Research on Travel Mode Choice Behaviors Based on Evolutionary Game Model Considering the Indifference Threshold

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ABSTRACT In order to improve the mode share of public transportation, an evolutionary game model based on the indifference threshold is established to analyze the travelers’ mode choice behavior. The model supposes that the travelers’ behavioral adjustment of decision-making of travelers follows the principle of random utility maximization only when the perceived difference in utility between modes is greater than the indifference threshold; otherwise, travelers choose randomly. A transportation network that includes private and public transportation is presented as an example to show how travelers adjust their mode choice when traffic management policy is changed. We divided the travelers into three categories based on the online survey data: high sensitivity, neutral sensitivity and low sensitivity to cost difference. The results show that, the proposed $\Delta$-logit evolutionary game model has a unique stable equilibrium point and the point is the choice probability of the $\Delta$-logit stochastic user equilibrium. Moreover, compared with the logit evolutionary game model, the $\Delta$-logit evolutionary game model can predict the implementation effect of traffic policy and the time it takes for the traffic system to stabilize more accurately. In addition, the degree of sensitivity of travelers to cost difference affect the implementation effect of the policy.

INDEX TERMS Travel mode choice, evolutionary game theory, indifference threshold, traffic management policy, evolutionary stable strategy.

I. INTRODUCTION

An effective approach to solve the problem of traffic congestion and promote the sustainable development of transportation is the use of traffic demand management to encourage travelers to transfer from private transportation to public transportation. A suitable mode choice model is essential when implementing traffic management policies. Discrete choice models are frequently applied to the analysis of mode choice behavior [1]–[4]. However, these models do not reflect the dynamic evolution process of travel behavior. In reality, mode choice behavior is affected by factors such as travel information and individual preferences, and it needs to be adjusted repeatedly for a period of time before it reaches a stable state [5].

In recent years, Evolutionary Game Theory (EGT) has been applied to research on the dynamic evolution of travel behavior. EGT is derived from biological evolution. It emphasizes dynamic equilibrium and hypothesizes that the behavior of game participants is subject to a process of dynamic adjustment [6]. Since Maynard Smith proposed the concept of the Evolutionarily Stable Strategy (ESS), EGT has been applied in many fields [7], [8]. Van Vugt et al. [9] were the first to apply EGT to research on travel behavior and analyze the evolutionary process of commuters’ choice behavior. Later, the evolutionary game model was used to study many transportation problems, such as mode choice, route choice, investment in public transportation, and high-speed railway supervision [10]–[13]. For example, Li [14] asserted that traffic guidance is a game between the driver and the manager. The evolutionary game model was used to analyze the evolution of a driver’s route choice behavior with traffic guidance. Levinson [15] established an evolutionary game model, analyzed the relationship between travel behavior and congestion, and proposed that congestion charging policy could reduce the travel cost of travelers.
Chen et al. [16] analyzed the dynamic evolution process of urban travelers’ mode choice. They concluded that adjusting equilibrium parameters could result in the evolution of a traveler’s mode choice toward management policy goals. Guan and Pu [17] built an evolutionary game model of route choice behavior and proved that evolutionary stability is equivalent to stochastic user equilibrium (SUE). Xiao and Wang [18] proposed an evolutionary game model of travel behavior with government regulation. The results showed that the government’s incentives for public transport and the control of private cars would affect the evolution of travelers’ choice behavior. Guo and Dong [19] established a dynamic evolutionary game model in which motor vehicles and non-motor vehicles were players and discussed the influence of traffic enforcement on traffic violations. Yang and Qian [20] analyzed the evolutionary path from private transportation to public transportation for different kinds of commuters. Zhang et al. [21] claimed that participants in the evolutionary game cannot accurately calculate the benefits of the strategy. Therefore, they described the expected benefits using prospect values and established a dynamic traffic flow evolutionary game model based on prospect theory.

