A Tripartite Evolutionary Game Model for Air-Rail Intermodal Transportation Stakeholders Based on Perspective of Airspace Congestion

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Abstract: A tripartite evolutionary game model of enterprise, air traffic control (ATC) and passengers in an air-rail intermodal transport (ARIT) system was developed and investigated. The optimal interaction among enterprise, ATC and passengers was explored based on the congestion charging mechanism, as presented in terms of the payoffs and decision-making behaviors of three participants. Payoff matrices were established for three game players, wherein fare, mileage cost, en-route charge and generalized travel cost were taken into consideration. After that, the replicated dynamic equations were derived and employed to analyze the reliability of the proposed model and the dynamic behaviors of each game player under initial conditions. Eventually, the Beijing-Shanghai, Beijing-Guangzhou and Beijing-Kunming corridors were used as practical cases to clarify the impact of key factors (e.g., distance, en-route charge and passenger sharing ratio) on the evolutionary trend and final strategy. The results showed that three players tend to choose the strategy which is always profitable. The enterprises would choose to introduce the ARIT strategy in medium-distance route, but not in short- and long-distance route, ATC chose to implement the congestion charging strategy, and passengers preferred the ARIT strategy. In addition, the final strategies were affected by any changes in key factors, and enterprises were more sensitive and likely to introduce the ARIT strategy out of individual interest.

Key words: air-rail intermodal transport (ARIT); air traffic control (ATC); passengers; tripartite evolutionary game model

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0 Introduction

With the growing demand for air travel, establishing a robust and efficient aviation system has become increasingly urgent. However, the utilization of China's airport network remains highly uneven. Major hubs such as Beijing, Shanghai, and Guangzhou handle nearly 40% of the national passenger volume, leading to severe airspace congestion, frequent flight delays, heavy air traffic control (ATC) workloads, while there are less airports in less-developed regions. To address these challenges, air-rail intermodal transport (ARIT) has emerged as an effective strategy for enhancing network efficiency and alleviating congestion by integrating the advantages of both aviation and high-speed rail (HSR). Globally, it has proven effective in improving travel connectivity and passenger experience. Although air and rail transport operators may compete in certain markets, within the ARIT framework, they cooperate to form a unified service chain in which airlines generally act as the leading enterprise, responsible for designing and managing the intermodal product. The HSR component functions as a complementary feeder or substitute segment incorporated within the airline's operational strategy rather than as an inde-

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pendent stakeholder. However, the lack of effective infrastructure integration and coordinated transfer management in ARIT means that HSR plays a relatively passive role, resulting in ARIT systems are often neither user-friendly nor efficient. Hence, the "enterprise" related with the integrated operator managing ARIT services must interact strategically with ATC and passengers—The two other key participants to find their optimal strategies in the game to achieve a win-win situation, which reflects the coordination mechanism observed in ARIT practice.

There are many factors affecting in designing ARIT, which could effectively guide flight flow to alleviate airspace congestion, and reduce ATC workload and the airline's air route charges. Obviously, ATC sets different air route charges in different congested airspaces, which may guide airlines to operate more ARIT routes to gain more profits by saving more mileage fuel consumption costs and air route charges in the case of less passenger traffic revenues, while guide passengers adopt ARIT to sacrifice travel time to reduce travel costs. Obviously, three stakeholders (i.e., ARIT enterprises, ATC, and passengers) in the ARIT will significantly interact with each other to reach a dynamic balance.

Although several studies have investigated ARIT, existing research has primarily focused on operational optimization, service design, and passenger travel behavior under the air-rail integrated framework. Most of these studies emphasize the technical or operational coordination between air and HSR systems, while the strategic interaction among multiple stakeholders, such as civil aviation enterprises, HSR operators, passengers, and air traffic control departments, has received limited attention. To the best of our knowledge, no existing work has systematically examined the evolutionary behavioral mechanisms among these interdependent participants. Therefore, this study fills this research gap by constructing a tripartite evolutionary game model to explore the coupled strategic decisions of enterprises, passengers, and ATC within the ARIT system, thereby highlighting the novelty and contribution of this research.

In this study, the evolutionary game theory was employed to explore two aspects: (1) How do the interactions among decision-makers affect strategy design and payoffs? (2) What factors drive changes in the strategy selection behaviors of each decision-maker? Specifically, the dynamic decision-making behaviors of ARIT enterprises, ATC, and passengers were thoroughly investigated with various factors (e.g., distance, en-route charges, and the allocation coefficient of ARIT passengers) taken into consideration. This study aims to achieve a balance where ARIT enterprises provide high-quality intermodal services, ATC rationalizes en-route charge pricing, and passengers embrace ARIT as a viable alternative to traditional transport modes, so that flight delays and airspace congestion are alleviated to promote the sustainable development of ARIT.

The main contribution is the development of a tripartite evolutionary game model for ARIT, which can be used to clarify the dynamic relationships among air-rail intermodal transport enterprise (ARITE), ATC, and passengers under different conditions (e.g., distance, en-route charges, and passenger allocation coefficients). Specifically, a three-dimensional dynamical system that can calculate the revenue of the key players across three transport modes (i.e., air, air-rail, and HSR) in ARIT was developed. A tripartite evolutionary game model that can analyze the effects of stakeholder behaviors on the final strategies and payoffs under different attributes was developed. Three typical transport corridors (i.e., Beijing-Shanghai, Beijing-Guangzhou, and Beijing-Kunming) were investigated by using the proposed model, wherein sensitivity analysis was involved to assess its feasibility. This study may facilitate the top-level strategic design of ARIT, guide direct-flight passengers to transit options, alleviate congestion on busy corridors, foster stakeholder cooperation, and balance multiple transport modes.

Herein, Section 1 presents a literature review. Section 2 describes the methodology. Section 3 presents a discussion on the model and stability analysis under different conditions. Section 4 delivers demonstration of the proposed model on three typical transport corridors in terms of sensitivity analysis. Section 5 presents conclusions and outlook.

1 Literature Review

1.1 Air traffic congestion

Traffic congestion is caused by intensive flight flows at airports located in traffic hubs. To date, air traffic congestion has been investigated in terms of optimizing and predicting air traffic flow. For instance, Cai et al.[1] reported a routing slot allocation algorithm for multi-objective optimization of air traffic flow, aiming to mitigate airspace congestion and flight delays by integrating ground-holding, airborne-holding, rerouting, and speed control. Chen et al.[2] established a mesoscopic dynamic air traffic model and applied the pairwise decomposition method to achieve air traffic flow optimization, so that airspace capacity and the dynamic traffic demand can be balanced and flight delays can be reduced. Yang et al.[3] proposed a hybrid SCLN-TTF with three-way temporal features to predict the airway obstruction index, based on spatial, temporal and spatio-temporal features, aiming to improve air traffic safety and operational efficiency. Cummings et al.[4] developed a theoretical macroscopic air traffic flow model connecting vehicle density to the frequency of conflicts in the airspace, allowing for rapid prediction of future traffic flow conditions. Dos Santos et al.[5] developed a decision support framework by using machine learning and optimization, and the framework was demonstrated for air traffic flow management of an airport in Brazil. These studies discussed alleviation of airspace congestion and flight delay mitigation by theoretical modelling. However, flight delays may be negatively related to airspace congestion[1] and regional limitations with low airspace freedom may be present for air traffic flow management. López-Pita et al.[6] reported that HSR can effectively share passenger at airports, and cooperation of HSR and civil aviation may improve the transport system if transport modes collaborate instead of compete. This is essentially a pioneer work in the air traffic congestion.

1.2 ARIT

ARIT emerged in Europe and was then expanded to Asia[7]. Indeed, ARIT has been applied to mitigate airport congestion. For instance, Vespermann et al.[8] proposed an optimal implementation option for air-rail integration and argued that it could effectively facilitate airport expansion, alleviate tightening aircraft slots, and address the intermodal transport demand. Jiang et al.[9] reported that market structure and social welfare were influenced by air-rail integration, wherein four air-rail cooperation patterns were investigated. Meanwhile, the travelling preferences and need of passengers, a key player in the ARIT, have been explored. For instance, Li et al.[10] constructed a modal segmentation model to investigate the transport behaviours of intercity travelers, and found that the intermediate travel time was an important factor affecting the market share of ARIT. Jiang et al.[11] investigated the determining factors diverging passengers in overloaded hub airports to integrated air-rail services by comparative analyses of historical data and stated preferences. Yuan et al.[12] investigated the correlation of passenger psychology and behavior by using used a passenger satisfaction index model. The investigation was based on an airport in China, and passengers were accurately classified to achieve the improvement of air-rail international transport system (ARITS). Jiang et al.[13] explored the ground behavioral preferences of intermodal passengers by utilizing a mixed multinomial logit model. The results showed that passengers prefered options with a longer safety margin at low air-rail integration. Chen et al.[14] constructed a framework of the passenger mixed choice model, wherein the preferences of intermodal passengers regarding the transfer time, the transit time, and the influencing mechanisms of the checked baggage were explored on the basis of the mutual recognition mechanism of security checks. Despite the great advances, ARIT has a relatively low market share as a new transport mode[10,15]. Some researchers believed that this was attributed to construction investment and cumbersome procedures of ARIT[16], while few studies dicussed the complex relationships and synergistic operations efficiency of ARIT stakeholders. As a result, collaborative behaviors or synergistic decision-making efficiencies of ARIT stakeholders remain unclear.

1.3 Application of evolutionary game theory

As a predecessor of evolutionary game theory, game theory has been employed for competitive or cooperative behaviors of public transport players. Zhu et al.[17] investigated the influences of flight delays on the competition of air transport and HSR on the basis of game theory. Liu et al.[18] proposed a novel approach for data sharing competition based on game theory in the public transport oligopoly. Also, the roles of game theory in pricing behavior[19], route planning[20], and policy optimization[21] in transport have been explored. In recent years, an evolutionary game theory has emerged. In this theory, players in the game are not completely rational. The evolutionary game theory serves as a powerful tool to analyze behavioral logics (e.g., interaction, cooperation, confrontation) of stakeholders in a complex system. Recently, simulation of complex or intermodal transport systems, including civil aviation[22], road-rail multimodal transport[23], water-land transportation[24], and urban railways[25], have attracted increasing attention. Shao et al.[22] constructed an evolutionary game model for airlines, airports and passengers, aiming to avoid collective passenger incidents induced by flight delay. Yuan et al.[23] applied an evolutionary game model to optimize auction game strategies and routes for container road-rail transshipment. Sheng et al.[24] developed a three-strategy evolutionary game model involving the government, port enterprises and shipping companies, and investigated the evolutionary strategic decisions among stakeholders. Zhao et al.[25] proposed an evolutionary game model involving subway company, passengers and government to mitigate interline transfer failure.

