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Research article

Research on a collaborative evolution model of multi-airport route network considering subsidy strategies

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Abstract: To efficiently utilize subsidy strategies for optimizing multi-airport route networks and promoting collaborative development among multiple airports, we delve into the tripartite strategic interactions between passengers, airlines and airports. A dual-layer game-theoretic model is constructed to optimize subsidy strategies, facilitating a synergistic alignment between multi-airport positioning and route networks. In the upper-layer game-theoretic model, Fermi rules are employed to analyze the interplay between pricing strategies of distinct airline brands and passenger travel preferences, aiding in determining optimal pricing strategies for airlines. The lower-layer game-theoretic model introduces an asymmetric stochastic best response equilibrium (QRE) model, drawing insights from optimal airline pricing and the impact of airport subsidies on airline route adjustments to formulate effective multi-airport subsidy strategies. The results reveal that: (i) Airline revenues display varying peaks based on travel distances, with optimal fare discount intervals clustering between 0.6 and 0.9, contingent upon travel distances and passenger rationality; (ii) dynamic monopolistic intervals and inefficient ranges characterize airport subsidy strategies due to diverse competitive strategies employed by rivals; (iii) targeted airport subsidy strategies can enhance inter-airport route coordination in alignment with their functional positioning. This research provides decision-making insights into collaborative airport group development, encompassing airport subsidy strategies and considerations for airline pricing.

Keywords: air transportation; airport cluster; route network; subsidy strategy; evolutionary game

1. Introduction and literature review

With the expansion of economies within urban agglomerations and the ongoing trend toward integrated development, the proliferation of airports in regional areas has been a consistent phenomenon. This has led to the emergence of scenarios characterized by “one city, multiple airports”, consequently forming regional airport clusters. These clusters exhibit a shared allocation of spatial resources among their constituent airports, resulting in overlapping catchment areas and intense homogeneous competition in airport operations. However, this competitive environment presents challenges for optimizing route networks and fails to fully capitalize on the operational potential of individual airports. As a solution, a collaborative approach among airports becomes imperative to enhance passenger travel services. However, the existing deficiencies in airport collaboration largely stem from the inadequate synchronization of route networks. The core issue lies in enabling airlines to optimize route networks based on the functional positioning of airports, thereby transcending the zero-sum mindset. In light of this, we aim to investigate the role of airport subsidies in achieving harmonized route networks among airports. The goal is to scientifically devise subsidy strategies that ensure minimal costs in achieving optimal route adjustments, thereby fostering the efficient collaborative development of airports within airport clusters.

Both domestic and international scholars have conducted extensive research on the evolution of route networks within airport clusters, primarily focusing on the following three dimensions. First, from the perspective of airlines, scholars have analyzed pricing strategies, market competition and the evolution of route networks. For instance, Min et al. [1] constructed a model of passenger travel preferences to examine the competitive dynamics between high-speed rail and air transport in terms of acquiring market share. Their study also includes case studies for illustration. Yusuke et al. [2] formulated a revenue model for airline route selection and investigated how the competition between multiple airports for charging impacts airline route network decisions. Dobruszkes et al. [3] delved into the evolution patterns of airline choices in relation to airports of different tiers, drawing insights from the operational practices of airlines in the United States and Europe. Moreover, Zhou et al. [4] explored the influence of various combinations of route networks on airline pricing strategies, devising corresponding pricing algorithms. Peng et al. [5] established an evaluation index system to analyze the network effects of airline alliances formed in highly competitive environments. Their study focuses on examining how alliances impact airlines’ strategic decisions. Additionally, Luo et al. [6] employed game theory to construct a competition and cooperation model between high-speed rail and civil aviation, analyzing their strategies within a win-win framework. Chandra et al. [7] reevaluated the impact of competition on price discrimination, highlighting varying effects on price differences based on consumer traits. Empirical findings underscored the role of consumer heterogeneity in reconciling conflicting research outcomes. Wei et al. [8] aimed to reveal and correct the impact of HSR mileage, as an external factor, on airport PTE from the perspective of urban economic structure using a three-stage DEA model and a single-logarithmic OLS model using Beijing-Tianjin-Hebei regional airport data from 2008 to 2019.

Furthermore, Silva et al. [9] integrated network analysis and econometric techniques to explore the relationship between network topology, competition dynamics and ticket pricing in the context of air transportation, utilizing evidence from Brazil. Their research sheds light on the intricate interplay between network structure and pricing strategies. Suzuki et al. [10] conducted empirical data analysis to examine the influence of airfare variations and convenient ground transportation options on passenger choices among multiple airports within a multi-airport system. Their findings provide valuable insights for airlines seeking to devise optimal ticket pricing strategies. Nigel et al. [11] conducted a comprehensive investigation into how route development impacts airport performance, drawing on a survey of 124 global airports. Their research revealed that larger, private and European airports exhibit heightened route development activity, thereby enhancing overall performance. The study also highlights the positive influence of market growth on performance while noting the adverse impact of airport constraints. Moreover, the research underscores that business environment factors do not significantly alter the relationship between route development and performance. In sum, the existing body of research underscores the significance of cooperative strategies among airports to optimize route networks and enhance operational efficiency within airport clusters.

Second, we investigated the Analyzing Route Adjustment Impacts from the Perspective of Passenger Travel Choices. Kim et al. [12] conducted an examination of the "escape" phenomenon wherein passengers shift from small and medium-sized airports to larger ones, drawing from fifteen years of data from the US air transportation industry. Liao et al. [13] developed an evaluation model grounded in operational data to assess the degree of overlap within airport group route networks. Their study delved into the competition index and substitutability between airports within an airport cluster, considering passenger needs as a crucial factor. Their findings serve as a decision-making foundation for the coordinated development of airports. Qian et al. [14] employed game theory to dissect the competition dynamics between high-speed rail and aviation in medium-distance transportation. They employed reverse induction to derive optimal game strategies, providing valuable insights into strategic decision-making. Colladon et al. [15] harnessed social network and semantic analysis of TripAdvisor forums spanning a decade across seven European capitals. By incorporating variables like forum language complexity and communication network centralization, they enhanced predictive models. This augmentation led to improved accuracy in forecasting international airport arrivals. Grosche et al. [16] introduced two gravity models designed to estimate air passenger volume between city pairs, encompassing economic and geographical factors. These models prove useful for scenarios lacking established air service or accessible transportation metrics, demonstrating accuracy through calibration with booking data from Germany and 28 European countries. Usami et al. [17] conducted empirical research into airport choice and passenger movement on international flights originating from various local Japanese cities, specifically Narita and Haneda Airports. Leveraging microdata from Japan's Ministry of Land, Infrastructure, Transport and Tourism in 2010, the study underscores the significance of flight connectivity in airport selection. Haneda's appeal in attracting passengers, especially for business purposes, is highlighted. Ishii et al. [18] delved into how air travel consumers departing from multi-airport regions balance attributes of both airports and airlines. This trade-off was empirically explored through a weighted conditional logit model of airport-airline choice, utilizing survey data on departing travelers. Choi et al. [19] investigated the factors influencing air passengers' selection of transfer airports between Southeast Asia and North America. Using a discrete choice model and a dataset comprising 78 city-pairs, the study unveiled the substantial impact of airport characteristics such as minimum connection time and service quality, alongside conventional factors like airfares and travel time. Rafael et al. [20] introduced an Econometric Dynamic Model (EDM) to predict passenger demand and applied it to address the Airline Airport Hub (AAH) location problem. Gao et al. [21] underscored the critical nature of accurately estimating airport catchment areas for well-informed decision-making. Focusing on Indiana, their study employed a cost-based model to assess traffic leakage from Indianapolis International Airport (IND) to hub airports in Illinois. The findings underscore the sensitivity of catchment areas to the attributes of nearby airports and travel-related factors. In summary, this dimension of research investigates the intricate dynamics of passenger travel choices in response to route adjustments. Scholars in this field have provided insights into diverse aspects of passenger behavior, ranging from preference shifts between airports to the impact of various attributes on airport and airline selection. These studies collectively contribute to a more comprehensive understanding of the factors influencing passenger travel choices within the context of evolving airport networks.

Third, we analyze the behavior selection strategies of airports and airlines from the perspective of mutual influence. Yang et al. [22] devised a preference model that integrates both airport and route selection, culminating in a two-dimensional strategy map. This map serves as a foundation for formulating pricing strategies for both airports and airlines. Nobuaki et al. [23] constructed a system dynamics model to assess the survival dynamics of feeder airports. Their study adopted an ecosystem perspective to analyze policies' impacts on airlines and passengers, subsequently formulating optimal strategies. Hou et al. [24] examined the influence of subsidies from larger airports on route resumption at smaller airports, aiming to restore routes during epidemic situations. Wei et al. [25] employed a two-stage approach to analyze airport operational efficiency, provided a quantitative foundation for multi-airport route optimization. Chen et al. [26] harnessed game theory and reverse induction to delve into the interactions among airports, airlines and passengers. Their study analyzed the impact of this game on the structure of the route network. Bezerra et al. [27] employed partial least squares–structural equation modeling to uncover factors influencing passenger loyalty to a specific airport within a multi-airport region. Yirgu et al. [28] investigated passenger leakage between various airports in Wisconsin and Michigan, utilizing proximity and hierarchical logit models. Their analysis considered the influence of airport distance and service levels on passenger leakage. Antunes et al. [29] examined determinants of air connectivity in European regions, accounting for spatial effects, regional attributes and airline business models. Their spatial econometric model, based on data from 284 European regions, revealed significant spatial effects and highlighted the positive impact of low-cost carriers on air connectivity, particularly in remote areas. Basso et al. [30] conducted a comparative investigation of two airport pricing methods: The traditional approach (charges and congestion) and the vertical-structure approach (airline oligopoly). Their findings underscored the suitability of the traditional approach for airlines lacking market power while favoring the vertical-structure approach for addressing strategic airport pricing within contexts of market power. Richard et al. [31] explored equilibria of extensive form games through econometric models for quantal choice. They introduced an agent quantal response equilibrium (AQRE) based on the quantal-choice model, which challenged the invariance principle. The logit-AQRE successfully predicted experimental behavior in signaling game experiments, providing insights that challenge previous explanations.

In summary, existing scholarly investigations primarily focus on diverse facets of airport operations, airline strategic development, passenger travel behaviors and the intricate interactions among these elements. While historical data and static models have yielded commendable progress, they exhibit limitations in addressing the dynamic nature of aviation dynamics. Notably, research on route network optimization tends to prioritize airlines' profitability, potentially overlooking the importance of aligning route expansions with the contextual functional orientation of airport clusters. Additionally, while passenger decisions influenced by fare differences are extensively studied, other crucial factors such as travel habits and brand loyalty are often overshadowed. Furthermore, the integration of experiential insights into passenger decision-making paradigms during route selection remains underexplored. On the topic of airport subsidy strategies, current research mainly quantifies airline revenue within predefined strategic frameworks, neglecting the nuanced influence of competitor strategies on airlines' dynamic decision-making. Additionally, there is a gap in analyzing how asymmetric information affects the effectiveness of airline competition in the context of airport subsidy effects. Further research is warranted to address these limitations and offer a more comprehensive understanding of the multifaceted interactions within the aviation landscape.