All of the above evolutionary game models are based on the replicator dynamic, and they assume that travelers adjust their travel behavior by comparing the utility of their current traffic behavior with the average utility of the system. Nevertheless, some researchers have pointed out several limitations in replicator dynamics [5], [18]. Firstly, the hypothesis may not always be accurate. In addition, a binary replication dynamic model only has a unique stable equilibrium point when some constraints are satisfied, and there is no stable equilibrium point in a multiple replication dynamic model. Therefore, Xiao [22] established an evolution model of traffic flow based on logit dynamics. In addition, the influence of congestion charging on the dynamic evolution of traffic flow was analyzed. Lin et al. [5] compared replication dynamics with logit dynamics. Their results indicated that the replication dynamic model only has a unique stability strategy when some constraints are satisfied, and the logit dynamic has the only evolutionary stability strategy.

The logit dynamic evolution game model maintains that the traveler’s strategy of behavioral adjustment follows the principle of random utility maximization. It considers the impact of individual preferences and incomplete information on travel behavior. However, Simon [23] proposed that people tend to seek a satisfying solution among available feasible solutions rather than find an optimal one. Then, Krishnan [24] hypothesized that the “satisficer” in Simon’s theory will again become a “utility maximizer” if one alternative appears to be sufficiently more attractive than another. He defined indifference thresholds as “minimum perceivable differences” between the utility of two alternatives and proposed a minimum perceivable difference (MPD) model. Since then, many studies have expanded the theory of random utility maximization on the basis of the “indifference threshold” [25]–[30]. These researchers have suggested that when the absolute value of the utility difference between two choices is less than the indifference threshold, travelers are unable to see the difference between them and thus choose randomly. Otherwise, travelers choose the option that has maximum utility. This hypothesis is more consistent with actual traffic behavior. However, none of the research has considered the effect of the indifference threshold on the dynamic evolution of travel behavior. This study aims to fill this gap by combining the concept of the indifference threshold with evolutionary game theory to explore the evolution of travel behavior. The conclusions of the study are significant to the sustainable development of transportation.

The remainder of this paper is organized as follows. The next section presents the evolutionary game for travel mode choice. Section 3 describes a logit evolutionary game model for mode choice, and the stability of the model is proved. A Δ-logit evolutionary game model for mode choice is established in Section 4, and the stability of the model is discussed. Section 5 presents an algorithm to solve the model. A numerical example is detailed in Section 6 to demonstrate the model. Finally, conclusions are presented in Section 7.

II. THE EVOLUTIONARY GAME FOR MODE CHOICE

Consider a network that includes both private and public transportation modes, as shown in Figure 1. Private transportation refers to traveling by car, and public transportation refers to traveling by subway. In this bimodal network, the evolutionary game elements are as follows:

**Group:** It is assumed that the total traffic demand between OD pairs is a group, and the total demand is D.

**Pure strategy set:** The pure strategy set refers to a set of two modes, \( Y = \{i, j\} \), where i represents private transportation and j represents public transportation.

**Mixed strategies:** Mixed strategies are expressed as the probability of mode choice. If the probability of choosing private transportation is \( p \), then the probability of choosing public transportation is \( 1 - p \).

**Payoff function:** The payoff function is expressed as the negative of the travel cost.

Evolutionary game theory assumes that the way in which a traveler chooses a strategy is gradually adjusted, and it is necessary to judge whether the dynamic process can finally converge to the Nash equilibrium point. A dynamic equation is generally used to characterize the evolution of a group over time:

\[
\dot{p} = F(p)
\]
where \( \dot{p} \) is the derivative of the probability of mode choice with respect to time.

If the current mode choice of a traveler is \( i \), then the probability that he or she transfers from the current mode to mode \( j \) is called a modifying agreement, denoted by \( \omega_{ij} \). Therefore, the dynamic equation can be expressed as:

\[
\dot{p} = F_i(p) = \sum_{j \in \mathcal{Y}} p_j \omega_{ji} - p \sum_{j \in \mathcal{Y}} \omega_{ij} \tag{2}
\]

The first term on the right side of the equation represents the proportion of participants in strategy (mode choice) \( i \), and the second term represents the proportion of participants who move from the current strategy (mode choice) to strategy (mode choice) \( j \). Different forms of \( \omega_{ij} \) correspond to different evolution dynamics. If the travelers’ dynamic choice process is described by the Replicator Dynamic (RD), that is, when \( \omega_{ij} \) is represented by \( p_j \left[ E_j - E_i \right]_+ \), then the Replicator Dynamic Model can be obtained:

\[
\dot{p} = p \left( E_i - \overline{E} \right) \tag{3}
\]

where \( \overline{E} = \sum_{j \in \mathcal{Y}} p_j E_j \), \( E_i, E_j \) are the payoff functions of mode \( i \) and mode \( j \).

