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Research Article

Dynamic Evolution of Traveler's Bounded-Rational Route Choice Behavior

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Travelers' route choice shows bounded-rationality because of different perceptions of route attributes. Based on the bounded-rationality, the paper proposes the dynamic evolution rules and route choice model, and simulation method is applied to study the evolution process and results. The model includes three parameters reflecting the bounded-rationality of travelers. First, simulation results show that the bounded-rationality affects the evolution process. The switching threshold or the perception deviance is larger, convergence rate is faster, and shorter time is needed to reach equilibrium state. Also, fewer perfect rational travelers will lead to similar results. Second, the system can reach equilibrium and the final equilibrium volume of every route is almost unaffected by bounded-rationality. The equilibrium volume of every route is an approximately fixed value under all simulation scenes. At last, it is found that equilibrium volume of every route obeys normal distribution. That is, bounded-rationality affects the equilibrium convergence rate, but volume equilibrium results will not be influenced.

1. Introduction

Researchers have conducted many studies on route choice behavior, based on which various theories of traffic assignment have been derived. Expected utility theory has been widely used in route choice modeling. However, numerous studies show that even in the perfect experiment, travelers can only select the route according to incomplete information under bounded-rationality. That is, the traveler does not select the shortest route every time [1]. Then theories based on bounded-rationality (Prospect Theory, Cumulative Prospect Theory, Regret Theory) and Game Theory have been developed gradually.

Because of the uncertainty of traffic environment, difference perception, and judgement deviance of traveler, it is unrealistic to find the optimal strategy for each traveler every time. The traveler must adjust his strategy according to the previous choice of other travelers. For traffic managers, it is of great significance to study the dynamic decision-making process of travelers' route choice and formulate traffic guidance measures to alleviate traffic congestion.

The traveler route choice behavior reflects traffic assignment results, and all traditional traffic assignments are based on traffic equilibrium theory. However, whether the traffic network achieves equilibrium requires further discussion. Some study indicated that the network traffic flow was difficult to reach balance [2, 3]. Then, from the view of Game Theory, relationship between bounded-rational route choice behavior and traffic assignment must be verified.

Based on the hypothesis of bounded-rationality and incomplete information, the paper proposes a learning mechanism and route choice model based on bounded-rationality by applying the evolutionary game. Three parameters representing bounded-rationality are added in the model to analyze the switching process of travelers' route choice under different rationality degree.

2. Literature Review

2.1. Bounded-Rational Route Choice. Perfect rationality was widely used in modeling traveler route choice behavior.

For perfect rationality, travelers are required to have perfect judgement and forecast ability, and they must have rational common cognition and trust other participants. To compensate for the hypothesis defect of economic man of perfect rationality, Simon proposed the concept of bounded-rationality [4]. He thinks that all decision-makers are not completely rational because of the uncertainty and perception deviance. Then, Kahneman and Tversky proposed the Prospect Theory (PT, 1979) and Cumulative Prospect Theory (CPT, 1992), which both assume that every individual was bounded-rational during decision-making process [5, 6]. Now, boundedly rational behavior has been widely analyzed for travel behavior.

Numerous experiments and investigation showed that the travel time and route choice behavior under uncertainty is consistent with the Prospect Theory. Di provides a survey on bounded-rational travel behavior modeling and estimation [7]. Ye established a Bounded-Rational User Equilibrium (BRUE) model, studying the evolution processes under various bounded-rationality thresholds and different initial states [8]. Zhang established the day-to-day route choice model under CPT and Bounded-Rational theory, respectively, [9, 10]. Evidence shows that bounded-rational behavior exists in route choice process.

Some researchers established traveler route choice model based on bounded-rationality. Sun established a route choice model considering the travelers' subjective preference for travel cost [11]. Based on the hypothesis of bounded-rationality, Li established the multiroute choice model and proposed the dynamic reference points and the evolution rules of heterogeneous travelers [12]. Huang established a model considering both travel cost and comfort based on Prospect Theory [13]. Considering the existence of selfish travelers in a network, Rambha proposed an average cost Markov decision process to describe the route switching behavior of day-to-day [14]. The results show that the system equilibrium and toll pricing are influenced by the bounded-rationality. Zhao conducted a Bounded-Rational User Equilibrium (BRUE) model and numerical simulation was used to obtain the equilibrium point [15].

Perception deviance is the crucial origination of bounded-rationality. Luca and Zhou studied the risk perception under uncertainty and proved the existence of preference [16, 17]. Yang established a Stochastic User Equilibrium (SUE) model base on Cumulative Prospect Theory [18]. Zhang [9], Jiang [19], Di [20], and Li [21] established the model of dynamic learning and updating regular based on the theory of bounded-rational, revealing the existence of perception deviance in microcosmic decision process.

Some researches focused on factors influencing traveler route choice behavior. Findings show that information release [22–24], socioeconomic attributes [25], accidents [26], driver's familiarity with road network [27], and the threshold of route effective difference [28] all have influence on route choice behavior.

Additionally, Regret Theory (RT) [29, 30] based on bounded-rationality is also widely applied.

2.2. Dynamic Evolution of Route Choice. Dynamic evolution reflects the learning mechanism of route choice process and the most representative theory is Game Theory. Nash published two articles about noncooperative game in 1950 and 1951 and proposed the Nash Equilibrium. In 1973, Maynard and Price proposed the fundamental concept of evolutionary game [31, 32]. The hypothesis of perfect rationality for classical Game Theory is inconsistent with the real decision process. Evolutionary Game Theory has developed quickly during the skepticism and confusion of the rationality. Evolutionary Game Theory supposes the participants are bounded-rational and cannot make the best response to information changes. Duplicate dynamic function is usually applied in evolutionary game to reflect the strategies updating process.

Application of Game Theory focuses on two aspects, route choice modeling and optimal route solving [33]. The utility function matrix considering some influence factors was proposed to establish the route choice model based on Game Theory; the game process and results were studied when utility function changes [34–36]. These studies discussed the game results' difference through analyzing the Evolution Stable Strategy (ESS). Some researchers focused on solving the game question applying Nash Equilibrium [37, 38]. However, evolutionary game cannot reveal the learning and updating mechanisms of travelers' route switching behavior deeply at microlevel.