The contributions of this study are as follows. (1) Although the potential role of the integrated transport modes in mitigation of traffic congestion has been explored, ARIT was not considered in effective conjunction with air traffic congestion. In this study, air traffic congestion charging was proposed for the first time, wherein passengers were redistributed from the top-level decision-making of ARIT stakeholders to mitigate airspace congestion. (2) Previous studies focused on ARIT promotion by external factors (e.g., transport demand, social welfare and related policies), while the complex relationships and behavioral logic among individuals within the ARIT system were not considered. Herein, we investigated the decision-making behaviors of stakeholders in ARIT on the basis of the evolutionary game theory, so as to reveal the dynamic relationship of ARITE, ATC and passengers. (3) With ARIT as the subject, we discussed the influencing factors that may change their game strategies (mileage, en-route charge, and allocation coefficient of air-rail passengers) based on air traffic congestion, and considered ARIT stakeholders' payoff mechanism, thereby filling the gap between the evolutionary game theory and the study of ARIT.

2 Hypotheses and Models

2.1 Hypotheses

The interactive behavioral strategies of the evolutional game players are shown in Fig.1. As indicated, ARITE, ATC and passengers are ARIT stakeholders, wherein ARITE is the service provider, ATC is the service articulator, and passengers are the service recipients. If passenger demand continues to grow and significantly overflows, both airspace and ground will become severely congested, resulting in imbalance of transport market. As a result, the three stakeholders will continuously optimize their final strategies throughout the game until a balance is established. In this study, we propose a multimodal network with three transport modes (i.e., air, HSR and air-rail), as shown in Fig.2. The following hypotheses were made for the tripartite evolutionary game.

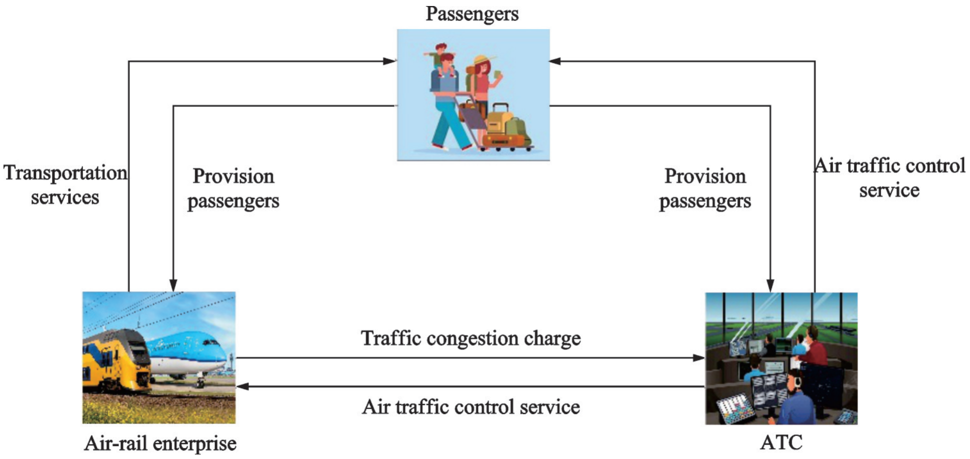


Fig.1 Interactive strategic behavior framework among ARIT stakeholders

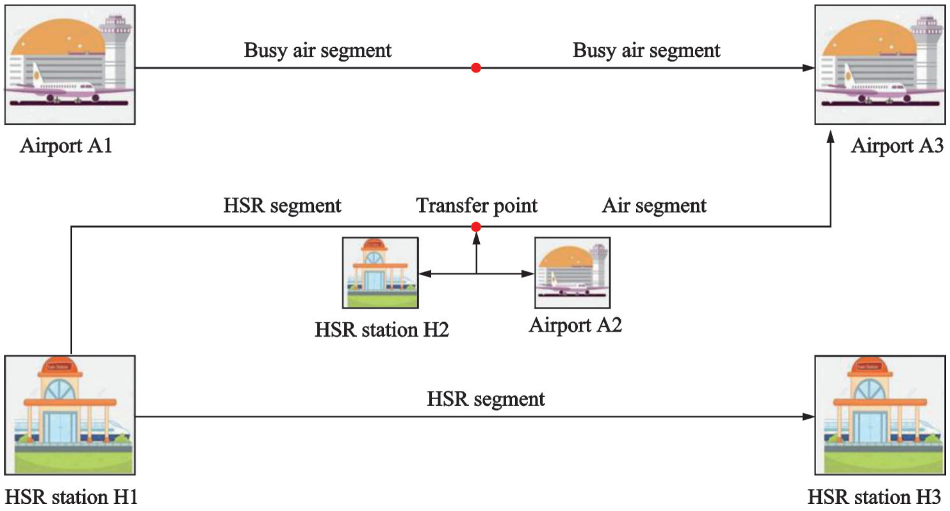


Fig.2 A multimodal network in ARIT

Hypothesis 1 Participants

This game comprises three players: ARITE, ATC, and passengers. The ARITE is responsible for two high-speed transport operations (air and HSR) and provides diversified, high-quality transport services by introducing ARIT products. ATC supervises and manages flight activities in specific airspace, which in turn helps enterprises to distribute passengers and conserve airspace based on congestion charging mechanisms. Passengers are the mainstay of ARIT.

Hypothesis 2 Strategy

Hypothesis 2-1 The congestion charging aims to guide direct-flight passengers to ARIT products and increase the revenue of three players. Nevertheless, the introduction of ARIT may not achieve the goal due to information asymmetry, while resource consumption is inevitable. Hence, ARITE needs to make decisions on "introduce ARIT" and "not introduce ARIT".

Hypothesis 2-2 As for ATC, congestion charging mechanisms, which involve additional en-route charges, were applied. As enterprises may refuse to pay the cost, ATC needs to make decisions on two strategies: "implement congestion charge" or "not implement congestion charge".

Hypothesis 2-3 Likewise, passengers need to make decisions on two strategies: "support ARIT" or "oppose ARIT". However, the attitudes of passengers (fixed amount) towards ARIT services can lead to dynamic loss or growth of passenger flow in different transport modes, thereby affecting the revenues of the players.

Hypothesis 3 Behavior

It is hypothesized that all game players exhibit bounded rationality during strategy formulation. Participants are unable to directly identify the optimal strategy and must be engaged in continuous learning to achieve a balance. Ultimately, participants may abandon low-payoff strategies and adopt high-payoff strategies, thereby achieving the selection of the optimal strategy.

2.2 Model parameters

2.2.1 ARITE-related parameters

P_1 refers to the air fare, which is the direct-flight passengers' ticket price of segment A_1A_3. P_2 refers to the HSR fare, which is the passengers' ticket price of segment H_1H_3. P_3 refers to the ARIT fare, which is the passengers' ticket price of segment H_1A_3. As the "one-ticket service" is a unique feature of intermodal passenger transport[24], ΔP refers to the extra payment when the ATC promotes the congestion charging, and it is reflected in the fluctuation of ticket price. c_1 and c_2 refer to cost of available seat-kilometer for air and HSR, respectively, and they are average costs of investment and cost related to the corresponding transport service.

The primary purpose of defining ARITE-related parameters is to clarify its profitability across direct air, HSR, and air-rail intermodal transport modes, and to support the analysis of strategic choices regarding the introduction of ARIT. To achieve this, this section defines air fare P_1, HSR fare P_2, and air-rail intermodal fare P_3 to accurately quantify the revenue levels of its three core services. It also introduces the fare fluctuation ΔP caused by congestion charging to capture the direct transmission impact of ATC's congestion control policies on air transport revenue, while clearly delineating the average investment and operational cost boundaries of the two transport modes through the air cost per seat-kilometer c_1 and HSR cost per seat-kilometer c_2. The core logic of constructing these metrics is to systematically divide ARITE's revenue sources and cost structure, establish a basic framework for profitability calculation, and provide key support for evaluating the profit feasibility of its "introduce" or "not introduce" ARIT strategies.

2.2.2 ATC-related parameters

l_1 refers to the distance of A_1A_3, which refers to the whole airline. Especially, the distances of congested segments and non-congested segment are l_{11} and l_{12}, respectively. $l_1 = l_{11} + l_{12}$, ω refers to the ratio of busy routes in the overall routes. The distances of segments H_1H_3, H_1H_2 and A_2A_3 are l_2, l_3 and l_4, respectively. Total distance of l_3 and l_4 makes up the full length of the air-rail link. f_1 refers to the average route charge under congested charging, and it includes en-route charges collected by ATC on both busy and non-busy airway. Therefore, f_2 refers to the normal en-route charge and f_3 refers to the busy route charge. $f_1 = (1-\omega)f_2+\omega f_3$. Additionally, the en-route charge is closely related to milage and frequency of flights, and an aircraft capacity parameter v is proposed.

The primary purpose of defining ATC-related parameters is to quantify its revenue from en-route charges and analyze the profitability of implementing or not implementing congestion charging policies, centered on its core function of airway governance. To this end, this section constructs a multidimensional parameter system: In the spatial dimension, it fully depicts the physical coverage of air and HSR networks and the route integration mode of air-rail intermodal transport through the total airline distance l_1 (further decomposed into congested segment l_{11} and non-congested segment l_{12}), HSR line distance l_2, air segment distance l_3, and HSR segment distance l_4 in air-rail intermodal routes; in the congestion and charging dimension, it characterizes the congestion distribution with the proportion of busy routes ω, and constructs a differentiated pricing mechanism combined with the average en-route charge f_1, non-congested segment charge f_2, and congested segment charge f_3; it then directly links en-route charges to flight frequency and aircraft operational scale through the aircraft capacity v. These metrics ensure the scientificity and pertinence of ATC's decision-making analysis by accurately measuring revenue across different route types and transport modes.

2.2.3 Passenger-related parameters

Q_T refers to the total passenger demand of high-speed transport market. ARITE strategy may change passenger decision on travel mode. When ARITE makes a decision to introduce ARIT, a_1 and a_2 denote air passengers who are positive and negative, respectively. b_1 refers to passengers favored the ARIT and b_2 represents passengers with a negative attitude. With only air and rail transport in the market, a_3 and a_4 denote air passengers with positive and negative attitudes for ARIT, respectively. For passengers, G_1, G_2, and G_3 indicate the generalized travel cost of air passengers, HSR passengers, and air-rail passengers, respectively. Especially, ΔG refers to the passenger cost induced by congestion charging.

The primary purpose of defining passenger-related parameters is to model passengers' demand distribution across transport modes and analyze the chain impact of their support or opposition to ARIT on the tripartite profits, based on their decision-making logic and behavioral characteristics. To realize this, this section defines the total passenger demand Q_T in the high-speed transport market to clarify the overall market volume boundary. It comprehensively measures passengers' acceptance and preference tendency towards ARIT through the attitude probabilities a_1, a_2, a_3, a_4 of air passengers when ARITE introduces or does not introduce ARIT, as well as the attitude probabilities b_1, b_2 of intermodal passengers after introduction; it also systematically quantifies the comprehensive costs (including policy-induced implicit costs) for passengers to choose different transport modes by combining the generalized travel costs G_1, G_2, G_3 for air, HSR, and air-rail intermodal passengers with the additional travel cost ΔG caused by congestion charging. These metrics ensure that the analysis of market interaction relationships is more in line with actual scenarios by directly linking passenger choices to the revenue of ARITE and ATC.

