II describes the problem studied in mathematical language. Based on the analysis in Section II, the EG model of EMA under bounded rationality is established in Section III. Section IV designs a case verifies the rationality of the model constructed in Section III, and analyzes the influence of some parameter changes on the results. Finally, the conclusion of this paper is in Section V.

II. Problem Description

Assuming that a disaster occurs in a certain place, a total of n disaster locations is formed. The set of disaster locations is $P=\{P_j|j=1,2,\cdots,n\}$. There is a total of m emergency material deployment centers, and the set of deployment centers is $R=\{R_i\ |i=1,2,\cdots,m\}$. In practice, emergency material allocation is a multi-stage dynamic decision-making process, the emergency response stage set is denoted as S, and the material kind set is denoted as K. In stage s, the demand for the material k at the disaster location P_j is $d_j^k(s)$, the storage capacity of the material k in the deployment center R_i is $g_i^k(s)$, and the material transportation time from R_i to P_j is $t_{ij}(s)$, the allocation quantity of material k that R_i assigned to P_j is $x_{ij}^k(s)$, and the total quantity of material k allocated to P_j is $X_j^k(s)=\sum_{i=0}^{m} x_{ij}^k(s)$, $s\in S$, $k\in K$.

Secondary disasters have an impact on material demand and transportation time. In view of the deficiencies in the literature [13], this paper deems that in the absence of rescue and secondary disasters, the material demand function roughly conforms to the right half of the normal distribution function curve, that is, roughly obeys $N(0,\sigma^2)$. Meanwhile, the demand for emergency supplies at the disaster locations change dynamically with the development of the disaster situation, as shown in Fig. 1. Then, the dynamic demand for emergency supplies is calculated as follows:

$$d_j^k(s)=\frac{1}{\sqrt{2\pi}\sigma_k}e^{-\frac{t^2}{2\sigma_k}} \tag{1}$$

$$\Delta d_j^k(s)=p_j^k(s)-D_j^k(s) \tag{2}$$

$$d_j^k(s+1)=d_j^k(s)-\Delta d_j^k(s) \tag{3}$$

Where: (1) represents the material k demand of the disaster location P_j when there is no rescue after the disaster; (2) represents the remaining quantity of the material k at the disaster location P_j in stage s, where $p_j^k(s)$ represents the quantity of the material k in stage s delivered to the disaster location P_j, $D_j^k(s)$ represents the additional material demand caused by the secondary disaster in stage s at the disaster location P_j; (3) represents the material k demand of the disaster location P_j in stage s+1.

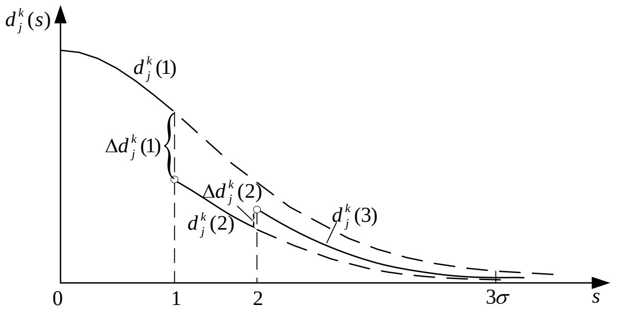


Fig.1. Schematic diagram of dynamic change of demand for any kind of emergency supplies

Considering that different sections of the emergency material transportation path are affected by the disaster to different extents, the transportation path between the deployment center R_i and the disaster location P_j is divided into several small sections, and the material transportation time is calculated using the integral idea, namely:

$$t_{ij}^r(s)=\frac{L_{ij}^r}{v(1-\varphi_{ij}^r)} \tag{4}$$

$$t_{ij}(s)=\sum_r t_{ij}^r(s) \tag{5}$$

Where: (4) represents the transportation time on the r road section between the deployment center R_i and the disaster location P_j in stage s, where L_{ij}^r is the distance of the r section, v is the average traveling speed of the vehicle, and φ_{ij}^r is the influence coefficient of the secondary disaster on the transportation time in the r road section, $\varphi_{ij}^r \in [0,1]$; (5) represents the transportation time of emergency materials from the deployment center R_i to the disaster location P_j in stage s.

III. EG Research on EMA Under Bounded Rationality

A. EG Model Construction

A.1. Participant Population

In the EG of this article, the disaster location $P_j \in P$ that produces the material competition is regarded as n participant populations. Individuals in the population freely choose strategies during the game, and conduct random repeated games.

A.2. Strategy

The strategy of the participant population is the quantity of material obtained from each deployment center. The strategy h of population P_j is $S_{j,h}^k$={ $x_{1j,h}^k$, $x_{2j,h}^k$,⋯, $x_{ij,h}^k$,⋯, $x_{mj,h}^k$}, h=1,2,…,H, as shown in Fig. 2, where $x_{ij,h}^k$ represents the material k quantity obtained by the population P_j from the deployment center R_i in the strategy h; the pure strategy set of the population P_j is S_j^k={ $S_{j,1}^k$, $S_{j,2}^k$,⋯, $S_{j,h}^k$,⋯, $S_{j,H}^k$}; the strategy combination w of all populations is S_w={$S_{1,w}^k$, $S_{2,w}^k$,⋯, $S_{j,w}^k$}. The materials allocation of the deployment center R_i in the strategy combination w is shown in Fig. 3. There may be unreasonable combinations in the above-mentioned strategy combinations, so the unreasonable combinations can be eliminated according to (6) and (7) to simplify the problem.

$$d_j^k(s) \geq \sum_{i=1}^{m} x_{ij,h}^k \tag{6}$$

$$g_i^k(s) \leq \sum_{j=1}^{n} x_{ij,h}^k \tag{7}$$

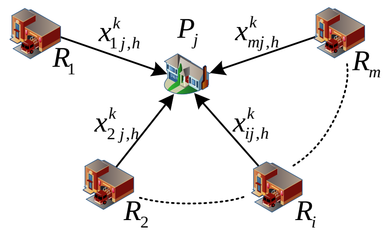


Fig.2. Schematic diagram of strategy h in the disaster location P_j

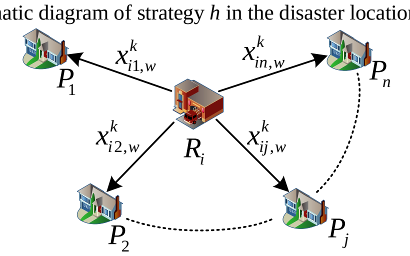


Fig.3. Schematic diagram of material allocation in the deployment center

A.3. Payment

The payment function is used to measure the payment that the players can obtain when they choose the action strategy in the game. Although EG has broken through the limitations of the assumption of complete rationality of participants, its payment function is still completely rational [35]. In order to eliminate the completely rational residue in EG, PT is introduced in this paper to describe the payment function of the participants in EG. In the EMA, the disaster locations usually judge the benefits from the attributes of allocation quantity and delivery time. Therefore, this paper starts with the attributes of the allocation quantity and the delivery time to construct the payment function of the population at the disaster locations.