2.3. Summary. As noted in the previous subsections, there is a huge body of literature on travelers bounded-rational route choice. Previous references paid more attention to the modeling process and route choice results. For route choice dynamic evolution, some papers focused on the equilibrium point solving methods. As a whole, less papers analyzed the bounded-rational microcosmic behavior evolution mechanism. How bounded-rationality affects the route switching behavior cannot be revealed clearly.

In the paper, route choice evolution rules and three parameters representing the bounded-rationality were proposed and discussed. Combining the evolution game theory, we proposed route switching rules and establish the route choice models. Different from the previous studies, the evolution rules consider the travelers' heterogeneity and bounded-rationality and can describe the individual route switching mechanism, not only the route choice results. The route choice model is based on the concept of switching threshold, which is different from Kahneman and Tversky [5, 6]. According to the individual heterogeneity, we assume that the bounded-rational parameters follow normal distribution. The results were studied deeply under different distribution parameters. Results show that the bounded-rational parameters affect the convergence rate and equilibrium volumes. The study reveals the relationship between network equilibrium and traveler's individual characteristic.

As a whole, the study can manifest travelers' route choice behavior at the microlevel. And it is the complement and improvement for current research on traffic behavior at macrolevel.

3. Dynamic Evolution Model Based on Bounded-Rationality

3.1. Dynamic Evolution Rules. Evolutionary Game Theory uses replicator dynamic model to manifest the participant's decision process. However, the replicator dynamic model cannot express the behavior adjustment process under different specific game rules.

Then, the authors propose a dynamic evolution rule assuming that all the travelers constantly adjust their routes and decide whether to switch to another route or keep the current route unchanged. All travelers are bounded-rational and do not always select the shortest route. Travelers sequentially select the routes, and the traveler who selected later can observe the behavior of other travelers who select earlier. The travelers can adjust their strategies at next round according to the behavior of other participants at last round. With continuous adjustment, the system may reach equilibrium state finally.

Assume the following: (1) Every round, travelers sequentially enter into the system and select their routes successively. (2) Travelers can obtain the routes' history information (that is, the travel time after all travelers' selection at last round) and cannot obtain real-time information (the travel time before selection at current round). (3) Travelers can obtain the selection results of other travelers who selected before them. (4) Travels will not switch the current route if the time difference between shortest route and current route do not exceed the switching threshold. There is an OD pair. The total number of travelers is q and number of travelers is constant.

In this paper, "traveler" refers to motor drivers, "round" means evolution times.

Assume that there are some routes between the origin and the destination. The travel time (h) for route k can be expressed as

$$U_k = t_{0,k} \times \left[1 + \alpha \left(\frac{q_k}{C_k}\right)^{\beta}\right] \tag{1}$$

where $t_{0,k}$ is the travel time (h) for free-flow. q_k is the volume (persons/h) for route k, and the total volume for the network is $q = \sum q_k . C_k$ is the capacity (persons/h) of route k. α and β are parameters. Generally, $\alpha = 0.15$, $\beta = 4$.

Other variables are defined as follows.

i: traveler;

I: subset of travelers who arrived before the ith traveler, $I = \{1, 2, 3, \ldots, i\text{-}1\}$;

q: total number of travelers;

K: set of all routes, $K = \{1, 2, \ldots, k\}$;

k: route, $k \in K$;

R: number of routes;

t: evolution times (round);

$y^k(t)$: number of travelers who select route k in round t;

$E^k(t)$: actual travel time for route k after round t;

$x_i^k(t)$: number of travelers who select route k at round t among the other i-1 travelers;

$r_i(t)$: route that traveler i selects in round t;

$T_i^k(t+1)$: predicted travel time for route k of traveler i at round $t+1$;

$RE_i(t+1)$: optimal route for travel i at round $t+1$.

Because travelers subsequently arrive at the system, travelers should only consider the strategies of other travelers who selected before them. Number each traveler according to the arriving sequence; then, traveler i should consider the strategies of travelers $1, 2, 3, \ldots, i$-1.

(1) At first round, original selection strategies: all travelers select the shortest routes according to historical information.

(2) Strategy-updating scheme: from round 2, traveler i determines his selection at next round according to the strategies of all (i-1) travelers in last round. Because of the universal information technology, such as mobile navigation, broadcast, and variable message signs, travelers can observe other travelers' previous choice. The principle can be explained as follows: traveler i calculates the actual travel time E for each route according to the results of travelers before him at last round and predicts the travel time T for each route at next round. Assume traveler i selected route k at last round; if the predicted travel time for route k at next round has no significant difference with the actual travel time at last round, traveler i will select route k at next round. Otherwise, travelers i will choose the shortest route. In other words, the traveler will change his selection result only if he believes that the route's travel time will sharply increase.

For the first traveler, there are no other travelers on the system when he enters first; then the first traveler chooses the shortest route always.

3.2. Bounded-Rational Route Choice Model. Assuming that travelers will not switch to the new route unless travel time saving goes beyond the switching threshold, a boundedly rational route choice model is proposed.

In round t, if travel i selects route k, the actual travel time for traveler i can be explained as follows.

$$E^k(t) = t_{0,k} \times \left[1 + \alpha \left(\frac{y^k(t)}{C_k}\right)^{\beta}\right] \tag{2}$$

The perception travel time at next round of route k for traveler i is as follows.

$$T_i^k(t+1) = t_{0,k} \times \left[1 + \alpha \left(\frac{x^k(t) + 1}{C_k}\right)^{\beta}\right] \times \exp(\theta_i) \tag{3}$$

Traveler i can only predict the travel time at next round according to the selection of other travelers j ($j \in I$). Traveler i cannot obtain the selection results of all travelers, so at next round, the number of travelers who select route k can be described as the number of travelers who select route k in set I and him (traveler i).

Further, all travelers are bounded-rational and have limited perception ability. Better perception ability means the perception travel time is closer to actual predicted travel time. θ_i is the perception deviance of traveler i. Traveler with smaller θ_i has accurate predicted travel time. $\theta_i \in [0, 1]$.

In round $t+1$, for traveler i, the optimal route should satisfy the following condition.

$$RE_i(t+1) = \arg\min T_i^k(t+1), \quad k \in K \tag{4}$$

In other words, the optimal route (that is, the shortest route for travelers i) is the route with shortest perception travel time.

