

Received January 22, 2020, accepted February 11, 2020, date of publication February 19, 2020, date of current version March 2, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2975053

# Simulating the Market Share Variation in Multi-Airport Area Incorporating Airport Choice Habit

JING LU<sup>1</sup>, YUCAN MENG<sup>1</sup>, AND YINGJING GU<sup>2</sup>

<sup>1</sup>College of Civil Aviation, Nanjing University of Aeronautics and Astronautics, Nanjing 21006, China

<sup>2</sup>Business School, Nanjing Xiaozhuang University, Nanjing 211171, China

Corresponding author: Yingjing Gu (guyingjing2019@njzcu.edu.cn)

This work was supported by the National Natural Science Foundation of China under Grant 71701094 and Grant 71431001.

**ABSTRACT** For the reason that passengers commonly need some time to change their habitual airport choice, the demand attracted by a newly conducted service of an airport may gradually increase at the start-up time. We refer to this duration as the cultivation period and analyze the variation in the market share within the period by simulating the switch of habitual airport choice. Considering the effects of habit on passengers' cognitive risks, the cumulative prospect theory is applied to model the habitual airport choices, and the habit decay pattern is determined to construct the mechanism that links the sequential choices. The case of Lukou Airport in the Yangtze Delta Region is considered as an example to validate the simulation approach. The results show that the simulated market share fits the real data well, and the coach frequency and the on-time performance are two key factors that determine the efficiency of the coach service in the cultivation period. Meanwhile, setting dynamic coach frequencies is an effective strategy to guide passengers in quickly switching their habitual airport choice, which reduces the cultivation period.

**INDEX TERMS** Cultivation period, airport market share, switch of habitual airport choice, cumulative prospect theory.

## I. INTRODUCTION

Within a multi-airport region, one of the most popular approaches to improve the airport market share is to provide better access services [1] such as the long-distance coach service connects the airports and surrounding cities [2]. To clarify the efficiency of the airport coach, numerous articles have focused on predicting the air travel demand attracted by services with different attributes (such as different frequencies, ticket prices, and on-time performance) [3]. Most of the results seem to be related to predicting the final market share that an airport may capture with coach service [4] but seldom address the duration before the target market share is obtained.

However, the airport market share may not jump from an original level to a substantially higher level as soon as the coach service is conducted; conversely, it always gradually increases within a long duration [5]. Referring to the definition of market cultivation in the marketing science [6],

The associate editor coordinating the review of this manuscript and approving it for publication was Chaitanya U. Kshirsagar.

we define the previously mentioned duration as the cultivation period of penetrating a new market using the improved coach service. According to the experiences, the length of the cultivation period and the demand volume, which increased within the duration, may determine the final efficiency of the coach services on improving the airport market share [7]. Thus, airport managers expressed a strong desire to explore the mechanism that pushes the variation in the market share in the cultivation period; they will have the opportunity to propose some appropriate strategies for marketing [8].

Considering the theoretical relationships between travel demand and travel behavior, the variation in the airport market share is caused by a change in passengers' airport choice within a multi-airport region [9]. If airport A conducts the coach service, passengers would give up their previously preferred airports and switch to A. However, because some passengers who have habitual preferences would spend a long time switching their airport choices, the airport market share will certainly gradually increase until all passengers finish their switch behavior.

The mechanism that underlies the variation in the airport market share in the cultivation period is relevant to the airport choice switch and passengers' choice habit. Therefore, the task of our work is to model the switch of habitual airport choice. Our proposed model should not only interpret the habitual behavior but also build links that connect the sequential airport choices for describing the switch process. Per the benefits of the simulation method in modeling the time-varying behavior [10], we choose to establish a simulation framework based on an airport choice model.

To obtain a suitable method for modeling the habitual airport choice, we should analyze the influences of the habits on the choice preferences. Reported by Feng and Timmermans [11], passengers commonly decrease the cognitive risks of the habitual choices but inversely raise the uncertainty of an unfamiliar alternative. For instance, if people are not familiar with one airport and its coach service, they may be worried about the on-time performance of the coach; thus, their perceptions of the risks of missing flights would increase ([12], [13]). Therefore, we decide to use the difference between cognitive risks and objective risks to describe the influence of habits on airport choices and model the habitual airport choice using the cumulative prospect theory, which is proved suitable to interpret the risky choices [14].

Therefore, based on simulating the switch of airport choice with the habitual preferences, this paper attempts to predict the variation in market share in the cultivation period for the airports, which newly conduct the coach services. The simulation framework is constructed based on the cumulative prospect theory, and the multi-airport region in the southeast part of China is set as the case study to test our proposed approach. Following this introduction, section 2 reviews the related literature; section 3 describes the airport choice switch with habitual preferences; section 4 proposes the simulation framework based on the cumulative prospect theory; section 5 presents the case study; section 6 details the scenario analysis; and section 7 provides the conclusions.

## II. LITERATURE REVIEW

To establish the simulation framework for predicting the market share variation within the cultivation period, we should simulate the switch of habitual airport choice in a multi-airport region with two steps: first, to model the airport choice with habitual preferences, and second, to build the switch mechanism. Therefore, in this section, we will summarize the studies that are relevant to the airport choice within multi-airport region, the habit quantification and the choice switch simulation.

### A. AIRPORT CHOICE IN MULTI-AIRPORT REGION

In the existing literature, numerous studies have focused on analyzing the airport choice in a multi-airport region. Discrete choice models became the most popular approaches since Skinner [15] employed the multinomial logit (MNL) model to analyze the airport choice in New York. With the discrete choice framework, researchers have discussed the

effects of different service attributes on airport choice, such as ticket prices, ground accessibility, flight delay, and flight frequency ([16]–[20]).

To be specific, Harvey [16] used the MNL model to investigate the airport choice in San Francisco Bay area. He found that the access time and the frequency of service were significant for both leisure and business travelers. Besides, business travelers more insensitive to cost because they rarely pay their own travel expenses. Lian and Rønnevik [17] also used the MNL model to find that the inconvenience of access, they pointed out that the absence of direct services may result in the leakage of demand from regional airport to neighboring airports where direct services are available. Then, the correlation between the access modes was taken into consideration, for example, De and Di Pace [18] compared different types of discrete choice models in studying the airport choice in Rome. They took 7 attributes into consideration, such as airfare, frequency, car access travel time, car availability etc. They found that MNL model performed best when airport is the only choice dimension. NL model provided statistically significant result when studying the joint choice of airport and airport access mode. That is to say the NL model outperforms MNL model when we consider the joint choices. Meanwhile, Pels *et al.* [19] also proposed a two-level nested logit to study the joint choice of airport and access service. They tried to provide insight into passenger sensitivity to fare, frequency, airport access time and airport access cost. And they proved that the NL model would explain the hierarchical structure well. At the same time, Hess & Polak [20] applied a cross-nested logit (CNL) model to analyze the airport choice in Great London area, the model considered the correlation between airport, airline and access-mode, and the results also highlighted that the access time was a determining factor and the access cost also played a role in affecting the airport choice.

Referring to the highly cited studies related to airport choice, we discover that the discrete choice model would be the popular one that used in modelling airport/airline choice and airline-airport-access mode joint choice. It has the advantages in interpreting passengers' choice preferences to the alternatives attributed to different service characteristics and also can explain the hierarchical structure of the joint choice.

By exploring the airport choice behaviors in different regions of the world, the ground access time to airport, the flight frequency and the air ticket price are the three top factors that influence the airport choice behavior; however, the access time seems more important for the airport choice in a multi-airport region [21]. We can imagine that the improved coach service would have a distinct stimulus on airport choice behavior; however, other factors should be incorporated into the simulation approach.

### B. HABIT MEASUREMENT AND RISK PERCEPTION

In addition to the attributes about airports or airlines, the psychological attributes were also proved to be essential for

modeling the airport choice. For instance, Suzuki *et al.* [22] determined that passengers preferred to choose the airports that are linked to positive experiences that would determine the selection of alternative airports in the future [23]. Wood & Neal [24] indicated that passengers would form the airport choice habit until sufficient travel experiences were cumulated, and the habit would lead to the bounded rationality in decision-making (passengers would choose an airport based not only on the objective utility). Therefore, the habitual airport choice needs to be carefully incorporated into the airport choice.

However, few studies modeled the habitual airport choice, which may be attributed to two reasons: the difficulty in quantifying the habit and modeling airport choice with bounded rationality. Although habitual choice was disregarded for air transportation, it has been discussed in other research fields.

In the field of travel mode choice modeling, Aarts *et al.* [25] stated that habit can change the cognitive reliability of different travel modes; thus, the level of habit should be quantified by understanding passengers' cognition. Some researchers in the field of psychology science established self-reported criteria to calculate the habit strength, which can describe the level of habitual preferences to alternatives [26]. In this study, we will design self-reported criteria for calculating the strength of passengers' airport choice habits and will attempt to apply the cognitive risks of using a coach service to quantify the effects of different habit strengths on airport choices.

### C. MODELLING METHOD FOR RISKY CHOICE

When considering the cognitive risks, habitual airport choice can be treated as a risky choice. The risk comes from the uncertainty ([27], [28]). In our study, the risk comes from the uncertainty of the travel time of new airport coach to an unfamiliar airport, the uncertainty is important because passengers may miss the flight if the coach is late.

According to existing literature, game theory and prospect theory are two approaches for modeling choices with uncertainty. For game theory, a well-known approach is to model the strategy choice in the competition between two or multiple decision makers [29]. For example, Littlechild & Thompson used game theory to discuss the best landing fee pricing strategies for competitive airports by considering their risk aversion attitude to lose flights [30]. Hansen applied noncooperative game theory to model the hub domination game among airlines, and the environment risks caused by competitors' marketing strategies were incorporated in the model [31].