If the enterprise chooses not to introduce the ARIT strategy, the total revenue = the fare revenue from direct air + the fare revenue from HSR services—the operating costs. Meanwhile, the enterprise is required to pay en-route charges to ATC department, and the payment standard depends on whether the ATC implements a congestion charging strategy. This may also lead to fare fluctuations for the enterprise. If the enterprise chooses to introduce the ARIT strategy, the total revenue comprises the operating revenue and costs of the ARIT routes. The primary revenue for the ATC department comes from the en-route charges paid by the enterprise, which is dependent on the passenger sharing ratio and strategic adjustments. For passengers, the travel decision is determined by the generalized utility of different travel modes, wherein travel time is quantified as a monetary value and incorporated into the generalized travel cost. Specifically, the probability of passenger choice in the logit model can be expressed as

$$P_i = \frac{\exp(V_i)}{\sum_{j \in C} \exp(V_j)}$$

where P_i denotes the probability that passengers choose travel mode i, V_i the systematic utility of travel mode i, and C the set of available travel modes. The denominator represents the summation of the exponential utility terms over all available travel modes j in set C. Eventually, a payoff matrix can be generated by calculating the revenues of the three players under different strategy plans.

2.3 Development of expected payoff metrics

x refers to the proportion of ARITE choosing the strategy of "introduce ARIT", while $(1-x)$ refers to the proportion of ARITE choosing the strategy of "not introduce ARIT". y refers to the proportion of the ATC choosing the strategy of "implement congestion charging", while $(1-y)$ refers to the proportion of the ATC choosing the strategy of "not implement congestion charging". z refers to the proportion of passengers choosing the strategy of "support ARIT", while $(1-z)$ refers to the proportion of passengers choosing the strategy of "oppose ARIT". Table 1 shows the game payoff matrix. The corporate revenue of ARIT is based on transportation costs and ticket prices, while the revenue of ATC comes from route charges, and the revenue of passengers is related to the cost and time cost of the travel mode they choose.

Table 1 Tripartite game matrix of enterprise, ATC management and passenger

ARITE	ATC management	Passenger	
		Positively support ARIT(z)	Negatively support ARIT($1-z$)
Introduce ARIT (x)	Implement congestion charge (y)	$a_1Q_{\mathrm{T}}\left(P_1+\Delta P-l_1c_1-\frac{l_1f_1}{v}\right)+(1-a_1-b_1)Q_T(P_2-l_2c_2)+b_1Q_{\mathrm{T}}\left(P_3+\Delta P-l_3c_1-\frac{l_3f_2}{v}-l_4c_2\right)$, $a_1Q_{\mathrm{T}}\frac{l_1f_1}{v}+b_1Q_{\mathrm{T}}\frac{l_3f_2}{v}$, $-a_1Q_{\mathrm{T}}(G_1+\Delta G)-(1-a_1-b_1)Q_{\mathrm{T}}G_2-b_1Q_{\mathrm{T}}(G_3+\Delta G)$	$a_2Q_{\mathrm{T}}\left(P_1+\Delta P-l_1c_1-\frac{l_1f_1}{v}\right)+(1-a_2-b_2)Q_{\mathrm{T}}(P_2-l_2c_2)+b_2Q_{\mathrm{T}}\left(P_3+\Delta P-l_3c_1-\frac{l_3f_2}{v}-l_4c_2\right)$, $a_2Q_{\mathrm{T}}\frac{l_1f_1}{v}+b_2Q_{\mathrm{T}}\frac{l_3f_2}{v}$, $-a_2Q_{\mathrm{T}}(G_1+\Delta G)-(1-a_2-b_2)Q_{\mathrm{T}}G_2-b_2Q_{\mathrm{T}}(G_3+\Delta G)$
	Not implement congestion charge ($1-y$)	$a_1Q_{\mathrm{T}}\left(P_1-l_1c_1-\frac{l_1f_2}{v}\right)+(1-a_1-b_1)Q_{\mathrm{T}}(P_2-l_2c_2)+b_1Q_{\mathrm{T}}\left(P_3-l_3c_1-\frac{l_3f_2}{v}-l_4c_2\right)$, $a_1Q_{\mathrm{T}}\frac{l_1f_2}{v}+b_1Q_{\mathrm{T}}\frac{l_3f_2}{v}$, $-a_1Q_{\mathrm{T}}G_1-(1-a_1-b_1)Q_{\mathrm{T}}G_2-b_1Q_{\mathrm{T}}G_3$	$a_2Q_{\mathrm{T}}\left(P_1-l_1c_1-\frac{l_1f_2}{v}\right)+(1-a_2-b_2)Q_{\mathrm{T}}(P_2-l_2c_2)+b_2Q_{\mathrm{T}}\left(P_3-l_3c_1-\frac{l_3f_2}{v}-l_4c_2\right)$, $a_2Q_{\mathrm{T}}\frac{l_1f_2}{v}+b_2Q_{\mathrm{T}}\frac{l_3f_2}{v}$, $-a_2Q_{\mathrm{T}}G_1-(1-a_2-b_2)Q_{\mathrm{T}}G_2-b_2Q_{\mathrm{T}}G_3$
Not introduce ARIT ($1-x$)	Implement congestion charge (y)	$a_3Q_{\mathrm{T}}\left(P_1+\Delta P-l_1c_1-\frac{l_1f_1}{v}\right)+(1-a_3)Q_{\mathrm{T}}(P_2-l_2c_2)$, $a_3Q_{\mathrm{T}}\frac{l_1f_1}{v}$, $-a_3Q_{\mathrm{T}}(G_1+\Delta G)-(1-a_3)Q_{\mathrm{T}}G_2$	$a_4Q_{\mathrm{T}}\left(P_1+\Delta P-l_1c_1-\frac{l_1f_1}{v}\right)+(1-a_4)Q_{\mathrm{T}}(P_2-l_2c_2)$, $a_4Q_{\mathrm{T}}\frac{l_1f_1}{v}$, $-a_4Q_{\mathrm{T}}(G_1+\Delta G)-(1-a_4)Q_{\mathrm{T}}G_2$
	Not implement congestion charge ($1-y$)	$a_3Q_{\mathrm{T}}\left(P_1-l_1c_1-\frac{l_1f_2}{v}\right)+(1-a_3)Q_{\mathrm{T}}(P_2-l_2c_2)$, $a_3Q_{\mathrm{T}}\frac{l_1f_2}{v}$, $-a_3Q_{\mathrm{T}}G_1-(1-a_3)Q_{\mathrm{T}}G_2$	$a_4Q_{\mathrm{T}}\left(P_1-l_1c_1-\frac{l_1f_2}{v}\right)+(1-a_4)Q_{\mathrm{T}}(P_2-l_2c_2)$, $a_4Q_{\mathrm{T}}\frac{l_1f_2}{v}$, $-a_4Q_{\mathrm{T}}G_1-(1-a_4)Q_{\mathrm{T}}G_2$

The primary purpose of constructing the tripartite profit matrix is to characterize the strategic interaction among ARITE, ATC management, and passengers, and to quantify the payoff of each stakeholder under different strategy combinations. For this reason, the matrix integrates all aforementioned parameters to capture the complex interdependencies in the air-rail intermodal transport system: For each combination of strategies (ARITE: Introduce/not introduce ARIT; ATC: Implement/not implement congestion charging; Passengers: Support/oppose ARIT), ARITE's profit is accurately calculated by subtracting operational costs (c_1, c_2) and the impact of passenger attitudes (a_i, b_j) from the total revenue of P_1, P_2, P_3; ATC management's profit is weighted and calculated based on en-route charges (f_1, f_2, f_3) combined with congestion distribution (ω) and aircraft capacity (v); passengers' utility is comprehensively reflected through generalized travel costs (G_1, G_2, G_3, ΔG) and attitude probabilities (a_i, b_j), which directly determine their transport mode choices and transmit to the revenue levels of ARITE and ATC.

3 Evolutionary Game Model

3.1 Dynamic replication analysis

The decision-making behaviors of the three players in the model were investigated on the basis of evolutionary game theory, aiming to resolve issues regarding dynamic process and ultimate optimal strategy. The strategy-filtering mechanism represents a replicative dynamic process, which varies over time. The final decisions will be manifested in a system-level macro-behavioral pattern. During the evolutionary game, the evolution rate of a strategy is contingent upon both the current frequency of that strategy within the system and its relative fitness. If the strategy fitness exceeds the average system fitness, the strategy frequency increases; otherwise, the strategy frequency decreases[26].

On the basis of the evolutionary game matrix, we can derive expected profits under different strategy plans. Specifically, the returns with high frequency can be identified based on expected returns of different strategies. Then, the corresponding strategy plan will be chosen during long-term evolution and ultimately reach a balance[27]. In this way, we can ultimately determine desired strategies for ARITS in the evolutionary game model. If ARITE decides to introduce ARIT, the expected benefit is E_{11}; if ARITE decides not to introduce ARIT, the expected utility is E_{12}, and the expected average benefit of enterprises is $\overline{E_1}$, shown as

$$\begin{aligned}E_{11}=\Bigg\{&[z(1-a_1-b_1)+(1-z)(1-a_2-b_2)]\cdot\\&(P_2-l_2c_2)+[zb_1+(1-z)b_2]\cdot\\&\left(P_3-l_3c_1-\frac{l_3f_2}{v}-l_4c_2\right)+y[z(a_1+b_1)+\\&(1-z)(a_2+b_2)]\Delta P+[za_1+(1-z)a_2]\cdot\\&\left[(P_1-l_1c_1)-y\frac{l_1f_1}{v}-(1-y)\frac{l_1f_2}{v}\right]\Bigg\}Q_{\mathrm{T}}\end{aligned}\tag{1}$$

$$\begin{aligned}E_{12}=\Bigg\{&[z(1-a_3)+(1-z)(1-a_4)](P_2-l_2c_2)+\\&[za_3+(1-z)a_4]\left[y\left(\Delta P-\frac{l_1f_1}{v}\right)-(1-y)\cdot\right.\\&\left.\frac{l_1f_2}{v}+P_1-l_1c_1\right]\Bigg\}Q_{\mathrm{T}}\end{aligned}\tag{2}$$

$$\overline{E_1}=xE_{11}+(1-x)E_{12}\tag{3}$$

The replicator dynamics for ARITE can be determined by

$$\begin{aligned}F(x)=x(E_{11}-\overline{E_1})=x(1-x)Q_{\mathrm{T}}\Bigg\{&(P_2-c_2l_2)\cdot\\&[z(a_3-1)+(1-z)(a_4-1)]-[za_3+\\&(1-z)a_4]\left[P_1-c_1l_1+y\left(\Delta P-\frac{l_1f_1}{v}\right)+\right.\\&\left.(y-1)\frac{l_1f_2}{v}\right]-[zb_1+(1-z)b_2]\left(c_1l_3-\right.\\&\left.P_3+c_2l_4+\frac{l_3f_2}{v}\right)+[za_1+(1-z)a_2]\cdot\\&\left[P_1-c_1l_1-y\frac{l_1f_1}{v}-(1-y)\frac{l_1f_2}{v}\right]+[(1-z)\cdot\\&(1-a_2-b_2)+z(1-a_1-b_1)]\cdot(P_2-c_2l_2)-\\&y\Delta P[(1-z)(a_2+b_2)-z(a_1+b_1)]\Bigg\}\end{aligned}\tag{4}$$