Because of the bounded-rationality, the travelers will not necessarily select the shortest route every time. Introducing the concept of switching threshold, in round t, if the difference between the actual travel time for route k at last round and the predicted time at next round is acceptable to traveler i, then at next round, traveler i continues to select route k; otherwise, traveler i switches to the shortest route, which can be explained as follows.

$$r_i(t+1) = \begin{cases} k & \text{if } \left|\dfrac{E^k(t) - T_i^k(t+1)}{E^k(t)}\right| \leqslant \Delta_i \\ RE_i(t+1) & \text{if } \left|\dfrac{E^k(t) - T_i^k(t+1)}{E^k(t)}\right| > \Delta_i \end{cases} \tag{5}$$

In this formula, Δ_i measures the rational degree of traveler i. Smaller Δ_i means lower switching threshold and traveler is more rational. When $\Delta_i = 0$, the traveler is completely rational and will select the shortest route every time.

Δ_i is used as the standard to determine whether the traveler will switch his choice. Travelers with larger Δ_i are more tolerant for travel time and are inclined to bounded-rationality. Meanwhile, travelers with smaller Δ_i are more rational and prone to change their selection frequently.

For traveler i, the decision process is explained in Figure 1.

4. Numerical Simulations Analysis

4.1. Basic Scene and Parameters of Numerical Simulations. Considering travelers with different bounded-rationality degrees, study the dynamic evolution process of travelers' route choice.

Figure 2 shows the routes between Xi'an Jiaotong University and Chang'an University. Generally, travelers will make choice between the 5 routes shown in Figure 2. Routes 1 and 2 are based on the expressway-Nan'er Huan road. Routes 3, 4, and 5 are based on arterial roads, such as Youyi Road and Yanta Road. Attributes of the roads are shown in Table 1.

Nonpeak traveling is chosen as simulating scene. Assume q is constant. The proportion of completely rational ($\Delta_i = 0$) travelers is α, the rationality degree of each traveler is Δ_i, and the perception deviance is θ_i. Parameters of basic scene are shown in Table 2.

4.2. Numerical Simulations Results. For the basic simulation scenes, when the system reaches equilibrium, volume of each route is 169, 194, 255, 177, and 205, respectively. Figure 3 shows the evolution process.

After 929 rounds' evolution, the system reaches equilibrium state. All route's volumes will not change when the evolution times are increased continually. During the evolution process, volumes changing amplitudes of each route gradually decrease and volume is converged to the equilibrium point.

Then study the effects of one parameter when other parameters are constant, and analyze the equilibrium volume of each route and evolution rounds required to converge.

(1) Effect of the Rationality Degree. ① Assume all travelers have the same rational degree and analyze the effects of Δ's increase.

Figure 4 shows the equilibrium volume of each route and evolution rounds required. We can conclude that smaller Δ leads to longer evolution time. In contrast, when Δ is large, the volume can fast converge.

A smaller Δ indicates that the travelers are more rational, and the evolutionary process is more similar to the user equilibrium under complete rationality. Then most travelers may change their routes frequently to choose the shortest routes. However, when Δ is large, routes switching frequency declines and most travelers keep their choice unchanged, so it takes less time to reach equilibrium, which implies that when the travelers are more rational, the network requires more time to reach equilibrium.

There is minor change for equilibrium volume of each route comparing to the basic scene. Equilibrium volume of each route almost keeps constant when Δ is increasing.

② Assume Δ_i is subject to normal distribution. $\Delta_i \sim N(0.2, \sigma_1)$. Then analyze the effects of σ_1 on volume evolution. Evolution result is shown in Figure 5.

Results are similar to those in Figure 4. With σ_1 increase, evolution rounds show decline tendency overall. However, there is some vibration in the declining process. For different deviance of rationality degree, equilibrium volume of each route can remain stable approximately with Figures 3 and 4.

③ Assume Δ_i is subject to normal distribution. $\Delta_i \sim N(u_1, 0.05)$. Δ_i is different for every traveler and randomly obtained from the normal distribution. Evolution result is shown as Figure 6.

Results are the same as those in Figures 4 and 5.

Results of Figures 4~6 show that travelers are more rational, the equilibrium process is closer to user equilibrium, and evolution rounds are longer. However, when the system reaches equilibrium, every route has the approximate same volume for different simulation scene with different rational degree.

(2) Effect of the Proportion of Completely Rational Travelers. ① Assume other parameters are constant and analyze the effects of α. Values of parameter are shown in Table 3.

Results of Table 3 show that, for a constant Δ, the system needs more time to reach equilibrium with the increase of parameter α. Obviously, the comparatively large α indicates that there are more completely rational travelers, so in each

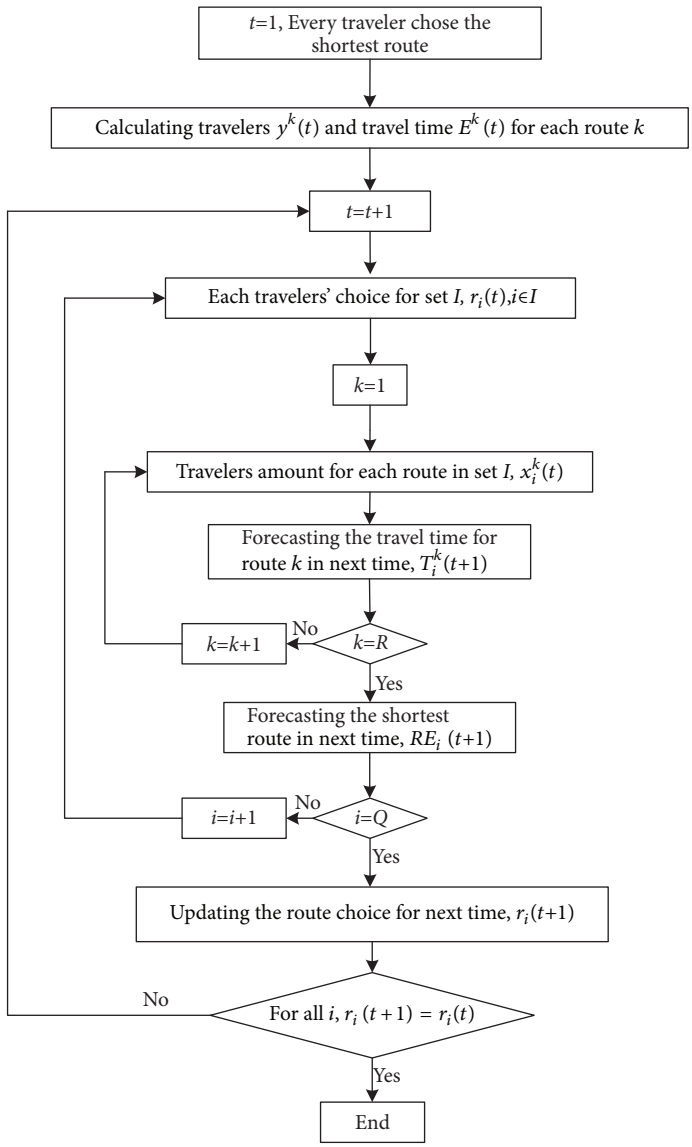


Figure 1: Decision process for travelers.

evolution time, more travelers will switch to the shortest route. In other words, the travelers change routes more frequently, so the evolution time is longer. In contrast, when α is small, more travelers can accept the selection results at last round under the bounded-rationality principle, which indicates that more travelers keep the route selection stable, and the evolution time is shorter.