a. Material Allocation Quantity

It is reasonable to use PT to describe the psychology of disaster victims. The victims form a psychological reference point based on the material reserves of the deployment center and the material demand of the disaster location, and then judge the gains and losses according to the relative relationship between the plan and the reference point. Assuming that the reference point of the allocation quantity of materials is X_0^k, the reference point of the allocation quantity in stage s and the initial reference point are respectively as (8) and (9):

$$X_0^k(s)=\max\{X_j^k(s-1), X_0^k(s-1)\}, s \geq 2 \tag{8}$$

$$X_0^k(1)=\frac{1}{m}\sum_{i=0}^{m} g_i^k(1) \tag{9}$$

According to PT, the value function of allocation quantity of the disaster location P_j as (10). That is, when $X_j^k(s) \geq X_0^k(s)$, the scheme is expressed as a profit, and the value function is a concave function; when $X_j^k(s) < X_0^k(s)$, it is expressed as a loss, and the value function is a convex function. It reflects that disaster victims are risk-averse when facing gains, but are risk-appetite when facing losses, and are more sensitive to losses than gains. The value function curve is shown in Fig. 4.

$$v(X_j^k(s))=\begin{cases}[X_j^k(s)-X_0^k(s)]^{\alpha}, & X_j^k(s)\geq X_0^k(s)\\ -\lambda[X_0^k(s)-X_j^k(s)]^{\beta}, & X_j^k(s)<X_0^k(s)\end{cases} \tag{10}$$

Where, α and β indicate the risk attitude coefficient, $0<\alpha, \beta<1$; λ indicates the loss aversion coefficient, $\lambda>1$.

The objective probability set of population P_j strategy set is $Q_j=\{p_{j,1}^k, p_{j,2}^k,\cdots, p_{j,h}^k,\cdots, p_{j,H}^k\}$, where $p_{j,h}^k$ is the probability of strategy h, and H is the total number of strategies. Then the subjective probability function of the material allocation quantity is shown in (11) and (12). That is, the subjective probability is smaller than the actual value when the actual probability of the plan is large; the subjective probability is larger than the actual value when on the contrary. This is the principle of PT "favorite small probability events". The subjective probability function curve is shown in Fig. 5.

$$\omega^{+}(p)=\frac{(p_{j,h}^k)^{\gamma}}{[(p_{j,h}^k)^{\gamma}+(1-p_{j,h}^k)^{\gamma}]^{1/\gamma}} \tag{11}$$

$$\omega^{-}(p)=\frac{(p_{j,h}^k)^{\delta}}{[(p_{j,h}^k)^{\delta}+(1-p_{j,h}^k)^{\delta}]^{1/\delta}} \tag{12}$$

Where, γ and δ represent the perceptual probability coefficient, and $\gamma, \delta>0$.

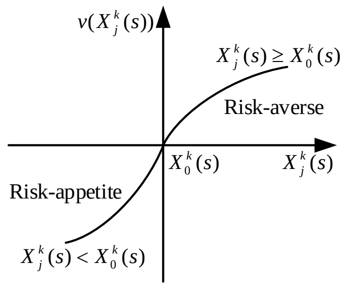


Fig.4. Allocation value function curve

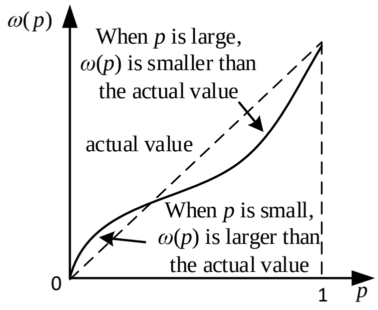


Fig.5. Subjective probability function curve

In summary, the payment of the allocation quantity of emergency material k of the population P_j in stage s is:

$$U1_j^k(s)=[X_j^k(s)-X_0^k(s)]^{\alpha}\omega^{+}(p)-\lambda[X_0^k(s)-X_j^k(s)]^{\beta}\omega^{-}(p) \tag{13}$$

b. Delivery Time of Materials

The judgment of the disaster locations on the materials delivery time is a behavior based on a priori information, that is, the disaster location will generate the perceived material delivery time of current stage based on the delivery time of the previous stage [36]. Assume that the perceptual delivery time of the disaster locations in stage s obeys the normal distribution: $T_j(s) \sim N(\tau_{j,s},\sigma_{j,s}^2)$. Where, $\tau_{j,s}$ and $\sigma_{j,s}^2$ are calculated as follows:

$$\tau_{j,s}=\frac{1}{s-1}\sum_{i}^{s-1}(T_j(i)) \tag{14}$$

$$\sigma_{j,s}^2=\frac{1}{s-2}\sum_{i}^{s-1}[(T_j(i))-\tau_{j,i}]^2 \tag{15}$$

When $s=1$ (the first allocation), disaster location can only estimate the possible delivery time based on the physical characteristics of the path. Here, the free flow time $T_{j,free}$ of the path is used to represent the physical characteristics of the path: $\tau_{j,1}=T_{j,free}$ and $\sigma_{j,1}^2=0$, where, $T_{j,free}=\max_i\{t_{ij,free}\}$. Assume that the delivery time reference point determined by the disaster location P_j in stage s according to the prior information is:

$$T_j^0(s)=\frac{1}{m}\sum_{i=1}^{m}t_{ij}(s-1) \tag{16}$$

The value function of the disaster location P_j to the delivery time of the materials is shown in (17). In other words, when $T_{j,free}\leq T_j(s)\leq T_j^0(s)$, the materials can be delivered to the disaster location in time, and the scheme is shown as a gain; when $T_j(s)>T_j^0(s)$, the delivery is overdue, and the scheme is shown as a loss. The value function curve is shown in Fig. 6.

$$v(T_j(s))=\begin{cases}[T_j^0(s)-T_j(s)]^{\alpha}, & T_{j,free}\leq T_j(s)\leq T_j^0(s)\\ -\lambda[T_j(s)-T_j^0(s)]^{\beta}, & T_j(s)>T_j^0(s)\end{cases} \tag{17}$$

Assuming that the possible result of the material delivery time is A_l, its subjective probability is shown in (19) and (20):

$$A_l=\begin{cases}\text{"Timely delivery"}, & T_{j,free}\leq T_j(s)\leq T_j^0(s)\\ \text{"Delay in delivery"}, & T_j(s)>T_j^0(s)\end{cases} \tag{18}$$

$$\begin{aligned}p_j^1(s)&=P(A_l=\text{"Timely delivery"})\\ &=P(T_{j,free}\leq T_j(s)\leq T_j^0(s))\\ &=\frac{1}{\sqrt{2\pi}\sigma_{j,s}}\int_{T_{j,free}}^{T_j^0(s)}e^{-\frac{(T_j(s)-\tau_{j,s})^2}{2\sigma_{j,s}^2}}dT\end{aligned} \tag{19}$$

$$p_j^2(s)=1-p_j^1(s) \tag{20}$$

Therefore, the subjective probability function of the material delivery time is as shown in (21) and (22), and the function curve is the same as that in Fig. 5.

$$\omega^{+}(p)=\frac{(p_j^1(s))^{\gamma}}{[(p_j^1(s))^{\gamma}+(1-p_j^1(s))^{\gamma}]^{1/\gamma}} \tag{21}$$

$$\omega^{-}(p)=\frac{(p_j^2(s))^{\delta}}{[(p_j^2(s))^{\delta}+(1-p_j^2(s))^{\delta}]^{1/\delta}} \tag{22}$$