To address this concern, we adopt a perspective that centers on the synergistic development stemming from the intricate interplay of routes within an airport cluster. The investigation focuses on the process where major airports divest non-core routes. To accomplish this, a comprehensive evolutionary game model is constructed, encompassing variables such as passenger travel choices, airline pricing, route selection and airport subsidy strategies. Acknowledging the diverse decision behaviors exhibited by passengers, airlines and airports, the study introduces a dual-layer evolutionary game model to enhance methodological precision. The upper-layer model employs Fermi rules to compute passenger choice probabilities across various levels of airline ticket price discounts. By evaluating airline revenues corresponding to different choice probabilities, optimal fare discounts and passenger choice probabilities are determined and fed into the lower-layer model. In this lower-layer model, the Quantal Response Equilibrium (QRE) model is employed to effectively consider the impact of competition on the effectiveness of airport subsidy strategies, particularly under conditions of asymmetric information. Consequently, this approach enables the identification of optimal airport subsidy strategies and informed airline route selections. The upper-layer model is designed to optimize airlines' exploitation of market potential when introducing new routes, ultimately maximizing passenger benefits. On the other hand, the lower-layer model systematically examines how subsidy strategies influence airline route adjustments, ensuring a methodologically rigorous analysis.

The subsequent sections of this paper are structured as follows: Sections 2–4 introduces the proposed model in detail. Section 5 introduced the simulation processes in detail. Section 6 elaborates on the results derived from the application of the proposed model. Last, Section 7 succinctly summarizes the research's key findings and conclusions.

2. Materials and methods

2.1. Problem description

The emergence of regional airport clusters highlights the critical importance of harmonious route operations among airports to enhance the overall operational efficiency of these clusters. Within these clusters, airports can be classified into various types based on their coordinated development strategies, encompassing international hub airports, domestic hub airports and regional airports. As these airport categories evolve, international hub airports often grapple with resource constraints, necessitating the divestment of routes that deviate from their designated roles. On the other hand, regional airports within the cluster, benefiting from relatively abundant resources, can accommodate the reassignment of these routes. In cases where flights converge at the same destination airport, airlines have the flexibility to depart from any airport within the regional cluster. This orchestrated development of regional airports involves the collaborative optimization of route networks by redistributing and accommodating routes in alignment with their functional roles. Nevertheless, the establishment of route networks is shaped by market dynamics, demanding the implementation of subsidy policies to guide airlines in optimizing these networks.

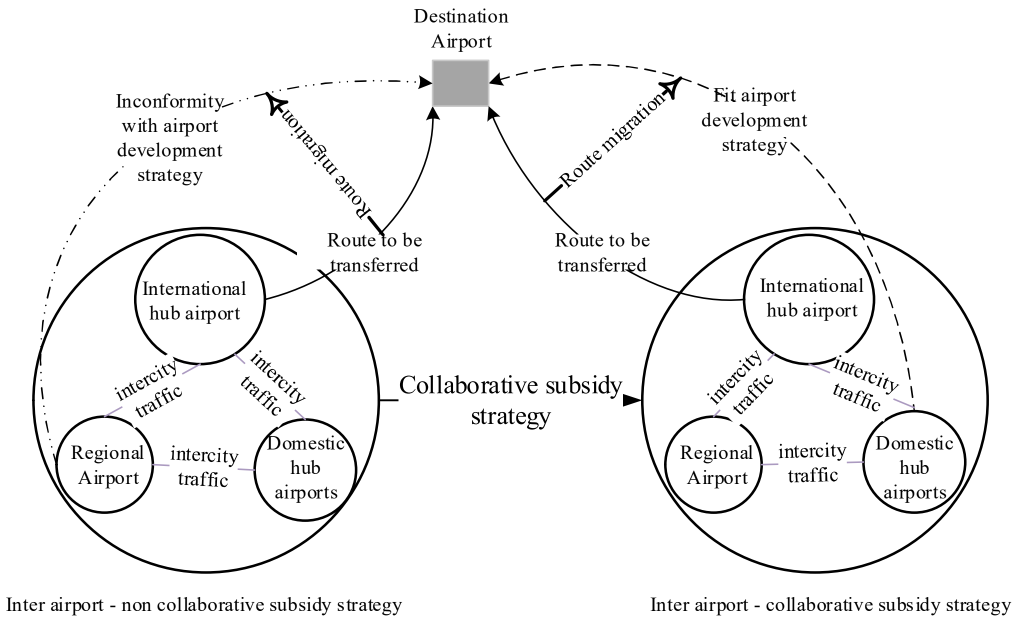

Figure 1. Optimization diagram of airline network between airports.

As depicted in Figure 1 made by Miscroft Visio, it becomes evident that formulating subsidy strategies for airports without considering their synergistic functional roles within the airport cluster can lead airlines to make incorrect route selections due to their interests and developmental needs. For instance, divergent airport subsidy strategies might cause airlines to shift routes from international hub airports to regional airports, even when such routes do not align with the functional positioning of those regional airports themselves. As a result, a complementary route network, built upon the foundation of functional roles among airports, may not materialize. This underscores the strategic interplay between airlines and airports regarding route adjustments. Coordinated airport subsidy strategies can effectively incentivize airlines to select routes that correspond to their functional roles within the airport cluster, all while incurring relatively minor subsidy costs.

Throughout this process, airlines decide whether to transfer routes and, if so, which airport to choos, based on their earnings, comprising ticket revenue and airport subsidies. Ticket revenue hinges on the airline's route pricing and passenger dynamics, while airport subsidies are influenced by the airport's functional positioning and competitive dynamics among airlines. Diverse subsidy strategies adopted by airports can alter airline revenues, thus initiating an evolutionary game process. The core of ticket revenue originates from the interplay between passengers and airlines, where airlines aim to attract the maximum number of passengers at a specific ticket price, while passengers strive to minimize their travel costs. Airlines target two passenger segments: "hinterland" passengers (within the administrative scope of the airport's designated service area) and "leakage" passengers (Refers to the loss of passengers in the hinterland of the airport service who choose a new airport after the airline transfers routes instead of their corresponding airport). Passenger choices regarding airline routes are shaped by travel costs and ticket discounts associated with different airport choices. Airlines adjust ticket prices in response to influence travel choice behavior, ultimately achieving equilibrium in this interplay.

The essence of airport subsidy benefits lies in the strategic interplay between airlines and airports. Airports seek routes aligned with their functional roles by offering minimal subsidies, while airlines endeavor to maximize earnings by selecting routes that yield higher airport subsidies. When providing subsidies, different airports pay different prices to attract suitable airlines, influenced by the functional positioning of airports. To ensure comparability between different airports, the concept of “subsidiary subsidy” is introduced (refers to the minimum basic subsidy that meets the functional positioning of the airport as the standard, and the subsidy level of different airports is reflected by the ratio of actual subsidy to minimum basic subsidy). During the decision-making process, airlines first evaluate potential passenger revenue resulting from route transfers. Subsequently, they make decisions based on total revenue, encompassing both passenger revenue and comprehensive airport subsidies. This process inherently unfolds in stages. Concurrently, passengers’ decisions to change their departure airport choices in response to airline route shifts introduce heterogeneity and staging into the game process. Guided by ticket price information, awareness of fellow passengers’ benefits and individual trip earnings, passengers adapt their travel choices through self-learning dynamic evolution. The influence of passenger decision-making also reflects the clustering characteristics of a small-world network.

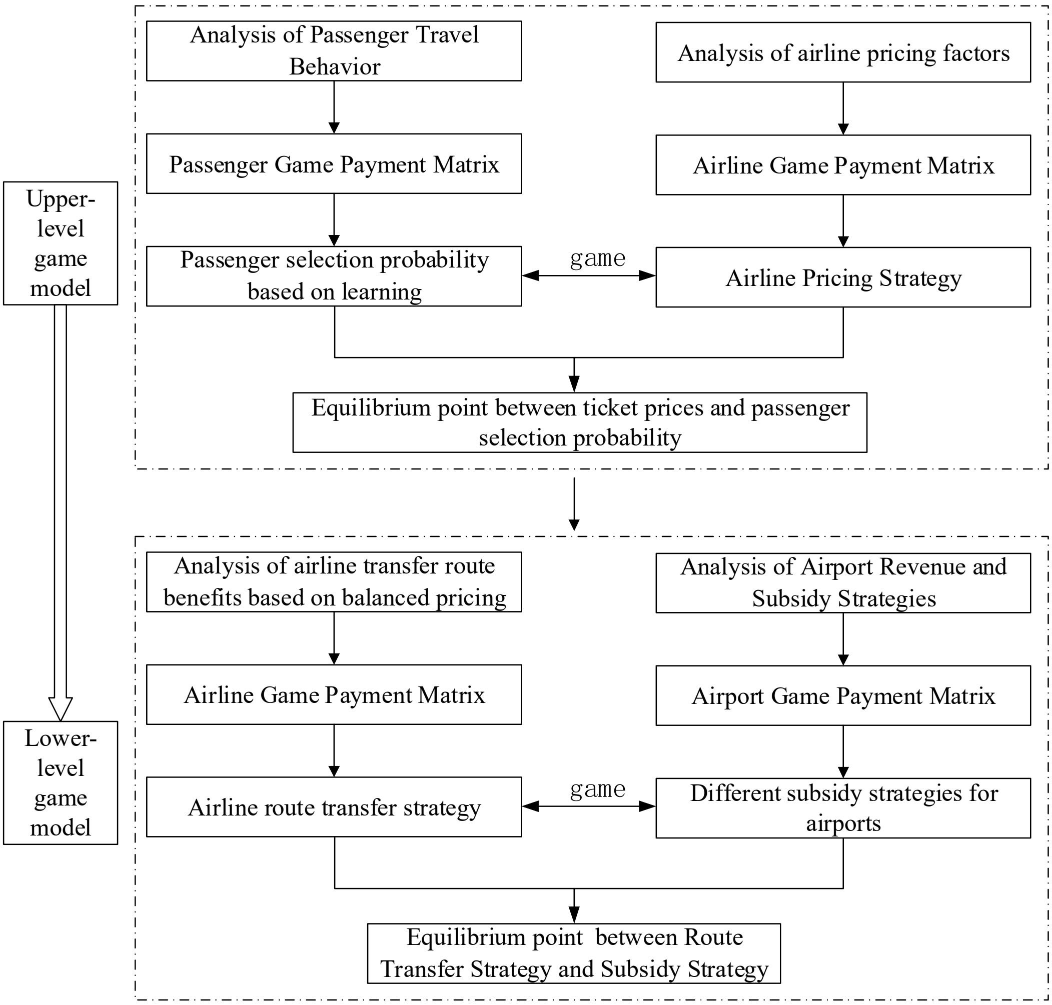

Figure 2. The flowchart of dual-layer game-theoretic model.

Table 1. Notations.

