Analysis of Tourists' Route Selection in Scenic Areas Based on Game Theory Model

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Keywords: Route Choice Behaviour, Evolutionary Game Model, Guidance Information, Numerical Simulation.

Abstract: This paper focuses on analysing the game behaviour of tourists within the scenic area sightseeing system. It examines how tourists' decision-making in choosing routes is influenced by their perception of crowds and guidance information. A game pay-off matrix is constructed, taking into account the impact of guidance information, to understand the decision-making process and optimal choices under different strategies. Additionally, a replication dynamic equation is established to study the evolution of route choice behaviour over time. Numerical simulations are conducted to assess the effects of guidance information on tourists' route choices. The findings indicate that the uniqueness of the Evolutionarily Stable Strategy (ESS) depends on the magnitude of payoffs loss resulting from congestion, as conveyed through the guidance information.

1 INTRODUCTION

In China, tourist congestion during holiday travel is a common issue, often resulting in stranded tourists unable to exit the scenic areas. To alleviate this problem and enhance the overall tourism experience, the concept of "smart" has garnered the attention of scenic area managers. They have introduced various advanced information technologies such as GPS positioning, RFID, and Mobile Network Technologies (4G), as well as handheld navigation terminals and tourism apps for visitors. These advanced information technologies facilitate the collection of spatio-temporal data on tourists, which in turn supports scenic area managers in designing effective visitor management and control measures, and enables them to provide timely and accurate guidance information. Conversely, for the tourists, this means they can now access information released by the scenic area managers, enabling them to proactively identify congested areas in advance. Armed with this knowledge, tourists can plan their visits more effectively, avoiding crowded spots and optimizing their overall experience and satisfaction.

The impact of guidance information on tourist flow within the scenic area can be understood as the macroscopic manifestation of game behaviors between tourists and other tourists, as well as between tourists and scenic area managers. From the tourists' perspective, they aim to enhance their travel experience by following the guidance information and switching to alternative routes. On the other hand, there may be other tourists who choose to continue with the original route for sightseeing, disregarding the guidance information. This creates a game-like dynamic where individual tourists seek to maximize their own experience. From the viewpoint of scenic area managers, their objective is to optimize the fraction of tourists who choose alternative routes based on the re-evaluation of the utility of remaining scenic spots along the original route using the guidance information. By achieving an optimal balance, the managers aim to improve the overall tourist experience (assuming that fewer visitors on a certain tour route would result in a better experience). Additionally, this approach helps reduce tourist congestion along the original route.

The remainder of this study is organized as follows. In Section 2, we present a literature review. The evolutionary game model to deal with the tourist route choice behavior is established in Section 3. Numerical experiment is done in Section 4. Finally, we summarize the findings in Section 5.

2 LITERATURE REVIEW

In recent years, there has been significant research conducted on the scientific management of scenic

Ma, R. and Yao, L.
Analysis of Tourists' Route Selection in Scenic Areas Based on Game Theory Model.
DOI: 10.5220/0012283300003807

In *Proceedings of the 2nd International Seminar on Artificial Intelligence, Networking and Information Technology (ANIT 2023)*, pages 344-349
ISBN: 978-989-758-677-4

areas, particularly in tourist volume forecasting. Several prediction methods have been proposed by scholars. Chen et al. proposed a hybrid approach that combines Support Vector Regression (SVR) with adaptive genetic algorithm (AGA) and seasonal index adjustment to forecast holiday daily tourist flow (R. Chen, 2015). Assaf et al. introduced a comprehensive approach based on a Bayesian global vector autoregressive (BGVAR) model for tourism demand analysis (A.G. Assaf, 2019). Yang et al. used web search query volume to predict visitor numbers for a popular tourist destination in China, comparing the predictive power of Google and Baidu search data (X. Yang, 2015). Li et al. proposed a model named PCA-ADE-BPNN for forecasting tourist volume based on Baidu index (S. Li, 2018). Sun et al. developed a forecasting framework using machine learning and internet search indexes to forecast tourist arrivals in popular destinations in China, comparing the performance of Google and Baidu search results (S. Sun, 2019). Researchers have also focused on tourist shunt schemes, which aim to direct visitors along specific travel routes. Zheng et al. proposed shunt strategies based on different behavior characteristics and applied them to Jiuzhaigou as a case study (W. Zheng, 2013). Kamruzzaman and Karmakar presented a dynamic content distribution scheme for sharing contents in tourist attractions, taking practical issues into consideration (J. Kamruzzaman, 2019). Furthermore, in the post-modern tourism era, tourist route recommendation has become a hot topic. Various methods have been developed based on the popularity of attractions and available time for tourists (F. M.Hsu-W. Zheng). However, tourists' route preferences often change during their tour, leading to errors in practical application. Moreover, existing methods do not consider the influence of guidance information. Therefore, this paper aims to discuss the route choice behavior of different tourist groups in scenic areas using evolutionary game theory.