For a constant α, smaller Δ results in longer evolution time. The results are consistent with (1) ①. No matter what values of Δ and α are, every route has similar equilibrium evolution volume for every simulation scene.

(3) Effects of Perception Deviance θ_i. ① Assume all travelers have the same perception deviance θ and analyze the effects of θ when θ is increased. Evolution results are shown in Figure 7.

We can find that, as the perception deviance (θ) increases, equilibrium rounds gradually decline. Smaller θ means the travelers have accurate perception travel time and are more rational, which will lead to longer equilibrium rounds.

② Assume θ_i is subject to normal distribution. $\theta_i \sim N(0.2, \sigma_2)$. θ_i is different for every traveler and randomly obtained from the normal distribution. Evolution process is shown in Figure 8.

③ Assume θ_i is subject to normal distribution. $\theta_i \sim N(u_2, 0.05)$. θ_i is different for every traveler and randomly obtained from the normal distribution. Evolution process is shown in Figure 9.

Combining Figures 8 and 9, we can conclude that it needs less rounds to reach equilibrium for both larger σ_2 and u_2. u_2 and σ_2 indicate the perception deviance. Larger perception deviance means traveler is bounded-rational; he

Figure 2: Road network.

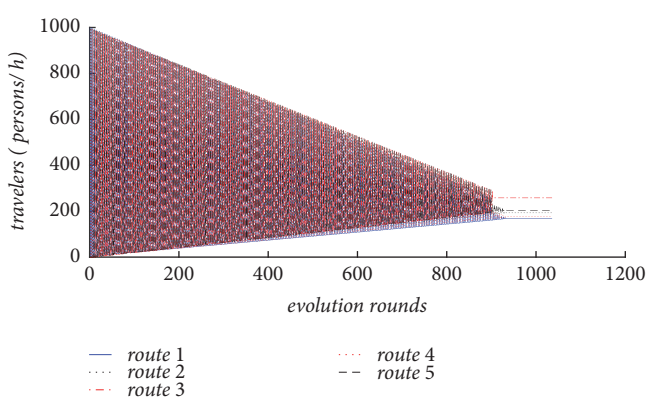


Figure 3: Volume evolution of five routes for $q = 1000$, $\alpha = 0.3$, $\Delta_i = 0.2$, $\theta_i = 0.2$.

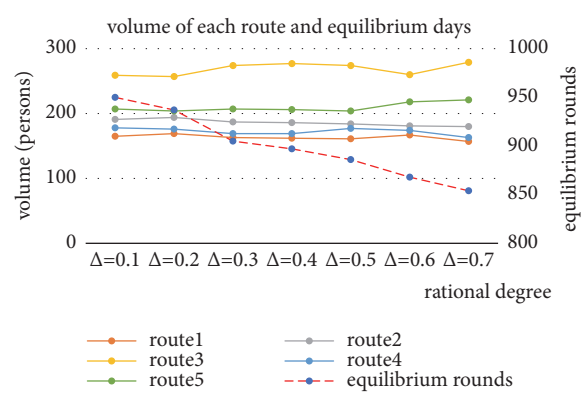


Figure 4: Volume evolution of five routes for $q = 1000$, $\alpha = 0.3$, $\theta_i = 0.2$.

cannot forecast the travel time accurately and may choose the near-optimal route.

Further, if θ_i obeys normal distribution, the evolution process is different from that when θ_i is a constant. At the basic simulation scene, all routes can evenly reach equilibrium state. That is, volume of all routes evenly declines or rises to convergent point and has no obvious vibration. However, when θ_i obeys normal distribution, volume of some routes fluctuates greatly in the equilibrium process. When $u_2 = 0.3$, the irregular vibration lasts for a long time. We can deduce that, when distribution of perception deviance is discrete, the evolution process exhibits some vibration and uneven convergence characteristic.

(4) Volume Evolution of the Routes. We can find that, no matter what the value of each parameter is, every route

Table 1: Attributes of the roads.

Road	Capacity (pcu/h, one-way)	Design speed (km/h)	Length
Nan'er Huan	3600	60	Route 1:2.5 km Route 2:1.8 km Route 3:0.8 km
Youyi Road	3600	60	Route 3: 1.5 km Route 2:0.6 km
Yanta Road	3600	60	Route 3:1.2 km Route 4:1.2 km
Jiandong Road	1400	20	Route 4:1.4 km Route 5:2.3 km
Jianshe Road	1400	20	Route 4:0.9 km
Wenyi Road	3200	40	Route 4:2.0 km Route 5:0.4 km
Taiyi Road	3200	40	Route 2:0.8 km
Jingjiu Road	3200	40	Route 1:2.5 km Route 2:0.5 km Route 3:0.5 km

Table 2: Parameters of basic scene.

Parameter	q	α	Δ_i	θ_i
value	1000	0.3	0.2	0.2

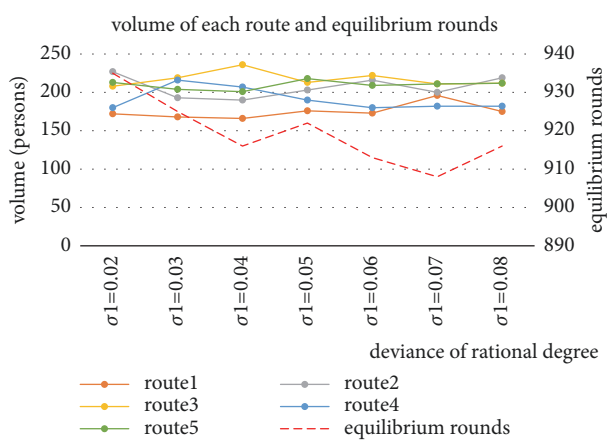


Figure 5: Volume evolution of five routes for $q = 1000$, $\alpha = 0.3$, $\theta_i = 0.2$, $\Delta_i \sim N(0.2, \sigma_1)$.