The first derivative of x of ARITE can be calculated by

$$\begin{aligned}F'(x)=(1-2x)Q_{\mathrm{T}}\Bigg\{&(P_2-c_2l_2)[z(a_3-1)+\\&(1-z)(a_4-1)]-[za_3+(1-z)a_4]\cdot\\&\left[P_1-c_1l_1+y\left(\Delta P-\frac{l_1f_1}{v}\right)+(y-1)\frac{l_1f_2}{v}\right]-\\&[zb_1+(1-z)b_2]\left(c_1l_3-P_3+c_2l_4+\frac{l_3f_2}{v}\right)+\\&[za_1+(1-z)a_2]\left[P_1-c_1l_1-y\frac{l_1f_1}{v}-\right.\\&\left.(1-y)\frac{l_1f_2}{v}\right]+[(1-z)(1-a_2-b_2)+\\&z(1-a_1-b_1)](P_2-c_2l_2)-y\Delta P[(1-z)\cdot\\&(a_2+b_2)-z(a_1+b_1)]\Bigg\}\end{aligned}\tag{5}$$

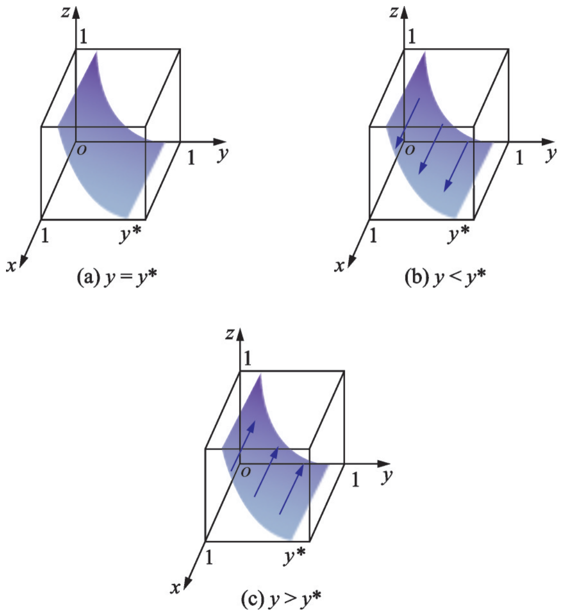
If $F(x)=0$, then $x_1=0$, $x_2=1$, and $y=y^*=\{(P_2-c_2l_2)[z(a_3-1)+(1-z)(a_4-1)]-[za_3+(1-z)a_4](P_1-c_1l_1-l_1f_2/v)-[zb_1+(1-z)b_2](c_1l_3-P_3+c_2l_4+l_3f_2/v)+[za_1+(1-z)a_2]\cdot(P_1-c_1l_1-l_1f_2/v)+[(1-z)(1-a_2-b_2)+z(1-a_1-b_1)](P_2-c_2l_2)\}/\{[za_3+(1-z)a_4][\Delta P+(l_1f_2-l_1f_1)/v]+[za_1+(1-\mathrm{z})a_2](l_1f_1-l_1f)/v+\Delta P[(1-z)(a_2+b_2)-z(a_1+b_1)]\}$ are possible balance thresholds. Eventually, the following conclusions can then be drawn:

(1) If $0<y<y^*$, then $F'(0)>0$ and $F'(1)<0$, and $x=1$ is the balance strategy. In other words, if the probability of ATC choosing implementing congestion charging is less than y^*, ARITE will eventually select introducing ARIT.

(2) If $y^*<y<1$, then $F'(0)<0$ and $F'(1)>0$, and $x=0$ is the balance strategy. In other words, if the probability of ATC choosing implementing congestion charging is greater than y^*, then ARITE will eventually select "not introducing ARIT".

(3) If $y=y^*$, then $F(x)=0$ is a constant. In other words, if the probability of ATC choosing implementing congestion charging is equal to y^*, then integration and competition makes no difference to the enterprise.

The mathematical expressions of the conclusions are demonstrated in Fig.3.



(a) $y=y^*$ (b) $y<y^*$ (c) $y>y^*$

Fig.3 Evolving trends in ARITE's strategic choices

For ATC, the expected benefit choosing to implement congestion charging can be determined by

$$E_{21}=xz\left(a_1Q_{\mathrm{T}}\frac{l_1f_1}{v}+b_1Q_{\mathrm{T}}\frac{l_3f_2}{v}\right)+x(1-z)\cdot\left(a_2Q_{\mathrm{T}}\frac{l_1f_1}{v}+b_2Q_{\mathrm{T}}\frac{l_3f_2}{v}\right)+(1-x)za_3Q_{\mathrm{T}}\frac{l_1f_1}{v}+(1-x)(1-z)a_4Q_{\mathrm{T}}\frac{l_1f_1}{v} \tag{6}$$

The expected payout to ATC when it adopts implement congestion charging can be determined by

$$E_{22}=xz\left(a_1Q_{\mathrm{T}}\frac{l_1f_2}{v}+b_1Q_{\mathrm{T}}\frac{l_3f_2}{v}\right)+x(1-z)\cdot\left(a_2Q_{\mathrm{T}}\frac{l_1f_2}{v}+b_2Q_{\mathrm{T}}\frac{l_3f_2}{v}\right)+(1-x)za_3Q_{\mathrm{T}}\frac{l_1f_2}{v}+(1-x)(1-z)a_4Q_{\mathrm{T}}\frac{l_1f_2}{v} \tag{7}$$

The average expected benefit of the decision-making processes of ATC can be expressed as

$$\overline{E_2}=yE_{21}+(1-y)E_{22} \tag{8}$$

The replication dynamic equation $F(y)$ of ATC can then be expressed as

$$F(y)=y(E_{21}-\overline{E_2})=y(1-y)Q_{\mathrm{T}}\frac{l_1(f_1-f_2)}{v}\cdot[a_4+x(a_2-a_4)+z(a_3-a_4)+xz(a_1-a_2-a_3+a_4)] \tag{9}$$

Finally, the first derivative of y of ATC can be calculated by

$$F'(y)=(1-2y)Q_{\mathrm{T}}\frac{l_1(f_1-f_2)}{v}[a_4+x(a_2-a_4)+z(a_3-a_4)+xz(a_1-a_2-a_3+a_4)] \tag{10}$$

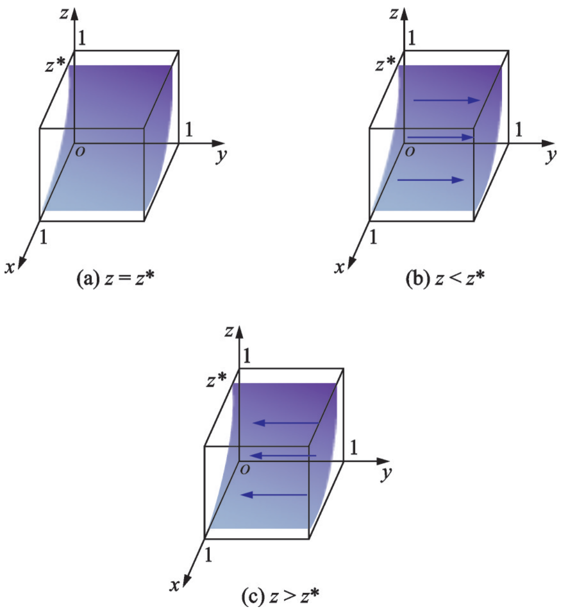
If $F(y)=0$, then $y_1=0$, $y_2=1$, and $z=z^*=[-a_4+x(a_4-a_2)]/[(a_3-a_4)+x(a_1-a_2-a_3+a_4)]$ are possible balance thresholds. As a result, the following conclusions can be drawn:

(1) If $0<z<z^*$, then $F'(0)>0$ and $F'(1)<0$, and $y=1$ is the balance strategy. In other words, if the probability of passengers choosing "supporting ARIT" is less than z^*, then ATC will eventually select implementing congestion charging.

(2) If $z^*<z<1$, then $F'(0)<0$ and $F'(1)>0$, and $y=0$ is the balance strategy. In other words, if the probability of passengers choosing "supporting ARIT" is greater than z^*, then ATC will eventually select "not implementing congestion charging".

(3) If $z=z^*$, then $F(y)=0$ is a constant. In other words, if the probability of passenger choosing "supporting ARIT" is equal to z^*, implementing congestion charging or not makes no difference to ATC.

Fig.4 depicts mathematical descriptions of ATC evolution during the decision-making process.



(a) $z=z^*$ (b) $z<z^*$ (c) $z>z^*$

Fig.4 Evolving trends in ATC's strategic choices

For the passenger, the expected passenger welfare in cases of "supporting ARIT" can be determined by

$$\begin{aligned} E_{31} = & -x(1-a_1-b_1)Q_T G_2 - (1-x)Q_T \cdot \\ & [(1-a_3)G_2 + a_3 G_1] - xQ_T(a_1 G_1 + b_1 G_3) + \\ & (1-2y)Q_T \Delta G[x(a_1+b_1)-(1-x)a_3] \end{aligned} \tag{11}$$

The expected passenger welfare in cases of "opposing ARIT" can be determined by

$$\begin{aligned} E_{32} = & -x(1-a_2-b_2)Q_T G_2 - (1-x)Q_T[(1- \\ & a_4)G_2 + a_4 G_1] - xQ_T(a_2 G_1 + b_2 G_3) + (1- \\ & 2y)Q_T \Delta G[x(a_2+b_2)+(1-x)a_4] \end{aligned} \tag{12}$$

The average passenger welfare can be deduced by

$$\overline{E_3} = zE_{31} + (1-z)E_{32} \tag{13}$$

The replicator dynamic can be described by

$$\begin{aligned} F(z) = & z(E_{31} - \overline{E_3}) = z(z-1)Q_T\{[(x-1) \cdot \\ & (a_4 G_1 + (1-a_4)G_2] - (x-1)[a_3 G_1 + \\ & (1-a_3)G_2] + x(a_1 G_1 + b_1 G_3) - x(a_2 G_1 + \\ & b_2 G_3) + (2y-1)[(x-1)a_4 + \\ & x(a_1+b_1)]\Delta G + (1-2y)[(1-x)a_4 + \\ & x(a_2+b_2)]\Delta G + x(1-a_1-b_1)G_2 - \\ & x(1-a_2-b_2)G_2\} \end{aligned} \tag{14}$$