Notations	Description
$\tilde{A}_{R^g}^{\tilde{r}}$	the fare of airlines R operating the route g at the original airport $\tilde{r}$
$A_{R^g}^{r}$	the fare of airlines R operating the route g at the at the target airport r
$U_A^{\tilde{r}-r}$	additional travel costs for the "leakage" passengers
$U_p^{\tilde{r}-r}$	travel costs include inter-airport transportation costs for the "leakage" passengers
$U_T^{\tilde{r}-r}$	time costs for the "leakage" passengers
$\pi_{R^g}^{i^k}$	the revenue of passenger i choosing route g opened by airline R in strategy k
τ_{R^g}	the discount coefficient of airline R brand effect
$D_i(t)$	the decision strategy adopted by passenger i in period t
$P_{s_i \leftarrow s_j}\left(t+1\right)$	the probability that passenger i in period t+1 adopts the strategy adopted by passenger j in period t
$\Pi_{R^g}^{r}(t)$	the revenue of airline R in the period t at airport r for route g
$\tilde{N}_{R^g}^{r}$	the number of passengers of airline R's route g in the original hinterland of the airport r
$C_{R^g}^{r}$	is the capacity of airline R's route g
$\Pi_{\tilde{R}^g}^{r}$	the revenue of neighboring airline $\tilde{R}$ in the period t at airport r for route g
$S_{\tilde{g}}^{r}$	the amount of subsidy set by airport r for short-haul routes $\tilde{g}$
Γ^r	the airport's total revenue
$B_{\hat{g}}^{r}, B_{\tilde{g}}^{r}$	the standard of charge at airport r for short-haul routes and medium-haul routes
M_R^r	flight operation variable cost
F_R^r	flight fixed operating cost
$P(\partial_{R^g}^{h})$	the probability that airline R can choose the strategy $\partial_{R^g}^{h}$ for route g

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Notations	Description
$\tilde{P}(\partial^{d}_{\tilde{R}^{g}})$	the probability that airline $\tilde{R}$ can choose the strategy $\partial^{d}_{\tilde{R}^{g}}$ for route g
$\beta_{R}(\partial^{h}_{R^{g}})$	airline R ‘s cognitive belief that it is rational to take the strategy decision $\partial^{h}_{R^{g}}$
$\tilde{\beta}_{\tilde{R}}(\partial^{d}_{\tilde{R}^{g}})$	the airline $\tilde{R}$ believes its cognitive belief that it is rational to take the strategy decision $\partial^{d}_{\tilde{R}^{g}}$
μ_{R} , $\mu_{\tilde{R}}$	the income functions of airline R and airline $\tilde{R}$ in different policy choices

2.2 Methods description

The selection of different airports for route deployment by airlines represents a decision-making process marked by competition among airlines to secure a share of airport subsidies under conditions of asymmetric information. The decision-making behavior in this game exhibits randomness due to the presence of information asymmetry. Notably, passenger travel choices are significantly influenced by airline pricing. By studying the relationship between passenger behavior and airline pricing, one can deduce the corresponding connection between passenger choice behavior and airline discounts. This understanding aids in calculating passenger revenue for different airport choices when airlines deploy routes. By comprehensively considering various airport subsidy scenarios, airlines can make well-informed decisions. To achieve this, a two-layer heterogeneous game model is constructed to delve into the interplay between airport subsidies and airline route selection behaviors.

By analyzing passenger travel behavior and changing airline pricing strategy, the upper model explores the relationship between ticket price and passenger selection probability, obtains the best advantage of airline fare discount and inputs it into the lower layer as the basic condition. Under the premise that airports adopt different subsidy strategies, the lower model analyzes the total revenue of airlines, and explores the equilibrium point of subsidy strategies and route transfer in line with airport functional positioning. The flowchart of dual-layer game-theoretic model, as shown in Figure 2 made by Miscroft Visio.

To facilitate the understanding of the model, a unified description of the notations involved in the dual-layer game-theoretic model is provided in Table 1.

3. Upper-level game model

3.1. Assumptions

The upper-layer model primarily investigates the impact of different ticket price discounts offered by airlines on passenger choices regarding which airport within the airport cluster to travel from. This analysis aims to determine the quantity of passengers that can be attracted by varying ticket price discounts. The game entities involved in this layer are airlines and non-hinterland passengers. The game process involves airlines adjusting ticket prices for route transfers in each period. The specific strategies encompass high-discount strategy and low-discount strategy. Non-hinterland passengers comprehensively consider travel costs and ticket price discounts to formulate travel choice strategies, which include becoming leakage passengers (k = 1) and non-leakage passengers (k = 2).

The basic assumptions of this evolutionary game process include:

H1: Airlines, in order to attract leakage passengers, will adjust ticket prices in each period to ensure passenger benefits while considering the total revenue generated by their operated routes. This is done to determine the ticket price discounts corresponding to different routes that maximize the total revenue.

H2: To eliminate the influence of differentiated airline ticket prices on passenger decision-making behavior. When making decisions, passengers assume there is no pricing differentiation between airlines, such as frequent flyer programs, but their decisions might be influenced to some extent by potential factors like airline size and brand effects.

H3: To ensure that passengers can make rational and scientific decisions. Under fixed routes, the total number of passengers remains constant, all passengers have access to airline ticket price information and they make decisions based on prices and costs adjustments.

H4: Airlines establish fare discounts based on the specific conditions of different airports. Here, $\tilde{A}_{R^g}^{\tilde{r}}$ denote the fare of airlines R operating the route g at the original airport (referred to as OD route, corresponding to airport pairings), $A_{R^g}^{r}$ denote the fare of airlines R operating the route g at the target airport after transferring. $\tilde{r}$ and r values are 0, x or y, 0 represents that the airline does not transfer the route and remains at the original airport; and x or y are the other two types of airports in the regional airport cluster; among them, x is the domestic hub airport in the airport cluster, and y is a regional airport in the airport cluster.

H5: The total number of non-hinterland passengers is denoted as n. $U_A^{\tilde{r}-r}$ represent additional travel costs for “leakage” passengers. The additional travel costs include inter-airport transportation costs $U_p^{\tilde{r}-r}$ and time costs $U_T^{\tilde{r}-r}$. “Transportation costs” primarily encompass inter-city rail transportation costs and intra-city transportation costs. “Time costs” refer to the added duration during passenger transfer, computed using the hourly wage cost of local passengers, and a threshold of 3 hours is established. After the passenger transfer time exceeds 3 hours, the impetus for transfer significantly diminishes, and the transfer cost increases proportionally to the transfer time.

H6: Passengers still choosing the original airport will increase costs Q due to added transfer or waiting time.

H7: When passengers choose routes operated by multiple airlines, they will consider the brand effect of airlines, so the brand value of airlines is divided into three levels: High, medium and low. Since brand value is a long-term shaping process, the cost of building brand value is not considered in this game process.

According to H1 to H7, the game process is the influence of different fare discounts of airlines on the probability of travel choice under the given fare discount and travel cost (different airports in the region are selected as the starting point). The travel choice cost matrix is shown in Table 2.

Table 2. Cost matrix for different passenger selection strategies.

Payoff		Passenger j: Leakage	Passenger j: Non-Leakage
Passenger i	Leakage	$A^{r}_{R^g} + U^{\tilde{r}-r}_{A}$	$A^{r}_{R^g} + U^{\tilde{r}-r}_{A}$
		$A^{r}_{R^g} + U^{\tilde{r}-r}_{A}$	$\tilde{A}^{g}_{\tilde{r}} + Q$
	Non-Leakage	$\tilde{A}^{\tilde{r}}_{R^g} + Q$	$\tilde{A}^{\tilde{r}}_{R^g} + Q$
		$A^{r}_{R^g} + U^{\tilde{r}-r}_{A}$	$\tilde{A}^{\tilde{r}}_{R^g} + Q$

3.2. Game model

According to the cost matrix in Table 2, the revenue function obtained by passengers choosing different airlines is $\pi^{i^k}_{R^g}$, indicating that the revenue of passenger i choosing route g opened by airline R in strategy k is

$$\pi^{i^k}_{R^g}(t) = \begin{cases} \tau_{R^g}\cdot\left(\tilde{A}^{\tilde{r}}_{R^g} - A^{r}_{R^g}\right) - U^{\tilde{r}-r}_{A}, & k = 1 \\ -Q, & k = 2 \end{cases} \tag{1}$$

where τ_{R^g} represents the discount coefficient of airline R brand effect.

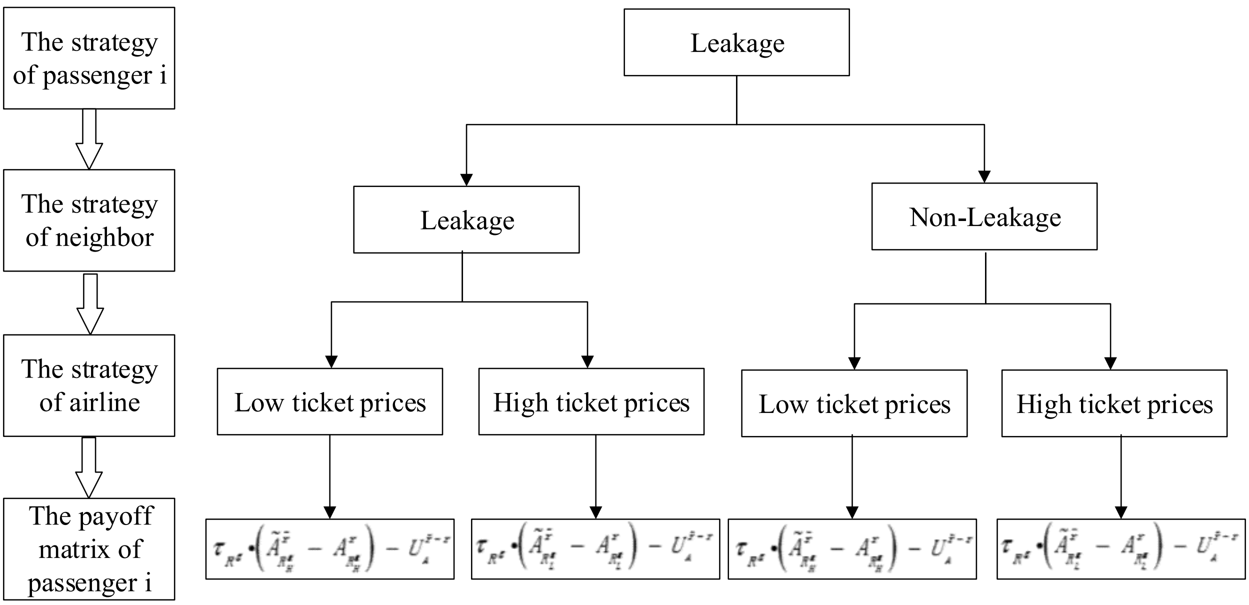

Figure 3. The benefit matrix of passengers under different strategies.

Passenger revenue is affected by their own strategy, neighbor strategy and airline strategy. Therefore, the revenue matrix of passengers under different decision-making environments is constructed, as shown in Figure 3 made by Miscroft Visio.

In the game process, passenger decision-making is mainly based on the income matrix, that is, passengers decide whether they become seepage passengers according to the size of the income function, but passengers will also be interfered by neighbors because passengers and neighbors are not fully connected, so they will be connected with a certain probability to obtain each other's information, and information sharing among airlines is also obtained with a certain probability. According to complex network theory, there are WS and NW types of small-world network. WS small-world network randomly disconnects the previous connection with a certain probability and connects with any node in the network with a fixed probability to establish a new connection. NW small-world network, on the basis of not changing the nodes and relations of the original network. The connectivity of complex networks is enhanced by the mechanism of randomly adding relationships with new nodes. When passengers choose different airlines of the same route, they tend to focus on their own benefits and have low requirements for maintaining the original connections of the network. WS small-world network can simulate the game process among passengers more accurately. As for the decision-making process among airlines, the subjects that affect their income are relatively fixed, and the maintenance degree of the original network is high, it is more suitable to use the NW small-world network to simulate the evolutionary game relationship of airline strategy selection.