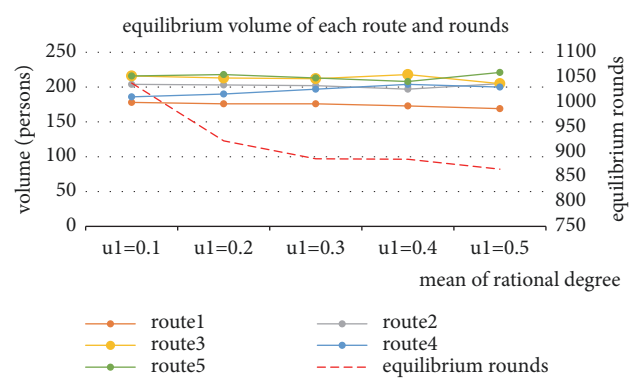


Figure 6: Volume evolution of five routes for $q = 1000$, $\alpha = 0.3$, $\theta_i = 0.2$, $\Delta_i \sim N(u_1, 0.05)$.

has similar equilibrium volume for all simulation scenes. Then, 29 scenes are randomly chosen to simulate and obtain the equilibrium volume. Volume for each route focuses on a certain range. From the distribution of volume, we can assume and prove the equilibrium volume for each route obeys normal distribution. Test results are shown as Figure 10.

Assume the equilibrium volume of each route is Q_1, Q_2, Q_3, Q_4, and Q_5. From the normal distribution fitting, $Q_1 \sim N(168, 6.70)$, $Q_2 \sim N(195, 8.65)$, $Q_3 \sim N(251, 8.65)$, $Q_4 \sim N(176, 5.72)$, and $Q_5 \sim N(208, 6.4)$.

5. Discussion

According to the simulation results, the bounded-rationality is objectively present in the route choice behavior of travelers. The conclusion is consistent with Di [7, 20] and Li [12]. All results indicate that the bounded-rationality is applicable to travel behavior analysis and traveler's behavior is affected by individual rational degree. In this paper, the indicator Δ_i practically represents the traveler's habit. Conclusions suggest the habit was the important factor that affected the traveler's selection. A larger Δ_i indicates that the traveler is more accustomed to the previous selection. The conclusion is identical to Di's conclusion [28].

The selection results show that not all travelers select the shortest route, which depends on their habits and tolerance. Our findings are consistent with Zhu [1], which proves the effect of habit and other uncertain factors on the traveler's behavior. In practical travel, when travelers face uncertain factors, they should only select the near-optimal path because

Table 3: Volume evolution of five routes for $q = 1000$, $\theta_i = 0.2$.

Parameters	Equlilibrium rounds	Volume				
		route 1	route 2	route 3	route 4	route 5
$\Delta = 0.5, \alpha = 0.3$	896	163	187	284	169	197
$\Delta = 0.5, \alpha = 0.5$	915	167	192	265	174	202
$\Delta = 0.5, \alpha = 0.8$	971	178	204	216	186	216
$\Delta = 0.2, \alpha = 0.3$	929	167	192	265	174	202
$\Delta = 0.2, \alpha = 0.5$	965	173	198	239	180	210
$\Delta = 0.2, \alpha = 0.8$	977	177	203	220	185	215

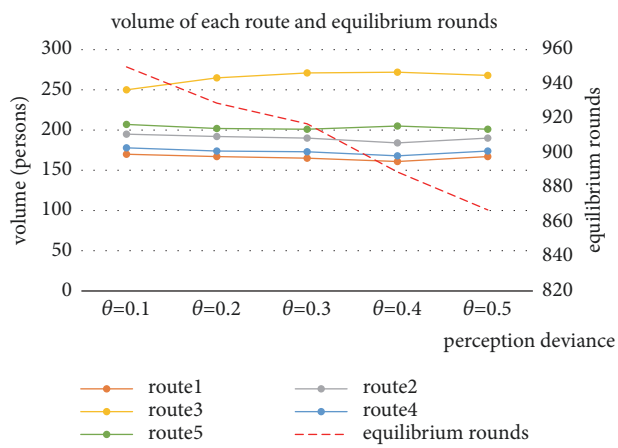


Figure 7: Volume evolution of five routes for $q = 1000$, $\alpha = 0.3$, $\Delta = 0.2$.

they generally could not obtain the optimal scheme as a result of information limitation and variability.

The traffic volume can finally reach an equilibrium state. The conclusion answers the question asked by Lida [2] and He [3], who suggested whether the traffic volume can reach equilibrium. According to our conclusions, when all travelers have a uniform objective, volume equilibrium is the final state of the network, regardless of travelers' rationality degree.

In addition, authors find the rationality degree is closely related to volume evolution process. When travelers are more rational, volume convergence rate is slower and it needs more time to reach equilibrium. The results are similar with more rational travelers and less perception deviance.

From this discussion, most of our conclusions are consistent with existing studies, which illustrates that the proposed evolution rules and regulations are proper to travelers' decision-making.

6. Conclusions

In the examples, authors analyze the traveler's route switching under different rationality degree. The conclusions are shown as follows.

(1) More rational travelers require more time to achieve equilibrium. With the increase of complete rational travelers, more travelers select the shortest route. Then, the travelers may frequently change routes. Therefore, the travelers take more time to obtain the optimal strategies.

(2) Larger perception deviance and less rational behavior both lead to shorter equilibrium rounds, which means the travelers are more tolerant to the travel time, and fewer travelers will select the shortest route. Then the system can easily obtain the optimal strategy.

(3) The volume of each route fluctuates around the equilibrium point, and the vibration amplitude decreases. In the evolution process, all travelers adjust their decision according the behavior of the travelers who arrived earlier. Then, the travelers who arrive earlier can more quickly find the optimal routes. Therefore, the volume fluctuation of each route decreases and gradually stabilizes with increasing evolution time. Further, when θ_i obeys normal distribution, convergence process illustrates some uneven fluctuation.