Finally, the first derivative of z to the passengers can be calculated by

$$\begin{aligned} F'(z) = & (2z-1)Q_T\{[(x-1)(a_4 G_1 + (1-a_4) \cdot \\ & G_2] - (x-1)[a_3 G_1 + (1-a_3)G_2] + \\ & x(a_1 G_1 + b_1 G_3) - x(a_2 G_1 + b_2 G_3) + (2y-1) \cdot \\ & [(x-1)a_4 + x(a_1+b_1)]\Delta G + (1-2y) \cdot \\ & [(1-x)a_4 + x(a_2+b_2)]\Delta G + x(1-a_1-b_1) \cdot \\ & G_2 - x(1-a_2-b_2)G_2\} \end{aligned} \tag{15}$$

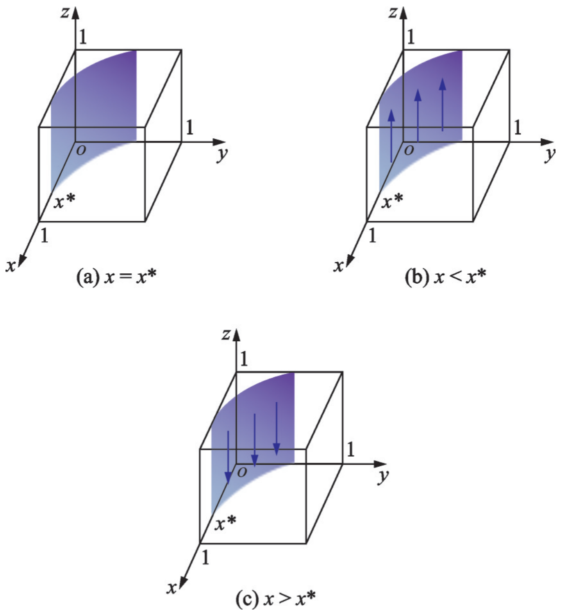
If $F(y)=0$, then $z_1=0$, $z_2=1$, and $x=x^*=(G_1-G_2)(a_3-a_4)/G_1(a_4-a_3+a_1-a_2)+G_2(a_3-a_4\quad+a_2+b_2-a_1-b_1)+G_3(b_1-b_2)+\Delta G(2y-1)(a_1+b_1-a_2-b_2)$ are possible balance thresholds. As a result, the following conclusions can be drawn:

(1) If $0<x<x^*$, then $F'(0)>0$ and $F'(1)<0$, and $z=1$ is the balance strategy. In other words, if the probability of enterprises choosing introducing ARIT is less than z^*, then passengers will eventually support ARIT. This can be attributed to the fact that the enterprises' willingness to promote ARIT product significantly affects the passenger attitude towards ARIT, and it is related to the multimodal transport.

(2) If $x^*<x<1$, then $F'(0)<0$ and $F'(1)>0$, and $z=0$ is the balance strategy. In other words, if the probability of enterprises choosing introducing ARIT is greater than x^*, then passengers will eventually oppose ARIT.

(3) If $x=x^*$, then $F(z)=0$ is a constant. In other words, if the probability of passenger choosing "supporting ARIT" is equal to x^*, then implementing congestion charging makes no differences to ATC.

Fig.5 depicts mathematical descriptions of decision-making by passengers.



(a) $x=x^*$ (b) $x<x^*$ (c) $x>x^*$

Fig.5 Evolving trends in passengers' strategic choices

3.2 Stability analysis

In a dynamic game, x, y, z are all time-variant. Hence, $[0,1]\times[0,1]\times[0,1]$ is the solution domain of the replicated dynamic equation system. If solutions of all the replicated dynamic equations are 0, the system tends to be stabilized, and the dynamic replication equations can be solved based on Eqs.(4,9,14), shown as

$$\left\{\begin{aligned} &F(x)=x(1-x)Q_{\mathrm{T}}\biggl\{(P_2-c_2l_2)\,[z(a_3-1)+(1-z)(a_4-1)]-[za_3+(1-z)a_4]\biggl[P_1-c_1l_1+\\ &\qquad y\left(\Delta P-\frac{l_1f_1}{v}\right)+(y-1)\,\frac{l_1f_2}{v}\biggr]-[zb_1+(1-z)b_2]\left(c_1l_3-P_3+c_2l_4+\frac{l_3f_2}{v}\right)+[za_1+(1-z)a_2]\cdot\\ &\qquad \left[P_1-c_1l_1-y\frac{l_1f_1}{v}-(1-y)\,\frac{l_1f_2}{v}\right]+[(1-z)(1-a_2-b_2)+z(1-a_1-b_1)](P_2-c_2l_2)-y\Delta P\cdot\\ &\qquad [(1-z)(a_2+b_2)-z(a_1+b_1)]\biggr\}\\ &F(y)=y(1-y)Q_{\mathrm{T}}\frac{l_1(f_1-f_2)}{v}\,[a_4+x(a_2-a_4)+z(a_3-a_4)+xz(a_1-a_2-a_3+a_4)]\\ &F(z)=z(z-1)Q_{\mathrm{T}}\{[(x-1)(a_4G_1+(1-a_4)G_2]-(x-1)[a_3G_1+(1-a_3)G_2]+x(a_1G_1+b_1G_3)-\\ &\qquad x(a_2G_1+b_2G_3)+(2y-1)[(x-1)a_4+x(a_1+b_1)]\Delta G+(1-2y)[(1-x)a_4+x(a_2+b_2)]\Delta G+\\ &\qquad x(1-a_1-b_1)G_2-x(1-a_2-b_2)G_2\} \end{aligned}\right. \tag{16}$$

Let $F(x)=F(y)=F(z)=0$, the Jacobian matrix can be obtained by Eq.(10). As indicated, eight special equilibrium points, including $E_1=(0, 0, 0)$, $E_2=(1, 0, 0)$, $E_3=(0, 1, 0)$, $E_4=(0, 0, 1)$, $E_5=(1, 1, 0)$, $E_6=(1, 0, 1)$, $E_7=(0, 1, 1)$, $E_8=(1, 1, 1)$, were present, and all stakeholders have definite strategies at each point.

The stabilized solution of the evolutionary game is a highly stable Nash equilibrium, and (x^*, y^*, z^*) is an unstable asymptotic state. As a result, this set was not considered. As shown in Table 2, three eigenvalues of each equilibrium point can be derived by connecting the eight stable equilibrium points to the Jacobian matrix.

According to the Lyapunov theory, the equilibrium point in game model is essentially the asymptotic stability point if the eigenvalue has negative real parts. If all corresponding eigenvalues are negative, the equilibrium point denotes the evolutionary stability strategy (ESS). The equilibrium point of the evolutionary game system is the unstable point if the eigenvalue contains positive real components. Also, the equilibrium point is a saddle point if the eigenvalue has a negative real part in addition to a positive real part. Their stability can be determined as indicated by Table 2.

Signs of some eigenvalues are difficult to be determined due to abundant parameters and high scenario complexity. In this section, we would discuss the stability of each equilibrium point in different scenarios under the following conditions: $G_3<G_2<G_1$, $\Delta G<G_1$, $\Delta G<G_2$, $\Delta G<G_3$, $f_1>f_2$, $c_1>c_2$, $\Delta P<P_1$, $\Delta P<P_2$, $\Delta P<P_3$.

The evolutionary game behaviors and stabilized equilibria of enterprise and ATC were investigated and the results revealed that three stable equilibria were generated by three equilibrium solutions ($E_5=(1, 1, 0)$, $E_7=(0, 1, 1)$, and $E_8=(1, 1, 1)$).

In Scenario 1, the huge benefit gain from ARIT motivates enterprises to choose this strategy. Along with attracting direct-flight passengers and HSR passengers to choose the new travel mode, ATC tends to implement congestion charging to expand its returns. Due to limited transit time, travelling cost, and passenger acceptance of ARIT, the positive returns to passengers may be lower than the expected reporting by enterprise and ATC. As a result, passengers tend to choose "opposing ARIT". As a result, the evolutionarily stable equilibrium is $E_5=(1, 1, 0)$.

In Scenario 2, the enterprise selects the "not introducing ARIT" strategy due to the huge construction and operation costs for ARIT. As congestion charging is mainly targeted at air passengers, ATC will insist on this mechanism for high returns. In this case, passengers are inclined to support the construction of ARIT in order to maximize their benefits. As a result, the evolutionarily stable equilibrium is $E_7=(0, 1, 1)$.

Table 2 Local stability analysis of the equilibrium point

Equilibrium point	λ_1	λ_2	λ_3
$E_1(0,0,0)$	$a_4Q_Tl_1/[v(f_1-f_2)]$	$[(a_2-a_4)P_1+(-a_2+a_4-b_2)P_2+b_2P_3+(-a_2+a_4)l_1f_2/v-b_2l_3f_2/v+(-a_2+a_4)l_1c_1+(a_2-a_4+b_2)l_2c_2-b_2l_3c_1-b_2l_4c_2)]Q_T$	$[(a_3-a_4)(-G_1+G_2)-2a_4\Delta G]Q_T$
$E_2(1,0,0)$	$a_2l_1(f_1-f_2)Q_T/v$	$[(-a_2+a_4)P_1+(a_2-a_4+b_2)P_2-b_2P_3+(a_2-a_4)l_1f_2/v+b_2l_3f_2/v+(a_2-a_4)l_1c_1+(-a_2+a_4-b_2)l_2c_2+b_2l_3c_1+b_2l_4c_2]Q_T$	$[(-a_1+a_2)G_1+(a_1-a_2+b_1-b_2)G_2+(-b_1+b_2)G_3+(a_1-a_2+b_1-b_2)\Delta G]Q_T$
$E_3(0,1,0)$	$[(a_2-a_4)P_1-(a_2+a_4+b_2)P_2+b_2P_3+(a_2-a_4+b_2)\Delta P-(a_2-a_4)l_1f_1/v-b_2l_3f_2/v-(a_2-a_4)c_1l_1+(a_2-a_4+b_2)c_2l_2-b_2c_1l_3-b_2c_2l_4)]Q_T$	$a_4l_1(f_2-f_1)Q_T/v$	$[(-a_3+a_4)G_1+(a_3-a_4)G_2+2a_4\Delta G]Q_T$
$E_4(0,0,1)$	$a_3l_1(f_1-f_2)Q_T/v$	$[(a_1-a_3)P_1+(-a_1+a_3-b_1)P_2+b_1P_3+(-a_1+a_3)l_1f_2/v-b_1l_3f_2/v+(a_3-a_1)c_1l_1+(a_1-a_3+b_1)c_2l_2-b_1c_1l_3-b_1c_2l_4)]Q_T$	$[(a_3-a_4)G_1+(-a_3+a_4)G_2+2a_4\Delta G]Q_T$
$E_5(1,1,0)$	$[(-a_2+a_4)P_1+(a_2+a_4+b_2)P_2-b_2P_3+(-a_2+a_4-b_2)\Delta P+(a_2-a_4)l_1f_1/v+b_2l_3f_2/v+(a_2-a_4)c_1l_1+(-a_2+a_4-b_2)c_2l_2-b_2c_1l_3-b_2c_2l_4)]Q_T$	$a_2l_1(f_2-f_1)Q_T/v$	$[(-a_1+a_2)G_1+(a_1-a_2+b_1-b_2)(G_2-\Delta G)+(-b_1+b_2)G_3]Q_T$
$E_6(1,0,1)$	$a_1l_1(f_1-f_2)Q_T/v$	$[(-a_1+a_3)P_1+(a_1-a_3+b_1)P_2-b_1P_3+(a_1-a_3)l_1f_2/v+b_1l_3f_2/v+(a_1-a_3)c_1l_1-(a_1-a_3+b_1)c_2l_2+b_1c_1l_3+b_1c_2l_4)]Q_T$	$[(a_1-a_2)G_1+(-a_1+a_2-b_1+b_2)(G_2+\Delta G)+(b_1-b_2)G_3]Q_T$
$E_7(0,1,1)$	$[(a_1-a_3)P_1+(-a_1+a_3-b_1)P_2+b_1P_3+(-a_1+a_3)l_1f_2/v-b_1l_3f_2/v+(a_3-a_1)c_1l_1+(a_1-a_3+b_1)c_2l_2-b_1c_1l_3-b_1c_2l_4)]Q_T$	$a_3l_1(f_2-f_1)Q_T/v$	$[(a_3-a_4)(G_1-G_2)-2a_4\Delta G]Q_T$
$E_8(1,1,1)$	$[(-a_1+a_3)P_1+(a_1-a_3+b_1)P_2-b_1P_3+(a_1-a_3)l_1f_2/v+b_1l_3f_2/v+(a_1-a_3)c_1l_1+(-a_1+a_3-b_1)c_2l_2+b_1c_1l_3+b_1c_2l_4)]Q_T$	$a_1l_1(f_2-f_1)Q_T/v$	$[(a_1-a_2)G_1+(-a_1+a_2-b_1+b_2)(G_2-\Delta G)+(b_1-b_2)G_3]Q_T$