3 MODEL AND ANALYSIS

A. Hypothesis

In order to analyze the problem of tourist route choice behavior under guidance information, this paper makes the following assumptions:

H1: Game participants are tourist groups in scenic area system, which meet the characteristics of bounded rationality.

H2: Tourists in the system show heterogeneity and adjust their tour plans based on their perception of crowding. Some tourists, who are sensitive to crowded areas, may choose to visit less crowded spots first by taking a detour. In this paper, we categorize tourists into two groups based on their perception of crowding: Group G_1, consisting of tourists with low crowding perception or sensitivity to travel distance, and Group G_2, consisting of tourists with high crowding perception or less sensitivity to travel distance.

H3: All visitors in the system will visit each scenic spot in turn, as shown in Figure.1, the strategy set of game players is $S=\{S_1$:*Route* 1; S_2:*Route* 2 $\}$, where S_1 represents tourists first visit the scenic spot A_1 and then visit A_2, S_1 represents tourists first visit the scenic spot A_2 and then visit A_1. S_1 is the planned tour route before the tour, which conforms to the predilection of tourist route choice. S_2 is an alternative route, which need to take a longer distance.

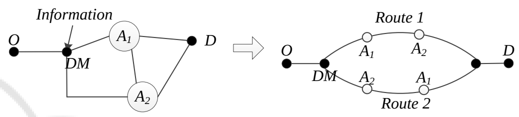


Figure 1. Analysis on the evolution of tourist routing behavior.

B. Evolutionary Game Model

1) Payoffs Matrix and Variables

Based on the above analysis and model assumptions, the costs and benefits of tourist groups in different strategies can be obtained. Let V_{ij} be the payoffs of tourist group G_i selecting the strategy S_j. In this paper $i=1,2$ and $j=1, 2$. Table 1 shows the payoffs matrix of the tourist group route choice with guidance information.

Table 1: Payoffs matrix tourist group G_1 and $G_{2.}$

Tourist group G_1	Tourist group G_2	
	S_1	S_2
S_1	V_{11}-R, V_{11}-R	V_{11}+R_1, V_{22}-D_1
S_2	V_{12}-D_2, V_{21}+R_2	V_{12}-D_3, V_{22}-D_4

In Fig. 1, upon receiving the induced message of congestion on route 1, tourists in G_1 will reconsider their travel routes at point DM, considering the behavior of other tourists and payoffs of different route choices to maximize their benefits. If G_1 adopts strategy S_1 (traveling on the original route), with no changes from other tourists, G_1 will experience more serious congestion (payoff loss denoted as V_{11}-R). If G_1 adopts strategy S_2 (traveling on the alternative route), there will be temporary path replacement effects and detour losses (payoff loss denoted as V_{12}-

D_2). If G_2 adopts strategy S_1 after receiving the information, G_1's payoff varies depending on whether G_1 chooses strategy S1 or S_2. Choosing S_1 leads to congestion reduction and benefits for G_1 (V_{11}+ R_1). Choosing S_2 results in congestion on the alternative route due to the shift in tourists and detour losses (V_{12}-D_3). For G_2, their payoffs depend on G_2's strategy decisions: V_{21}-R and V_{21}+R_2 for strategy S_1, V_{22}-D_1 and V_{22}-D_4 for strategy S_2. Due to G_1's low crowding perception and sensitivity to travel distance, detours result in more payoff loss for G_1 ($D_3 > D_4$). When the two groups choose different strategies, congestion on route 1 is eased. Tourists on route 1 benefit without the need for detours, while those on route 2 incur losses from detour costs.