In an airport group with complex network characteristics, the passenger's strategy choice is diffused among passengers through the edges in the network. In the initial state, each passenger has a pure policy choice. Furthermore, passengers will adjust their decision by the change of their own income and the benefit of neighbor selection strategy.

Neighbors are randomly selected for strategy comparison. In period t, passengers will compare their own strategy income with that of their neighbors and update the probability of changing to neighbor strategy in period $t+1$ according to Fermi rules:

$$P_{D_i \leftarrow D_j}\left(t+1\right) = \begin{cases} \dfrac{1}{1+\exp\left(\dfrac{\pi^i_{R^g}\left(\mathrm{t}\right) - \pi^j_{R^g}\left(\mathrm{t}\right)}{m}\right)}, D_i(\mathrm{t}) \neq D_j(t) \\ 1, D_i(t) = D_j(t) \end{cases} \tag{2}$$

In the formula, parameter m measures the intensity of individual irrational decision making. The smaller the value, the higher the rational degree of individual decision making; $D_i(t)$ is the decision strategy adopted by passenger i in period t. $P_{s_i \leftarrow s_j}\left(t+1\right)$ represents the probability that passenger i in period t+1 adopts the strategy adopted by passenger j in period t. When the income of passenger i in period t is lower than that of passenger j, passenger i easily accepts the strategy adopted by passenger j in period t; On the contrary, if the profit of passenger i is higher than that of passenger j in period t, passenger i will adopt the strategy of passenger j with a weak probability in period $t+1$.

When comparing with neighbors, it will also compare with its own strategic returns in the period $t-1$ to determine whether its own returns have reached the expectation and whether to change its own strategies. The choice probability is

$$P_{D_i \leftarrow D_i}\left(t+1\right) = \begin{cases} \dfrac{1}{1+\exp\left(\dfrac{\pi^{i}_{R^g}\left(\mathrm{t{-}1}\right) - \pi^{i}_{R^g}\left(\mathrm{t}\right)}{m}\right)}, D_i(\mathrm{t}) \neq D_j(t) \\ 0, D_i(t) = D_j(t) \end{cases} \tag{3}$$

Considering the influence of neighbor strategy and its own strategy, the probability of the next passenger adjusting to neighbor strategy is

$$P^{k}_{D_j}\left(t+1\right) = 0.8 \bullet \frac{P_{D_i \leftarrow D_j}\left(t\right)}{1 - P_{D_i \leftarrow D_j}\left(t\right) + P_{D_i \leftarrow D_j}\left(t\right)} + 0.2 \bullet \frac{1 - P_{D_i \leftarrow D_i}\left(t\right)}{1 - P_{D_i \leftarrow D_i}\left(t\right) + P_{D_i \leftarrow D_i}\left(t\right)} \tag{4}$$

The revenue of passengers is affected by the pricing of airlines, and the pricing of airlines is affected by their own earnings. Therefore, we calculate the revenue $\Pi^{r}_{R^g}(t)$ of airline R in the period t at airport r for route g is

$$\Pi^{r}_{R^g}(t) = A^{r}_{R^g}(t) \bullet \min\left\{P^{k=1}_{R^g}\left(t\right) \bullet n + \tilde{N}^{r}_{R^g}\ , C^{r}_{R^g}\right\} \tag{5}$$

where n is the total number of non-hinterland passengers; $\tilde{N}^{r}_{R^g}$ is the number of passengers of airline R's route g in the original hinterland of the airport r; $C^{r}_{R^g}$ is the capacity of airline R's route g.

In the game process, the airline will consider its own income and the income of neighboring airlines to formulate the next fare strategy. The price reduction strategy for the next period is evaluated according to the revenue of a single route after the fare discount. If the revenue of an airline increases compared with that of the previous period, it will continue to adopt the discount strategy to further increase the choice probability of passengers and improve the revenue. If there is a decline in revenue in the current period, the airline will reduce the discount to maintain the maximum profit, so the fare adjustment strategy is:

$$A^{r}_{R^g}(t) = \begin{cases} \left(1 - \dfrac{\Pi^{r}_{R^g}(t-1) - \Pi^{r}_{R^g}(t-2)}{\Pi^{r}_{R^g}(t-1) + \Pi^{r}_{R^g}(t-2)}\right) \bullet \left(1 + \dfrac{A^{r}_{\tilde{R}^g}(t-1) - A^{r}_{R^g}(t-1)}{\Pi^{r}_{\tilde{R}^g}(t-1) - \Pi^{r}_{R^g}(t-1)}\right) \bullet A^{r}_{R^g}(t-1),\ \Pi^{r}_{\tilde{R}^g}(t-1) \neq \Pi^{r}_{R^g}(t-1) \\ \left(1 - \dfrac{\Pi^{r}_{R^g}(t-1) - \Pi^{r}_{R^g}(t-2)}{\Pi^{r}_{R^g}(t-1) + \Pi^{r}_{R^g}(t-2)}\right) \bullet A^{r}_{R^g}(t-1),\ \Pi^{r}_{\tilde{R}^g}(t-1) = \Pi^{r}_{R^g}(t-1) \end{cases} \tag{6}$$

where $A^{r}_{\tilde{R}^{g}}$ is the fare of a neighboring airline; $\Pi^{r}_{\tilde{R}^{g}}$ for neighboring airline. In the formula, the first half is divided into the influence of its own income on ticket price, and the second half is divided into the influence of neighbor income on ticket price.

By comparing the fare discount and passenger selection probability corresponding to the maximum $\Pi^{r}_{R^{g}}(t)$ income of airlines on route g under different fare discounts, they are input into the lower layer model.

4. Lower-level game model

4.1. Assumptions

The major players of this layer are airlines and airports. The game process is that each airport adjusts the subsidy strategy according to the route selection situation. Under a certain subsidy strategy, the airline formulates the transferable medium and short route selection strategy according to the upper level ticket revenue and airport subsidies. The selection strategy includes selecting the original airport, domestic hub airport and regional airport respectively for medium and short routes.

The basic assumptions of the evolutionary game process in this layer include:

H8: To achieve airline route adjustments through market behavior. Large airports need to transfer some routes, and small to medium-sized airports take on these transferred routes. Whether airlines transfer their routes from large airports is a market behavior rather than an administrative mandate. Therefore, subsidy strategies directly influence airline decisions.

H9: To ensure that airline route optimization is primarily determined by airport subsidy policies, and there is competition among airlines. There is a limit to airport subsidies, so when multiple airlines choose the same airport for route transfer, it can lead to a decrease in their own revenue. Subsidy policies become a key factor for airlines when adjusting routes. When multiple airlines choose an airport, they share the airport subsidy S and the airport subsidy is capped. As the functional positioning of airports needs to match the route type, OD route g in the airport group is divided into medium-haul route $\hat{g}$ and short-haul route $\tilde{g}$. $S^{r}_{\hat{g}}$ represents the subsidy amount of airport r against the medium-haul route $\hat{g}$. $S^{r}_{\tilde{g}}$ indicates the amount of subsidy set by airport r for short-haul routes $\tilde{g}$.

$$S^{r} = \sum_{\hat{g}} S^{r}_{\hat{g}} + \sum_{\tilde{g}} S^{r}_{\tilde{g}},\ r = \{0, x, y\} \tag{7}$$

In order to ensure the sustainable development of the airport, the airport will set a subsidy ceiling, which according to the survey is 40% of the airport subsidy revenue, and the airport subsidy will no longer increase when it exceeds the value. The airport's revenue Γ^{r} mostly includes business revenue $B^{r}_{\hat{g}}, B^{r}_{\tilde{g}}$ from increased routes, and the potential revenue from the airport strategy reached.

$$\Gamma^r = \sum_{\hat{g}} n_{\hat{g}}^r \bullet B_{\hat{g}}^r + \sum_{\tilde{g}} n_{\tilde{g}}^r \bullet B_{\tilde{g}}^r + \omega \bullet V^r \tag{8}$$

In the equation, $n_{\hat{g}}^r$ and $n_{\tilde{g}}^r$ indicate whether the airline runs the routes $\hat{g}$ or $\tilde{g}$ at airport r.The value is 0 or 1. 0 indicates that the airline does not select this airport, and 1 indicates that the airline chooses this airport. $B_{\hat{g}}^r$ and $B_{\tilde{g}}^r$ indicates the standard of charge at airport r for short-haul routes and medium-haul routes; the degree to which V^r adds routes to the airport is in line with its own positioning development; ω increases the discount rate for airports on how well the route network matches the airport's positioning.

$$S^r \leq 0.4 * \Gamma^r \tag{9}$$

Moreover, in order to avoid the excessive accumulation of transfer routes that exceed the airport time requirements and realize the coordinated development of the three airports, the specific amount of airport subsidies should be dynamically adjusted according to the actual number of flights in the transfer airports, and the growth rate of subsidies should be controlled, which meets the following formula:

$$S^r(t+1) = \left[1 - \frac{\sum_{\hat{g}} n_{\hat{g}}^r(t)}{2\mathrm{N}_{\hat{g}}^r} - \frac{\sum_{\tilde{g}} n_{\tilde{g}}^r(t)}{2\mathrm{N}_{\tilde{g}}^r}\right] S^r(t),\ r = \{x, y\} \tag{10}$$

$\mathrm{N}_{\hat{g}}^r$ and $\mathrm{N}_{\tilde{g}}^r$ indicate the number of times the airport has attracted medium-haul routes $\hat{g}$ and short-haul routes $\tilde{g}$.Due to the mature supporting facilities of domestic hub airports and good route network effect, the airport has a relatively high resource shortage at all times, so the overall cost of transferring to domestic hub airport x is higher than that of transferring to regional hub airport y.

H10: This layer model uses the conclusion of the upper layer model. Under the condition of maximization of revenue, the fares and the number of passengers attracted by an airline are taken as the ticket revenue of the airline in this layer. There is only competition among airlines in this tier to share airport subsidies, and there is no competition among passenger tickets. Among them, $\Pi_{R^{\hat{g}}}^r$ means the best fare revenue calculated by the upper deck model at airport r for the medium-haul routes $\hat{g}$ of airline R and $\Pi_{R^{\tilde{g}}}^r$ means the best fare revenue calculated by the upper deck model at airport r for the short-haul routes $\tilde{g}$ of airline R.

H11: Airline route operating costs include: Airline to airport r flight operation variable cost M_R^r;Airport r charges B^r;Flight fixed operating cost F_R^r.

According to H8 to H11, the corresponding utility matrix of airlines' transfer strategies for the medium-haul route $\hat{g}$ and the short-haul route $\tilde{g}$ is shown in Table 3.