The meaning of the replicator dynamic equation is that the change rate of the probability of a mode choice is proportional to the probability of the mode choice and proportional to the difference between its expected payoff and average payoff.

The research on the replicator dynamic evolution stability of mode choice has been relatively thorough [16]–[18] and is not repeated here.

III. THE LOGIT EVOLUTIONARY GAME MODEL FOR MODE CHOICE

A. MODEL ESTABLISHMENT

The logit evolutionary game model assumes that travelers follow the principle of random utility maximization when adjusting strategies for mode choice. In this case, the modifying agreement in equation (2) is equal to the probability of choosing mode \( j \), namely,

\[
\omega_{ij} = \frac{\exp \theta E_j}{\sum_{k \in \mathcal{Y}} \exp \theta E_k} \tag{4}
\]

where, \( E_k \) is the payoff function of mode \( k \).

Substituting equation (4) into equation (2) results in a bimodal logit evolutionary game model:

\[
\dot{p} = \omega_{ji} - p = \frac{\exp \theta E_j}{\sum_{k \in \mathcal{Y}} \exp \theta E_k} - p \tag{5}
\]

The model accounts for individual preference and incomplete information, and it is closer to the actual decision-making behavior for travel mode choice compared with the replicator dynamic model.

B. THE PAYOFF FUNCTION

Firstly, assume that all travelers form a homogeneous group. Then, suppose that the cost of traveling by car is:

\[
V_i = \alpha \cdot T_i(f_i) + F_i \tag{6}
\]

where \( \alpha \) is the value of time (VOT), \( f_i \) is the traffic volume of cars, \( f_i = D \cdot p, T_i(f_i) \) is the travel time by car and is represented by the Bureau of Public Roads (BPR) function, \( T_i(f_i) = t_i^0 \cdot \left[ 1 + \beta \left( \frac{f_i}{c_i} \right)^n \right] \). In the BPR function, \( t_i^0 \) is the free flow of time for car travel, \( c_i \) denotes the capacity of a road, \( \beta, n \) are parameters of the BPR function, and \( F_i \) is the monetary cost of car travel.

Suppose that the cost of traveling by subway is:

\[
V_j = \alpha \cdot t_j + F_j + \mu \cdot g_j(f_j) \tag{7}
\]

where \( f_j \) is the traffic volume of the subway, \( f_j = D \cdot (1 - p) \). \( t_j \) is the travel time by subway, \( F_j \) is the monetary cost of traveling by subway, \( \mu \) is the unit congestion cost, and \( g_j(f_j) \) is the congestion cost of the subway and represented by the congestion function [31], \( g_j(f_j) = t_j \cdot \left( a \cdot f_j^2 + b \cdot f_j \right) \), in which \( a, b \) are parameters of the function.

Then, when the mixed strategies are \( P = (p, 1 - p) \), the payoff function of choosing car \( E_i \) and subway \( E_j \) are respectively:

\[
E_i = - \left\{ \alpha \cdot t_i^0 \cdot \left[ 1 + \beta \left( \frac{D \cdot p}{c_i} \right)^n \right] + F_i \right\} \tag{8}
\]

\[
E_j = - \left\{ \alpha_j \cdot t_j + F_j + \mu \cdot t_j \cdot a \cdot [D \cdot (1 - p)]^2 + \mu \cdot t_j \cdot b \cdot D \cdot (1 - p) \right\} \tag{9}
\]

C. THE EVOLUTIONARILY STABLE STRATEGY OF THE LOGIT EVOLUTIONARY GAME MODEL

One theorem is presented here before establishing the evolutionarily stable strategy of mode choice.

Theorem 1 (Stability Theory of Equilibrium Point in Differential Equations [32], [33]): The real root \( x = x_0 \) of the algebraic equation \( f(x) = 0 \) is called the equilibrium point of the differential equation \( x'(t) = f(x) \). If \( f'(x_0) < 0 \), the equilibrium point is stable. If \( f'(x_0) \geq 0 \), the equilibrium point is not stable.