For the group selecting S_1, G_1's benefits exceed G_2's ($R_1 > R_2$). For the group selecting S_2, G_1's loss is smaller than G_2's due to travel distance sensitivity ($D_2 > D_1$). The losses incurred by detouring (D_3) are greater than intensified congestion ((D_2), and the same applies to D_4 and D_1. In summary, the relations are: $D_3 > D_2 > D_4 > D_1$ and $R_1 > R_2$.

2) Replicator Dynamic Equation and Equilibrium Points

In this paper, we refer to the replication dynamic mechanism to address the strategies selecting problem of the tourist group G_1 and G_2 with the influence of guidance information. The idea is that the next stage the growth rate of population in some strategy and select the strategy in the current population and the proportion of the profits were positively correlated, evolve over time, high yield of population proportion will increase, low income population proportion will be reduced, until dying. Let the fraction of G_1 choosing S_1 be x, then the fraction of G_2 choosing S_2 be 1-x. Let the fraction of G_2 choosing S_1 be y, then the fraction of G_2 choosing S_2 be 1-y.

The payoffs of G_1 choosing S_1 are:

$$U_{11}^{x} = -(R+R_1)y + (V_{11}+R_1) \tag{1}$$

The payoffs of G_1 choosing S_2 are:

$$U_{12}^{1-x} = (D_3-D_2)y + (V_{12}-D_3) \tag{2}$$

Then, the average expected payoffs of different strategies of G_1 is:

$$\bar{U}_1 = (D_2-D_3-R-R_1)xy + (R_1+D_3)x + (D_3-D_2)y + (V_1-D_3) \tag{3}$$

The payoffs of G_2 choosing S_1 are:

$$U_{21}^{y} = -(R+R_2)x + (V_{21}+R_2) \tag{4}$$

The payoffs of G_2 choosing S_2 are:

$$U_{22}^{1-y} = (D_4-D_1)x + (V_{22}-D_4) \tag{5}$$

Similarly, the average expected payoffs of different strategies of G_2 is:

$$\bar{U}_2 = (D_1-D_4-R-R_2)xy + (R_2+D_4)y + (D_4-D_2)x + (V_2-D_4) \tag{6}$$

The replicated dynamic equation of G_1 choosing route 1 is as follows:

$$\frac{dx}{dt} = V(x) = x(U_{11}-\bar{U}_1) = x(x-1)[(D_3+R+R_1-D_2)y-(R_1+D_3)] \tag{7}$$

The replicated dynamic equation of G_2 choosing route 1 is as follows:

$$\frac{dy}{dt} = V(y) = y(U_{21}-\bar{U}_2) = y(y-1)[(D_4+R+R_2-D_1)x-(R_2+D_4)] \tag{8}$$

When y=(R_1+D_3)/(D_3+R+R_1-D_2), at this time $V(x)\equiv 0$, that means if the initial fraction of G_2 choosing route 1 satisfies the above equation, the system must be stable, no matter whatever the strategies are chosen by the tourists in G_1, the payoffs they get are the most satisfactory.

When 0<y<(R_1+D_3)/(D_3+R+R_1-D_2), at the moment, $V'(0)>0$ and $V'(1)<0$, the evolutionary stable strategies of the dynamic system (abbreviated as ESS) is $x^*=1$. That means if the initial fraction of G_2 choosing route 1 satisfies the above equation, the payoffs of G_1 choosing route 1are larger than the payoffs of G_1 choosing route 2, so that, as time goes on, all the tourists in G_1 in the dynamic system will choose route 1.

When (R_1+D_3)/(D_3+R+R_1-D_2)<y<1, at the time, $V'(0)<0$ and $V'(1)>0$, the ESS of dynamic system is $x^*=0$. That means if the initial fraction of G_2 choosing route 1 satisfies the above equation, the payoffs of G_1 choosing route 2 are larger than the payoffs of G_1 choosing route 1, so that, as time goes on, all the tourists in G_1 in the dynamic system will choose route 2.