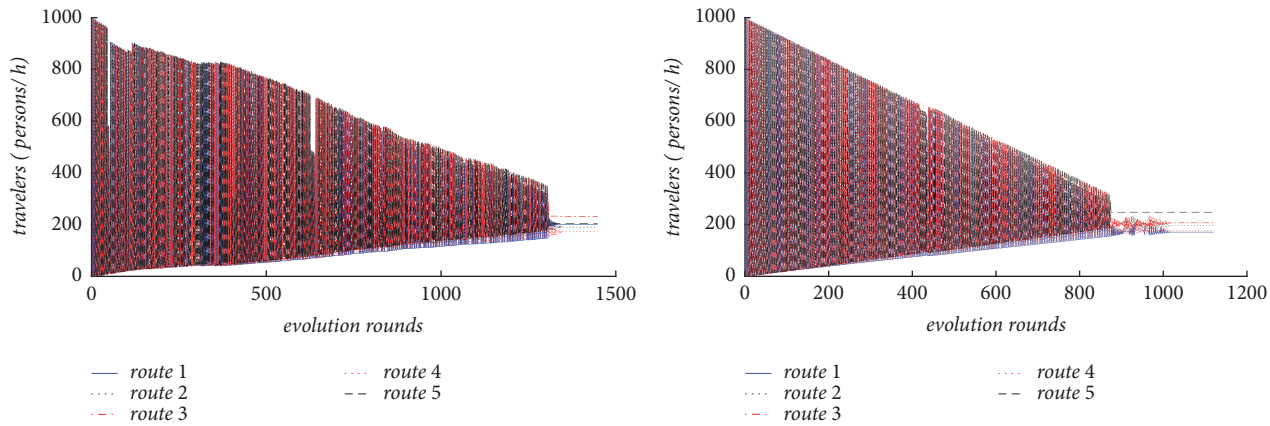
(4) The volume of each route can reach equilibrium stably. At the equilibrium point, volume of each route is similar for every simulation scene. Through calculating and testing, equilibrium volume for each route obeys normal distribution, that is, $Q_1 \sim N(168, 6.70)$, $Q_2 \sim N(195, 8.65)$, $Q_3 \sim N(251, 8.65)$, $Q_4 \sim N(176, 5.72)$, and $Q_5 \sim N(208, 6.4)$.

Therefore, the bounded-rationality of travelers can improve the evolution process. When most travelers select the near-optimal route instead of the shortest route, then the system can quickly achieve equilibrium.

For city managers, dynamic traffic information could be published to public. In terms of information content, fuzzy information is applicable so that travelers can not calculate travel time of each route but can only understand the traffic status. Then, the travelers can only select the near-optimal route according to the published information. In terms of information style, a combination of image and linguistic information should be published. Image information is used to inform the traffic condition, and linguistic information is designed to provide the suggested information. Additionally, suggestive induce information can be published to guide the selection of travelers.

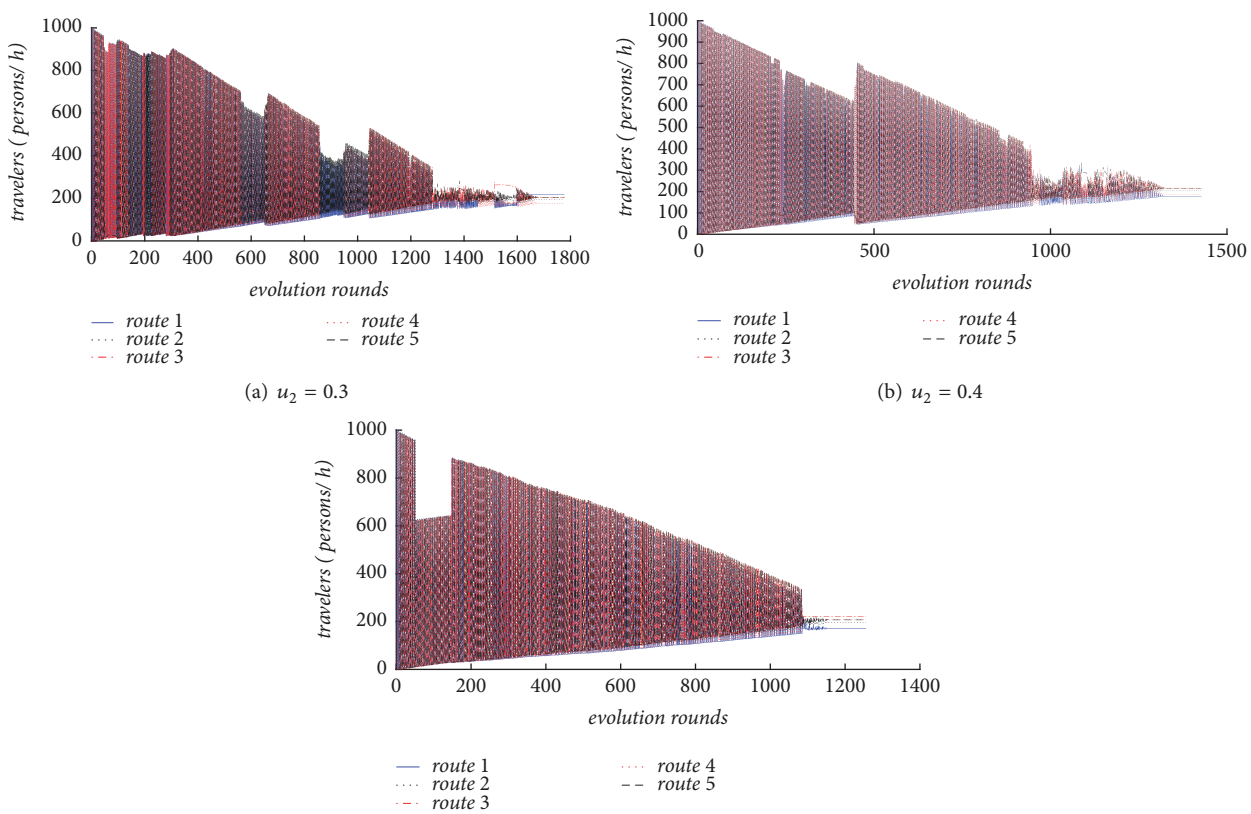
Data Availability

Data of this work comprised output of simulation and some figures. Output.xlsx contains the volumes of each route under different simulation scene. All the figures constitute the



(a) $\sigma_2 = 0.02$ (b) $\sigma_2 = 0.08$

Figure 8: Volume evolution of five routes for $q = 1000$, $\alpha = 0.3$, $\Delta = 0.2$.