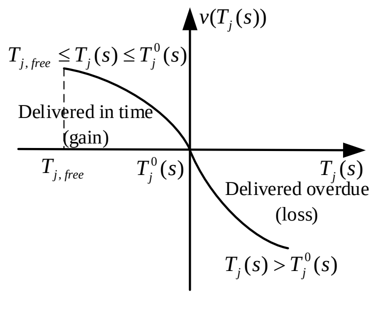


Fig.6. Delivery time value function curve

In summary, the payment of materials' delivery time of population P_j in stage s is:

$$U2_j(s) = [T_j(s) - T_j^0(s)]^{\alpha}\omega^+(p) - \lambda[T_j(s) - T_j^0(s)]^{\beta}\omega^-(p) \quad (23)$$

c. Population Payment Function

Since the allocation quantity attribute $U1$ and delivery time attribute $U2$ are different in dimension, each attribute payment needs to be dimensionless. Suppose $U1_{j,h}^k$ and $U2_{j,s}$ respectively denotes the allocation quantity payment and delivery time payment of strategy h, and the payments of two attributes are processed dimensionless as follows:

$$U1_{j,h}^{k\,*}(t) = \frac{U1_{j,h}^k(t)}{\max\limits_h\{|U1_{j,h}^k(t)|\}} \quad (24)$$

$$U2_{j,h}^{\ *}(t) = \frac{U2_{j,h}(t)}{\max\{|U2_{j,h}(t)|\}} \quad (25)$$

Suppose ε_1 and ε_2 are the decision preference coefficients of attributes $U1$ and $U2$ respectively, and $\varepsilon_1+\varepsilon_2=1$, then the payment function of the strategy h of population P_j in stage s is:

$$U_{j,h}^k(s) = \varepsilon_1 U1_{j,h}^{k\,*}(s) + \varepsilon_2 U2_{j,h}^{\ *}(s) \quad (26)$$

A.4. The Replicator Dynamics Equation

EG uses evolutionary dynamics to characterize the adaptive learning behaviors of game players. The most common evolutionary dynamic is the replicator dynamics. The evolutionary state is analyzed by establishing the dynamic equation of replicator. Let $y_{j,h}^k$ be the proportion of individuals in the selection strategy $S_{j,h}^k$ in the total population, and $\sum_h y_{j,h}^k = 1$. Let f_j^h be the fitness function of population P_j when the strategy $S_{j,h}^k$ is adopted, namely:

$$f_j^h = \sum_{q=1}^{H} y_{b,q}^k \cdots \sum_{p=1}^{H} y_{a,p}^k U_{j,h}^k \qquad a,b,j \in R_j \quad (27)$$

The average fitness of the population P_j is:

$$\bar{f}_j = \sum_{h=1}^{H} y_{j,h}^k f_j^h \qquad j \in R_j, k \in K \quad (28)$$

Then the replicator dynamics equation of population P_j can be expressed as:

$$\dot{y}_{j,h}^k = y_{j,h}^k \cdot (f_j^h - \bar{f}_j) \quad (29)$$

B. Evolutionary Equilibrium Solution

In evolutionary equilibrium, the strategies of each population are the optimal response to the other groups' strategies, so the individual representing the evolutionary equilibrium has the optimal fitness. The strategy chosen by this individual is the evolutionarily stable strategy (ESS). Regarding ESS, there is the following theorem [37]: For $\forall p \in S$, and $p \neq q$, if $\exists \varepsilon_p \in (0,1)$, the fitness function of the population when the strategy is q satisfies: $f[q, \varepsilon p + (1-\varepsilon)q] > f[p, \varepsilon p + (1-\varepsilon)q], \forall \varepsilon \in (0, \varepsilon_p)$, then $p \in S$ is called ESS.

The ESS of various groups together constitute the evolutionary equilibrium of the game, and solving the evolutionary equilibrium is to solve the ESS of various populations. Therefore, the solution process of evolutionary equilibrium in this paper is shown in Fig. 7.

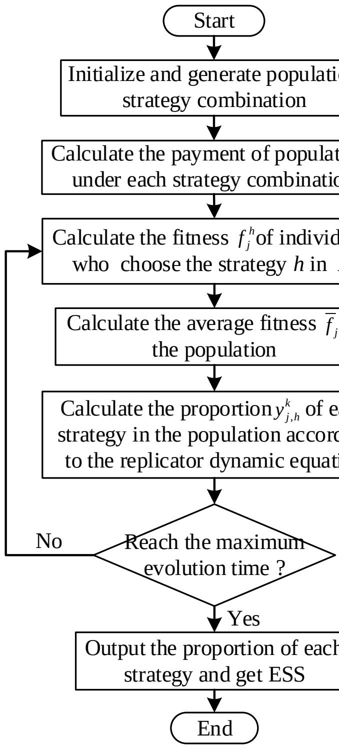


Fig.7. Evolutionary equilibrium solution process

IV. Case Study

A. Case Background

When a natural disaster occurred in an area, there were a total of 3 material deployment centers, and 3 disaster locations were formed. Assuming that the demand for a certain kind of emergency materials at the disaster locations P_1, P_2, and P_3 is 1,700, 1,500, and 1,900 respectively during a certain stage of emergency response. At this stage, 1,200, 1,100, and 1,300 materials have been delivered to the three disaster locations, The new material demand caused by the secondary disaster in the current stage is 1000, 600, and 900 pieces respectively. According to (2) and (3), the material demand of each disaster location in the next stage is calculated, as shown in Table I. The emergency material reserves of each deployment center in the current stage are shown in Table II.

TABLE I
EMERGENCY MATERIALS DEMAND AT THE DISATER LOCATION

Disaster locations	P_1	P_2	P_3
Demand (100 units)	15	10	15

TABLE II
EMERGENCY MATERIAL RESERVES OF THE DEPLOYMENT CENTER

Deployment centers	R_1	R_2	R_3
Reserves (100 units)	10	15	10

The distance L of each road section between the deployment center and the disaster location and the influence coefficient φ of secondary disasters on the road section are all known, as shown in Table III.

TABLE III
ROAD SECTION DISTANCE AND SECONDARY DISASTER IMPACT COEFFICIENT

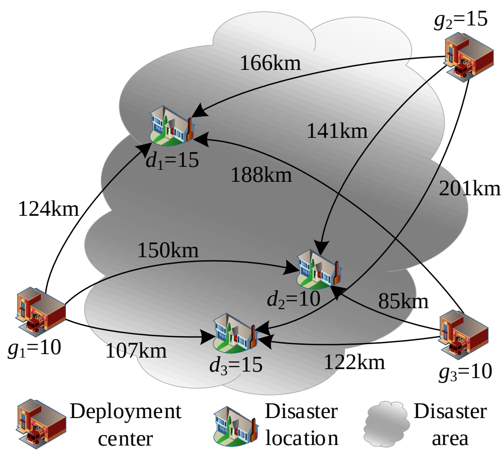
<table>
<tr><td colspan="3">Disaster locations</td><td colspan="12">P_1</td><td colspan="6">P_2</td><td colspan="12">P_3</td></tr>
<tr><td rowspan="6">Deployment centers</td><td rowspan="2">R_1</td><td>L (km)</td><td colspan="6">55</td><td colspan="6">69</td><td colspan="2">50</td><td colspan="2">46</td><td colspan="2">54</td><td colspan="6">49</td><td colspan="6">58</td></tr>
<tr><td>φ</td><td colspan="6">0.45</td><td colspan="6">0.45</td><td colspan="2">0.33</td><td colspan="2">0.63</td><td colspan="2">0.57</td><td colspan="6">0.00</td><td colspan="6">0.24</td></tr>
<tr><td rowspan="2">R_2</td><td>L (km)</td><td colspan="4">63</td><td colspan="4">38</td><td colspan="4">65</td><td colspan="3">65</td><td colspan="3">76</td><td colspan="3">45</td><td colspan="3">42</td><td colspan="3">63</td><td colspan="3">38</td></tr>
<tr><td>φ</td><td colspan="4">0.32</td><td colspan="4">0.24</td><td colspan="4">0.40</td><td colspan="3">0.42</td><td colspan="3">0.45</td><td colspan="3">0.00</td><td colspan="3">0.44</td><td colspan="3">0.32</td><td colspan="3">0.24</td></tr>
<tr><td rowspan="2">R_3</td><td>L (km)</td><td colspan="3">35</td><td colspan="3">47</td><td colspan="3">57</td><td colspan="3">49</td><td colspan="3">42</td><td colspan="3">43</td><td colspan="4">40</td><td colspan="4">35</td><td colspan="4">47</td></tr>
<tr><td>φ</td><td colspan="3">0.00</td><td colspan="3">0.37</td><td colspan="3">0.37</td><td colspan="3">0.51</td><td colspan="3">0.30</td><td colspan="3">0.45</td><td colspan="4">0.33</td><td colspan="4">0.00</td><td colspan="4">0.37</td></tr>
</table>