Table 3. Transfer strategy utility matrix.

		short-haul routes of airline R		
		No transfer	Transfer to airport x	Transfer to airport y
medium-haul routes of airline R	No transfer	$\Pi^0_{R^{\hat{g}}} - F^0_{R^{\hat{g}}}$ $\Pi^0_{R^{\tilde{g}}} - F^0_{R^{\tilde{g}}}$	$\Pi^0_{R^{\hat{g}}} - F^0_{R^{\hat{g}}}$ $\Pi^x_{R^{\tilde{g}}} + S^x_{R^{\tilde{g}}} - M^x_{R^{\tilde{g}}} - F^x_{R^{\tilde{g}}} - B^x_{R^{\tilde{g}}}$	$\Pi^0_{R^{\hat{g}}} - F^0_{R^{\hat{g}}}$ $\Pi^y_{R^{\tilde{g}}} + S^y_{R^{\tilde{g}}} - M^y_{R^{\tilde{g}}} - F^y_{R^{\tilde{g}}} - B^y_{R^{\tilde{g}}}$
	Transfer to airport x	$\Pi^x_{R^{\hat{g}}} + S^x_{R^{\hat{g}}} - M^x_{R^{\hat{g}}} - F^x_{R^{\hat{g}}} - B^x_{R^{\hat{g}}}$ $\Pi^0_{R^{\tilde{g}}} - F^0_{R^{\tilde{g}}}$	$\Pi^x_{R^{\hat{g}}} + S^x_{R^{\hat{g}}} - M^x_{R^{\hat{g}}} - F^x_{R^{\hat{g}}} - B^x_{R^{\hat{g}}}$ $\Pi^x_{R^{\tilde{g}}} + S^x_{R^{\tilde{g}}} - M^x_{R^{\tilde{g}}} - F^x_{R^{\tilde{g}}} - B^x_{R^{\tilde{g}}}$	$\Pi^y_{R^{\hat{g}}} + S^y_{R^{\hat{g}}} - M^y_{R^{\hat{g}}} - F^y_{R^{\hat{g}}} - B^y_{R^{\hat{g}}}$ $\Pi^y_{R^{\tilde{g}}} + S^y_{R^{\tilde{g}}} - M^y_{R^{\tilde{g}}} - F^y_{R^{\tilde{g}}} - B^y_{R^{\tilde{g}}}$
	Transfer to airport y	$\Pi^y_{R^{\hat{g}}} + S^y_{R^{\hat{g}}} - M^y_{R^{\hat{g}}} - F^y_{R^{\hat{g}}} - B^y_{R^{\hat{g}}}$ $\Pi^0_{R^{\tilde{g}}} - F^0_{R^{\tilde{g}}}$	$\Pi^y_{R^{\hat{g}}} + S^y_{R^{\hat{g}}} - M^y_{R^{\hat{g}}} - F^y_{R^{\hat{g}}} - B^y_{R^{\hat{g}}}$ $\Pi^x_{R^{\tilde{g}}} + S^x_{R^{\tilde{g}}} - M^x_{R^{\tilde{g}}} - F^x_{R^{\tilde{g}}} - B^x_{R^{\tilde{g}}}$	$\Pi^y_{R^{\hat{g}}} + S^y_{R^{\hat{g}}} - M^y_{R^{\hat{g}}} - F^y_{R^{\hat{g}}} - B^y_{R^{\hat{g}}}$ $\Pi^y_{R^{\tilde{g}}} + S^y_{R^{\tilde{g}}} - M^y_{R^{\tilde{g}}} - F^y_{R^{\tilde{g}}} - B^y_{R^{\tilde{g}}}$

4.2. Game model

The secrecy of airline business strategies leads to strong asymmetry in decision-making information among airlines. Based on limited information, airlines always think that their own decisions are better than those of their counterparts when making their own decisions, which has obvious asymmetric random response characteristics and a certain probability of making mistakes, and they are more cautious when facing strategies with lower expected returns. Therefore, an asymmetric random response (QRE) equilibrium model is introduced in this layer.

In the decision-making process, airlines will judge the benefits of three strategies: When the benefits of transfer strategy are greater than those of no transfer, airlines will adopt transfer strategy; otherwise, they will adjust to no transfer strategy; when an airline chooses to transfer, if the profit of the strategy of transferring to x airport is greater than that of transferring to y airport, the airline will transfer to x airport; otherwise, it will transfer to y airport. Therefore, based on the QRE model, the airline's route selection probability is

$$P(\partial^h_{R^g}) = \frac{\exp\left[\beta_R(\partial^h_{R^g})\sum_{h=1}^{r}\tilde{P}(\partial^d_{\tilde{R}^g})\bullet\mu_R(\partial^h_{R^g},\partial^d_{\tilde{R}^g})\right]}{\sum_{h=1}^{r}\exp\left[\beta_R(\partial^h_{R^g})\sum_{d=1}^{r}\tilde{P}(\partial^d_{\tilde{R}^g})\bullet\mu_R(\partial^h_{R^g},\partial^d_{\tilde{R}^g})\right]} \tag{11}$$

$$\tilde{P}(\partial^d_{\tilde{R}^g}) = \frac{\exp\left[\tilde{\beta}_{\tilde{R}}(\partial^h_{\tilde{R}^g})\sum_{h=1}^{r}P(\partial^d_{R^g})\bullet\mu_{\tilde{R}}(\partial^h_{R^g},\partial^d_{\tilde{R}^g})\right]}{\sum_{d=1}^{r}\exp\left[\tilde{\beta}_{\tilde{R}}(\partial^d_{\tilde{R}^g})\sum_{h=1}^{r}P(\partial^h_{R^g})\bullet\mu_{\tilde{R}}(\partial^h_{R^g},\partial^d_{\tilde{R}^g})\right]} \tag{12}$$

where R stands for the airline making the decision, $\tilde{R}$ stands for the airline competing with R,

$P(\partial^h_{R^g})$ stands for the probability that airline R can choose the strategy $\partial^h_{R^g}$ for route g; $\tilde{P}(\partial^d_{\tilde{R}^g})$ represents the probability that airline $\tilde{R}$ can choose the strategy $\partial^d_{\tilde{R}^g}$ for route g; $\beta_R(\partial^h_{R^g})$ represents airline R 's cognitive belief that it is rational to take the strategy decision $\partial^h_{R^g}$ (cognitive belief is a representation of how an airline considers the influence of its competitor's strategies on its decision making). In other words, when making decisions, airlines will first predict its competitors' strategies and airport subsidy policies , and the more accurate they think the prediction is, the stronger their cognitive belief in the rationality of their own strategies; $\tilde{\beta}_{\tilde{R}}(\partial^d_{\tilde{R}^g})$ indicates that the airline $\tilde{R}$ believes its cognitive belief that it is rational to take the strategy decision $\partial^d_{\tilde{R}^g}$; μ_R and $\mu_{\tilde{R}}$ are the income functions of airline R and airline $\tilde{R}$ in different policy choices, respectively. See the utility matrix of choice strategies in Table 3. $P(\partial^h_{R^g})$ and $\tilde{P}(\partial^d_{\tilde{R}^g})$ form a cyclic nested relationship, which better explains airline R 's rational understanding of its own decision making and the influence of different airline $\tilde{R}$'s strategies on its decision making.

5. Simulation case

Selecting Sichuan-Chongqing airport group as the research background, we make coordinated adjustments to the functions of Shuangliu Airport, Tianfu Airport and Mianyang Airport according to the positioning of urban development and the overall development of comprehensive traffic. In order to realize the optimal allocation of inter-airport routes through market behavior to the maximum extent and meet the functional positioning of inter-airport collaboration, it is necessary for each airport to adopt different subsidy strategies to achieve the best route network adjustment. In the simulation, Tianfu and Mianyang airports are mainly used to undertake the overflow routes of Shuangliu Airport. The overflow routes belong to 6 airlines of different sizes, respectively, the medium-haul routes $\hat{g}$ and the short-haul routes $\tilde{g}$ total 63, of which 27 are medium-haul routes and 36 are short-haul routes. The simulation takes Tianfu Airport as the representative of domestic hub airport and Mianyang airport as the representative of regional airport. The 63 routes of Shuangliu Airport will be transferred to two airports, with Tianfu Airport aiming to attract medium-haul routes and Mianyang Airport aiming to attract short-haul routes. The airport charge standard shall be calculated according to the Civil Airport Charge Standard Adjustment Plan issued by Civil Aviation Administration in 2017. According to the situation of three airlines surveyed and literature, the route operation cost of airlines was determined.

Upper-level model simulation process:

Step 1: At t = 0, the NW Small World network of n passengers and the NW Small World network of 6 airlines are generated, each passenger is connected to a neighboring passenger, according to the proportion of airline classes, that is, high-end airlines: Middle airlines: Low-end airlines:

0.35:0.35:0.3: Seepage passengers: Non-seepage passengers: 1:1. The initial strategy selection of passengers is randomly generated, each airline is connected with a neighboring airline and the initial fare of a single route is given.

Step 2: At t = 1, each passenger and airline update the selection of neighbors, establishes new contacts, completes horizontal and vertical comparisons of passenger revenue and airlines and adjusts the next strategic selection according to the improved Fermi rules.

Step 3: At t = 2, each passenger and the airline disconnect from the previous period to establish a new connection, calculates the revenue according to the previous period's selection strategy, updates the passenger strategy using the improved Fermi rule and the airline optimizes the next period's discount fares according to the two consecutive periods' revenue.

Step 4: Repeat steps 2 and 3 until t = 1000.

Step 5: In order to avoid the error caused by random process, the simulation of steps 1–4 was repeated 100 times.

Step 6: The average of 100 passenger selection probabilities is taken as the final passenger selection result.

The travel cost parameters between Sichuan and Chongqing airports were calculated according to the inquiry of China Railway 12306 official website and the Gaode Maps app, as shown in Table 4.

Table 4. Passenger transfer cost parameters between airports.

	Inter-city transportation cost (yuan)	Inter-city transportation time (hours)	Intra-city transportation cost (yuan)	Intra-city transportation time (hours)	Time cost (yuan per hour)
Shuangliu Airport-Mianyang Airport	45–140	45	13	12	60
Shuangliu Airport-Tianfu Airport	0	0	120	60	60

Intra-city transportation refers to the average online ride-hailing cost transferred between the urban high-speed rail station and the airport, and time cost refers to the hourly time cost determined according to the average wage level in Sichuan and Chongqing.

Lower-level model simulation process:

Step 1: At t = 0, determine the cost parameters of the airline and the initial probability of strategy selection $P(\partial^{r}_{R^g})$. Furthermore, input the airline ticket price, optimal discount and passenger transfer situation from the upper model to the lower model.

Step 2: At t = 1, the airline updates its strategy selection based on the asymmetric QRE model.

Step 3: At t = 2, the airline calculates its earnings based on the previous strategy selection and adjusts its strategy through the asymmetric QRE model.

Step 4: Repeat steps 2 and 3 until t = 100.

Step 5: In each simulation process, take the mean of the stable value of the airline company's final selection probability as the result.

To visually demonstrate the evolution process of the game, MATLAB2016b is used for simulation.

6. Results

6.1. Upper-level model solution

By analyzing the game between airline fare and passenger travel choice, the upper layer model determines the best pricing for airlines to attract the largest “seepage” passengers to maximize profits after transferring routes. According to the model described in 3.2, the initial parameters of the upper model are set as follows. Airline fare discount on the degree of passenger attraction will be affected by the initial fare price, i.e., the passenger travel cost; therefore, the impact of different initial fare, passenger travel cost on the selection probability is discussed. The initial fare is set at 460 yuan, 850 yuan and 1900 yuan in accordance with the domestic short, medium and long distance average voyage and fare rules; Airlines are divided into three categories according to different brand values. Set the initial simulation parameters as follows based on the upper-layer model simulation requirements.

Table 5. Initial value of upper model parameter.

$\hat{g}$	$\tilde{g}$	m	τ_{R^g} (Low-end)	τ_{R^g} (Medium-end)	τ_{R^g} (High-end)
0.5	0.5	0.2	0.3	0.3	0.15

Table 6. Comparative analysis of parameter sensitivity.