According to Theorem 1, the equilibrium points \( P^* = \{p^*, (1 - p^*)\} \) of equation (5) are satisfied:

\[
\dot{p}^* = \frac{\exp \theta E_i}{\sum_{k \in \mathcal{Y}} \exp \theta E_k} - p^* = 0 \tag{10}
\]

That is,

\[
p^* = \frac{\exp \theta E_i}{\sum_{k \in \mathcal{Y}} \exp \theta E_k} \tag{11}
\]

If

\[
f(p^*) = \frac{1}{1 + \exp \{\theta (E_i(p^*) - E_j(p^*))\}} - p^* \tag{12}
\]
then
\[ f(0) = \frac{1}{1 + \exp\left[\theta (E_j(0) - E_i(0))\right]} > 0 \quad (13) \]
\[ f(1) = \frac{1}{1 + \exp\left[\theta (E_j(1) - E_i(1))\right]} - 1 < 0 \quad (14) \]

By the zero-point theorem, we know that equation (12) has equilibrium points when \( p \in [0, 1] \) and
\[ f'(p^*) = -\frac{\theta \exp\left[\theta (E_j(p) - E_i(p))\right]}{\left[1 + \exp\left[\theta (E_j(p) - E_i(p))\right]\right]^2} \cdot \left(E_j'(p) - E_i'(p)\right) - 1 < 0 \quad (15) \]
where
\[ E_j'(p) = (2a + b) \cdot D > 0 \quad (16) \]
\[ E_i'(p) = -\alpha \cdot n \cdot t_i^0 \cdot \beta \cdot \frac{D}{c_i} \cdot \left(D \cdot p\right)^{n-1} < 0 \quad (17) \]

Therefore, \( f'(p^*) < 0 \). We can deduce that the logit evolutionary game model for mode choice in a bimodal network has a unique equilibrium point and that the point is stable. That is, the model has a unique evolutionary stability strategy. It is clear that the equilibrium point is the choice probability of travel mode under the logit random user equilibrium state.

IV. THE Δ-LOGIT EVOLUTIONARY GAME MODEL FOR MODE CHOICE
A. MODEL ESTABLISHMENT

One definition is presented here before establishing the Δ-logit evolutionary game model.

Definition 1 Indifference threshold refers to the perceived utility difference between modes that enables the traveler to move from one travel mode to another. That is, it is only when the perceived utility difference between modes is greater than the indifference threshold that travelers’ decision-making follows the principle of random utility maximization; otherwise, travelers choose randomly. The indifference threshold represents the degree of the sensitivity to the difference in utility between modes of the traveler. A larger \( \Delta \) indicates that the traveler is less sensitive.

It can be expressed mathematically as:
\[ p_{ij|\Delta} = \begin{cases} 1, & E_j - E_i < -\Delta \\ 0.5, & -\Delta \leq E_j - E_i \leq \Delta \\ 0, & E_j - E_i > \Delta \end{cases} \quad (18) \]

where, \( \Delta \) is the indifference threshold; \( p_{ij|\Delta} \) represents the conditional choice probability of mode \( j \) considering the indifference threshold.

According to the [29], the choice probability of mode \( j \) can be written as:
\[ p_j = \frac{0.5}{1 + \exp(E_i - E_j - \Delta)} + \frac{0.5}{1 + \exp(E_i - E_j + \Delta)} \quad (19) \]

The Δ-logit evolutionary game model supposes that the traveler does not refer to the choices of other travelers when adjusting strategies, but instead, chooses directly according to satisfactory decision criteria. That is, it is only when the perceived utility difference between modes is greater than the indifference threshold that travelers’ behavioral adjustment of decision-making follows the principle of random utility maximization; otherwise, travelers choose randomly. In this case, the modifying agreement in equation (2) is equal to the choice probability of mode \( j \). The mathematical expression can be written as:
\[ o_{ij} = \frac{0.5}{1 + \exp(\theta (E_j - E_i - \Delta))} + \frac{0.5}{1 + \exp(\theta (E_i - E_j + \Delta))} (20) \]