Assuming that the average travel speed of the vehicle v=50km/h, the emergency material transportation time between the disaster location and the deployment center is calculated according to (4) and (5), and the results are shown in Table IV.

TABLE IV
MATERIAL TRANSPORTATION TIME

Time (h)		Disaster locations		
		P_1	P_2	P_3
Deployment centers	R_1	4.5	6.5	2.5
	R_2	5	5	6.75
	R_3	6	2.75	4

Fig. 8 can be obtained by integrating the comprehensive disaster information of the disaster area in the current stage.



Note: The darker the color of the disaster area, the more serious the disaster

Fig.8. Comprehensive disaster information in the disaster area

B. Case Solving

Let the PT risk attitude coefficient α and β be 0.88, the loss aversion coefficient λ be 2.25, the perceived probability coefficient γ and δ be 0.61 and 0.69. The preference coefficients of attribute decision making ε_1 and ε_2 are both 0.5. In order to reduce the difficulty of the solution without loss of generality, the calculation example uses 5 units as the step size to generate a population strategy set, and eliminates the strategies that do not meet the demand constraints of the disaster locations. The final number of strategies for the three populations is 17, 9, and 17, respectively. The objective probability of each strategy in the population strategy set is determined by the fuzzy comprehensive evaluation method proposed in [38].

The EG model is solved by Matlab2016b in this paper. The maximum evolution time is set to 100s, and the evolutionary state of each population is shown in Fig. 9, Fig. 10, and Fig. 11. The proportion of each strategy in the game environment is constantly changing with the continuous evolution of the population, and the final evolutionary stable state has nothing to do with the initial state of the population, but is only related to the game environment. Fig. 9 shows the evolution state curve of population P_1 at the disaster location.

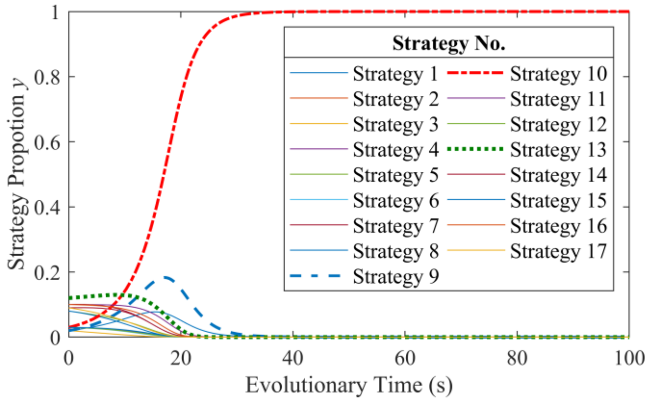


Fig.9. Evolution state of population P_1

As can be seen from Fig. 9, the proportion of each strategy changes constantly as the evolution progresses, and the population evolves most violently in the first 25s. When it evolves to about 10s, the growth rate of Strategy 14 accelerates and its proportion in the population increases sharply. When it evolves to about 30s, the proportion of Strategy 14 approaches 1, and the proportion of other strategies gradually tend to 0. This indicates that in the long-term evolution process, strategy 14 becomes the dominant strategy of population P_1 and is gradually retained in the "survival of the fittest", whereas the other strategies are all inferior strategies and gradually eliminated. Obviously, strategy 14 is the ESS of population P_1. Fig. 10 shows the evolution state curve of population P_2 at the disaster location.

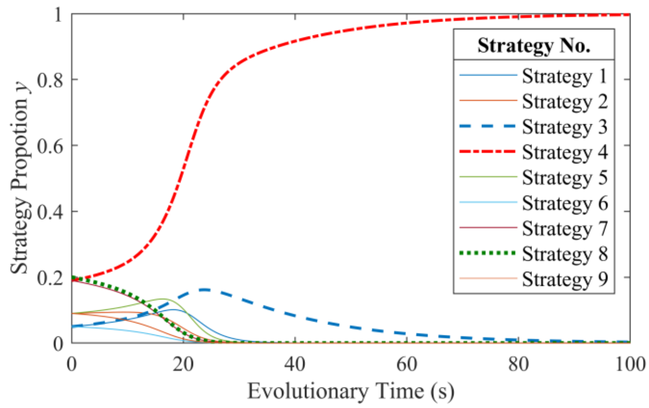


Fig.10. Evolution state of population P_2

It can be found from Fig. 10 that the growth rate of strategy 4 has been rising since the beginning of evolution. The population evolution was most intense in the first 25s, and most strategies were eliminated in the current stage. The evolution gradually slows down after 30s, and there is almost only strategy 3 and strategy 4 in the population. When it evolves to about 90s, the proportion of strategy 4 approaches 1, and the proportion of strategy 3 approaches 0. That is to say, after a long period of "survival of the fittest", strategy 4 becomes the ESS of population P_2. Fig. 11 shows the evolution state curve of population P_3.

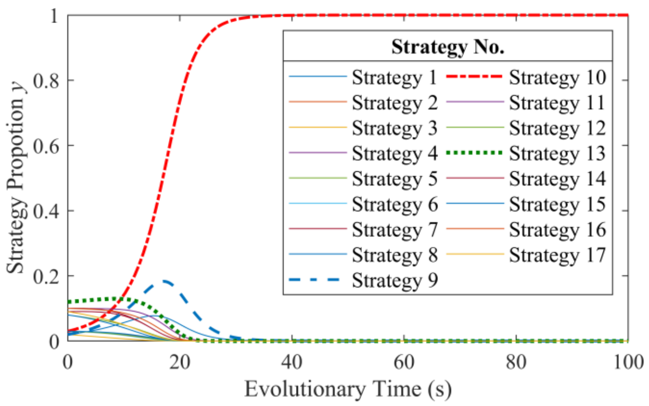


Fig.11. Evolution state of population P_3

From Fig. 11, we can find that the evolution process of population P_3 is similar to that of population P_1, which is intense in the first 25s. In the 30s, the inferior strategies are gradually eliminated, leaving only strategy 10 in the population, and the proportion of strategy 10 reaches 1. This indicates that all individuals in the population eventually choose strategy 10 with the evolution, which is the dominant strategy and eventually becomes the ESS of population P_3.