Compared with game theory, prospect theory is the most widely used framework to model decisions under risk [32] and extensively applied to depict individual's travel choice [33]. As reported by Ben-Elia and Shiftan [34] and Zhang *et al.* [35], prospect theory can accurately analyze the risky decision-making in travel mode choice and route choice. In addition, with the model, the heterogeneous attitudes to the uncertainty and risks can be interpreted in

modeling the choice behavior. For example, Zhou *et al.* [36] used the prospect theory to capture the drivers' risk attitudes in the route choice and stated that the heterogeneity in the risky attitude was very important and should be incorporated in modelling the driver's route choice behavior. Therefore, we could say that the prospect theory would have the benefits of revealing the risky attitude discussed in our paper.

However, the prospect theory also has some disadvantages. For instance, some literatures have pointed out the shortages by comparing the prospect theory with the discrete choice models. Li *et al.* [37] presented that prospect theory was used to determine the best alternative by comparing the prospect value of every alternative. So the prospect theory ignored the correlations between alternatives. In addition, Baucells & Villasís [38] compared the prospect theory with the utility theory, they summarized that the prospect theory ignored the unobserved utility in the choice. But as passengers' attitude to the uncertainty of coach travel time is important in modeling the airport choice. Although there are some disadvantages in using the prospect theory, considering the performance of the prospect theory in modeling the risky airport choice, it will be applied to model the habitual airport choice in a multi-airport region.

These studies help us clarify the proper approaches for modeling the habitual airport choice. However, we also have to think about how to describe the switch of habitual airport choice in the simulation. In previous studies, the switch of airport choice was always simulated without considering the change in habitual preferences; however, numerous studies have announced that passengers' habits would form during day-to-day learning ([39]–[41]) but also may change due to changes in the external environment [42]. We will attempt to establish the simulation mechanism, which can explain the interaction between the change in airport choice habit and the switch of airport choice, and calculate the market share variation in the cultivation period for airports with new coach services.

### III. PROBLEM STATEMENT

Assuming that two airports ( $A$  and  $B$ ) exist around city  $C$ , the distance from  $C$  to  $A$  and  $B$  is almost equivalent. In city  $C$ , the market share of  $A$  is higher than that of  $B$ . To attract additional passengers,  $B$  begins to offer coach service. In the context, passenger  $Y$  (lives in  $C$ ) who has a habitual preference to  $A$  may switch his/her airport choice. In this section, we attempt to clarify two questions: i) how the habitual preference affects  $Y$ 's airport choice, and ii) how the airport choice switches with the change in habit.

To answer the first question, we should analyze the airport choice.  $Y$  who has a very strong habitual preference to  $A$  should travel by air on March 23, 2007. He will choose the airport with five steps: collecting objective information, cognizing the objective information, selecting the airport, using the chosen airport and providing feedback about the experience. The steps are described in Figure 1. Collecting the objective information is the first step, in which  $Y$  may

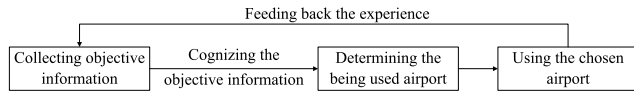


FIGURE 1. Description of “airport choice for a single trip”.

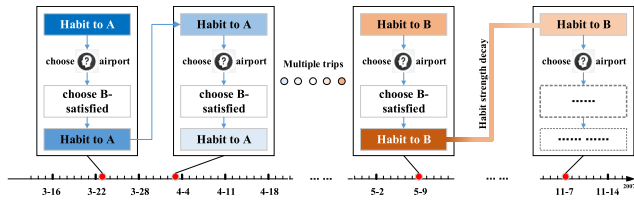


FIGURE 2. Switch of habitual airport choice.

search the flight frequency, the air carrier and the coach service conducted by *B*. In the second step, he will cognize the information with the impact of his *A*-preferred habit strength. For example, the cognized probability that the coach to *B* is delayed would be higher than the real delay. The third step is to select the airport based on the cognized information, in which *Y* will decide to shift to *B* for coach service or habitually choose *A*; here, we assume that *Y* chooses *B*. Using the chosen airport is the fourth step; the satisfaction or the disappointment will affect the next step, which is the feedback of the experience. If *Y* is satisfied with *B*, his habit strength of choosing *A* may decline, and vice versa. Although the last step does not work on the current choice, it will work on future choices.

Based on this analysis, we can discover that the habitual preference affects the airport choice by influencing the cognition of the on-time performance of the coach to *B*, and the magnitude of the habit strength would enable different cognition of travel risk. Thus, we should quantify the relationship between the habit strength and the cognized on-time performance of the coach service and then model the risky airport choice.

After clarifying the relationship between the habitual preference and airport choice, the interaction between the airport choice switch and the habit change should be explored. As stated in Figure 1, *Y*’s positive experience on *B*’s coach on March 23 would cause the decline of his *A*-preferred habit strength. To describe the change in habit strength, we use a deep blue color to represent *Y*’s *A*-preferred habit strength before the trip and use a lighter blue color to show the declined habit strength in the first block in Figure 2.

We observe that the declined habit strength would further affect the airport choice on April 3rd (Block 2); however, the color representing the habit strength before the new trip seems substantially lighter. Because the habit strength decays over time [39], and the damping speed is determined by the interval between two consecutive trips, the habit strength may decay to 0 if the interval is sufficiently long.

From Block 1 to Block 4, *Y* gradually changes his habitual preference to *A* and forms a *B*-preferred habit during the trips from March 23<sup>rd</sup> to November 7<sup>th</sup>. In the process, habit

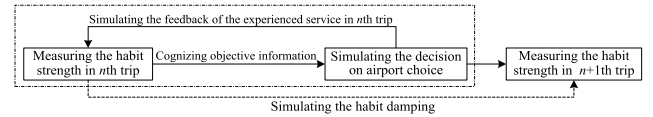


FIGURE 3. Framework of simulating the habitual airport switch for one passenger.

strength decay is the key to linking the prior airport choice to the latter choice. Thus, we should carefully model the decay in the simulation to establish the switch of habitual airport choice with time.

#### IV. SIMULATION FRAMEWORK

Section III analyzes the key work in simulating the switch of habitual airport choice: i) measuring the on-time performance of coach service cognized by passengers with different habit strengths, ii) modeling the risky airport choice, and iii) quantifying the habit strength decay. In this section, we will establish the simulation framework to solve the key work.

The simulation is designed using 5 steps: 1) measuring the habit strength, 2) measuring the recognized access time to an airport, 3) simulating the risky airport choice with habitual preference, 4) simulating the experience feedback, and 5) simulating the habit decay; these steps are shown in Figure 3. The work in the dotted box is used to simulate the habitual airport choice in the *n*th trip for one passenger, and the dashed arrow means the mechanism of linking the *n*th airport choice to *n*+1th choice in the simulation. After gathering the simulation results of all passengers, we can obtain the variation in the market share in the cultivation period.

##### A. MEASUREMENT OF THE HABIT STRENGTH

Note that “the habit strength increases as an act has been repeated” [40]. Most psychologists use the “frequency of an act in the past” to measure the habit strength ([41]–[43]). This method is referred to as the “retrospective self-reported frequency method”. Although it is the most straightforward way to measure the habit strength [42], this method has some defects ([45]–[48]) because the frequency of an act cannot reflect the most important feature of the habit: the automaticity ([49]–[51]). Therefore, some researchers have proposed the “self-reported habitual strength method”. In the method, persons are asked to report the “automaticity” or “the impact of the habit” for measuring their habit strength ([52]–[54]).

Here, we develop self-reported criteria to measure the habit strength based on these two methods. The criteria are composed of three parts: The first part (No. 1–No. 4 in Table 1) measures the degree of the automaticity when passengers make airport choices. The second part (No. 5) measures the frequency of choosing a specific airport. The third part (No. 6–No. 8) measures the satisfaction level for the airports.



TABLE 1. Indexes for measuring the habit strength.

No.	Criterion	No.	Criterion
1	The airport first comes to mind for the business trip	5	The most used airport
2	The airport first comes to mind for the private trip	6	The airport with the highest reliability
3	The airport first comes to mind for the domestic trip	7	The airport with the best service
4	The airport first comes to mind for international trip	8	The airport with the best accessibility

**B. COGNIZING THE ON-TIME PERFORMANCE OF COACH SERVICES**

As per the results summarized by Bogers [37], the cognized uncertainty of the coach travel time, which is affected by habit strengths, may differ from the uncertainty in reality. Using the same example in section 3, if *Y* has the habitual preference to airport *A*, his recognized travel time to airport *A* should be more stable. The habit will reduce the perceived risks of choosing airport *A*. Conversely, because *Y* is unfamiliar with airport *B* and the coach service, he may be afraid that the coach travel to airport *B* would not be on time as reported and he may miss his flight. Based on the previous analysis, we will use the difference between the cognized risks and the objective risks to reveal the effects of the habitual preferences on airport choices. In the study, the distributions of cognized access time will be constructed using the survey data to quantify the perceived risks, and the habit strength calculated in section IV-A will be linked to the relevant access time distribution to explain passengers’ heterogeneity of risk perceptions.

**C. SIMULATING HABITUAL AIRPORT CHOICE**

As previously discussed, habitual preferences can affect the risk perceptions of the coach service in the airport choice. Confronted with risks, passengers may try the new coach service of an unfamiliar airport for convenience or just retain their habitual airport choice due to risk aversion. Considering passengers’ different attitudes to the risks, we apply cumulative prospect theory (CPT) to model the risky airport choice [20]. According to previous research, CPT is a combination of the original prospect theory [55] and the rank-dependent expected utility model [56].