Substituting equation (20) into equation (2) results in a bimodal Δ-logit evolutionary game model:
\[ \dot{p} = \frac{0.5}{1 + \exp(\theta (E_j - E_i - \Delta))} + \frac{0.5}{1 + \exp(\theta (E_j - E_i + \Delta))} - p \quad (21) \]

B. THE EVOLUTIONARILY STABLE STRATEGY OF THE Δ-LOGIT EVOLUTIONARY GAME MODEL

According to theorem 1, the equilibrium points of equation (21) are satisfied:
\[ p^* = \frac{0.5}{1 + \exp(\theta (E_j - E_i - \Delta))} + \frac{0.5}{1 + \exp(\theta (E_j - E_i + \Delta))} - p^* = 0 \quad (22) \]

If
\[ f(p^*) = \frac{0.5}{1 + \exp(\theta (E_j - E_i - \Delta))} + \frac{0.5}{1 + \exp(\theta (E_j - E_i + \Delta))} - p^* \quad (23) \]
\[ f(0) = \frac{0.5}{1 + \exp(\theta (E_j(0) - E_i(0) - \Delta))} + \frac{0.5}{1 + \exp(\theta (E_j(0) - E_i(0) + \Delta))} > 0 \quad (24) \]
\[ f(1) = \frac{0.5}{1 + \exp(\theta (E_j(1) - E_i(1) - \Delta))} + \frac{0.5}{1 + \exp(\theta (E_j(1) - E_i(1) + \Delta))} - 1 < 0 \quad (25) \]

By the zero-point theorem, we know that equation (21) has equilibrium points when \( p \in [0, 1] \), and
\[ f'(p^*) = -0.5 \cdot \theta \cdot \exp\left[\theta (E_j(p^*) - E_i(p^*)) - \Delta\right] \cdot \frac{E_j'(p^*) - E_i'(p^*)}{\left[1 + \exp\left[\theta (E_j(p^*) - E_i(p^*)) - \Delta\right]\right]^2} - \frac{0.5 \cdot \theta \cdot \exp\left[E_{\theta} (p^*) - E_i(p^*) + \Delta\right] \cdot \frac{E_j'(p^*) - E_i'(p^*)}{\left[1 + \exp\left[E_{\theta} (p^*) - E_i(p^*) + \Delta\right]\right]^2} \quad (26) \]
We can deduce that the Δ-logit evolutionary game model for mode choice in a bimodal network has a unique equilibrium point and that the point is stable. That is, the model has a unique evolutionary stability strategy. It is clear that the equilibrium point is the choice probability of travel mode under the Δ-logit random user equilibrium state.

V. SOLUTION ALGORITHM
This section details the algorithm designed for the proposed dynamic travel mode choice model.

The payoff function $E(p^*)$ in the models is a function for the traffic flow of a travel mode in the network. Therefore, it is necessary to calculate the probability of choosing different modes to obtain the utility of two modes and further calculate the equilibrium choice probability $p^*$. According to the previous analysis, the equilibrium point of the evolutionary game model is the choice probability of travel mode when the stochastic user equilibrium applies. Therefore, the solution of the model is equivalent to the solution of the equilibrium problem for the bimodal network. It can be solved by using the method of successive averages (MSA). In addition, the evolutionary process of dynamic equations can be defined by solving differential equations in Matlab. The steps of the MSA are as follows.

- **Step 1:** Initialization. According to the total OD demand, the initial traffic flows of different modes that meet the demand are generated randomly, and the maximum iteration number and convergence accuracy are set.
- **Step 2:** Cost calculation. According to the initial traffic flows, the travel costs are calculated by the cost functions.
- **Step 3:** Flow update. Auxiliary traffic flow is set, and it can be expressed as

$$\bar{f}_k = D \cdot p_k = D \cdot \frac{0.5}{1 + \exp \left( \theta (E_i - E_j - \Delta) \right)} + \frac{0.5}{1 + \exp \left( \theta (E_i - E_j + \Delta) \right)}$$

(27)

- **Step 4:** Checking the convergence. If the convergence equation (26) is satisfied or if the number of iterations exceeds the maximum value, the algorithm stops and outputs the current operation result. Otherwise, it returns to Step 1.