3) Equilibrium Point Stability Analysis

According to Friedman's evolutionary game theory, the equilibrium points of the dynamic system may include (0,0), (0,1), (1,0), (1,1), and (x_0, y_0). The equilibrium points can be determined by analyzing the local stability of the Jacobian matrix. Specifically, in this paper, the Jacobian matrix of the path selection game system is examined:

$$\mathbf{J} = \begin{bmatrix} (2x-1)[(D_3+R+R_1-D_2)y-(R_1+D_3)] & x(x-1)(D_3+R+R_1-D_2) \\ y(y-1)(D_4+R+R_2-D_1) & (2y-1)[(D_4+R+R_2-D_1)x-(R_2+D_4)] \end{bmatrix}$$

The determinant of Jacobian matrix $\det\mathbf{J}$ is:

$$\begin{aligned}\det\mathbf{J} = {} & (2x-1)[(D_3+R+R_1-D_2)y-(R_1+D_3)](2y-1)[(D_4+R+R_2-D_1)x-(R_2+D_4)] \\ & -x(x-1)(D_3+R+R_1-D_2)y(y-1)(D_4+R+R_2-D_1)\end{aligned}$$

The trajectory of Jacobian matrix $tr\mathbf{J}$ is:

$$tr\mathbf{J} = (2x-1)[(D_3+R+R_1-D_2)y-(R_1+D_3)] + (2y-1)[(D_4+R+R_2-D_1)x-(R_2+D_4)]$$

In this paper, we will pay more attention on how the guidance information has an effect on the evolution process of tourists' route choice, so we will not give more discussion about the point (x_0, y_0). This paper analyzes how the value of R influences the dynamic evolution process of tourists' route choice behavior. The discussion of R is mainly divided into the following four situations, the stability analysis about different values of R is shown in Table 2.

Table 2. The evolutionary stability state under various cases.

	R=0				0<R<D_1			
(x, y)	(0, 0)	(0, 1)	(1, 0)	(1, 1)	(0, 0)	(0, 1)	(1, 0)	(1, 1)
det **J**	+	-	-	+	+	-	-	+
tr**J**	+	Uncertain	-	-	+		-	-
State	Unstable	Saddle point	Unstable	ESS	Unstable	Saddle point	Unstable	ESS
	D_1<R<D_2				R>D_2			
(x, y)	(0, 0)	(0, 1)	(1, 0)	(1, 1)	(0, 0)	(0, 1)	(1, 0)	(1, 1)
det **J**	+	-	+	-	+	+	+	+
tr**J**	+	Uncertain	-		+	-	-	+
State	Unstable	Saddle point	ESS	Saddle point	Unstable	ESS	ESS	Unstable

When R=0, tourists cannot obtain information about tourist congestion in the subsequent tour route during the tour. Therefore, they will follow the pre-planned route without any route choice during the tour. The evolutionary trajectory will ultimately stabilize at the ESS (1,1), where all tourists choose route 1. This is because without real-time guidance information, tourists lack awareness of the congestion status on route 2 and choosing route 2 would result in detouring and loss of payoffs. Hence, tourists prefer to choose route 1 based on finding the most satisfactory travel route.

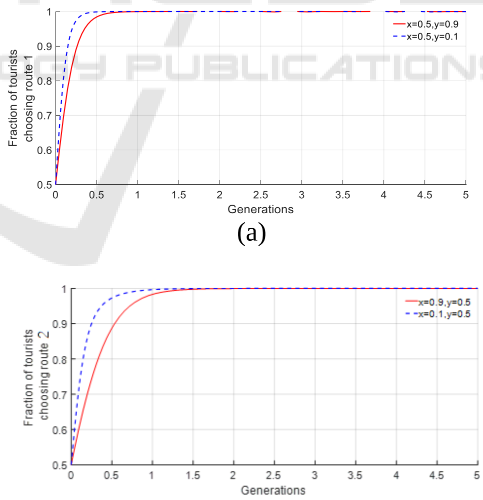
When 0<R<D_1, the scenic area provides guidance information indicating congestion on route 1, but the payoffs loss caused by congestion is less than the payoffs loss of detouring to route 2. The evolutionary trajectory will also stabilize at the ESS (1,1), with all tourists continuing to choose route 1. Despite the release of real-time guidance information, the congestion's impact on payoffs is not significant enough to outweigh the detouring losses, resulting in no change in tourists' route choice.