Comprehensive analysis Fig. 9, Fig. 10, and Fig. 11, we can find that the population strategy can be roughly classified into three kinds. Take population P_1 as an example: the first kind is "obvious disadvantage strategy" represented by strategy 13. As the evolution progresses, fewer and fewer individuals choose this part of strategy, leading to a gradual decline in the proportion of this part of strategy, and the proportion approaching to 0 at about 25s. The second kind is "general disadvantage strategy" represented by strategy 12, In the evolutionary process, the proportion of these strategies increases first and then decreases to 0. In the stage of increasing proportion, this part of the strategy is better than the "obviously disadvantaged strategy" and become the local dominant strategy of the population. However, with the change of game environment, new dominant strategies appear and these strategies are eliminated eventually. The third kind is the ESS, whose proportion continues to increase during evolution and eventually evolves to 1, in line with the idea of "survival of the fittest". In addition, the most intense stages of evolution of the three populations are all concentrated in the first 25s, which indicates that the whole game environment is the most complex at this stage, and the populations influence and restrict each other, and the fluctuating of each strategy's proportion is related to others. The strategy combination jointly constituted by the ESS of various groups is evolutionary equilibrium. The evolutionary equilibrium in this paper is the 2050th strategy combination. The evolutionary equilibrium represents the final EMA scheme, and the scheme is shown in Table V.

TABLE V
THE 2050TH EMA SCHEME

Allocation quantity (100 units)		Disaster locations P_1	P_2	P_3
Deployment centers	R_1	5	0	5
	R_2	10	5	0
	R_3	0	5	5
Total allocation (100 units)		15	10	10

By integrating the distribution plan in Table 5 with the comprehensive disaster information in the disaster area in Fig. 8, the final schematic diagram of material allocation can be visualized, as shown in Fig. 12.

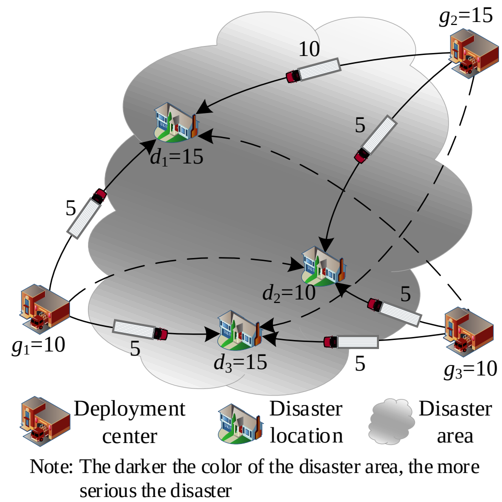


Fig.12. Schematic diagram of final material allocation

From Table V, we can find that the materials of the deployment center are all allocated to the disaster location. The total allocation of materials at the disaster location P_1 and P_2 meets the demand, whereas the total allocation of materials at P_3 does not meet the demand, which is in line with the background that emergency materials are in short supply. In Table V, the quantity of material allocated from some of the deployment centers to the disaster locations is 0. From Fig. 12, it is not difficult to find that the transportation routes between these disaster locations without material allocation and the corresponding deployment centers (indicated by the dotted line in the figure) have longer distance and are more severely affected by secondary disasters (the disaster area is in darker color in figure). As a result, the material transportation time is too long on these routes, and the disaster locations' psychological perception of the material delivery time is in a serious "loss" state. Therefore, these "loss" allocation schemes are gradually eliminated in the evolution of the game.

C. *Sensitivity Analysis of Decision Preference Coefficient*

The decision preference coefficient of attribute represents the proportion of different attributes in decision-making. In order to analyze the influence of decision preference coefficients ε_1 and ε_2 on the evolutionary equilibrium, a sensitivity analysis is performed on ε_1 and ε_2. The results are shown in Table VI.

TABLE VI
SENSITIVITY ANALYSIS OF DECISION PREFERENCE COEFFICIENT

.	1	2	3	4	5	6	7	8	9
ε_1	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
ε_2	0.9	0.8	0.7	0.6	0.5	0.4	0.3	0.2	0.1
Equalization Scheme No.	1234	1234	1234	2050	2050	2050	2050	1747	1747

It can be found from Table VI that when ε_1 and ε_2 take different values, the population will evolve different equilibrium schemes. When the delivery time preference coefficient ε_2 exceeds 0.6, the equalization scheme is 1234th scheme, as shown in Table VII.

TABLE VII
THE 1234TH EMA SCHEME

Allocation quantity (100 units)		Disaster locations		
		P_1	P_2	P_3
Deployment centers	R_1	5	0	5
	R_2	0	0	0
	R_3	0	5	5
Total allocation (100 units)		5	5	10

It can be found from Table VII that there is still a large quantity of surplus materials in the deployment center R_2, and the total allocation of materials in each disaster location does not meet the demand. Combining Table III and Table IV, it can be found that the allocation of materials only exists between the disaster location and the deployment center with a short transportation time. The reason is that when the value of ε_2 exceeds 0.6, the disaster location pays more attention to the delivery time when selecting the scheme, resulting in the scheme with longer transportation time was eliminated in advance. Although this scheme fully considers the timeliness of the delivery of emergency materials, it sacrifices the allocation quantity and is only applicable to emergency materials (such as medical materials) that require high timeliness. When the value of ε_2 less than 0.3, the equalization scheme is 1747th scheme, as shown in Table VIII.

TABLE VIII
THE 1747TH EMA SCHEME

Allocation quantity (100 units)		Disaster locations		
		P_1	P_2	P_3
Deployment centers	R_1	5	0	5
	R_2	5	5	5
	R_3	0	5	5
Total allocation (100 units)		10	10	15

It can be found from Table VIII that all the materials of the deployment center are allocated to the disaster location, and only the total material allocation of the disaster location P_1 does not meet the demand. Combining Table III and Table IV can be found that there is still material allocation between the OD pairs (from deployment center to disaster location) that have a long transportation time. The reason is that when the value of ε_2 is too small, the disaster location pays more attention to the allocation quantity in decision-making, and less timeliness is considered. This scheme is more suitable for resettlement materials (such as tents, clothing, etc.) that have an absolute demand for the allocation quantity.

When the value of ε_2 is between 0.3 and 0.6, the equalization scheme is 2050th scheme, as shown in Table V. The value of scheme ε_1 and ε_2 of the scheme is relatively balanced, which not only considers the quantity of material allocation, but also satisfies the timeliness of delivery, which is a relatively balanced scheme. This scheme is suitable for necessities of life (such as food) that have certain requirements for timeliness and distribution quantity. It can be seen that the ε_1 and ε_2 are both 0.5 in this case, which is in line with the actual situation of the allocation of daily necessities in general emergency decision-making. Fig. 13 is an intuitive comparison diagram of different EMA schemes when the decision preference coefficients ε_1 and ε_2 take different values.

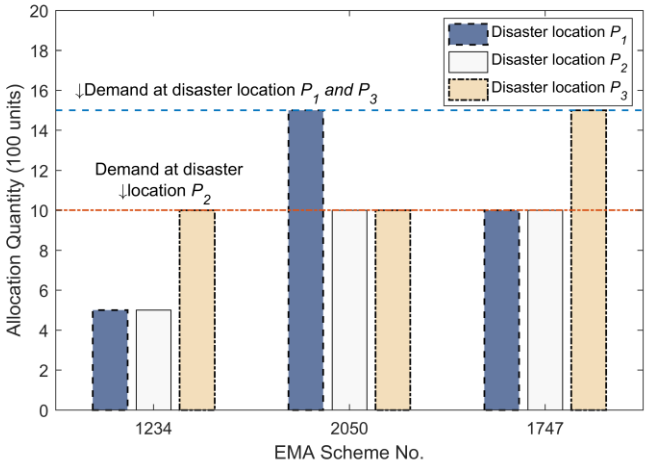


Fig. 13. Intuitive comparison bar graph of EMA scheme

From Fig. 13, it can be found that the total allocation of scheme 2050 and scheme 1747 is better than scheme 1234. This is because when the time decision preference coefficient ε_2 is too large, the comprehensive prospect value of the scheme is mainly determined by the time prospect value, that is to say, the disaster location is more concerned about the absolute delivery time, which leads to a backlog of materials in the relatively far away deployment center, which also shows that excessive attention to time attributes will reduce the utilization of emergency resources to a certain extent.