In Scenario 3, when enterprise and passengers adopt the strategy of positive development for ARIT, the extra benefits to them are relatively high. The benefits of maintaining normal operations of two modes (air and HSR) are higher than those generated by the introduction of ARIT. Also, the ATC captures additional congestion fee from the strategy of congestion charging. Therefore, enterprise and passengers will work together to promote the construction of ARIT, so as to maximize their returns under high route fee and avoid the dominance of ATC due to high charges. As a result, the evolutionarily stable equilibrium is $E_8=(1, 1, 1)$.

4 Numerical Analysis

In order to gain an overview of the revenue mechanism of the system after the introduction of ARIT, numerical simulations were conducted to clarify the evolution of the proposed model. On the basis of system characteristics of ARIT and congestion charging mechanisms, travelling mileage and transit points were set as the main considerations, and three instances (e. g., short-distance network, medium-long distance network, and long-distance network) carrying out specific simulations were designated for selecting different transit points. Different values were assigned to parameters in the three arithmetic examples, and they account for the influences of multiple factors, including passenger flow sharing ratio and congestion charging standard, on the evolution of game players. In this way, the final strategy selection and behavioral motivation of the game players under three scenarios can be determined.

We have systematically enhanced the scenario differentiation in our case studies by incorporating hub-specific characteristics across three transport corridors: Short-distance (Beijing-Shanghai) , medium-distance (Beijing-Guangzhou) , and long-distance (Beijing-Kunming). The analysis focuses on three representative transit hubs, Shijiazhuang, Shenzhen, and Dali, comparing them across three dimensions: Facility levels, extra fees, and extra distance.

The unique characteristics of each hub are accurately reflected in our model parameters:

(1) Within the Beijing-Shanghai corridor (short-distance), the Shijiazhuang hub, as a mature inland air-rail interchange, features highly integrated facilities and well-developed transfer services. In contrast, the Nantong hub, as an emerging junction, boasts modern facilities that are still under optimization.

(2) In the Beijing-Guangzhou corridor (medium-distance), the Shijiazhuang hub continues to leverage its advantages as a mature hub. Conversely, the Shenzhen hub, an air-rail node in a coastal economic center, offers high-quality, modern facilities, though its air-rail integration is still being enhanced.

(3) In the Beijing-Kunming corridor (long-distance), the Dali hub, serving primarily as a tourist destination, has facilities catering to tourist flows, presenting a significant functional contrast to the traditional, large-scale Shijiazhuang hub.

4.1 Simulation test

The Beijing-Shanghai corridor is one of the busiest passenger transport axes in China, characterized by dense air and HSR services and significant passenger mobility. For short-distance intercity travel, passengers exhibit a high degree of time sensitivity, and air-HSR substitution occurs frequently. This makes the corridor an ideal setting for validating the responsiveness and applicability of the proposed evolutionary game model under short-haul conditions. We selected Shijiazhuang and Nantong as transit hubs because: (1) Both cities have mature HSR networks and operational airports, and (2) each city represents a different type of regional transportation hub (Shijiazhuang as an inland HSR hub; Nantong as a coastal aviation-HSR gateway), their operational characteristics allow us to examine how hub attributes influence strategy evolution. The initial parameters used in both route scenarios were derived from actual airfares, HSR fares, travel distances, operation costs, en-route charges, and realistic transfer conditions. These parameters ensure that the simulation reflects real travel behavior and operational constraints.

As for short-distance network, an air-HSR intermodal service on the Beijing-Shanghai route was conducted in order to validate the applicability of the proposed evolutionary game model, wherein two transit hubs (i.e., Nantong and Shijiazhuang) were involved. In the Beijing-Shijiazhuang-Shanghai route, the initial parameters were set to be: $P_1=600$, $P_2=667$, $P_3=522$, $\Delta P=100$, $v=2.5$, $c_1=0.52$, $c_2=0.32$, $l_1=1\,069$, $l_2=1\,318$, $l_3=1\,063$, $l_4=297$, $f_1=0.65$, $f_2=0.45$, $a_1=0.241$, $b_1=0.263$, $a_2=0.3$, $b_2=0.1$, $a_3=0.3$, $a_4=0.4$, $G_1=210$, $G_2=229$, $G_3=179$, $\Delta G=20$, $Q_T=10$. Then, $E_7=(0, 1, 1)$ was obtained. Fig.6 illustrates the results of numerical simulation. The initial parameters in the Beijing-Nantong-Shanghai route were as follows: $P_1=600$, $P_2=667$, $P_3=487$, $\Delta P=100$, $v=2.5$, $c_1=0.52$, $c_2=0.32$, $l_1=1\,069$, $l_2=1\,318$, $l_3=1\,325$, $l_4=556$, $f_1=0.65$, $f_2=0.45$, $a_1=0.241$, $b_1=0.249$, $a_2=0.31$, $b_2=0.1$, $a_3=0.3$,

$a_4=0.35$, $G_1=210$, $G_2=229$, $G_3=169$, $\Delta G=20$, $Q_T=10$. As shown in Fig.7, the proposed system eventually converged to $E_7=(0,\ 1,\ 1)$.

To guarantee the rationality of simulation results, we randomly selected the initial probabilities of the evolutionary game. As shown in Figs.6, 7, the final results were $E_7=(0,\ 1,\ 1)$ regardless of the transit point, suggesting that when civil aviation and HSR have their own dominant position in short-haul routes, enterprises are reluctant to spend extra costs to introduce ARIT. On the contrary, passengers are inclined to "support ARIT" due to the lower travel costs for short-distance travel, resulting in diversified travel decisions. Since HSR dominates the Beijing-Shanghai route, ATC has firmly opted to implement a congestion charging strategy to raise revenue.

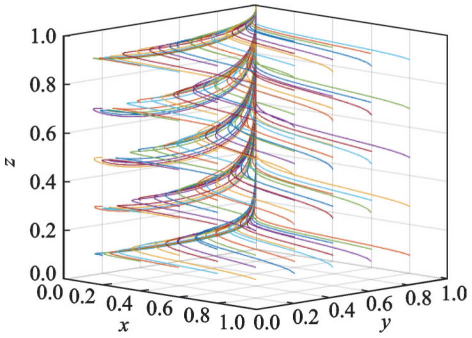


Fig.6 Results of 50 evolutionary games for the Beijing-Shijiazhuang-Shanghai route

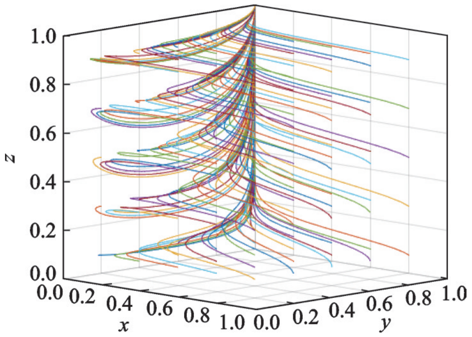


Fig.7 Results of 50 evolutionary games for the Beijing-Nantong-Shanghai route

The Beijing-Guangzhou corridor, spanning more than 2 000 km, is a classic medium-long distance north-south route. For this category of travel, mode choice is influenced not only by time and price but also by comfort, transfer convenience, and long-haul travel fatigue. This makes it an appropriate case to test how longer distances affect the strategic behaviors of the three players. We selected Shijiazhuang and Shenzhen as alternative ARIT transfer hubs for the following reasons: (1) Shijiazhuang lies along the central axis of the corridor, representing a traditional inland hub with balanced rail-air accessibility; (2) Shenzhen, located at the southern terminus of the route, is an international gateway with a large aviation market and strong multimodal transport connectivity; (3) the contrast between the two hubs allows us to analyze how hub positioning and regional economic conditions influence ARIT's performance. The parameter settings used in the simulation originate from actual operational indicators, including real ticket prices, distance-based en-route charges, HSR and air operating costs, and realistic transfer penalties. These values were taken to ensure that the medium-long distance simulation captures authentic demand patterns and competitive dynamics.

As for medium-long distance network, the Beijing-Guangzhou line, which runs north-south, was employed. When Shijiazhuang was employed as the transfer hub, the initial parameters were as follows: $P_1=1\,380$, $P_2=964$, $P_3=1\,002$, $\Delta P=100$, $v=2.5$, $c_1=0.52$, $c_2=0.32$, $l_1=1\,880$, $l_2=2\,298$, $l_3=1\,600$, $l_4=297$, $f_1=0.65$, $f_2=0.45$, $a_1=0.275$, $b_1=0.373$, $a_2=0.4$, $b_2=0.2$, $a_3=0.4$, $a_4=0.45$, $G_1=472$, $G_2=332$, $G_3=344$, $\Delta G=20$, $Q_T=10$. When ARIT routes for transit was set to be Shenzhen, the initial parameters were as follows: $P_1=1\,380$, $P_2=964$, $P_3=1\,174$, $\Delta P=100$, $v=2.5$, $c_1=0.52$, $c_2=0.32$, $l_1=1\,880$, $l_2=2\,298$, $l_3=1\,238$, $l_4=235$, $f_1=0.65$, $f_2=0.45$, $a_1=0.25$, $b_1=0.573$, $a_2=0.6$, $b_2=0.1$, $a_3=0.4$, $a_4=0.45$, $G_1=472$, $G_2=332$, $G_3=403$, $\Delta G=20$, $Q_T=10$. Figs.8, 9 illustrate the results of 50 evolutionary games, with varying initial probability settings and staging point designs. As indicated, the probability of ATC and passengers selecting integration approached 1 over time, while the probability of the enterprise selecting "introducing ARIT" approached 0. As shown in Figs.8, 9, medium-long network verifies $E_7=(0,\ 1,\ 1)$ as a final stable point for model. The results visualize that when line operation is mature and revenue is considerable, the enterprise has no motivation to expand the operation (i. e., introducing ARIT product). Passengers tend to “support ARIT” due to long travelling time of HSR and expensive air tickets. Regarding the option of ATC to implement congestion charging strategy, it leads to increased revenue while avoiding airspace congestion and passenger overflow.