According to [57], the prospect *f* is represented as a sequence of pairs (*x<sub>ijm</sub>*, *p<sub>ijm</sub>*), where *x<sub>ijm</sub>* is the *j*th kind of potential gain or loss of choosing airport *i* using access mode *m*, and *p<sub>ijm</sub>* is the associated probability. In our model, *x<sub>ijm</sub>* is calculated based on the *j*th kind of cost of using airport *i* with mode *m* (*C<sub>ijm</sub>*), which is the sum of air-borne costs and access costs. Meanwhile, *p<sub>ijm</sub>* is determined by the probability of the *j*th kind of cognized access time of mode *m* for airport *i*, which can be measured by the distribution of cognized access time.

Meanwhile, three assumptions are set for the modelling: 1) the origin and destination of each trip is assumed to be predetermined according to the realistic distribution of flight

demand, 2) passengers’ risky attitude to each access mode *m* is assumed to be independently identically distributed. 3) passengers are assumed to choose the airport by considering the time and price cost, other elements like service quality will not be incorporated in the model.

According to previous literature, *C<sub>ijm</sub>* always contains five parts: i) access time cost: the in-vehicle time cost from the origin city to one airport, ii) flight-missing cost: the costs that may occur when passengers miss booked flights, iii) waiting time cost: additional costs that may be incurred if a passenger’s waiting time in the lounge exceeds his tolerance, iv) waiting cost of changing a flight on the air route that departs from airport *i* to the destination (determined by the flight frequency) and v) air ticket price and access travel cost.

$$C_{ijm} = \rho_1 \left[ \theta^T \left( t_{ijm}^A - T_{im}^D \right) + \theta^L \cdot \eta + \theta^E \left( T_i^F - t_{ijm}^A \right) \cdot (1 - \eta) \right] + 24\rho_2\theta^F / N_{iF} + \rho_3(R_{iF}P_{iF} + P_{im}) \quad (1)$$

In the equation, *T<sub>i</sub><sup>F</sup>* is the departure time of the flight, *T<sub>im</sub><sup>D</sup>* is the passenger departure time at the origin city when using mode *m*, *t<sub>ijm</sub><sup>A</sup>* is the passenger arrival time at the airport,  $\theta^T$  is the unit cost of the in-vehicle time,  $\theta^E$  is the unit cost of the additional waiting time, and  $\theta^L$  is the cost of missing the flight. Note that  $\theta^L$  is not related to the delay time (*t<sub>ijm</sub><sup>A</sup>* - *T<sub>i</sub><sup>F</sup>*); regardless of the length of time, passenger *Y* cannot check-in. Thus, we know that  $\theta^T \left( t_{ijm}^A - T_{im}^D \right)$  is the access cost,  $\theta^T \left( T_i^F - t_{ijm}^A \right)$  is the waiting cost but  $\theta^L$  and  $\theta^T \left( T_i^F - t_{ijm}^A \right)$  cannot appear simultaneously. Thus, we define the 0-1 variable ( $\eta$ ), which is shown in (2).

$$\eta = \begin{cases} 0 & t_{ijm}^A - T_i^F < 0 \\ 1 & t_{ijm}^A - T_i^F \geq 0 \end{cases} \quad (2)$$

*N<sub>iF</sub>* is the flight volume from airport *i* to the destination,  $\theta^F$  is the corresponding unit cost in terms of money, and 24 means twenty-four hours a day. *P<sub>iF</sub>* is the full price of the economic class of the flight and *R<sub>iF</sub>* is the discount rate, *P<sub>im</sub>* is the access price of mode *m*.  $\rho_1$ ,  $\rho_2$  and  $\rho_3$  represent the importance of each part of the cost to the total travel cost in (1).

With *C<sub>ijm</sub>*, we can obtain *x<sub>ijm</sub>* by calculating the “gains” and “losses” based on the “reference point” in CPT. The reference point is an important element of the prospect theory. Existing literatures about travel choice behavior usually assume that the travelers make decisions based on their travel time budget to avoid the losses caused by uncertain travel time ([59]-[60]). Therefore, we consider the expected costs *C<sup>H</sup>* as the “reference point”, which is illustrated as (3).

$$C^H = \rho_1(\theta^T T^H + \theta^E W^H) + 24\rho_2\theta^F / N^H + \rho_3(R^H P_F + P_m) \quad (3)$$

*C<sup>H</sup>* is composed of four parts: the expected in-vehicle costs, the expected waiting costs, the expected waiting cost of changing flights and the expected air ticket price as well as access cost. In the equation, *T<sup>H</sup>* is the expected access time,

$W^H$  is the tolerable waiting time,  $N^H$  is the expected flight volume on the air route, and  $R^H$  is the expected discount rate,  $P_m$  is the expected access cost. If  $C_{ijm} > C^H$ , passengers will obtain the gains, then  $x_{ijm} > 0$ ; otherwise, passengers will obtain losses and  $x_{ijm} \leq 0$ .

After calculating  $x_{ijm}$  and  $p_{ijm}$ , we build the value function as (4), if  $x_{ijm} > 0$ ,  $V(x_{ijm})$  would be  $V^+(x_{ijm})$  in (7) and vice versa. The weighting functions (5) and (6) should be also calculated on  $x_{ijm}$  and  $p_{ijm}$ . The value function is concave for gains ( $\alpha \leq 1$ ) and convex for losses ( $\beta \leq 1$ ) according to the principle of the diminishing sensitivity, and  $\alpha$  and  $\beta$  measure the degree of the diminishing sensitivity. The losses curve is steeper than the gains curve ( $\lambda \geq 1$ ) because individuals are more sensitive to losses than to gains. Kahneman and Tversky [61] determine that  $\alpha = \beta = 0.88$ , and  $\lambda = 2.55$ .

$$V(x_{ijm}) = \begin{cases} x_{ijm}^\alpha & x_{ijm} \geq 0 \\ -\lambda(-x_{ijm})^\beta & x_{ijm} < 0 \end{cases} \quad (4)$$

We use the weighting function proposed by Kahneman and Tversky [61]; (5) is the gains weighting function and (6) is the losses weighting function. According to Kahneman and Tversky [61],  $\gamma = 0.61$  and  $\delta = 0.69$ .

$$w^+(p_{ijm}) = \frac{p_{ijm}^\gamma}{(p_{ijm}^\gamma + (1 - p_{ijm})^\gamma)^{1/\gamma}} \quad (5)$$

$$w^-(p_{ijm}) = \frac{p_{ijm}^\delta}{(p_{ijm}^\delta + (1 - p_{ijm})^\delta)^{1/\delta}} \quad (6)$$

Based on the value function and weighting function, we can use (7) to calculate the prospect utility ( $PS_{im}$ ) of choosing airport  $i$  with access mode  $m$ . In the equation,  $\pi_{ijm}^+$  denotes the decision weight of the  $j$ th kind of gain, and  $\pi_{ijm}^-$  is the corresponding decision weight for the loss;  $a$  and  $b$  represent the number of the situations of the possible gains and possible losses, respectively. In addition,  $\pi_{ijm}^+$  and  $\pi_{ijm}^-$  are calculated based on the weighting functions of (5) and (6). As a result, passengers are assumed to choose the airport and access with the largest  $PS_{im}$ .

$$PS_{im} = \sum_{j=1}^n V^+(x_{ijm}) \cdot \pi_{ijm}^+ + \sum_{j=-a}^0 V^-(x_{ijm}) \cdot \pi_{ijm}^- \quad (7)$$

$$\pi_{ijm}^+ = w^+(p_{ij+1,m} + \dots + p_{bm}) - w^+(p_{ij+1,m} + \dots + p_{nm}) \quad 0 < j \leq b - 1 \quad (8)$$

$$\pi_{ijm}^- = w^-(p_{i,-a,m} + \dots + p_{ijm}) - w^-(p_{i,-a,m} + \dots + p_{i,j-1,m}) - a \leq j < 0 \quad (9)$$

In the end, we let  $PS_i$  equal to the  $PS_{im}$  with the highest value, as (10).

$$PS_i = \max PS_{im} \quad (10)$$

#### D. SIMULATING THE FEEDBACK OF THE TRIP EXPERIENCE

The experienced utility ( $U_i$ ) for using airport  $i$  may differ from the prospect utility ( $PS_i$ ) before a trip. The difference will change a passenger's preferences to airport  $i$  and influence the habit strength.

Assuming that passenger (with A-preferred habit) chooses airport  $A$  in the  $k^{\text{th}}$  trip, if the experienced utility of using  $A$  ( $U_A$ ) is larger than the prospect utility ( $PS_A$ ) perceived before the trip, the habit strength ( $H^A$ ) of choosing  $A$  will increase; otherwise,  $Y$  will regret the choice and  $H^A$  will decline. Because the variation in  $H^A$  is related to the difference between  $U_A$  and  $PS_A$ , the changed habit strength  $H'^A$  can be described by (11).

$$H'^A = \max\{[1 + (U_A - PS_A)/PS_A] \cdot H^A, 0\} \quad (11)$$

In another situation, if  $Y$  has the habit of choosing  $B$  but chooses airport  $A$  in the  $k^{\text{th}}$  trip, then  $Y$  will compare  $U_A$  with both  $PS_A$  and  $PS_B$ . If  $(U_A - PS_B)$  is larger than  $(PS_A - PS_B)$ , the habit strength  $H^B$  of choosing  $B$  will decrease and the preference on  $A$  will increase. The changed habit strength  $H'^B$  can be calculated by (12).

$$H'^B = \max\{[1 - (U_A - PS_B)/(PS_A - PS_B)] \cdot H^B, 0\} \quad (12)$$

#### E. SIMULATING THE HABIT DECAY

The decay of the habit strength is caused by the forgotten law; thus, we can refer to studies about forgotten law to analyze the decay pattern. According to the knowledge of forgotten law, we know that decay may occur at once after a trip, and the speed of decay is higher in the early period but decreases over time ([62], [63]). Here, we propose a method to measure the decay of the habit strength based on the method proposed by Gärling and Axhausen [39] in (13).