On the contrary, when the value of the allocation decision preference coefficient ε_1 is too large, the disaster location will care more about the fairness of the allocated quantity, resulting in the distribution of materials between the ODs with longer transportation distances (for example, between the deployment center R_2 and the disaster location P_3 in scheme 1747), which shows that excessive emphasis on the attributes of the allocation will have a certain impact on the timeliness of emergency response.

In general, the disaster location should reasonably set the decision-making preference coefficient according to the disaster situation and the kinds of materials to ensure the maximum overall emergency response efficiency.

D. Parametric Analysis in PT

The population evolution direction is determined by the prospect value of the scheme, which is closely related to the values of parameters α, β, γ and δ. In order to analyze the sensitivity of the prospect value to the parameters α, β, γ and δ, the evolutionary equilibrium scheme (the 2050th strategy combination) is taken as an example. Fig. 14 shows the influence of risk attitude coefficients α and β on the comprehensive prospect value of population P_1.

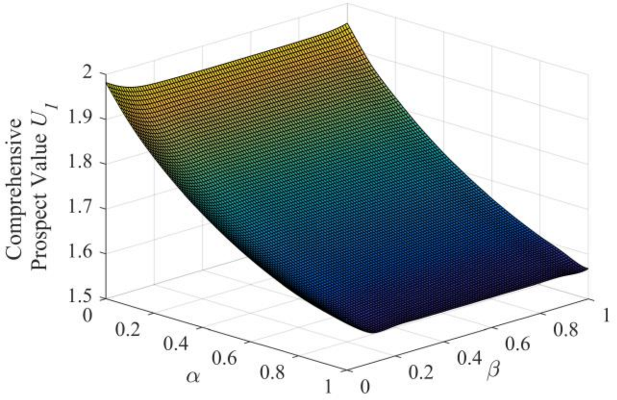


Fig. 14. The influence of parameters α and β on the prospect value of the scheme in P_1

As can be found from Fig. 14, the comprehensive prospect value of population P_1 is inversely proportional to the income risk attitude coefficient α, and almost irrelevant to the value of the loss risk attitude coefficient β. That is to say, the population P_1 is always in the profit area, indicating that the allocation quantity of materials is higher than the psychological expectations of the victims in the disaster location, and the delivery time is earlier than the psychological expectations of the victims. The disaster victims are too pessimistic about the disaster situation and are unwilling to take greater risks to pursue higher benefits, which is in line with the decision-making psychology of the disaster location eager to get emergency materials under bounded rationality. Fig. 15 shows the influence of α and β on the comprehensive prospect value of population P_2.

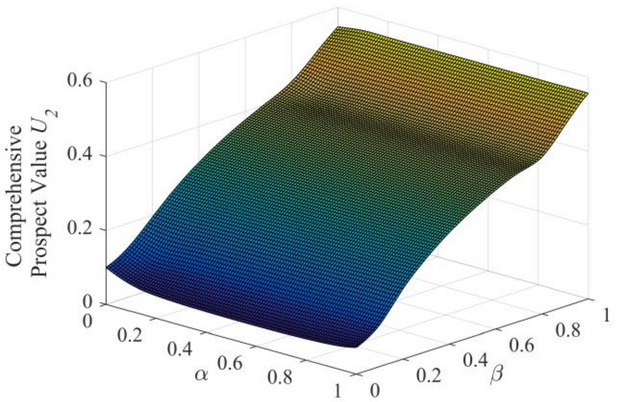


Fig. 15. The influence of parameters α and β on the prospect value of the scheme in P_2

As shown in Fig. 15, the comprehensive prospect of population P_2 decreases with the increase of β, which is almost independent of the value of α. That is to say, the value function of population P_2 is always in the loss area, indicating that the allocation quantity of materials is lower than the psychological expectations of the victims in the disaster location, and the delivery time is later than the psychological expectations of the victims. The disaster victims are too optimistic about the disaster situation and are willing to take risks to pursue benefits. It conforms to the decision-making psychology that the disaster location expects too much to the allocation scheme under bounded rationality. Fig. 16 shows the influence of α and β on the comprehensive prospect value of population P_3.

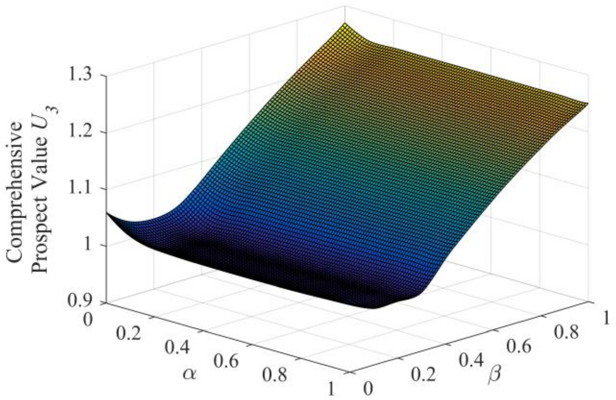


Fig. 16. The influence of parameters α and β on the prospect value of the scheme in P_3

As shown in Fig. 16, the comprehensive prospect value of population P_3 is sensitive to β but not to α, because the value function of population P_3 is always in the loss area, and the prospect value of the scheme is only affected by β, which indicates the victims' estimates of the disaster situation are too optimistic and are willing to take risks to pursue benefits, which is in line with the decision-making psychology that the disaster point is too expected to the allocation scheme under bounded rationality. Fig. 17 shows the influence of perceptual probability coefficients γ and δ on the comprehensive prospect value of population P_1.

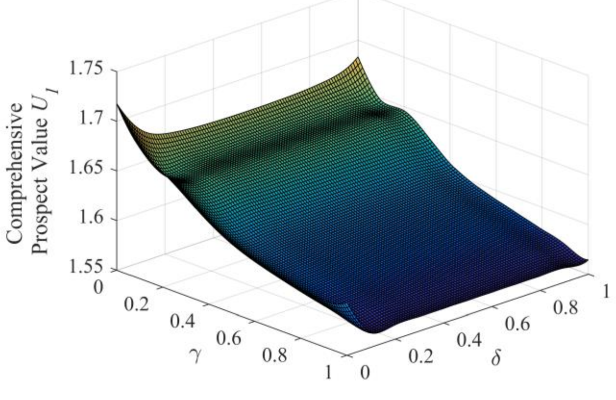


Fig.17. The influence of parameters γ and δ on the prospect value of the scheme in P_1

It can be found from Fig. 17 that the comprehensive prospect value of the population P_1 is closely related to the income perception probability coefficient γ, and is almost irrelevant to the value of the loss perception probability coefficient δ. This is because the allocation scheme for the population P_1 is shown as a benefit. As the increase of γ, the comprehensive prospect value of the scheme decreases, which conforms to the decision-making psychology of the disaster location that the allocation scheme is too high under bounded rationality. Fig. 18 shows the influence of the perceived probability coefficients γ and δ on the comprehensive prospect value of the population P_2.