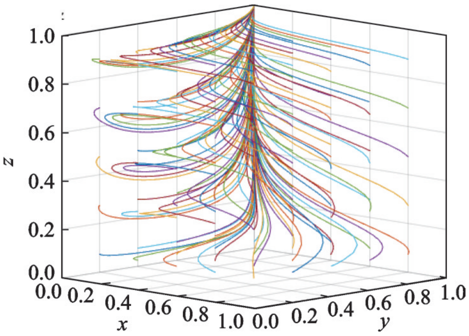


Fig.8 Results of 50 evolutionary games for the Beijing-Shijiazhuang-Guangzhou route

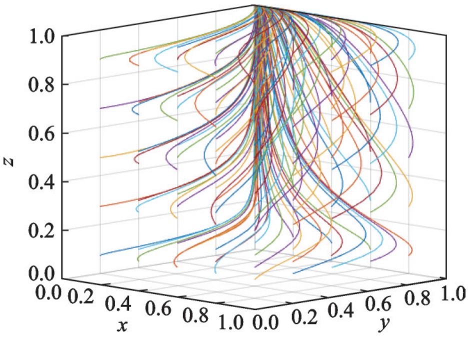


Fig.9 Results of 50 evolutionary games for the Beijing-Shenzhen-Guangzhou route

The Beijing-Kunming route exceeds 2 700 km and is representative of long-distance travel involving large variations in geography, economic conditions, and transportation accessibility. Due to the remote locations of many southwestern tourist destinations, travelers often face limited direct transportation options, making the route highly consistent with the non-direct travel characteristics emphasized in our model. Two transfer hubs were considered: (1) Dali, a major tourist destination in Yunnan Province with limited direct aviation links, representing regions where ARIT may significantly improve connectivity; (2) Shijiazhuang, a major HSR junction and air-rail hub in northern China, offering a contrasting operational environment. The parameters used in the long-distance scenario are based on real travel costs, operating expenses, distance-based charging, and passenger generalized travel costs. These authentic values ensure that the simulation reliably reflects long-distance travel behavior, especially passengers’ sensitivity to fatigue, cost, and transfer burdens.

As for long distance network, the Beijing-Kunming route was preferred as simulation object, with Dali and Shijiazhuang as stopover. The initial parameters in the Beijing-Dali-Kunming route were set as follows: $P_1=1\ 350$, $P_2=1\ 147$, $P_3=1\ 320$, $\Delta P=100$, $v=2.5$, $c_1=0.52$, $c_2=0.32$, $l_1=2\ 400$, $l_2=2\ 760$, $l_3=1\ 238$, $l_4=328$, $f_1=0.65$, $f_2=0.45$, $a_1=0.6$, $b_1=0.15$, $a_2=0.7$, $b_2=0.05$, $a_3=0.6$, $a_4=0.7$, $G_1=462$, $G_2=398$, $G_3=455$, $\Delta G=20$, $Q_\mathrm{T}=10$. The initial parameters in the Beijing-Shijiazhuang-Kunming route were set as follows: $P_1=1\ 350$, $P_2=1\ 147$, $P_3=2\ 130$, $\Delta P=100$, $v=2.5$, $c_1=0.52$, $c_2=0.32$, $l_1=2\ 400$, $l_2=2\ 760$, $l_3=1820$, $l_4=297$, $f_1=0.65$, $f_2=0.45$, $a_1=0.6$, $b_1=0.25$, $a_2=0.7$, $b_2=0.05$, $a_3=0.6$, $a_4=0.7$, $G_1=462$, $G_2=398$, $G_3=729$, $\Delta G=20$, $Q_\mathrm{T}=10$. According to Fig.10, the stable equilibrium state in the Beijing-Dali-Kunming route eventually converged to $E_7=(0,\ 1,\ 1)$, regardless of the initial probability set. The stable strategies of the three participants were consistent with those in the cases mentioned above. However, the stable equilibrium state eventually converged to $E_5=(1,\ 1,\ 0)$ under transiting in Shijiazhuang, as shown in Fig.11. In this case, ATC also selected to implement congestion charging strategy. Hence, the enterprise shall introduce ARIT so that passengers choose new transport mode to offset the high congestion charges levied by ATC for long-distance transport operation. Nevertheless, passengers tend to remain negative to ARIT due to fatigue and cost for long-distance travel.

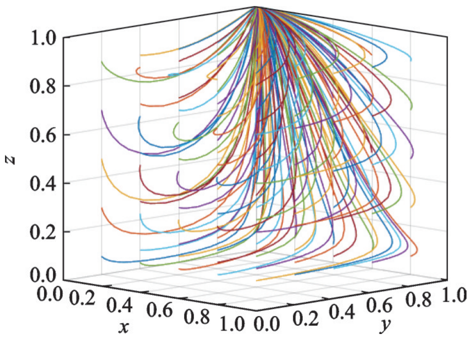


Fig.10 Results of 50 evolutionary games for the Beijing-Dali-Kunming route

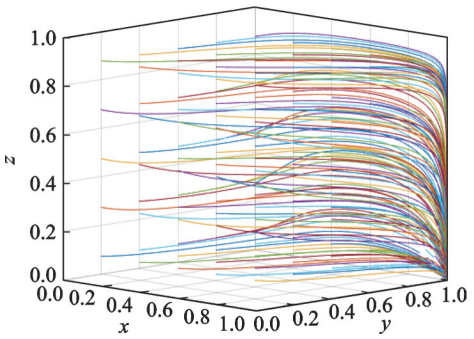


Fig.11 Results of 50 evolutionary games for the Beijing-Shijiazhuang-Kunming route

Figs.6—11 show results under different conditions, despite that the stability point was consistent in all cases. Transport distances and transit point settings may not change the final equilibrium strategy, but would affect the process of the evolutionary game and the density of outcome shapes. We will conduct sensitivity analysis of specific variables in subsequent sections to observe the evolution of the final strategy in difference scenarios.

4.2 Practical application

ARIT integration has become a hot topic in high-speed passenger transport owing to the exacerbating passenger overflow and airspace congestion. Government encourages integration of air transport and HSR and accelerates the development of ARIT using subsidy policies. Although these methods have relieved the competition of air transport and HSR, the fundamental problem, namely low integration degree, remains. In this study, we simulated path evolution and conducted sensitivity for each player by developing an evolutionary game model involving enterprises and ATC. Besides, we would discuss the influences of the en-route charge and the allocation coefficient of ARIT passengers on the equilibrium strategy. In the simulation figures, SJW, NTG, SZX, and DLU denote Shijiazhuang Zhengding International Airport, Nantong Xingdong International Airport, Shenzhen Bao'an International Airport, and Dali Fengyi Airport, respectively."

4.2.1 Average en-route charge

Congestion charging aims to address airspace congestion and flight delays on busy routes, thereby attracting air and HSR passengers to choose ARIT intermodal transport. It is realized by an increase in route fee on busy routes. The model parameters were fixed, except for f_1, whose values were 0.65, 0.85 or 1.

In short-distance cases, the evolutionary analysis results are depicted in Fig.12. With the increase in charge, passengers' preference on integration of air transport and HSR increased significantly, and the duration to reach ATC equilibrium also increased. Despite some additional benefits brought by the ARIT, enterprises believe that it cannot substitute HSR for short-distance journeys. The rate of convergence increases, but the three participants maintain the final strategy ($E_7=(0,\ 1,\ 1)$).

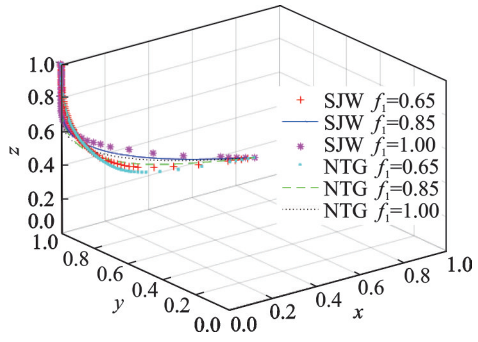


Fig.12 Evolution of tripartite behaviors under different route charges in short-distance cases (Beijing-Shijiazhuang/Nantong-Shanghai)

In medium-distance cases, the analysis results are depicted in Fig.13. The original pattern of parameter growth was maintained and the results showed that the en-route charge had more significant impacts on routes where transit point was set at Shijiazhuang. When f_1 increased to 0.85 and 1, the equilibrium point changed from $E_7=(0, 1, 1)$ to $E_8=(1, 1, 1)$. As SJW is a large transit airport with the potential to actively build a gateway to Beijing, it is more attractive to passengers compared with Shenzhen. Due to the positive attitude of passengers and the objective conditions, enterprises eventually choose to introduce ARIT to offset the cost of airspace congestion charging and reduce passenger traffic congestion.

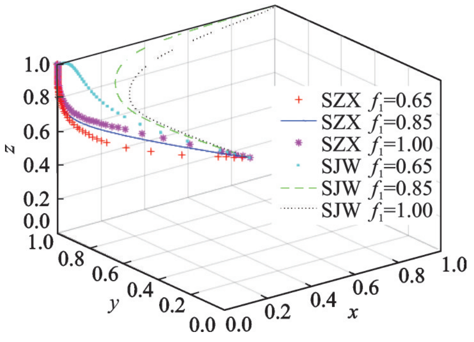


Fig.13 Evolution of tripartite behaviors under different route charges in medium-distance cases (Beijing-Shijiazhuang/Shenzhen-Guangzhou)

In long-distance cases, the analysis results are shown in Fig.14. As the congestion charging continues to increase, passengers' preference on ARIT intermodal transport decreases. Instead, enterprises are motivated to introduce ARIT. This evolutionary regularity is particularly evident with Shijiazhuang as the transit hub. When f_1 increases, passengers and enterprises select to oppose and support ARIT, respectively. The faster the route charge grows, the higher the convergence rates for passengers and enterprises. Overall, the final stabilized strategy is $E_5=(1, 1, 0)$.