In the equation,  $H_k^i$  is the habit strength of choosing airport  $i$  in the  $k^{\text{th}}$  trip;  $H_{k-1}^i$  is the original habit strength after the  $(k-1)^{\text{th}}$  trip;  $I_{k-1}$  is the time interval between the  $(k-1)^{\text{th}}$  and the  $k^{\text{th}}$  trip; and  $a$  is a parameter that needs to be estimated.

$$H_k^i = H_{k-1}^i \cdot e^{-aI_{k-1}} \quad (13)$$

#### F. ESTIMATION ALGORITHM

Eight parameters ( $\alpha, \beta, \lambda, \gamma, \delta, \rho_1, \rho_2, \rho_3$ ) in the simulation framework need to be estimated. Considering the nonlinear structure of the prospect theory and the complexity of fitting the discrete air travel demand, a genetic algorithm is applied. The fitness function of the genetic algorithm is shown as (14), the function calculates the difference between the simulated market share of airport  $i$  and the actual value.  $G_{yid}$  is a 0-1 variable and equals to 1 when passenger  $y$  chooses airport  $i$  with airport coach on day  $d$  with the condition that the prospect utility of the airport coach is larger than that of other alternatives;  $N_d$  is the total travel passenger volume on day  $d$ ; and  $R_{id}$  is the actual market share of airport  $i$  using the

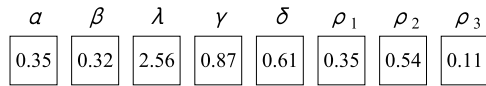


FIGURE 4. Sample of the chromosome code.

airport coach on day  $d$ .

$$F = \sum_D \left( \sum_Y G_{yid} / N_d - R_{id} \right)^2 / D \quad (14)$$

Figure 4 demonstrates the chromosome code, and each gene in the code represents the value of one parameter.

The roulette-wheel-selection operator is used to select the father chromosome, which will be used to perform crossover and mutation operations. We choose single point crossover operation, and the crossover rate and the mutation rate will be determined in the estimation. The loop will stop with the conditions that i) the loop evolves until the generation Gen, and ii) the convergence metric calculated by (14) is continuously less than a fixed value for a certain number of generations.

### V. EMPIRICAL ANALYSIS

With the proposed approach in section IV, the switch of habitual airport choice can be simulated to analyze the market share of airports that conduct improved access services. In this section, Lukou Airport in China will be considered as an example to perform the method validation, and the research duration is from June 2006 to June 2010.

Before the validation, we should highlight that the proposed method is applied to simulate the switch of habitual airport choice for each virtual individual created in the simulation, and the market share variation in the cultivation period should be predicted to gather the simulation results of all virtual travelers. In addition, the virtual individuals will be created as close as possible to the reality and they will be set to follow the decision rule regulated by the simulation approach in section IV.

In the following Section A introduces the background of the case study, section B discusses the virtual individual creation, and C focuses on the parameter estimation.

#### A. BACKGROUND OF THE CASE STUDY

In this case, Lukou Airport is a hub airport in the Yangtze Delta Region; it has become the largest multi-airport area in China since the authority localization in 2002. In the research, we assume that the main competitor to Lukou Airport is Pudong Airport, which is located in Shanghai, because Hongqiao airport was not attractive to passengers from Shanghai until the reconstruction is completed in March 2010.

Reported by the experienced managers of Lukou Airport, the overlapped markets between Pudong Airport and Lukou Airport are concentrated in three cities: Wuxi, Changzhou and Zhang Jiagang. Among these cities, Wuxi seems to be more important due to the attractive demand volume, which

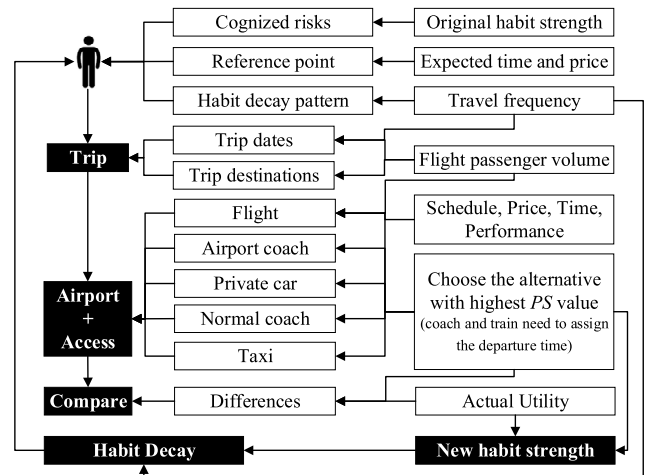


FIGURE 5. The procedure of simulation in the case study.

is approximately 62,000 flight trips per year (Statistical Data on Civil Aviation of China, 2010). The distance from Wuxi to Pudong Airport and Lukou Airport is 176 km and 165 km, respectively. Although the access distances are almost equivalent, Pudong airport captures 75% of the market share in Wuxi city before 2006 for its first-mover advantages in marketing (Statistical Data on Civil Aviation of China, 2006).

In the circumstances, Lukou airport began to offer the coach service to Wuxi in 2006. From 2006, the market share of Lukou airport in Wuxi gradually increased from 18% in 2005 to 58% in 2010.

Based on the previous discussion, the case of Lukou Airport may be the most suitable case for validating our simulation approach for four reasons. First, the airport competition in the Yangtze Delta Region in 2006 was not as serious as the current competition. Hongqiao airport and the Beijing-Shanghai high-speed rail were not placed in operation until June 2011. Thus, passengers in Wuxi primarily had a choice of two airports. Second, coach service was not common at either airport at this time and would be more attractive than it is today. Third, the market share shows a distinct increment, which is suitable for analyzing the market share variation during the cultivation period. Fourth, detailed air travel data was recently available in terms of joint research. Thus, we can obtain data about the flight schedule and the load factor, as well as the price of the real flights in the simulation. As per the complexity of the simulation, we use Figure 5 to declare the procedure, the data needed for each step. It needs to note that the mode “train” is not incorporated, as few passengers in Wuxi city go to Lukou airport by train for the inconvenience when transferring from train to shuttle bus.

#### B. CREATION OF VIRTUAL INDIVIDUALS

The virtual individual should be attributed to three characteristics: the original habit strength (to know the cognized the access time), the expected travel time and ticket price

(to measure the reference point) as well as the travel frequency (to simulate the habit decay pattern). The attributes will be set according to the statistics on the survey data collected in 2011.

In the survey, we delivered 3000 questionnaires, 34% in Pudong airport, 31% in Lukou airport, 21% in the company of Wuxi and 14% on the streets in Wuxi. In the end, a total of 2500 valid questionnaires were collected.

A preliminary descriptive analysis was conducted. The percentages of women and men were 45.6% and 54.4% respectively, which is almost evenly distributed. The percentage of the education level were below high school 13.8%, high school 38.2%, bachelor 36.3%, and master or over 11.7%. The percentage of age range were <18 3.2%, 19-25 9.1%; 26-35 25.9%, 36-45 34.9%, 46-55 16.7%, >55 10.2%. And the percentage of income per year (RMB) were <30000 37.8%, 30000-50000 35.8%, 50000-80000 17.9%, 80000-10000 8.5%. The statistical data stated that socio-economic attributes could follow the situation of the society, so the surveyed data would be valid in our research.

Among the respondents, 33.9% of them travel by air for once per year, 35.9% travel for 3 times per year, 13.2% travel for 4 times per year, 9.8% travel for 5 times per year and 4.3% travel for 6 times and 2.9 travel for 7 times or more. Besides, 75.3% respondents preferred use normal coach, 14.5% use taxi and 10.2% use private car. The high ratio of normal coach proved that the airport coach would be preferred by passengers in Wuxi city. Moreover, for the expected access time, 97% of the respondents prefer 2.5 hours. The average expected flight frequency and the average expected air ticket discount is calculated to be 3 per day and 0.6, respectively. For the expected access cost, 53% respondents can accept 100 RMB, 25% can accept 200 RMB 18% would accept higher 300 RMB, and 4% can accept 400 RMB. All the data analyzed above would be used in the simulation.

Apart from the demographical information and travel experiences, respondents were asked to answer the questions in Table 1 according to their habitual airport choice preferences in different time periods (before 2006, 2006 to 2008 and 2009 to 2010).

In the enquiry, the respondents needed to mark each question with -1 for Lukou airport, 0 for noun, and 1 for Pudong airport. We valued their habit strength by standardizing the averaged marks of all questions. For instance, 0.9 means passengers have a strong Pudong-preferred habit, and vice versa. Figure 6 shows the distribution of these habit strengths. According to the reported airport choice preferences before 2006, 13.1% of passengers had a Lukou-preferred habit; 69.4% of passengers had the habit of choosing Pudong airport; while the remaining passengers did not have any habits.