VI. EMPIRICAL ANALYSIS
From the transportation network exemplified in figure 1, which includes private and public transportation, a numerical example was computed to verify the suitability of the model and the validity of the algorithm. In addition, the dynamic adaptation process of travelers’ mode choice behavior under the control of traffic management policies was simulated.

There are two scenarios: one is the initial scene, and another one is the scene after the implementation of the management strategy that increases parking fees.

A. PARAMETERS IN THE MODEL
Data for this part comes from a survey applied in Beijing, China. The survey was carried out in the form of network questionnaire. The investigation was conducted from 4 July to 11 July 2019. The respondents met the following three conditions: 1) The respondent has a driver’s license; 2) The respondent’s family has at least one private car; 3) The respondent works in Beijing. The contents of the questionnaire included personal attributes, trip attributes and scenario questions. The respondents were requested to answer whether they would transfer from private transport to public transport when the cost of private transport, such as parking fee, increased. In total, 241 questionnaires were sent and recovered. Among them, 216 questionnaires are valid, with a validity rate of 89.63%.

The survey results are shown in table 1. Respondents have different degrees of sensitivity to cost differences. It appears as the cost difference that can make respondents transfer from private transportation to public transportation is different. We divided the respondents into three categories: high sensitivity to cost difference, neutral sensitivity to cost difference, and low sensitivity to cost difference. In order to facilitate the calculation, the value of the indifference threshold $\Delta$ in the model is divided into three cases accordingly: $\Delta = 5$, $\Delta = 10$, $\Delta = 20$.

<table>
<thead>
<tr>
<th>Indifference threshold</th>
<th>Sensitivity to cost differences</th>
<th>Frequency</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>high</td>
<td>64</td>
<td>29.6%</td>
</tr>
<tr>
<td>10</td>
<td>neutral</td>
<td>61</td>
<td>28.3%</td>
</tr>
<tr>
<td>20</td>
<td>low</td>
<td>91</td>
<td>42.1%</td>
</tr>
</tbody>
</table>

B. ANALYSIS OF RESULTS
The equilibrium points of the two models under different scenarios are shown in Table 3.

As revealed by the results in Table 3, firstly, scenario 2 adopts a management strategy that increases parking fees, and the probability of choosing to travel by car decreases, while that of subway travel increases. It can be inferred that increasing parking fees can encourage travelers to transition from traveling by car to traveling by subway. In addition, after the increase in parking fees, the choice probabilities of
### TABLE 2. Costs of travel modes under different scenarios.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Mode</th>
<th>Time (hour)</th>
<th>Fixed cost (Yuan)</th>
<th>Parking fee (Yuan)</th>
<th>Subway fares (Yuan)</th>
<th>Capacity (pcu)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Car</td>
<td>t_i^0 = 0.5</td>
<td>20</td>
<td>20</td>
<td>-</td>
<td>2200</td>
</tr>
<tr>
<td></td>
<td>Subway</td>
<td>t_j = 1</td>
<td>-</td>
<td>-</td>
<td>5</td>
<td>-</td>
</tr>
</tbody>
</table>

### TABLE 3. Equilibrium points of two models in different scenarios.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>logit model</th>
<th>(\Delta)-logit model (\Delta=5)</th>
<th>(\Delta)-logit model (\Delta=10)</th>
<th>(\Delta)-logit model (\Delta=20)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>p</td>
<td>l-p</td>
<td>p</td>
<td>l-p</td>
</tr>
<tr>
<td>1</td>
<td>32.96</td>
<td>67.94</td>
<td>34.35</td>
<td>65.65</td>
</tr>
<tr>
<td>2</td>
<td>28.19</td>
<td>71.81</td>
<td>31.15</td>
<td>68.85</td>
</tr>
</tbody>
</table>

Note: 1000 Yuan = USD 140

The change in the \(\Delta\)-logit evolutionary game model is smaller than the change in the logit evolutionary game model, and a larger indifference threshold corresponds to a smaller change. It can be argued that the logit evolutionary game model may overestimate the effectiveness of the management policy, and the \(\Delta\)-logit evolutionary game model can predict the implementation effect of traffic policy more accurately. Meanwhile, the lower the sensitivity of travelers to cost difference, the smaller the impact of the charge management policy on travel behavior.