(a) $u_2 = 0.3$ (b) $u_2 = 0.4$

(c) $u_2 = 0.6$

Figure 9: Volume evolution of five routes for $q = 1000$, $\alpha = 0.3$, $\Delta = 0.2$.

evolution equilibrium process involving equilibrium volumes and rounds under different simulation scene (Supplementary Materials available here).

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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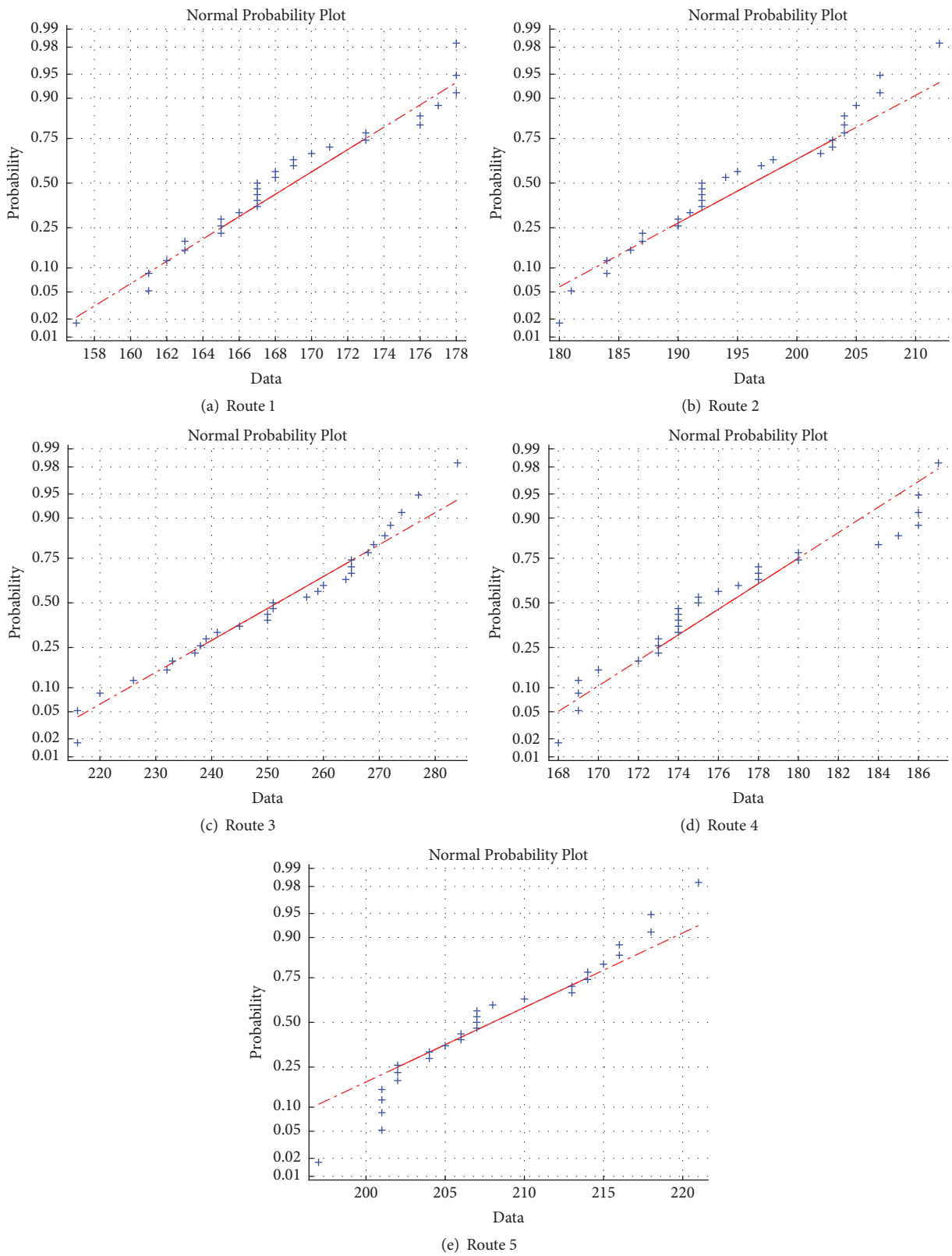

Figure 10: Normal distribution test for the equilibrium volume of each route.

Supplementary Materials

The supplementary materials of the manuscript contain the simulation results under different parameters, which means the different rationality of drivers, in addition to the volumes of each route and equilibrium rounds under different simulation parameters. *(Supplementary Materials)*

References

[1] S. Zhu and D. Levinson, "Do people use the shortest path? an empirical test of wardrop's first principle," *PLoS ONE*, vol. 8, pp. 1–18, 2015.

[2] Y. Iida, T. Akiyama, and T. Uchida, "Experimental analysis of dynamic route choice behavior," *Transportation Research Part B: Methodological*, vol. 26, no. 1, pp. 17–32, 1992.

[3] S.-X. He and B.-Q. Fan, "Analysis of unsteady stochastic equilibrium on urban traffic network," *China Journal of Highway and Transport*, vol. 21, no. 3, pp. 101–105, 2008.

[4] H. A. Simon, "Theories of bounded rationality," *Decision and Organization*, vol. 1, pp. 161–176, 1972.

[5] D. Kahneman and A. Tversky, "Prospect theory: an a nalysis of decision under risk," *Econometrica*, vol. 47, no. 2, pp. 263–292, 1979.

[6] A. Tversky and D. Kahneman, "Advances in prospect theory: cumulative representation of uncertainty," *Journal of Risk and Uncertainty*, vol. 5, no. 4, pp. 297–323, 1992.

[7] X. Di and H. X. Liu, "Boundedly rational route choice behavior: a review of models and methodologies," *Transportation Research Part B: Methodological*, vol. 85, pp. 142–179, 2016.

[8] H. Ye and H. Yang, "Rational behavior adjustment process with boundedly rational user equilibrium," *Transportation Science*, vol. 51, no. 3, pp. 968–980, 2017.

[9] W. Zhang, Z. He, W. Guan, and G. Qi, "Day-to-day rerouting modeling and analysis with absolute and relative bounded rationalities," *Transportmetrica A: Transport Science*, vol. 14, no. 3, pp. 256–273, 2018.