Parameter	Parameter reference value	Changed parameter	Parameter change rate (%)	Change rate of passenger selection probability (%)	Initial sensitivity index (%)
m	170	85	−50	36	−0.72
τ_{R^g} (Low-end)	1	2	100	23	0.23
τ_{R^g} (Medium-end)	40	80	50	43	0.86
τ_{R^g} (High-end)	150	120	−80	−32	0.4

In order to ensure the accuracy and stability of the simulation, the sensitivity of the passenger selection probability to each parameter value is compared, and the sensitivity index of the initial parameter value is evaluated by small changes in the initial parameter value (the change rate of the passenger selection probability/the change rate of the parameter).

As can be seen from Table 6, the strength of individual irrational decision making m and the discount coefficient of airline brand value τ_{R^g} are different within a certain range, and the selection probability of passengers fluctuates around the simulation result corresponding to the reference value of the parameter, which has no obvious impact on the simulation conclusion.

6.1.1. Effect of fare discount on travel choice probability of short-haul passengers

Under the condition that the initial fare and passenger transfer cost are fixed and the cost of shaping the brand value of the airline is not considered, the airline increases the passenger selection probability by adjusting the fare, and the passenger reduces the travel cost by choosing different airlines. The two methods reach stability through constant chess. After 1000 times of simulation, the corresponding choice probability of the passenger under different fares is obtained.

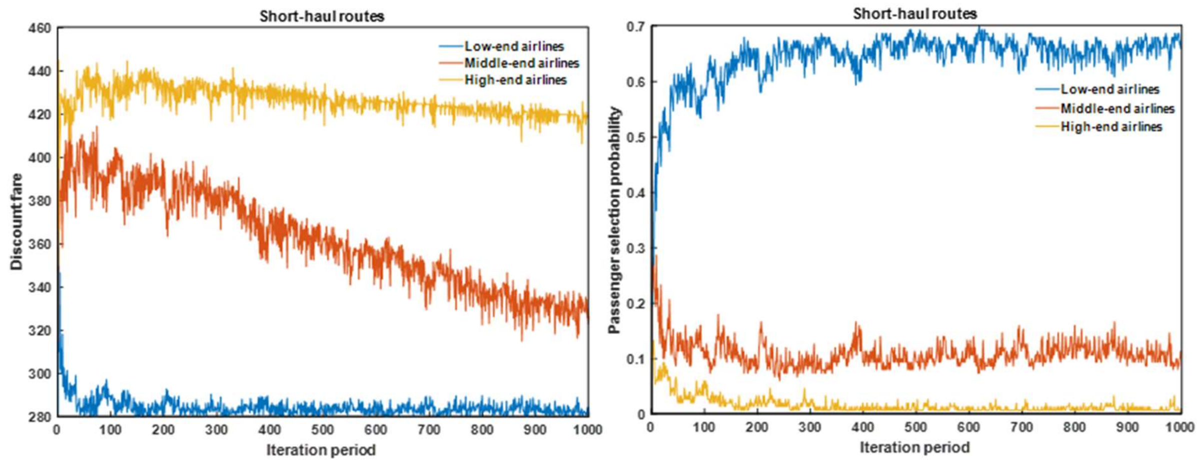

Figure 4. Influence of fare discount on selection probability of short-haul passengers.

The first subfigure of Figure 4 shows that the discount of fares adopted by three different airlines ranges from 6.1 discount to 8.9 discount, with a wide fluctuation range. As can be seen from the figure, the fares of airlines with low brand value are stable and fast with minimal fluctuation. In order to compete with other airlines, they adopt the strategy of price reduction and occupy a monopoly position in passenger attraction ability. There is an obvious competition process between medium brand value airlines and high brand value airlines, and the fare fluctuation is obvious. In order to maintain the ability of attracting passengers, medium brand value airlines adopt a fluctuating price reduction strategy and gradually determine the better fare range. Airlines with high brand value adopt the strategy of high fare and low choice probability of passengers to maintain their earnings, and the fare is maintained at 20% discount. The second subfigure of Figure 4 shows the selection probability of passengers under different fare discounts of airlines, among which the selection probability of airlines with high brand value is at least 0.02, that of airlines with medium brand value is 0.18 and that of airlines with low brand value is only 0.67.

It can be seen that on short-haul routes, airlines with high brand value have the lowest market share and lose their competitiveness on short-haul routes, while airlines with low brand value adopt the strategy of low price near the cost to obtain the most market share and ensure their own earnings. The simulation process reflects the influence of multi-source strategies adopted by different game players on each other's behavior when they pursue profit.

6.1.2. Effect of fare discount on travel choice probability of medium-haul passengers

The behavior of passengers choosing airlines on medium-haul routes was simulated, and the simulation period was 1000 times to obtain the corresponding selection probability of passengers of airlines with different brand values under different fares. The simulation results are shown in Figure 5.

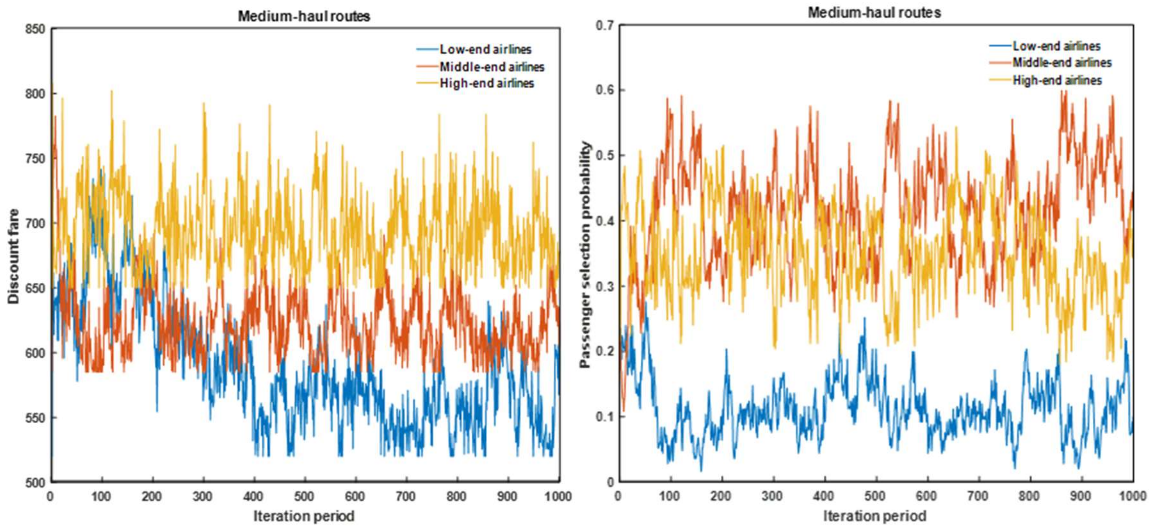

Figure 5. Influence of fare discount on selection probability of medium-haul passengers.

The first subfigure of Figure 5 shows that for medium-haul routes, airlines adopt fare discounts ranging from 6.3 to 8.5. The degree of fare fluctuation is relatively obvious, and the stable period becomes longer. The high brand value airlines adopt the higher fare strategy for the medium route, and the fare discount is mainly an 8.2 discount. Airline fare discount of medium brand value is stable at a 7.4 discount; low brand value airlines adopt a lower fare strategy, which can make them gain better profits in the competition, and the main discount they take is a 6.4 discount. The second subfigure of Figure 5 It can be seen that the brand value airline maintains its passenger selection probability at 0.45 by reducing the fare; the passenger selection probability of high brand value airlines remained at 0.31; it can be seen that high and medium brand value airlines have obvious influence on passenger selection probability, and there is a trade-off effect.

It can be seen that on medium-range routes, high-brand value airlines adopt high-fare strategy to sacrifice some passengers' selection probability to gain higher returns, while medium-brand value airlines compete for some passengers from high-brand value airlines to improve their own returns by reducing fares. Airlines with low brand value try to improve their own profitability through price reduction, but the effect is limited. Their selection probability is 0.12. In general, the difference between the effect of changing passenger travel behavior by fare on medium-range routes is decreasing.

6.1.3. Effect of fare discount on travel choice probability of long-haul passengers

The behavior of passengers choosing airlines on long-haul routes was simulated, and the simulation period was 1000 times to obtain the corresponding selection probability of passengers of airlines with different brand values under different fares. The simulation results are shown in Figure 6.

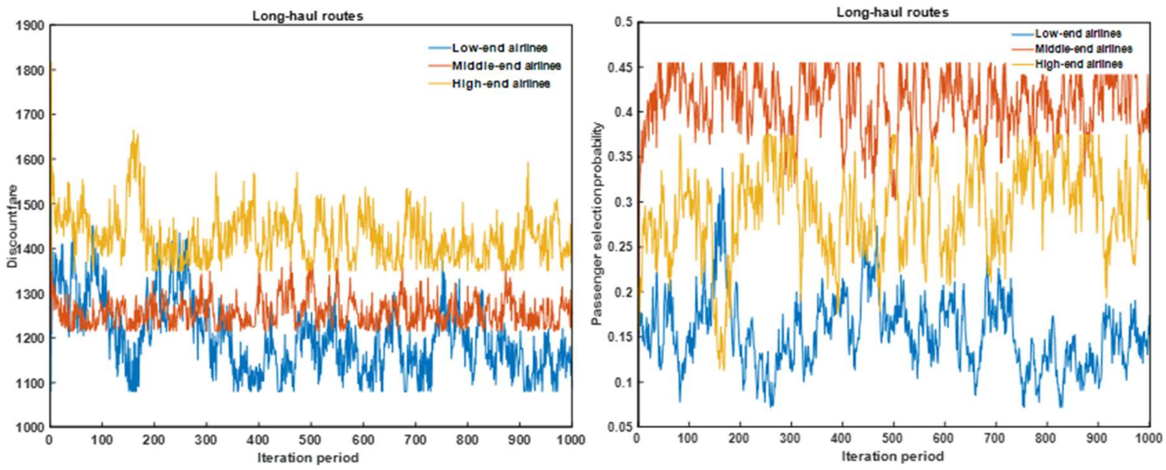

Figure 6. Influence of fare discount on selection probability of long-haul passengers.

The first subfigure of Figure 6 shows that for medium-haul routes, airlines adopt a fare discount range of 6.0 to 7.8, with a small degree of fare fluctuation, and the fare quickly becomes stable. Airlines with high brand value still adopt higher fare strategy, and their fare discount is mainly a 7.6 discount. Airline fare discounts of medium brand value were stable at 6.8 percent. Low brand value airlines take a stable discount of 6.1 percent, similar to the discount of medium brand value airlines. The second subfigure of Figure 6 Passenger selection probability of high brand value airlines is at a medium level and stable at 0.31. In the medium brand value airline passenger selection probability is stable at a high level of 0.43. The passenger selection probability of low brand value airlines is stable at 0.17.

It can be seen that on long-haul routes, airlines with high brand value still obtain high returns through the selection probability of medium passengers with high fares. Airlines with medium brand value maintain higher returns through lower fare strategy in exchange for more passenger selection probability; Airlines with low brand value do not gain more passengers by widening the fare gap for long-haul routes. Under the influence of airlines with high brand value, although the fare is higher, passengers' selection probability is also higher.