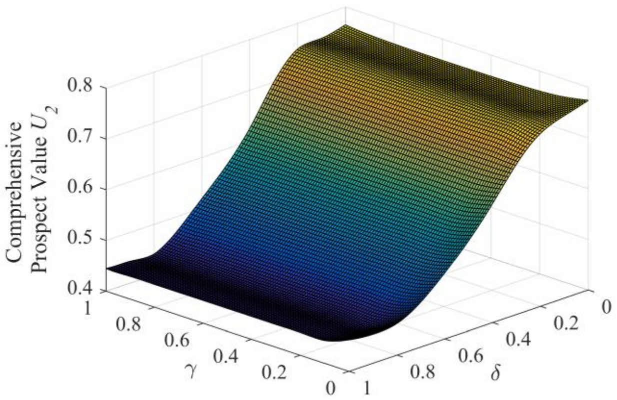


Fig.18. The influence of parameters γ and δ on the prospect value of the scheme in P_2

As can be seen from Fig. 18, the comprehensive prospect value of population P_2 is closely related to the loss perception probability coefficient δ and has almost nothing to do with the value of the income perception probability coefficient γ. This is because the allocation scheme for population P_2 is a loss. As δ increases, the comprehensive prospect value of the scheme decreases, which is in line with the decision-making psychology of excessively high expectation of disaster locations under bounded rationality. Fig. 19 shows the influence of the perceptual probability coefficients γ and δ on the comprehensive prospect value of population P_3.

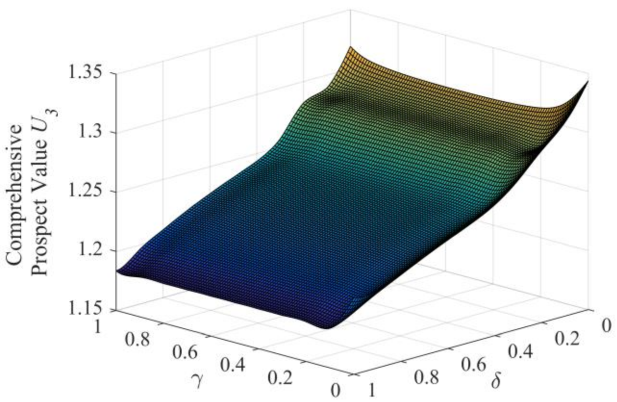


Fig.19. The influence of parameters γ and δ on the prospect value of the scheme in P_3

It can be seen from Fig. 19 that the sensitivity of population P_3 to the perceived probability coefficients γ and δ is the same as that of population P_3, that is, it is more sensitive to the loss perception probability coefficient δ. This is because the allocation scheme of population P_3 also in loss. As δ increases, the comprehensive prospect value of the scheme decreases, which is in line with the decision-making psychology of the disaster location with excessive expectation of the allocation scheme under bounded rationality.

Based on the aforementioned analysis, it is obvious that disaster victims are more inclined to pursue risk when the expected benefits are less and the disaster forecast is pessimistic. On the contrary, when there are more expected benefits and disaster forecasts are more optimistic, disaster victims are more inclined to risk aversion.

V. Conclusion

This study focuses on the bounded rationality of disaster victims in the actual emergency rescue process and the competitive game psychology of different disaster locations for materials under the background of short supply. PT is embedded in the EG model, and the EMA multi-population EG model under bounded rationality is established.

The case simulation results show that the model can effectively compensate for the lack of complete rationality of the participants in the study of EMA in non-cooperative game theory; further, the model also considers the impact of the changing game environment on the disaster location and the adaptive learning behavior of the disaster victims, which can explain the bounded rational game phenomenon more effectively in EMA and make the decision result more in line with reality, and can be applied to EMA problems in some scenarios.

Sensitivity analysis of the model parameters shows that on the one hand different kinds of materials have different preferences for the allocation quantity and delivery time. When formulating the EMA scheme, the preference coefficient should be set reasonably according to the kind of materials, and the disaster situation to make the scheme more in line with reality; on the other hand, the disaster victims' psychological perception of the EMA scheme is related to the disaster situation. When the disaster victims are too optimistic about the disaster situation, the EMA scheme may not meet the psychological expectations of disaster victims. On the contrary, when the estimation is too pessimistic, the EMA scheme may exceed their psychological expectations; in addition, in different income areas of PT, the risk attitude and probability perception ability of disaster victims have different influences on the EMA scheme. The disaster location should reasonably set a psychological reference point according to the disaster situation, so that the attributes of the distribution plan fall as far as possible in the income area that is beneficial to itself.

In practice, the demand for emergency materials is often diversified. Considering the diversified demand of materials and making the EMA scheme more realistic will be the focus of the next step of research.

References

[1] Y.Y. Wang, and B.Q. Sun, "A Multi objective Allocation Model for Emergency Resources That Balance Efficiency and Fairness," *Mathematical Problems in Engineering*, vol. 2018, Article ID. 7943498, 2018.

[2] J. Liu, L. Guo, J.P. Jiang, D.X. Jiang, P. Wang, "Emergency material allocation and scheduling for the application to chemical contingency spills under multiple scenarios," *Environmental Science and Pollution*

Research, vol. 24, no.3, pp. 956-967, 2017.

[3] D.Q. Chen, F. Ding, Y. Huang, D.Z. Sun, "Multi-objective optimization model of emergency material allocation in emergency logistics: a view of utility, priority and economic principles," *International Journal of Emergency Management*, vol. 14, no. 3, pp. 233-253, 2018.

[4] Hasti Seraji, Reza Tavakkoli-Moghaddam, Sobhan Asian, Harpreet Kaur, "An integrative location-allocation model for humanitarian logistics with distributive injustice and dissatisfaction under uncertainty," *Annals of Operations Research*, 2021. DOI: https://doi.org/10.1007/s10479-021-04003-5

[5] S.Y. Li, H. Liu, Y.F. Du, and C.G. E, "An Optimal Resource Allocation Scheme for Elastic Applications in Multipath Networks via Particle Swarm Optimization," *IAENG International Journal of Computer Science*, vol. 47, no. 2, pp. 278-283, 2020.

[6] S.Y. Li, J. Lin, Y. Zhang, Y. Wang, and W. Sun, "A Scheme of Resource Allocation for Heterogeneous Services in Peer-to-peer Networks using Particle Swarm Optimization," *IAENG International Journal of Computer Science*, vol. 44, no. 4, pp. 482-488, 2017.

[7] C.L. Hu, X. Liu, and Y.K. Hua, "A bi-objective robust model for emergency resource allocation under uncertainty," *Taylor & Francis*, vol. 54, no. 24, pp. 7421-7438, 2016.

[8] D.Q. Chen, F. Ding, Y. Huang, D.Z. Sun, "Multi-objective optimization model of emergency material allocation in emergency logistics: a view of utility, priority and economic principles," *Int. J. of Emergency Management*, vol. 14, no.3, pp. 233-253, 2018.

[9] Y.Y. Wang, Vicki M. Bier, B.Q. Sun, "Measuring and Achieving Equity in Multiperiod Emergency Material Allocation," *Risk Analysis*, vol. 39, no. 14, pp. 2408-2426, 2019.

[10] Y.Y. Wang, "Multiperiod Optimal Allocation of Emergency Resources in Support of Cross-Regional Disaster Sustainable Rescue," *International Journal of Disaster Risk Science*, vol. 12, no. 3, pp. 394-409, 2021.