[10] C. Zhang, T.-L. Liu, H.-J. Huang, and J. Chen, "A cumulative prospect theory approach to commuters' day-to-day route-choice modeling with friends' travel information," *Transportation Research Part C: Emerging Technologies*, vol. 86, pp. 527–548, 2018.

[11] J. X. Sun, J. R. Chen, and R. X. Wang, "Route choice model with preference based on prospect theory," *Journal of Lanzhou Jiaotong University*, vol. 35, no. 3, pp. 152–156, 2016.

[12] X. Y. Li, X. M. Li, and X. W. Li, "Dynamic reference points based bounded rational multi-agent model of route choice," *Complex Systems and Complexity Science*, vol. 13, no. 2, pp. 27–35, 2016.

[13] X. J. Huang and X. L. Shi, "Modeling and analysis of path selection with two dimensional condition based on prospect theory," *Comprehensive Transportation*, vol. 39, no. 7, pp. 38–42, 2017.

[14] T. Rambha and S. D. Boyles, "Dynamic pricing in discrete time stochastic day-to-day route choice models," *Transportation Research Part B: Methodological*, vol. 92, pp. 104–118, 2016.

[15] C.-L. Zhao and H.-J. Huang, "Experiment of boundedly rational route choice behavior and the model under satisficing rule," *Transportation Research Part C: Emerging Technologies*, vol. 68, pp. 22–37, 2016.

[16] S. D. Luca and R. D. Pace, "Evaluation of risk perception in route choice experiments: an application of the cumulative prospect theory," in *Proceedings of the 18th IEEE International Conference on Intelligent Transportation Systems, ITSC '15*, pp. 309–315, September 2015.

[17] L. Zhou, S. Zhong, S. Ma, and N. Jia, "Prospect theory based estimation of drivers' risk attitudes in route choice behaviors," *Accident Analysis & Prevention*, vol. 73, pp. 1–11, 2014.

[18] J. Yang and G. Jiang, "Development of an enhanced route choice model based on cumulative prospect theory," *Transportation Research Part C: Emerging Technologies*, vol. 47, part 2, pp. 168–178, 2014.

[19] X. Jiang and W. Deng, "Considering dynamic knowledge updating in bounded rationality-based route choice modeling," *Advances in Mechanical Engineering*, vol. 9, no. 9, pp. 1–10, 2017.

[20] X. Di, H. X. Liu, X. X. Ban, and J. . Yu, "Submission to the DTA 2012 special issue: On the stability of a boundedly rational day-to-day dynamic," *Networks and Spatial Economics*, vol. 15, no. 3, pp. 537–557, 2015.

[21] T. Li, H. Z. Guan, and K. K. Liang, "Day-to-Day dynamical evolution of network traffic flow under bounded rational view," *Acta Physic Sinica*, vol. 65, no. 15, pp. 11–21, 2016.

[22] C. Y. Li, J. Chen, and Z. A. Sun, "Drivers' route choice behavior analysis under ATIS," *Journal of Shenzhen University Science and Engineering*, vol. 33, no. 2, pp. 164–172, 2016.

[23] F. Ma, Q. Q. Wu, and L. Wang, "Impact of multi-source guidance information on path change of drivers," *Journal of Transportation Systems Engineering and Information Technology*, vol. 14, pp. 61–66, 2014.

[24] Y. Zhang, X. Yang, Q. Liu, and C. Li, "Who will use pre-trip traveler information and how will they respond?: Insights from Zhongshan metropolitan area, China," *Sustainability*, vol. 7, no. 5, pp. 5857–5874, 2015.

[25] A. Tawfik and H. Rakha, "Latent Class choice model of heterogeneous drivers' route choice behavior based on learning in a real-world experiment," *Transportation Research Record*, no. 2334, pp. 84–94, 2013.

[26] T. Kusakabe, T. Sharyo, and Y. Asakura, "Effects of traffic incident information on drivers' route choice behaviour in urban expressway network," *Procedia - Social and Behavioral Sciences*, vol. 54, pp. 179–188, 2012.

[27] T. Lotan, "Effects of familiarity on route choice behavior in the presence of information," *Transportation Research Part C: Emerging Technologies*, vol. 5, no. 3-4, pp. 225–243, 1997.

[28] X. Di, H. X. Liu, S. Zhu, and D. M. Levinson, "Indifference bands for boundedly rational route switching," *Transportation*, vol. 44, no. 5, pp. 1169–1194, 2017.

[29] M. Li and H. J. Huang, "Modeling route choice behavior based on regret theory," *Journal of Management Sciences in China*, vol. 20, no. 11, pp. 1–9, 2017.

[30] M. Li and H. Huang, "A regret theory-based route choice model," *Transportmetrica A: Transportation Science*, vol. 13, no. 3, pp. 250–272, 2016.

[31] S. J. Maynard and G. R. Price, "The logic of animal of conflicts," *Nature*, vol. 246, pp. 15–18, 1973.

[32] S. J. Maynard, "The theory of games and evolution of animal conflict," *Journal of Theory Biology*, vol. 47, no. 1, pp. 209–221, 1974.

[33] J. Y. Sun, X. Han, and X. Y. Yan, "Review of laboratory experiments on travel choice behavior," *Complex System and Complexity Science*, vol. 14, no. 3, pp. 1–7, 2017.

[34] N. Uchiyama and E. Taniguchi, "A study of dispatcher's route choice model based on evolutionary game theory," *Procedia - Social and Behavioral Sciences*, vol. 39, pp. 495–509, 2012.

[35] X. W. Jiang, "Research on driver's route choice mechanism in VMS and information release strategy," A dissertation submitted for the academic degree of doctor of engineering, Southeast University, Nanjing, China, 2017.

[36] Y.-Q. Feng, J.-Q. Leng, and Z.-Y. Xie, "Route choice model considering generalized travel cost based on game theory," *Mathematical Problems in Engineering*, vol. 2013, Article ID 464038, 5 pages, 2013.

[37] L. Yang, Y. Shi, S. Hao, and L. Wu, "Route choice model based on game theory for commuters," *Promet - Traffic - Traffico*, vol. 28, no. 3, pp. 195–203, 2016.

[38] J. X. Sun, Y. P. Yi, and J. R. Chen, "The route choice model based on the mixed strategy of game theory," *Mathematics in Practice and Theory*, vol. 4, pp. 136–141, 2017.