6.1.4. Equilibrium point between ticket prices and passenger selection probability

Through the above analysis, it can be seen that the fare strategy of airlines with high brand value plays a dominant role in the travel choice behavior of passengers and its fare strategy will significantly influence and transmit to airlines with medium and low brand value. Low brand effect airlines have a good system of choosing passengers through low fare strategy on long-haul routes, but high brand value airlines have too much impact on them on short-haul routes, and the effect of a low-price strategy is obviously insufficient. The competition between medium brand value airlines and high brand value airlines is obvious and the competition between them will obviously affect the choice behavior of passengers. According to the above process, the fare strategies adopted by airlines with different brand values for different routes are determined and input into the lower layer model.

The pricing strategy of airlines is based on the premise of maximum return. Therefore, the optimal return of airlines under different fare discounts is analyzed as the input of the lower-level model, which mainly studies the game of attracting short-haul routes between two airports. Therefore, for the short-haul and medium-haul routes of three types of airlines, the initial fare of 460 yuan and 850 yuan are selected respectively. Under different discounts, the best returns of three types of airlines are shown in Figure 7.

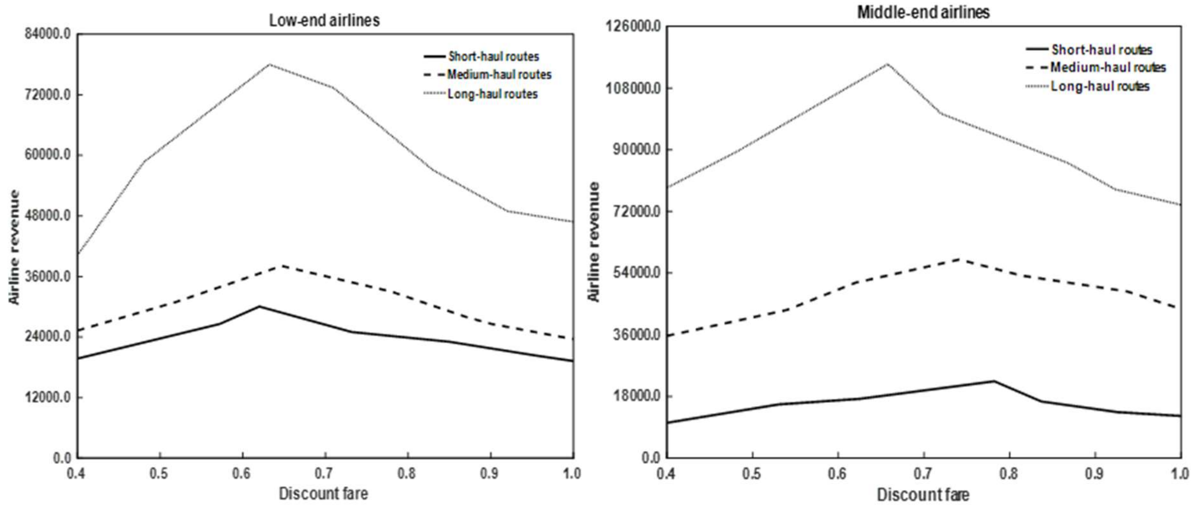

Figure 7. Apply the best pricing strategy of airlines in the lower model.

As can be seen in Figure 7, when the initial fare of short-haul route is 460 yuan, the fare discount of low, medium and high-end airlines is 0.62, 0.78 and 0.92 respectively, and the airline has the highest revenue. When the initial fare of the medium-range route is 850 yuan, the fare discount of the low, medium and high-end airlines is 0.64, 0.73 and 0.82 respectively, the airline company has the highest profit. Therefore, with the improvement of brand effect, the airline's fare discount should be appropriately reduced to meet the airline's income maximization. The above best discount and profit are taken as the basis of the game between the lower-level model and the airport subsidy strategy.

6.2. Lower-level model solution

According to the model described in Section 4.2, the simulation was carried out according to the route operating cost and different airport subsidy strategies. The airport subsidy strategy means that the airport subsidy strategy coefficient is multiplied by the initial value of the airport subsidy, where the airport subsidy strategy coefficient is adjusted according to the airport subsidy strategy, and the initial value of the subsidy means that 8% of the airport revenue is taken as the initial value of the subsidy. According to the charging standard of Sichuan-Chongqing airport group and the positioning situation of airport functions, the parameters are set as follows.

Table 7. Initial value of lower model parameter.

$P_0(\partial^X_{R^i})$	$P_0(\partial^X_{R^j})$	$P_0(\partial^Y_{R^i})$	$P_0(\partial^Y_{R^j})$	$P_0(\partial^0_{R^i})$	$P_0(\partial^0_{R^j})$
0.2	0.2	0.2	0.2	0.6	0.6

In order to verify the rationality of the set parameters on the simulation results, the initial probability values of six airlines transferring routes were randomly selected within the range of (0,0.5], and the simulation results were shown in Figure 8. It can be seen that the initial probability mainly affects the probability value that has not reached the stable stage, and the sensitivity of the final simulation result to the setting of the initial probability value is not obvious.

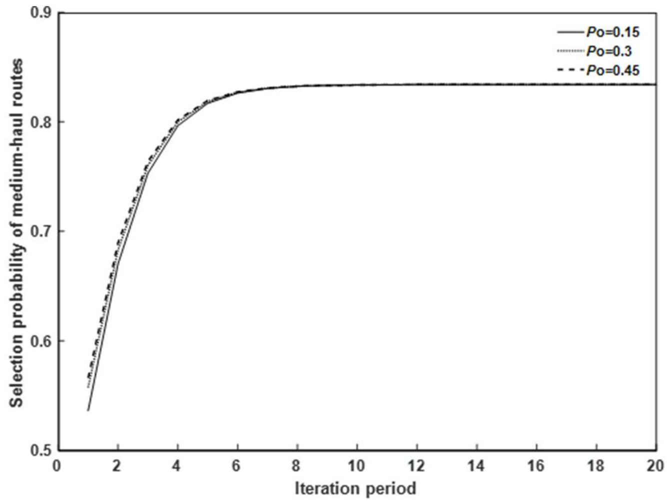

Figure 8. Sensitivity analysis of initial parameters in the lower level model.

6.2.1. Evolutionary game stability analysis

According to the target positioning that Tianfu Airport attracts medium-haul routes and Mianyang airport attracts short-haul routes, different subsidy strategies and airport charge strategies are adopted to analyze the average selection probability of medium-haul routes and short-haul routes corresponding to six airlines. The evolutionary game process is shown in Figure 9 below.

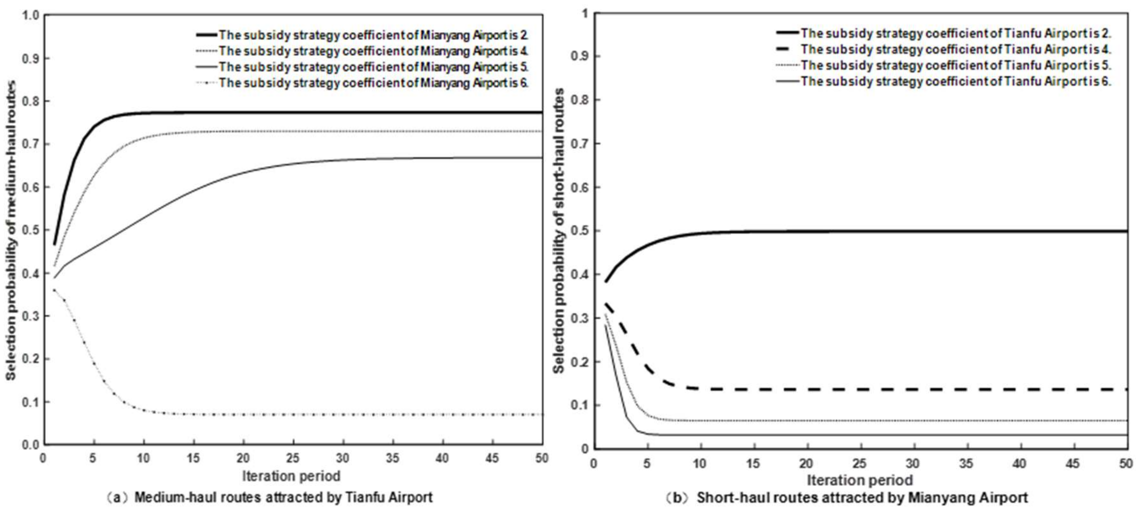

Figure 9. Game stability of different subsidy strategies.

As can be seen from Figure 9, after the iteration period is 15 periods, the effect of subsidy strategies is stable in the course of route selection game of 6 airlines. Different subsidy strategies among airports will affect the average selection probability of airlines, reflecting the game process between airport subsidies and airline selection. Figure 9(a) Fixed Tianfu Airport subsidy strategy. When the subsidy coefficient of Mianyang Airport is 5 or above, the subsidy strategy of Tianfu Airport will have a significant impact, resulting in a sharp decline in the average attraction ability of Tianfu Airport to six airlines on medium-haul routes (that is, the corresponding curves of positive definite airport subsidy coefficient of 5 and 6 decline); when the subsidy strategy of Mianyang Airport is low subsidy strategy (the figure corresponds to the curves corresponding to the coefficient of subsidy strategy of Mianyang Airport is 2, 3 and 4), the average attraction ability of Tianfu Airport to the medium-haul routes of the six airlines is enhanced, and the curve rises. Figure 9(b) show the fixed subsidy strategy of Mianyang Airport. When Tianfu Airport subsidy coefficient is 3 or above, the subsidy strategy of Mianyang Airport will have a significant impact, resulting in a sharp decline in the airline attraction ability of Mianyang Airport (curve with a downward trend in the figure). When Tianfu Airport adopts a low subsidy strategy for short-haul routes (the subsidy strategy of Tianfu Airport is curve 1 and curve 2 in the figure), Mianyang Airport's ability to attract short-haul routes is enhanced.

6.2.2. Cognitive belief in decision making and game stability analysis

Airlines constantly enhance their own decision-making experience in the decision-making process, which will change their cognition and belief in decision-making of themselves and other airlines. By fixing the subsidy strategy coefficient of two airports and changing the airline's cognition and belief in decision-making $\beta_R(\partial^h_{R^g})$, the effects of different airline's decision belief on airport subsidy strategy were analyzed.

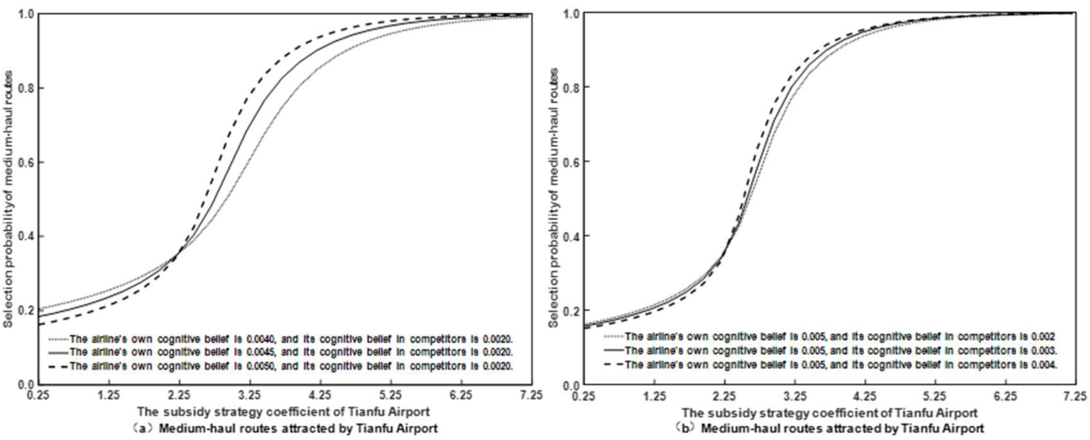

Figure 10. The influence of decision-making cognitive beliefs on game results.