[11] Z.S. Yang, H.X. Zhou, X.Y. Gao, and S.N. Liu, "Multiobjective Model for Emergency Resources Allocation," *Mathematical Problems in Engineering*, vol. 2013, Article ID. 538695, 2013.

[12] H.L. Sun, Y. Wang, and Y.F. Xue, "A bi-objective robust optimization model for disaster response planning under uncertainties," *Computers & Industrial Engineering*, vol. 155, Article ID. 107213, 2021.

[13] L. Zhu, J. Cao, J. Gu, Y. Zheng, "Dynamic emergency supply distribution considering fair mitigation of victim suffering," *Systems Engineering-Theory & Practice*, vol. 40, no. 9, pp. 2427-2437, 2020.

[14] J. Liu, L. Guo, J.P. Jiang, D.X. Jiang, P. Wang, "Emergency material allocation with time-varying supply-demand based on dynamic optimization method for river chemical spills," *Environmental Science and Pollution Research*, vol. 25, no. 18, pp. 17343-17353, 2018.

[15] W.F. Zhang, X.P. Yan, J.Q. Yang, "Optimized maritime emergency resource allocation under dynamic demand," *PloS one*, vol. 12, no. 12, pp.1-23, 2017.

[16] X.P. Wang, C. Ma, J.H. Ruan, "Emergency supplies optimal scheduling considering the public's psychological risk perception," *Systems Engineering-Theory & Practice*, vol. 33, no. 7, pp. 1735-1742, 2013.

[17] C.F. Zhu, Z.K. Zhang, and Q.R. Wang, "Path Choice of Emergency Logistics Based on Cumulative Prospect Theory," *Journal of Advanced Transportation*, vol. 2019, Article ID. 8512423, 2019.

[18] Y.Z. Zhong, "A flood disaster relief emergency material distribution strategy based on people's psychological perception," *Arabian Journal of Geosciences*, vol. 14, no. 10, pp. 1-9, 2021.

[19] L. Wang, Y.M. Wanga, Luis Martínez, "A group decision method based on prospect theory for emergency situations," *Information Sciences*, vol. 418-419, pp. 1-32, 2017.

[20] Z.X. Zhang, L. Wang, Y.M. Wang, "An Emergency Decision Making Method Based on Prospect Theory for Different Emergency Situations," *International Journal of Disaster Risk Science*, vol. 9, no. 3, pp. 407-420, 2018.

[21] Daniel Seaberg, Laura Devine, Jun Zhuang, "A review of game theory applications in natural disaster management research," *Natural Hazards*, vol. 89, no. 3, pp. 1461-1483, 2017.

[22] L. Wang, N. Zhao, D.H. Liu, "Complex disaster management: A dynamic game among the government, enterprises, and residents," *Journal of Cleaner Production*, vol. 266, Article ID. 122091, 2020.

[23] Diehlmann Florian, Lüttenberg Markus, Verdonck Lotte, Wiens Marcus, Zienau Alexander, Schultmann Frank, "Public-private collaborations in emergency logistics: A framework based on logistical and game-theoretical concepts," *Safety Science*, vol. 141, Article ID. 105301, 2021.

[24] Y.H. Zheng, C.F. Zhu, Q.R. Wang, S.N. Liu, Y.Y. Ma, "Bi-objective optimization of emergency material game allocation considering limited rationality," *China Safety Science Journal*, vol. 30, no. 11, pp. 168-174, 2020.

[25] S.N. Liu, C.F. Zhu, Y.H. Zheng, Q.R. Wang, "Research on Bi-level Game Scheduling for Emergency Rescue Workers under the Condition of Limited Rationality," *Engineering Letters*, vol. 28, no. 4, pp.1338-1347, 2020.

[26] T.L. Vincent, "Evolutionary Games," *Journal of Optimization Theory and Applications*, vol. 46, no. 4, pp. 605-612, 1985.

[27] Chaitanya S. Gokhale, Arne Traulsen, "Evolutionary Multiplayer Games," *Dynamic Games and Applications*, vol. 4, no. 4, pp.468-488, 2014.

[28] N.T. Huang, J.R.Q. Bao, G.W. Cai, S.Y. Zhao, D.B. Liu, J.S. Wang, P.P. Wang, "Multi-agent Joint Investment Microgrid Source-storage Multi-strategy Bounded Rational Decision Evolution Game Capacity Planning," *Proceedings of the CSEE*, vol. 40, no. 4, pp. 1212-1225+1412, 2020.

[29] Y.T. Sun, Y.Q. Song, L.Z. Yao, Z. Yan, "Study on Power Consumers' Choices of Electricity Retailers in Electricity Selling Market," *Power System Technology*, vol. 42, no. 4, pp. 1124-1131, 2018.

[30] X.G. Zhao, L.Z. Ren, Y.Z. Zhang, G. Wan, "Evolutionary game analysis on the behavior strategies of power producers in renewable portfolio standard," *Energy*, vol. 162, pp. 505-516, 2018.

[31] Y. Zuo, X.G. Zhao, Y.Z. Zhang, L.Z. Ren, "From feed-in tariff to renewable portfolio standards: An evolutionary game theory perspective," *Journal of Cleaner Production*, vol. 213, pp. 1274-1289, 2019.

[32] Y.P. Yang, W.X. Yang, H.M. Chen, Y. Li, "China's energy whistleblowing and energy supervision policy: An evolutionary game perspective," *Energy*, vol. 213, Article ID. 118774, 2020.

[33] Y. Qiu, M. Shi, X.N. Zhao, Y.P. Jing, "System dynamics mechanism of cross-regional collaborative dispatch of emergency supplies based on multi-agent game," *Complex & Intelligent Systems*, 2021. DOI: https://doi.org/10.1007/s40747-021-00303-2

[34] L.Y. Du, L. Qian, "The government's mobilization strategy following a disaster in the Chinese context: an evolutionary game theory analysis," *Natural Hazards*, vol. 80, no. 3, pp. 1411-1424, 2016.

[35] L. Ma, Q.L. Liu, Z.X. Qiu, Y.M. Peng, "Evolutionary game analysis of state inspection behavior for coal enterprise safety based on system dynamics," *Sustainable Computing: Informatics and Systems*, vol. 28, Article ID. 100430, 2020.

[36] L. Zhao, X.C. Zhang, "A Prospect Theory-Based Route Choice Model of Traveler with Prior Information," *Journal of Transportation Systems Engineering and Information Technology*, vol. 6, no. 2, pp. 42-46, 2006.

[37] Günther Palm, "Evolutionary stable strategies and game dynamics for n-person games," *Journal of Mathematical Biology*, vol. 19, no. 3, pp. 329-334, 1984.

[38] X.J. Guan, L. Qian, M.X. Li, H.Y. Chen, L.G. Zhou, "Earthquake relief emergency logistics capacity evaluation model integrating cloud generalized information aggregation operators," *Journal of Intelligent & Fuzzy Systems*, vol. 32, no. 3, pp. 2281-2294, 2017.

Bin Ma was born in Gansu, China, in 1998. He obtained his Bachelor degree in Traffic and Transportation from Lanzhou Jiaotong University, Lanzhou, China, in the year 2020.
He is currently pursuing his master degree in Traffic and Transportation (the Planning and Management of Traffic and Transportation) in Lanzhou Jiaotong University. His research interests include the optimization of emergency logistics network and the planning and management of traffic and transportation.