For virtual individuals, their cognized risks are described by the distributions of perceived access time to the alternative airports, and the distributions should be set relevant to the habit strength. Therefore, we also asked the respondents in the survey about their cognized access time to Lukou Airport

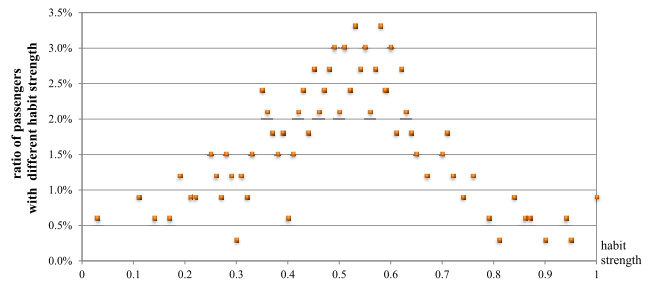
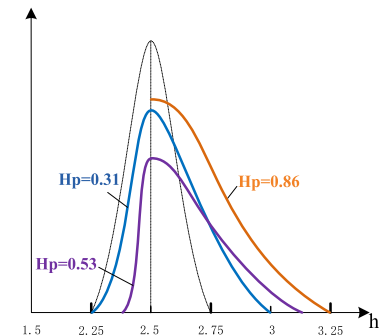
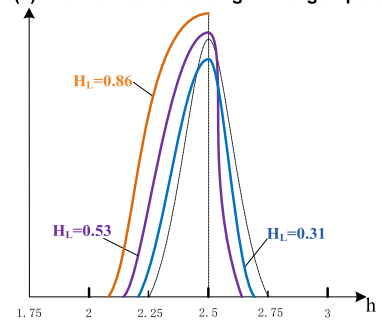


FIGURE 6. Habit strength of choosing Pudong Airport in 2005.



(a) With habit of choosing Pudong airport



(b) With habit of choosing Lukou airport

FIGURE 7. Travel time of the airport coach cognized by passengers with different habit.

and Pudong Airport in different periods (2006 to 2008 and 2009 to 2011). In the survey, the respondents used the group (access time and related probability) to describe the perceived access time, including the shortest, mean and longest access time. We linked the perceived access time by airport coach to respondents' habit strengths to obtain the distributions of perceived access time affected by different levels of habit strength. The distributions are partly illustrated in Figure 7.

In the figure, the black dotted curve represents the distribution of access time in reality, and the colored solid curves represent the distribution of perceived access time to Lukou Airport by coach.  $H_P$  and  $H_L$  are the habit strengths of choosing Pudong Airport and Lukou Airport, respectively. Considering Figure 7-(a) as an example, as  $H_P$  increases, the perceived access time to Lukou Airport by coach is more likely to be longer than 2.5 hours and will be absolutely longer than 2.5 hours when  $H_P$  is equal to 0.86. Similarly, in Fig. 7-(b), due to the habit strength of choosing Lukou Airport ( $H_L$ ), the perceived access time using coach will be



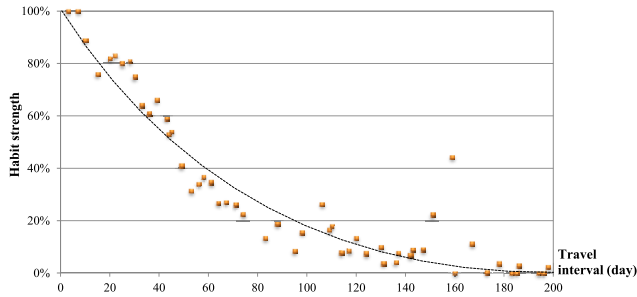


FIGURE 8. Decay pattern of the habit strength.

less than 2.5 hours with a substantially higher probability. The fitted distributions will be assigned to the virtual individuals with different habit strengths in the simulation, and the cognized access time will be used to value the time costs in (1) and the probability needed in (5) and (6).

As declared in the assumption: passengers' risky attitude to each access mode  $m$  is independently identically distributed, so the standard deviations of the access time distribution of different modes are the same but the average value change according to the reality.

According to the surveyed air travel frequency, the air travel interval was calculated and was further linked to the respondents' habit strengths for plotting the relationship between the habit strength and the travel interval in Figure 8. The longer is the trip interval, the lower is the habit strength. Thus, we use the data to estimate the parameter  $a$  ( $a = 0.019$ ) in (12), which represents the decay speed of the habit strength. In the simulation, the virtual individual will be assigned with a fixed travel interval according to the distribution of the air travel frequency in Wuxi and the decay of the habit strength between the two consecutive trips would follow the estimated values (12).

With the data, a total of 2500 individuals are generated with different original attributes, including habit strength, cognized access time; expected access time, expected waiting time at lounge, expected flight frequency, expected air ticket discount; and air travel frequency as well as habit strength decay pattern. Note that an individual's habit strength and cognized access time may change during the simulated switch of habitual airport choice.

### C. SIMULATION ENVIRONMENT

In this part, we set up the simulation environment to create the choice alternatives.

First, we set the alternative flights of Lukou Airport and Pudong Airport according to the realistic flight schedule. Each flight is depicted by the departure/arrival airport, the departure time as well as the average air ticket price (shown in gray because we are not permitted to access the data).

Second, we set the access time to different airports with different modes. The access time and costs to Pudong Airport is set as follows:  $2.4 \pm 0.12$  ( $\Delta$ ) hours and 350RMB by private car, (return price, as the car should be back to Wuxi);

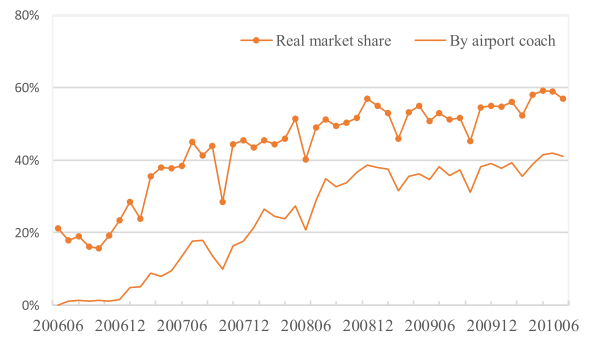


FIGURE 9. Realistic market share of Lukou airport.

$4.0 \pm 0.50$  ( $\Delta$ ) hours and 80 RMB by normal coach (the transfer would increase the fluctuation, and passengers would choose public transit such as subway and shuttle bus in Shanghai), and the coach frequency is 10 times per day;  $2.4 \pm 0.12$  ( $\Delta$ ) hours and 400 RMB by taxi. We should point out that, Pudong airport does not operate the airport coach.

For Lukou airport, the airport coach departing timetable is: 7:00, 9:00, 12:00, 14:00 and 16:00, the access time is  $2.5 \pm 0.25$  ( $\Delta$ ) hours with 85RMB; meanwhile, the access time by private car is  $2.5 \pm 0.12$  ( $\Delta$ ) hours with 360 RMB; the normal coach needs  $4.05 \pm 0.50$  ( $\Delta$ ) hours with 88 RMB; and the taxi needs  $2.5 \pm 0.12$  ( $\Delta$ ) with 410 RMB.

### D. PARAMETER ESTIMATION

Based on the simulation environment, each virtual individual will be assigned with multiple virtual trips. The dates of all trips should follow the distribution of the monthly air travel demand in Wuxi. For one trip, the destination and are determined according to the distribution of the load factor of different flights, and an individual is assumed to choose the coach departing time, which can make them wait the shortest time for the flight. A total of 2500 virtual individuals will travel 16,900 times in the simulation.

Then, to estimate the parameters ( $\alpha, \beta, \lambda, \gamma, \delta, \rho_1, \rho_2, \rho_3$ ), we should set the value of some variable in the simulation framework. The expected access time and the expected waiting time at lounge are set to be 2.5 hours and 1 hour, respectively, because 97% of the respondents agree with the value setting. The expected access time, flight frequency and access cost would be set according to the survey data which is introduced in section A of this chapter.

The unit costs  $\theta^T, \theta^E$  and  $\theta^F$  is equivalent to 18 RMB/hour considering the average salary per hour in Wuxi in 2011. However, the cost of missing a flight  $\theta^L$  is equal to 2000 RMB for penalty purposes.

With all the data, we set  $D = 1460$  and  $M = 2500$  in (13). Meanwhile, we also get the variation of market share of Lukou Airport in Wuxi as well as the ratio of passengers who use airport coach in Figure 9. We can see that the market share of Lukou Airport in Wuxi gradually increases from 20% to 60% from June 2006 to December 2008 and then fluctuates near 60% for a long time. And the percentage of airport coach

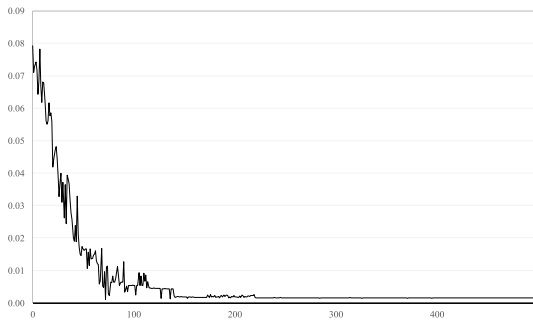


FIGURE 10. Evolution of average convergence metric.

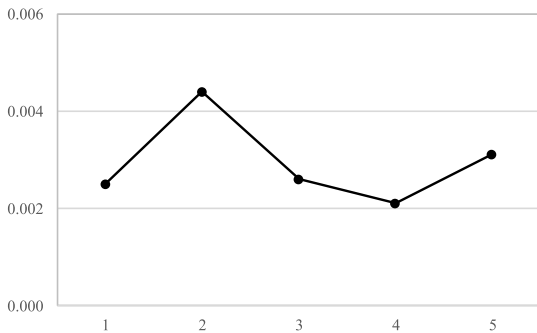


FIGURE 11. Robustness of the heuristic.

which is related to  $R_{id}$  in (13) increases gradually during the duration, which shows that the airport coach would be an important reason that drives the increase of the airport market share of Lukou airport.