When D_1<R<D_2 , the scenic area provides guidance information indicating congestion on route 1, and the congestion's impact on payoffs is larger than the detouring losses to route 2 but smaller than detouring losses to route 1. The evolutionary trajectory will stabilize at the ESS (1,0), with tourists in Group G1 (low crowding perception) continuing to choose route 1 and tourists in Group G2 (high crowding perception) choosing route 2. In this case, Group G1 is less sensitive to the payoffs loss caused by increasing tourist volume and prefers to tour with higher tourist density. However, Group G2, being more sensitive to crowding, chooses the alternative route (route 2) to avoid congested areas and mitigate payoffs loss.

When R>D_2, the scenic area provides guidance information indicating congestion on route 1, and the congestion's impact on payoffs is larger than the detouring losses to route 2. The evolutionary trajectory will stabilize at the ESS (0,1) and (1,0), with tourists either in Group G1 touring route 1 and tourists in Group G2 touring route 2, or vice versa. In this case, both groups bear the payoffs loss caused by congestion. When one group chooses the alternative route to alleviate congestion, the other group avoids the loss caused by congestion on the original route. The stable convergence of the system in this situation is uncertain, as it depends on the specifics of the payoffs matrix and initial parameter values.

4 NUMBERICAL SIMULATION

The MATLAB 2016a software is applied to simulate the dynamic evolutionary trajectories of the evolutionary system, for the purpose of verifying the accuracy of model consequences and making dynamic evolution trend more explicitly and vividly. The initial values of each parameter are listed as follows: D_1=4, D_2=8, D_3=10, D_4=6, R_1=5, R_2=6.



(a)

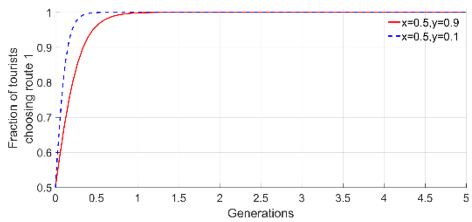
(b)

Figure 2. (a) and (b) Dynamic evolutionary paths (R=0).

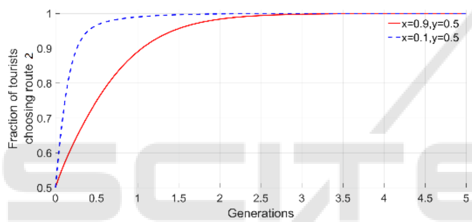
In Fig. 2(a), higher initial fractions of G2 choosing route 1 result in faster convergence to the ESS, while lower initial fractions of G1 choosing route 1 lead to faster convergence in Fig. 2(b).

In Fig. 3(a), higher initial fractions of G2 choosing route 1 result in faster convergence to the ESS.

Initially, some tourists in G2 try to tour on route 2 but eventually realize that the payoffs of choosing route 1 are larger. This realization takes a relatively long time for G2 to converge to the ESS. In Fig. 3(b), lower initial fractions of G1 choosing route 1 lead to faster convergence to the ESS. This is because G1, with high crowding perception, experiences larger payoffs for detouring compared to touring route 1 when the fraction choosing route 1 is high. As time progresses, the payoffs for G1 choosing route 2 decline gradually, leading G1 to evolve towards route 1 and ultimately stabilize on route 1.



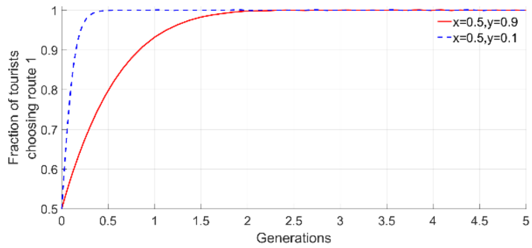
(a)



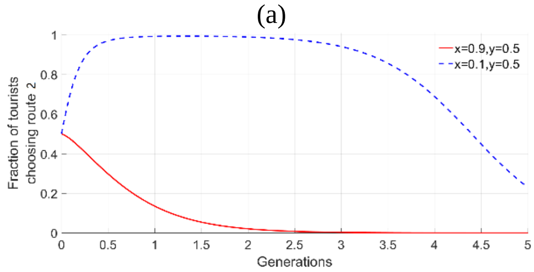
(b)

Figure 3. (*a*) and (*b*) Dynamic evolutionary paths (0<R<D_1, R=2).