Figure 10(a) shows the fixed subsidy strategy of Mianyang Airport and the airlines' cognitive beliefs about competitors' decision making $\tilde{\beta}_{\tilde{R}}(\partial^d_{\tilde{R}^g})$ and the changing airlines' cognitive beliefs about themselves $\beta_R(\partial^h_{R^g})$. It is found that when the subsidy strategy coefficient of Tianfu Airport is 2.6, the airlines' cognitive beliefs will have an inflection point on the growth trend of selection probability. That is, low cognitive beliefs correspond to high selection probability before the inflection point, and high cognitive beliefs correspond to high selection probability after the inflection point. Moreover, under the same cognitive belief after the inflection point, the airport subsidy strategy has a significant impact on the airline selection probability, and the growth rate is accelerated. Figure 10(b) shows that changing airlines' cognitive beliefs about competitors' decisions has a small effect on the selection probability, but accelerates the airline's selection strategy to reach its peak. Similar to Figure 10(a), when the airport subsidy strategy is 2.7, there is also an inflection point where the growth trend of selection probability is different. Therefore, before the inflection point, when the airport subsidy strategy is low, the weaker the cognitive belief, the stronger the airport's ability to attract routes with the increase of airport subsidy strategy; after the inflection point, the stronger the cognitive belief, the stronger the airport's ability to attract routes with the increase of airport subsidy strategy; according to the inflection point of airport subsidy strategy, the airline's cognitive belief was determined. As can be seen from the inflection point of Figure 10(a) curve, the airline's cognitive belief affects its ability to predict revenue. The higher the airport subsidy, the more likely it is to obtain high revenue, which enhances its belief in decision making. As can be seen from the inflection point of the curve in Figure 10(b), the airline enhances its cognitive belief of competitors, enhances its possibility of obtaining high returns and further enhances its decision selection probability.

6.2.3. Analysis of the optimal subsidy strategy

The subsidy strategies of the two airports are a dynamic adjustment process, and different subsidy strategies of the two airports will affect the selection probability of airlines. The simulation will change the average selection probability of six airlines on medium-haul routes and short-haul routes under different subsidy strategies of the two airports and determine the subsidy strategies of the two airports when realizing functional positioning.

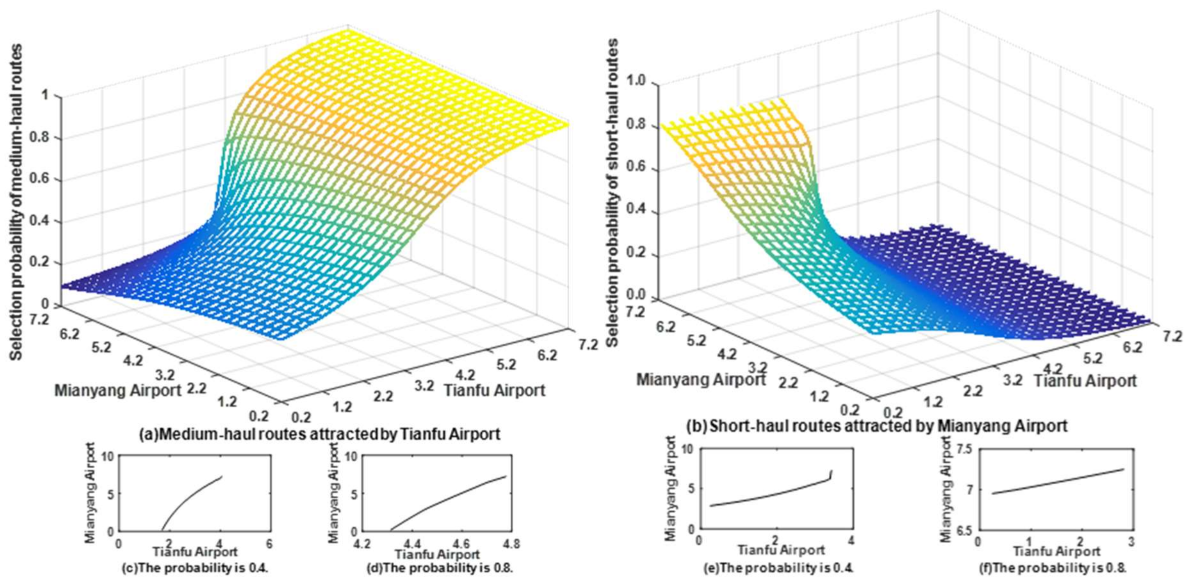

Figure 11. Relationship between airport subsidy strategy and route transfer probability.

Airports attract routes under the dual influence of their own subsidy strategies and the subsidy strategies of other airports. Airlines will compare the total revenue obtained from subsidies at different airports, so as to make route strategy choices. Figure 11 shows the probability of airlines choosing Tianfu Airport for medium-haul routes under different subsidy strategies at the two airports. Figure 11(a) shows the three-dimensional diagram of the effect of Tianfu Airport's subsidy strategy on airline selection probability under different subsidy strategies of Mianyang Airport, aiming at attracting medium-haul routes and positioning itself as a regional aviation hub. Figure 11(a) shows that when the subsidy strategy of Tianfu Airport is less than 4.3, the subsidy advantage of Mianyang Airport relative to Tianfu Airport has two sections. The first section is that the subsidy coefficient of Mianyang Airport is above 5.4, and the subsidy of Mianyang Airport has a strong advantage section, which makes the curved surface in the figure increase sharply, and the subsidy strategy of Mianyang Airport has an absolute advantage. Only when the subsidy strategy of Tianfu Airport is greater than 4.3 can it break the balance and enter the stage of comparative advantage. Therefore, when the subsidy coefficient of Mianyang Airport is above 5.4, Tianfu Airport should have a subsidy strategy greater than 4.3 if it wants to be attractive to the medium-haul routes of six airlines. The other interval is that the subsidy coefficient of Mianyang Airport is below 5.4, and the effect of the subsidy strategy of Tianfu Airport and Mianyang Airport has a relatively competitive interval (that is, the curve is relatively flat). Only when the subsidy strategy coefficient of Tianfu Airport exceeds 3.4. Compared with Mianyang Airport, the subsidy strategy of Tianfu Airport has an inflection point for the medium-haul routes of 6 airlines to establish a more obvious attracting ability. Therefore, considering the influence of the subsidy strategy of Mianyang Airport, the optimal subsidy strategy of Tianfu Airport is between 3.4 and 5.5. Figure 11(a) Neutron graph (c) indicates that if Tianfu Airport wants to maintain the selection probability of medium-haul routes at 0.4, the subsidy coefficient of Tianfu Airport is above 1.8 and shows a parabolic relationship with the increase of the subsidy coefficient of positive definite airport. Figure 11(d) shows that if Tianfu Airport wants to maintain the selection probability of medium-haul route at 0.8, the subsidy coefficient of Tianfu Airport should be greater than 4.3 based on different subsidy strategies of Mianyang Airport and increase with the increase of the subsidy coefficient of Mianyang Airport.

Figure 11(b) shows Mianyang Airport's positioning as a regional airport with the goal of attracting short-haul routes. Under different subsidy strategies of Tianfu Airport, the effect of subsidy strategies of Mianyang Airport on the probability of airline selection is shown in the three-dimensional diagram. Figure 11(b) shows that when the subsidy coefficient of Tianfu Airport increases to 3.9 or more, the subsidy strategy of Tianfu Airport has an absolute advantage compared with that of Mianyang Airport, that is, airlines are more willing to choose short-haul routes at Tianfu Airport; therefore, only when the subsidy coefficient of Tianfu Airport is less than 3.9, can Mianyang Airport establish a relative advantage by increasing the subsidy coefficient, especially when the subsidy strategy of Mianyang Airport reaches 4.9 or more (faster curve growth). Therefore, if the airport wants to realize the cooperative subsidy strategy for short-haul routes, the subsidy strategy of Tianfu Airport is below 3.8, and the optimal subsidy strategy of Mianyang airport is between 3.6 and 6.2, which can better guide airlines to realize the airport function positioning. Figure 11(b) Neutron graph (e) shows that if Mianyang Airport wants to maintain the short-haul route selection probability of 0.4, the corresponding relationship between its subsidy strategy and Tianfu Airport's subsidy strategy has a steep turning point, that is, if Mianyang Airport achieves high attractiveness, the subsidy coefficient of Tianfu Airport should be lower than 3.8; once the subsidy coefficient of Tianfu Airport is higher than 3.8, the subsidy efficiency of Mianyang Airport will decrease significantly. Figure 11(f) shows the relationship of the subsidy coefficient between Tianfu Airport and Mianyang Airport in order to maintain a selection probability of 0.8 for short-haul routes in Mianyang Airport. The two have a certain linear relationship.

According to functional positioning coordination among airports, Tianfu Airport and Mianyang Airport attract medium-haul and short-haul routes respectively, and attract 80% of transferable routes. According to Figure 11(c)(e), the optimal subsidy strategy for the two airports when realizing route coordination is that Tianfu Airport has a subsidy coefficient of 4.3, and Zhengding airport has a subsidy strategy of 6.8.

7. Conclusions

We use airport subsidy as a key driving factor to study the mechanism of the evolution of the route network among passengers, airlines and airports, and constructs a two-tier evolution model. The relationship between airline pricing strategy and passenger selection, airline route selection strategy and airport subsidy strategy is analyzed. The following conclusions are obtained through simulations:

1) When airlines transfer routes to attract non-hinterland passengers (passengers from other airports) through fare discounts, passengers on different flights have a significant impact on fare discounts and brand value of airlines. In short flights, the brand value of airlines is more advantageous and the corresponding strategy of high fares can maintain revenue;

2) Passenger selection probability is not in direct proportion to airline revenue. In order for airlines to maintain high revenue, it is necessary to comprehensively determine according to passengers' rational degree and flight distance, and the best discount range of airlines is a 0.6–0.9 discount.

3) The inter-airport subsidy strategy has obvious position difference advantages. When the subsidy coefficient of Tianfu Airport exceeds 3.8, it has a monopolistic subsidy effect, resulting in Mianyang Airport's difficulty in attracting routes without losing money; when the subsidy coefficient of the two airports is below 2.3, there is no gap competition interval, and the attraction ability of the two airports is similar.

4) In order to achieve route coordination between airports and maintain the best route attraction ability, the subsidy strategies of the two airports have parabolic and linear types, and the optimal strategy should be determined according to the curve type of the other airport's strategy. For example, Tianfu and Mianyang airports want to attract more than 80% of transferable medium and short-range routes, Tianfu Airport has a subsidy coefficient of 4.3, and Mianyang Airport has a subsidy strategy of 6.8.

The research results have strong theoretical value for in-depth understanding of the influence of passenger learning ability on the attractiveness of fare discounts and the influence of integrating competitors' route selection strategies on the attractiveness of airport subsidies. It provides the method support for realizing the cooperative development of airports within the airport group by optimizing the route network layout, and also provides the quantitative method for scientifically formulating the optimal airport subsidy strategy.

Use of AI tools declaration

The authors declare that they have used Artificial Intelligence (AI) tools in the drawing process of this article, with Miscroft Visio used in Figures 1–3 and MATLAB2016b used in Figures 4–10.

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Conflict of interest

The authors declare that there is no conflict of interest.

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