In order to demonstrate the dynamic adaptation process of travel mode choice behavior in response to traffic management policy regulation, we simulated the dynamic evolution process of the choice probability. The initial values of the choice probability were respectively set at \(p_i = (0.1, 0.2, 0.3), p_j = (0.9, 0.8, 0.7)\). The simulation results are shown in Figure 2 and Figure 3. The results show that the models have unique stability strategies, and the stable equilibrium of travel mode choice is not a one-step process. It gradually approaches stability as travelers learn and adjust. Figure 2 and Figure 3 respectively show the evolution process of the logit evolution model and the \(\Delta\)-logit evolution model under different scenarios. In Figure 2a, when \(p_i = 0.1, p_j = 0.9\), the system reaches stability after about 3 iterations; when \(p_i = 0.3, p_j = 0.7\), the system reaches stability after about 2 iterations. This suggests that the initial value of the choice probability affects the number of iterations required before the system reaches stability. Fig.2b and Fig.3 also show this regularity. In addition, a comparison between Figure 2a and Figure 3a-c shows that the system reaches stability after about 3 iterations under the conditions in Figure 2a, while stability requires 6 iterations, 10 iterations, and 16 iterations under the conditions in Figure 3a-c, respectively. This indicates that the time required to achieve stability in the \(\Delta\)-logit evolutionary game model is longer than that in the logit evolutionary game model, and a larger indifference threshold corresponds to more time. Figure 2b and Figure 3d-f show this regularity too. This suggests that the logit evolutionary game model may underestimate the time it takes for the traffic system to stabilize, and the \(\Delta\)-logit evolutionary game model can predict that time more accurately. Furthermore, the lower the sensitivity of travelers to cost difference, the longer the time it takes for the traffic system to stabilize.

Figure 4 shows the results of further simulating the evolution process of mode choice under different demands. The results reveal that when the total demand equals 6000 (pcu/iteration), the system reaches stability after 12 iterations;
when the total demand increases to 10000 (pcu/iteration), the system reaches stability after 5 iterations; and when the total demand equals 12000 (pcu/iteration), the system reaches stability after 3 iterations. This indicates that as the total demand increases, the time required for the system to reach stability decreases; that is, a higher total demand corresponds to less time required for the system to reach stability.

**FIGURE 3.** The evolution process of the $\Delta$-logit evolutionary game model for mode choice.
VII. CONCLUSION

This study proposes an evolutionary game model of travel mode choice based on an indifference threshold. The model hypothesizes that the traveler chooses directly according to satisfactory decision criteria. That is, it is only when the perceived utility difference between modes is greater than the indifference threshold that travelers’ behavioral adjustment of decision-making follows the principle of random utility maximization; otherwise, travelers choose randomly. An example is presented to simulate the evolutionary process of the model choice for a bimodal network. From the results, the following conclusions are drawn.

1. The proposed $\Delta$-logit evolutionary game model has a unique equilibrium point in the mixed strategy, and the equilibrium point is stable; that is, the system has a unique evolutionary stability strategy, and the equilibrium point is the choice probability of the $\Delta$-logit stochastic user equilibrium.

2. When traffic management policy changes, the change value of choice probabilities in $\Delta$-logit evolutionary game model is lower than the change value of the logit evolutionary game model. Moreover, a larger indifference threshold corresponds to a smaller change. It can be argued that the logit evolutionary game model may overestimate the effectiveness of the management policy, and the $\Delta$-logit evolutionary game model proposed in this article can predict the implementation effect of traffic policy more accurately. Meanwhile, the lower the sensitivity of travelers to cost difference, the smaller the impact of the charge management policy on travel behavior.

3. The initial value of the choice probability and the total demand affect the time required for the system to reach stability. In addition, the time required for the $\Delta$-logit evolutionary game model to achieve stability is longer than that required for the logit evolutionary game model. This indicates that the logit evolutionary game model may underestimate the time required for the transportation system to reach stability, and the $\Delta$-logit evolutionary game model proposed in this article can predict the time need for the system to reach a stable state more accurately. Furthermore, the lower the sensitivity of travelers to cost difference, the longer the time for the system to reach stability.

4. The evolutionary game model based on indifference threshold established in this paper only considers two travel modes, and future research can be extended to multiple modes.

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