In Fig. 4(a), lower initial fractions of G2 choosing route 1 lead to faster convergence to the ESS. When most tourists initially choose route 2, the higher payoffs for G2 choosing route 1 result in all tourists in G2 ultimately traveling on route 1, leading to a quick convergence to the stable state. Fig.4(b) illustrates that for initial fractions of (0.1,0.5) and (0.9,0.5), the trajectory towards the stable state varies greatly. Initially, G1 experiences a rapid increase in the fraction choosing route 1 due to higher payoffs. However, over time, the payoffs for G1 choosing route 1 decrease relative to choosing route 2, leading to a gradual increase in the fraction choosing route 2. Ultimately, all tourists in G1 choose route 2, converging to the stable state. When R=6, regardless of the initial x value, all tourists in G1 will eventually choose route 2.



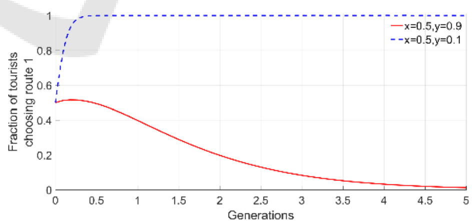
(a)



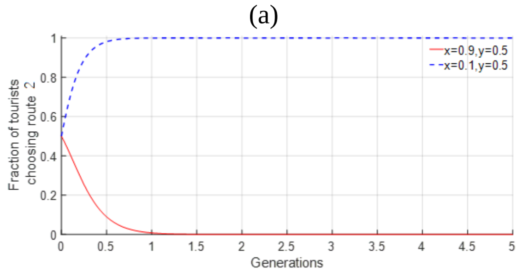
(b)

Figure 4. (*a*) and (*b*) Dynamic evolutionary paths (D_1<R<D_2, R=6).

In Fig. 4(*a*), for G1 with initial strategy fractions of (0.5,0.1) and (0.5,0.9), different evolutionary stable states are observed. When y=0.1, G_1 tends to ESS (1,0) due to higher payoffs on route 1. When y=0.9, despite low crowding perception, G_1 prefers route 2 due to larger congestion payoffs, leading to ESS (0,1). In Fig.4(*b*), for G_2 with initial strategy fractions of (0.1,0.5) and (0.9,0.5), different evolutionary stable states emerge. When x=0.1, G_2 tends to ESS (1,0) due to lower initial fraction on route 1. When x=0.9, higher crowded perception in G_2 makes congestion payoffs larger, resulting in a preference for route 2 and ESS (0,1) for G_1.



(a)



(b)

Figure 4. (*a*) and (*b*) Dynamic evolutionary paths (R>D_2, R=9).

5 CONCLUSIONS

This paper applies evolutionary game theory to study the route choice behavior of tourist groups with different perceptions of crowding within a scenic area. The influence of guidance information on route choice is analyzed, considering various strategies of information supply. A game model is constructed to examine the evolutionary stable states of tourist route choices under the impact of guidance information. Dynamic equations are used to analyze the long-term stability evolution trend of the scenic tours system. Numerical experiments are conducted to simulate the effects of different guidance information strategies on the system's evolution. The main conclusions are as follows: (1) Without guidance information, all tourists choose the original route (unique ESS). (2) With guidance information, the uniqueness of ESS depends on the size of payoffs loss caused by congestion revealed in the information: (a) When the payoffs loss from congestion is small, all tourists still choose the original route (little effect from guidance information); (b) When the payoffs loss from congestion falls between the detouring payoffs loss of two tourist groups, tourists with low crowding perception choose the original route and those with high crowding perception choose alternative routes (successful guidance information to ease congestion); (c) When the payoffs loss from congestion exceeds the detouring payoffs loss of both groups, the ESS for route choice becomes non-unique, with each group choosing different routes to avoid congestion.

ACKNOWLEDGMENTS

This work was supported by Humanities and social sciences fund of the Ministry of Education (No.19YJC630119).

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