The genetic algorithm is then applied: the crossover rate is set to 0.6, and the mutation rate is set to 0.15. The heuristic is coded in MATLAB.Net 2010 and executed on a PC equipped with 6.0 GB of RAM and a Pentium processor that runs at 4.53 GHz. The CPU time for the calculation is 32.3 hours.

Figure 10 demonstrates the evolution of the average convergence metric, which is calculated by (13). The heuristic converges to an optimal solution at the 235th generation. We run the heuristic 5 times and calculate the variation in the convergent fitness value. The results are shown in figure 11. No large fluctuation occurs in the variation. Thus, the robustness of the heuristic can be trusted.

According to the estimation results, the values of the parameters are listed as follows,  $\alpha = 0.34$ ,  $\beta = 0.52$ ,  $\lambda = 2.46$ ,  $\gamma = 0.66$ ,  $\delta = 0.71$ ,  $\rho_1 = 0.44$ ,  $\rho_2 = 0.22$ , and  $\rho_3 = 0.34$ . In the next section, the simulation results of virtual individuals and the market share variation obtained by gathering all simulation results will be analyzed.

VI. RESULT ANALYSIS

As per the variance in the simulated results, we choose one that has steady performance after performing the simulation process 5 times. In the results,  $V$  is a virtual individual who originally has a Pudong-preferred habit in the

TABLE 2. Airport choices of passenger  $V(H_p = 0.52)$  during 2006.6-2008.2.

Date	2006					2007				
	6-13	8-13	10-13	12-13	2-13	4-13	6-13	8-13	10-13	12-13
Trip No.	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
Chosen Airport	Pu	Pu	Pu	Lu	Pu	Lu	Lu	Lu	Lu	Lu

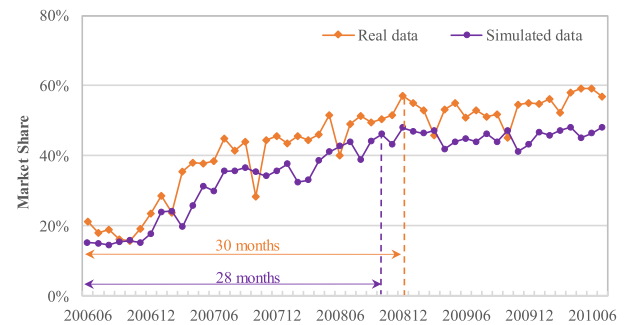


FIGURE 12. Market shares of Lukou airport in Wuxi after starting the coach service.

simulation; his habit strength ( $H_p$ ) is equal to 0.68 before Lukou Airport provided coach service and he learned about the service before the trip on June 13, 2006. Based on the simulation approach, we obtained  $V$ 's airport choice results of 11 trips from June 2006 to June 2008. The results are shown in Table 4. According to the results,  $V$  did not change his airport choice immediately after he learned about the airport coach service. Instead, he selected Lukou Airport for the fourth trip because the coach that departed at 16:00 provided a reasonable connection to his flight to Tianjin at 20:00 then the normal coach to Pudong airport. The results indicate that the frequency of choosing Pudong Airport is declining and  $V$  began to show the habitual preference to Lukou Airport after the trip on June. 13.  $V$  uses 10 months to switch his habitual airport choice; thus, Lukou airport should spend 10 months cultivating  $V$ 's habitual preference.

By gathering the simulation results of all virtual individuals, we obtained the ratio of individuals who chose Lukou Airport and Pudong Airport to obtain the market share variation of each airport from June in 2006 to June in 2010, and the results are shown in Figure 12.

In the figure, the diamond points represent the real market share of Lukou Airport and the circles represent the simulated shares. It can be seen that our results fit the real data well, but there is a difference between the real and simulated data, which indicates that there are other elements resulting in the increase of the market share such as the income, GDP or the population increment.

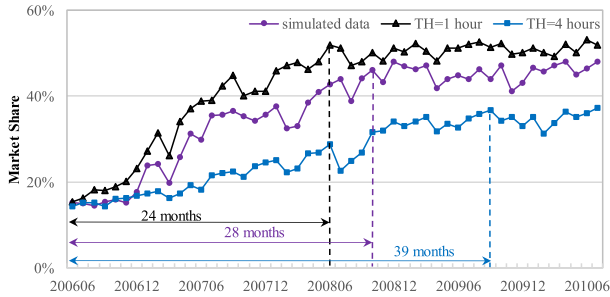


FIGURE 13. The market shares related to different time headways.

**VII. SCENARIO ANALYSIS**

In this section, we test the effect of the frequency and the on-time performance of the coach service on the market share variation of Lukou Airport in the cultivation period.

**A. EFFECTS OF COACH FREQUENCY**

We assume two scenarios with different coach frequencies: S1: one coach per hour and S2: one coach every four hours. The simulated results related to the two scenarios are shown in Figure 13. The length of the cultivation period was elongated by 11 months when the time headway (TH) of the coach service increased from 2 hours to 4 hours. The length of the cultivation period was reduced by 4 months when TH decreased from 2 hours to 1 hour. Thus, the coach frequency is an important factor that influences the length of the cultivation period. We should determine whether setting the appropriate coach frequency is an effective strategy.

**B. EFFECTS OF THE ON-TIME PERFORMANCE**

We assume two scenarios with different on-time performances of the coach: S1: the fluctuation of the coach travel time ( $\Delta$ ) is 5 minutes and S2:  $\Delta$  is equal to 25 minutes (note:  $\Delta = 15$  in reality). We discovered that if  $\Delta$  decreases from 15 minutes to 5 minutes, the length of the cultivation period will be decreased by 13.3%, and if  $\Delta$  increases from 15 minutes to 25 minutes, the market share will not show a distinct increment in the cultivation period. The variations are described in Figure 14. The results indicate that improving the on-time performance of the coach may have fewer positive impacts than the impact of increasing the coach frequency on shortening the cultivation period. However, we should guarantee that the on-time performance of the coach is appropriate, otherwise, the coach service would be ineffective in increasing the market share of Lukou Airport.

**C. EFFECTS OF THE DYNAMIC FREQUENCY**

Comparing figure 13 and figure 14, reducing the coaches' time headway seems to be more effective than improving the on-time performance for increasing Lukou's market share. We want to further explore the suitable coach frequency for Lukou Airport by assuming two scenarios: S1: one coach per hour from June 2006 to December 2007, one coach every two hours from January 2008 to June 2009, and one coach every

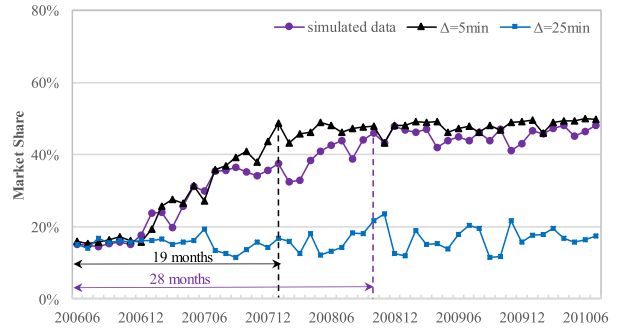


FIGURE 14. Market shares related to different on-time performances.

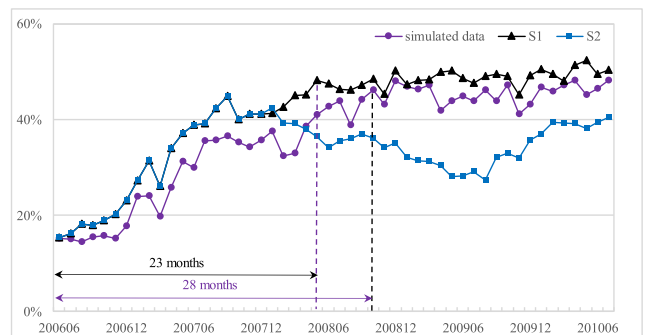


FIGURE 15. The market shares with varied coach frequency.

three hours from July 2009 to June 2010; S2: one coach per hour from June 2006 to December 2007, one coach every four hours from January 2008 to June 2009, and one coach every three hours from July 2009 to June 2010. The simulated results related to the three scenarios are shown in Figure 15.

When varying the coach frequency during the simulation, the length of the cultivation period in S1 is reduced by 4 months than that in reality. Lukou airport can spend a shorter time occupying the aviation market in Wuxi. The final market share of S1 is higher than the original market share at 5.7% increment, which shows the effect of the dynamic coach frequency on improving the market share. Therefore, the dynamic coach frequency should help reduce the cultivation period and improve the market share, which will increase the coach efficiency.

In S1, the virtual individuals switch their habitual airport choice very quickly from June 2006 to December 2007, which shows that the frequent coach service would help attract more passengers at the start-up time of the cultivation period. In S1, the coach frequency declines after January 2008 but the demand to Lukou Airport did decrease but continuously increases. Conversely, in S2, the market share of Lukou Airport decreased with a larger decline in the coach frequency.

Therefore, a useful approach is to shorten the cultivation period by optimizing the coach frequency. We could set a higher frequency to attract passengers and subsequently set lower frequencies. This approach will help shorten the cultivation period and reduce the operation cost in practice.

## VIII. CONCLUSION

This paper highlighted the importance of a cultivation period for marketing and analyzed the market share variation in airports, which started coach services in a multi-airport region. In the study, a simulation framework was proposed to model the switch of habitual airport choice, and a scenario analysis was conducted to test the effects of the coach service attribute on the length of the cultivation period.

In the simulation, we clarified that the habitual preferences would affect the risk cognition in airport choice. Thus, the habitual airport choice was treated as risky choice behavior in our study. The cumulative prospect theory was chosen to model the risky airport choice based on two jobs: quantifying the habit strength using self-reported criteria and constructing the relationship between the perceived access time and the habit strength. The mechanism that connects sequential airport choices was described by the habit strength decay pattern, which can be modeled using the forgotten law.

In the case study, Lukou Airport in the Yangtze Delta Region in China was considered as an example to validate our proposed simulation framework. The results showed that our simulation approach had excellent performance in simulating the market share variation. Lukou airport should spend 30 months to cultivating the aviation market of Wuxi because passengers would switch their habitual airport choice during multiple trips.

According to the scenario analysis in section 6, we learn that the coach frequency and on-time performance of the coach service were important to the switch of habitual airport choice. Although the effect of increasing the coach frequency on decreasing the length of the cultivation period was more significant than the effect of improving the on-time performance, the delay of the coach should be eliminated in the operation.

We attempted to vary the coach frequency during the cultivation period in section 6 and obtained interesting results that can guide passengers to quickly switch their habitual airport choice with higher frequency at the start-up time of the cultivation period and then properly reduce the frequency. The appropriate dynamic frequency would help shorten the cultivation period and improve the market share, as well as reduce the costs.

The contributions of our work are three-fold. First, the proposed simulation framework adequately explained the mechanism of market share variation in the cultivation period and would assist airports in evaluating the efficiency of the newly conducted services on the marketing. Second, in the simulation, we used the cognitive risks to reveal the influences of habit on the airport choice and applied the forgotten law to quantify the habit strength decay. All work would help interpret the complicated switch of the habitual airport choice in the model. Third, setting dynamic coach frequencies was as an effective strategy for guiding passengers to quickly switch their habitual airport choice and reduce operating costs.

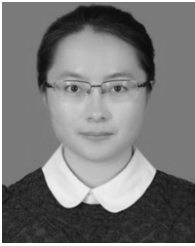
The limitations of our work are that we fixed the volume of the virtual individuals and did not incorporate the influences of induced air travel demand to the market share variation during the cultivation period and some factors, such as flight delay, were not incorporated in the costs function due to the difficulty of collecting data. Meanwhile, the prospect theory may have disadvantages in modeling the choice of correlated alternatives, so it may result in some inaccuracy of the predicted results. Following this work, the strategies related to the coach frequency, such as optimizing the dynamic coach timetable, will be considered to reduce the cultivation period. A more complicated situation that incorporates the competition from other airports and high-speed rail would also be taken into account in the future.

## REFERENCES

- [1] J. D. Innes and D. H. Doucet, "Effects of access distance and level of service on airport choice," *J. Transp. Eng.*, vol. 116, no. 4, pp. 507–516, Jul. 1990.
- [2] R.-C. Jou, D. A. Hensher, and T.-L. Hsu, "Airport ground access mode choice behavior after the introduction of a new mode: A case study of taoyuan international airport in taiwan," *Transp. Res. E, Logistics Transp. Rev.*, vol. 47, no. 3, pp. 371–381, May 2011.
- [3] G. Başar and C. Bhat, "A parameterized consideration set model for airport choice: An application to the san francisco bay area," *Transp. Res. B, Methodol.*, vol. 38, no. 10, pp. 889–904, Dec. 2004.
- [4] D. Paliska, S. Drobne, G. Borruso, M. Gardina, and D. Fabjan, "Passengers' airport choice and airports' catchment area analysis in cross-border upper adriatic multi-airport region," *J. Air Transp. Manage.*, vol. 57, pp. 143–154, Oct. 2016.
- [5] T. Feng and H. J. P. Timmermans, "Transportation mode recognition using GPS and accelerometer data," *Transp. Res. C, Emerg. Technol.*, vol. 37, pp. 118–130, Dec. 2013.
- [6] S. H. Chen and P. C. Wen, "Post catch-up with market cultivation and product servicing: Case of Taiwan's transportation equipment industries," *Asian J. Technol. Innov.*, vol. 24, no. sup1, pp. 33–52.
- [7] W. Mayer, "The infant-export industry argument," *Can. J. Econ.*, vol. 17, no. 2, p. 249, May 1984.
- [8] Q. Cui, H.-B. Kuang, C.-Y. Wu, and Y. Li, "Dynamic formation mechanism of airport competitiveness: The case of china," *Transp. Res. A, Policy Pract.*, vol. 47, pp. 10–18, Jan. 2013.
- [9] S. Hess and J. W. Polak, "Mixed logit modelling of airport choice in multi-airport regions," *J. Air Transp. Manage.*, vol. 11, no. 2, pp. 59–68, Mar. 2005.
- [10] M. P. Keane and K. I. Wolpin, "The solution and estimation of discrete choice dynamic programming models by simulation and interpolation: Monte Carlo evidence," *Rev. Econ. Statist.*, vol. 76, no. 4, p. 648, Nov. 1994.
- [11] T. Feng and H. J. P. Timmermans, "Comparison of advanced imputation algorithms for detection of transportation mode and activity episode using GPS data," *Transp. Planning Technol.*, vol. 39, no. 2, pp. 180–194, Jan. 2016.
- [12] R. Windle and M. Dresner, "Airport choice in multiple-airport regions," *J. Transp. Eng.*, vol. 121, no. 4, pp. 332–337, Jul. 1995.
- [13] Y. Zhang and Y. Xie, "Small community airport choice behavior analysis: A case study of GTR," *J. Air Transp. Manage.*, vol. 11, no. 6, pp. 442–447, Nov. 2005.
- [14] G. M. Ramos, W. Daamen, and S. Hoogendoorn, "A state-of-the-art review: developments in utility theory, prospect theory and regret theory to investigate travellers' behaviour in situations involving travel time uncertainty," *Transp. Rev.*, vol. 34, no. 1, pp. 46–67, Jan. 2014.
- [15] R. E. Skinner, "Airport choice—An empirical study," *J. Transp. Eng.*, vol. 102, no. 4, pp. 137–178, 1976.
- [16] G. Harvey, "Airport choice in a multiple airport region," *Transp. Res. A, Gen.*, vol. 21, no. 6, pp. 439–449, Nov. 1987.
- [17] J. I. Lian and J. Rønnevik, "Airport competition—Regional airports losing ground to main airports," *J. Transp. Geogr.*, vol. 19, no. 1, pp. 85–92, Jan. 2011.



- [18] L. S. De and R. Di Pace, "Modelling passenger departure airport choice: Implicit vs. explicit approaches," *Procedia-Social Behav. Sci.*, vol. 54, no. 2290, pp. 875–885, 2012.
- [19] E. Pels, P. Nijkamp, and P. Rietveld, "Access to and competition between airports: A case study for the san francisco bay area," *Transp. Res. A, Policy Pract.*, vol. 37, no. 1, pp. 71–83, Jan. 2003.
- [20] S. Hess and J. W. Polak, "Exploring the potential for cross-nesting structures in airport-choice analysis: A case-study of the greater London area," *Transp. Res. E, Logistics Transp. Rev.*, vol. 42, no. 2, pp. 63–81, Mar. 2006.
- [21] S. Y. Jung and K. E. Yoo, "A study on passengers' airport choice behavior using hybrid choice model: A case study of Seoul metropolitan area, South Korea," *J. Air Transp. Manage.*, vol. 57, pp. 70–79, Oct. 2016.
- [22] Y. Suzuki, M. R. Crum, and M. J. Audino, "Airport choice, leakage, and experience in single-airport regions," *J. Transp. Eng.*, vol. 129, no. 2, pp. 212–218, 2003.
- [23] Y. Suzuki, "Modeling and testing the 'two-step' decision process of travelers in airport and airline choices," *Transp. Res. E, Logistics Transp. Rev.*, vol. 43, no. 1, pp. 1–20, 2007.
- [24] W. Wood and D. T. Neal, "A new look at habits and the habit-goal interface," *Psychol. Rev.*, vol. 114, no. 4, pp. 843–863, 2007.
- [25] H. Aarts, B. Verplanken, and A. Van Knippenberg, "Habit and information use in travel mode choices," *Acta Psychol.*, vol. 96, pp. 1–14, Jun. 1997.
- [26] B. Verplanken and S. Orbell, "Reflections on past behavior: A self-report index of habit strength," *J. Appl. Social Psychol.*, vol. 33, pp. 1313–1330, Jun. 2003.
- [27] R. L. Winkler, "Uncertainty in probabilistic risk assessment," *Rel. Eng. Syst. Saf.*, vol. 54, nos. 2–3, pp. 127–132, Nov. 1996.
- [28] S. Marette, J. Roosen, S. Blanchemanche, and E. Feinblatt-Mélèze, "Functional food, uncertainty and consumers' choices: A lab experiment with enriched yoghurts for lowering cholesterol," *Food Policy*, vol. 35, no. 5, pp. 419–428, 2010.
- [29] A. M. Colman, *Game Theory and Experimental Games: The Study of Strategic Interaction*. Amsterdam, The Netherlands: Elsevier, 2016.
- [30] S. C. Littlechild and G. F. Thompson, "Aircraft landing fees: A game theory approach," *Bell J. Econ.*, pp. 186–204, 1977.
- [31] M. Hansen, "Airline competition in a hub-dominated environment: An application of noncooperative game theory," *Transp. Res. B, Methodol.*, vol. 24, no. 1, pp. 27–43, 1990.
- [32] A. Glöckner and T. Pachur, "Cognitive models of risky choice: Parameter stability and predictive accuracy of prospect theory," *Cognition*, vol. 123, no. 1, pp. 21–32, 2012.
- [33] E. Avineri and J. N. Prashker, "Do travellers make rational route-choice decisions? Modelling route-choice stated preferences with cumulative prospect theory," in *Proc. Conf. Risk, Decis. Hum. Error, Faculty Environ. Technol.*, London, U.K., Jun. 2004.
- [34] E. Ben-Elia and Y. Shiftan, "Which road do I take? A learning-based model of route-choice behavior with real-time information," *Transp. Res. A, Policy Pract.*, vol. 44, no. 4, pp. 249–264, May 2010.
- [35] 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," *Transp. Res. C, Emerg. Technol.*, vol. 6, pp. 527–548, Jan. 2018.
- [36] L. Zhou, S. Zhong, S. Ma, and N. Jia, "Prospect theory based estimation of drivers' risk attitudes in route choice behaviors," *Accident Anal. Prevention*, vol. 73, pp. 1–11, Dec. 2014.
- [37] X. Li, W. Wang, C. Xu, Z. Li, and B. Wang, "Multi-objective optimization of urban bus network using cumulative prospect theory," *J. Syst. Sci. Complex.*, vol. 28, no. 3, pp. 661–678, Apr. 2015.
- [38] M. Baucells and A. Villasís, "Stability of risk preferences and the reflection effect of prospect theory," *Theory Decis.*, vol. 68, nos. 1–2, pp. 193–211, 2010.
- [39] T. Gärling and K. W. Axhausen, "Introduction: Habitual travel choice," *Transportation*, vol. 30, no. 1, pp. 1–11, 2003.
- [40] S. Bamberg, I. Ajzen, and P. Schmidt, "Choice of travel mode in the theory of planned behavior: The roles of past behavior, habit, and reasoned action," *Basic Appl. Social Psychol.*, vol. 25, no. 3, pp. 175–187, Jun. 2010.
- [41] E. AI Bogers, F. Viti, and S. P. Hoogendoorn, "Joint modeling of advanced travel information service, habit, and learning impacts on route choice by laboratory simulator experiments," *Transp. Res. Rec.*, vol. 1962, no. 1, pp. 189–197, 2005.
- [42] L. Carden and W. Wood, "Habit formation and change," *Current Opinion Behav. Sci.*, vol. 20, pp. 117–122, Apr. 2018.
- [43] C. D. Bailey and E. V. McIntyre, "Using parameter prediction models to forecast post-interruption learning," *IIE Trans.*, vol. 35, no. 12, pp. 1077–1090, 2003.
- [44] B. Verplanken and H. Aarts, "Habit, attitude, and planned behaviour: Is habit an empty construct or an interesting case of goal-directed automaticity?" *Eur. Rev. Social Psychol.*, vol. 10, no. 1, pp. 101–134, 1999.
- [45] J. A. Ouellette and W. Wood, "Habit and intention in everyday life: The multiple processes by which past behavior predicts future behavior," *Psychol. Bull.*, vol. 124, no. 1, pp. 54–74, Jul. 1998.
- [46] D. L. Ronis, J. F. Yates, and J. P. Kirscht, "Attitudes, decisions, and habits as determinants of repeated behavior," in *Attitude Structure and Function*, A. R. Pratkanis and S. J. Breckler, Ed. New York, NY, USA: Lawrence Erlbaum Associates, 1989, pp. 213–224.
- [47] S. Fujii and R. Kitamura, "What does a one-month free bus ticket do to habitual drivers? An experimental analysis of habit and attitude change" *Transportation*, vol. 30, pp. 81–95, Feb. 2003.
- [48] S. Bamberg, "The promotion of new behavior by forming an implementation intention: Results of a field experiment in the domain of travel mode Choice1," *J. Appl. Social Psychol.*, vol. 30, no. 9, pp. 1903–1922, Sep. 2000.
- [49] B. Verplanken, H. Aarts, A. Van Knippenberg, "Habit, information acquisition, and the process of making travel mode choices," *J. Social Psychol.*, vol. 27, no. 5, pp. 539–560, 1997.
- [50] I. Ajzen, "The theory of planned behavior," *Org. Behav. Hum. Decis. Process.*, vol. 50, no. 2, pp. 179–211, 1991.
- [51] A. H. Eagly and S. Chaiken, *The Psychology of Attitudes*. Orlando, FL, USA: Harcourt Brace Jovanovich College Publishers, 1993.
- [52] A. M. Nordlund and J. Garvill, "Effects of values, problem awareness, and personal norm on willingness to reduce personal car use," *J. Environ. Psychol.*, vol. 23, pp. 339–347, Dec. 2003.
- [53] E. Blair and S. Burton, "Cognitive processes used by survey respondents to answer behavioral frequency questions," *J. Consum. Res.*, vol. 14, no. 2, p. 280, Sep. 1987.
- [54] G. Bornstein, L. Crum, J. Wittenbraker, K. Harring, C. A. Insko, and J. Thibaut, "On the measurement of social orientations in the minimal group paradigm," *Eur. J. Social Psychol.*, vol. 13, no. 4, pp. 321–350, Oct. 1983.
- [55] L. Eriksson, J. Garvill, and A. M. Nordlund, "Interrupting habitual car use: The importance of car habit strength and moral motivation for personal car use reduction," *Transp. Res. F, Traffic Psychol. Behav.*, vol. 11, no. 1, pp. 10–23, Jan. 2008.
- [56] B. Mittal, "Retrospective: Why do customers switch? The dynamics of satisfaction versus loyalty," *J. Services Marketing*, vol. 30, no. 6, pp. 569–575, Sep. 2016.
- [57] G. Towler and R. Shepherd, "Modification of Fishbein and Ajzen's theory of reasoned action to predict chip consumption," *Food Quality Preference*, vol. 3, no. 1, pp. 37–45, Jan. 1991.
- [58] B. Gardner, "Modelling motivation and habit in stable travel mode contexts," *Transp. Res. F, Traffic Psychol. Behav.*, vol. 12, no. 1, pp. 68–76, Jan. 2009.
- [59] D. Kahneman and A. Tversky, "Prospect theory: An analysis of decision under risk," *Econometrica*, vol. 47, no. 2, pp. 29–263, 1979.
- [60] J. Quiggin, "A note on the existence of a competitive optimum," *Econ. Rec.*, vol. 58, no. 2, pp. 174–176, 1982.
- [61] D. Kahneman and A. Tversky, "Choices, values, and frames," *Amer. Psychol.*, vol. 9, no. 4, pp. 341–350, 1984.
- [62] H. Shao, W. H. K. Lam, and M. L. Tam, "A reliability-based stochastic traffic assignment model for network with multiple user classes under uncertainty in demand," *Netw. Spatial Econ.*, vol. 6, nos. 3–4, pp. 173–204, Aug. 2006.
- [63] H. Xu, Y. Lou, Y. Yin, and J. Zhou, "A prospect-based user equilibrium model with endogenous reference points and its application in congestion pricing," *Transp. Res. B, Methodol.*, vol. 45, no. 2, pp. 311–328, Feb. 2011.
- [64] J. Yang and G. Jiang, "Development of an enhanced route choice model based on cumulative prospect theory," *Transp. Res. C, Emerg. Technol.*, vol. 47, pp. 168–178, Oct. 2014.
- [65] A. Tversky and D. Kahneman, "Advances in prospect theory: Cumulative representation of uncertainty," *J. Risk Uncertainty*, vol. 5, no. 4, pp. 297–323, 1992.
- [66] M. Y. Jaber and M. Bonney, "Production breaks and the learning curve: The forgetting phenomenon," *Appl. Math. Model.*, vol. 20, no. 2, pp. 162–169, Feb. 1996.
- [67] M. Y. Jaber and H. V. Kher, "Variant versus invariant time to total forgetting: The learn-forget curve model revisited," *Comput. Ind. Eng.*, vol. 46, no. 4, pp. 697–705, Jul. 2004.



**JING LU** was born in April 1987. She received the B.S., M.S., and Ph.D. degrees in transportation engineering from Dalian Maritime University.

Since 2016, she has been with the Nanjing University of Aeronautics and Astronautics, Nanjing, China. She has published more than 20 articles in the field of transportation planning and management, including the following articles: An Integrated Markov Decision Process and nested logit consumer response model of air ticket pricing, *Transportmetrica A*; Current and previous research interests end the paragraph; and Design of timetable for airport coach based on time-space network and passenger's trip chain, *Transport*. Her research interest is concentrated in simulation and deep learning application in transportation management.



**YUCAN MENG** was born in December, in 1996. She received the B.S. degree in traffic management from Chongqing Jiaotong University. She is currently pursuing the M.S. degree in transportation planning and management with the Nanjing University of Aeronautics and Astronautics, Nanjing, China. Her research interest includes simulation and deep learning application in transportation management.



**YINGJING GU** was born in Jiangsu, China, in December, in 1988. She received the B.S. and Ph.D. degrees in transportation management from the Nanjing University of Aeronautics and Astronautics.

Since 2018, she has been with Nanjing Xiaozhuang University, Nanjing, China. Her research interests include revenue management and transportation management. She published five articles during the Ph.D. period, including Capacity Allocation and Revenue Sharing in Airline Alliances; A Combinatorial Auction-Based Modeling; and Multistages Dynamic Combinatorial Auction-Based Capacity Allocation in Airline Alliances. In 2019, she joined the Research Team led by Dr. Lu and has performed certain research.

• • •