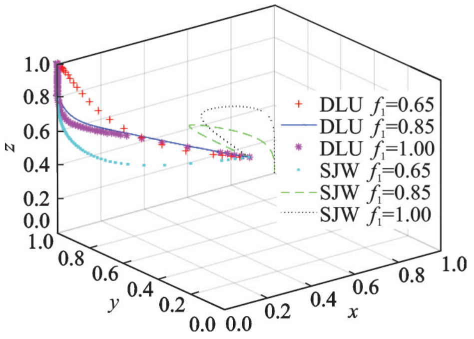


Fig.14 Evolution of tripartite behaviors under different route charges in long-distance cases (Beijing-Dali/Shijiazhuang-Kunming)

4.2.2 Allocation coefficient of ARIT passengers

Establishment of the ARIT requires meeting potential passenger demands and design of specific ARIT product. In China, ARIT is at an early stage, and low passenger demand is the reason why enterprises do not prefer to introduce ARIT products, as reflected by the simulation results. In this section, the strategy changes of the three game players as a function of increasing b_1 are explored.

Fig.15 shows the evolutionary results in short-distance cases. Herein, the model parameters were fixed, except that the allocation coefficient of ARIT passengers (b_1) was 0.24, 0.34 or 0.54. The three participants did not change the final strategy ($E_7=(0, 1, 1)$) and their converging rates were consistent. Overall, the enterprises stick to the original transport model despite the additional benefits of ARIT.

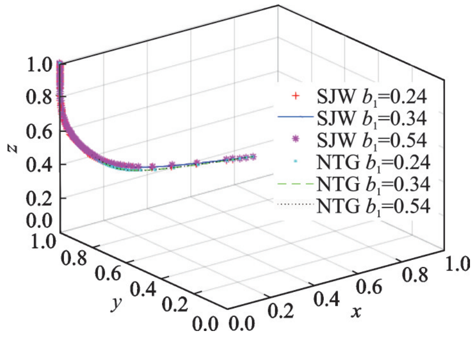


Fig.15 Evolution of tripartite behaviors under different allocation coefficient of ARIT passengers in short-distance cases (Beijing-Shijiazhuang/Nantong-Shanghai)

Fig.16 shows the evolutionary results in medium-distance cases. The model parameters were fixed, while $b_1=0.37, 0.47, 0.57$ when the transit hub was Shenzhen and $b_1=0.12, 0.22, 0.32$ when the transit hub was Shijiazhuang. As indicated, the probability of the passengers could affect enterprise behaviors in the Beijing-Shijiazhuang-Guangzhou route. Enterprises will eventually choose to introduce ARIT products, and the converging rate was proportional to the growth rate of b_1. Passengers, as a finite resource, will generate revenue that could balance the congestion charge and offset the investment in ARIT. Furthermore, enterprise has social benefits for complying with the government policies.

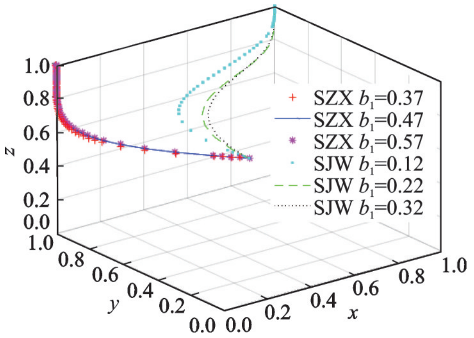


Fig.16 Evolution of tripartite behaviors under different allocation coefficient of ARIT passengers in medium-distance cases (Beijing-Shijiazhuang/Shenzhen-Guangzhou)

Fig.17 shows the evolutionary results in long-distance cases when $b_1 = 0.15, 0.25, 0.35$. As indicated, enterprises, ATC and passengers would choose not to introduce ARIT, implement congestion charging and support ARIT in the beginning, respectively, as the allocation coefficient of ARIT passengers increased, regardless of the transit hub. The converging rate to final strategies was inversely proportional to the growth rate of b_1. However, when b_1 increased to 0.35, the equilibrium point for enterprises and passengers in the Beijing-Shijiazhuang-Kunming route was exposed to changes. Although growing passenger flow attracts enterprises to introduce ARIT, the expected benefits of passengers supporting the ARIT intermodal transport have not been achieved, and passengers may turn into a negative attitude to ARIT.

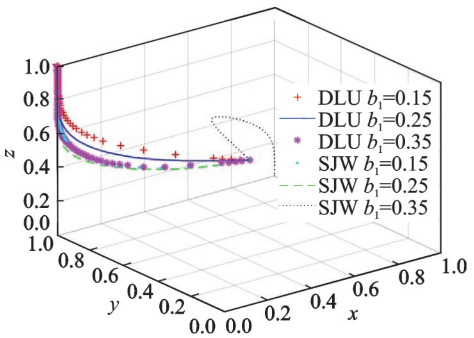


Fig.17 Evolution of tripartite behaviors under different allocation coefficient of ARIT passengers in long-distance cases (Beijing-Dali/Shijiazhuang-Kunming)

5 Conclusions

This study proposes a tripartite evolutionary game model clarifying the network connectivity for long-distance, medium-distance and long-distance travel. The game behaviors of enterprises, ATC and passengers, as well as their coping strategies under congestion charging in ARIT, were investigated. The developed model allows analysis of the payoffs and stabilized strategies of three participants under different conditions. The proposed model is an effective tool to investigate the development of an optimal strategy by each game player to optimize their benefits, or identify optimized strategies to changes in the system or game behaviors of other players. Three practical cases (i. e., Beijing-Shanghai, Beijing-Guangzhou and Beijing-Kunming) were used as examples to validate the proposed model. The following conclusions can be drawn:

(1) Only one stabilized point was present in the evolutionary system under different distance attributes and transit hubs. Based on original network and congestion charging levels, enterprises are not motivated to introduce ARIT transport, and ATC is willing to increase the en-route charge, wherein both sides prefer strategies maximizing their respective benefits. On the contrary, passenger behaviors were unpredictable. Passengers supported ARIT in short- and medium-distance routes to reduce traveling costs. On the other hand, passengers were negative to ARIT in long-distance routes due to the cumbersome procedures and transfer modes.

(2) All participants continuously adjusted and optimized their respective behaviors according to the changes in the strategic behaviors of other players to adapt to the system changes. Ultimately, all participants chose the profitable strategy and restore the equilibrium. The simulation results showed that ATC could quickly reach the equilibrium under any circumstances, and always prefer the congestion charging strategy and seek for revenue growth. Passengers showed higher strategy stability and tended to support the ARIT, thereby playing a positive

role in the construction of ARIT. Enterprises were more inclined to change strategies to ensure their profit, and the congestion charging mechanism would drive enterprises to introduce ARIT to alleviate airspace congestion and reduce operating costs.

(3) The implementation of congestion charging mechanism for medium- and long-distance routes would accelerate the introduction of ARIT. Both ATC and passengers benefit from high en-route charges, with ATC capturing additional revenue and passengers having more choices and improved services. Nevertheless, enterprises tend to be more careful in decision-making, as the costs of introducing ARIT and the incremental air route charges shall be considered, and different modes of transport shall be balanced. Indeed, the advantages of the congestion charging mechanism in relieving airspace congestion and diverging passengers would drive enterprises to introduce ARIT. In short-distance travel, however, the sensitivity of the three participants is not high, and the congestion charging mechanism affects the gaming process but does not change the final strategy.

(4) Allocation coefficient of ARIT passengers will also affect ARIT. Enterprises and passengers are likely to change their strategies. When more passengers choose ARIT, enterprises are more likely to introduce ARIT and initiate a new transport mode in medium-distance travel, and passengers are more motivated by the mass trend. In short and long-distance travel, direct flight and HSR services are well developed, and it is difficult to gain an absolute advantage by introducing ARIT. Also, passengers are reluctant to do so due to the complexity of the transfer process and travelling fatigue.

This paper has implications for practical applications. Civil aviation and HSR have advantages in long-distance routes and short-distance routes respectively, and enterprises can barely introduce the ARIT without a thorough evaluation. The congestion charging mechanism can balance the three transport modes, thereby relieving the airspace congestion, reducing flight delays, and relieving pressure on the ATC authorities. Also, enterprises will ultimately choose to introduce ARIT over a long period of evolution and stability in order to improve the utilization rate and network connectivity. The introduction of ARIT is a novel transport mode, and the congestion charging mechanism is a novel balancing mechanism. If the interchange and transit procedures can meet the requirements, passengers will always be on the favorable side, and enterprises and ATC tend to give positive feedbacks. As a result, all players benefit from ARIT and the transport market will be in an equilibrium.

However, it should be noted that the congestion charging mechanism proposed in this study is developed within a theoretical modeling framework. In current practice, en-route charging is generally implemented through a standardized and centrally coordinated mechanism, which is not explicitly designed to reflect dynamic congestion conditions as assumed in this model. Therefore, the proposed mechanism can be regarded as a theoretical extension and a potential direction for future refinement of charging strategies, rather than an immediately applicable operational approach. Future research may further examine its applicability under existing regulatory frameworks and explore feasible pathways for practical implementation.

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基于空域拥堵视角的空铁联运利益相关者的三方演化博弈模型

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摘要：针对航空铁路多式联运(Air-rail intermodal transport, ARIT)系统中空域资源紧张、航线拥堵与多主体策略选择相互影响的问题，本文从空域拥堵治理视角出发，构建了企业、空中交通管制(Air traffic control, ATC)部门和乘客三方参与的空铁联运利益相关者演化博弈模型，以揭示拥堵收费机制下不同主体策略选择的演化规律及其影响因素。首先，基于企业是否引入空铁联运服务、空中交通管制部门是否实施拥堵收费、乘客是否选择空铁联运出行3类策略，综合考虑票价收入、里程成本、途中费用、拥堵收费、乘客共享率以及广义出行成本等因素，建立三方博弈收益矩阵；随后，推导各参与主体的复制动态方程，分析系统在不同初始状态和参数条件下的演化稳定性；最后，以京沪、京广和京昆走廊为典型案例，考察距离、途中费用和乘客共享率等关键因素对企业、空中交通管制部门和乘客最终策略选择的影响。研究结果表明，三方主体均倾向于选择能够提升自身收益的策略组合；企业在中等距离运输走廊上更倾向于引入空铁联运策略，而在短距离和长距离运输走廊上引入意愿相对较弱；空中交通管制部门在多数情形下倾向于实施拥堵收费策略，以缓解空域拥堵并优化资源配置；乘客在广义出行成本较低、途中费用可接受且共享率较高时更倾向于选择空铁联运。进一步分析发现，系统最终演化结果对距离、途中费用和乘客共享率等关键参数变化较为敏感，其中企业策略选择受参数扰动影响最为显著，说明企业是空铁联运系统协同发展的关键驱动主体。本文研究可为拥堵收费机制设计、空铁联运产品优化以及多主体协同治理提供理论和决策参考。

关键词：空铁联运；空中交通管制；乘客；三方演化博弈模型

研究亮点：

1. 从空域拥堵治理视角构建企业、空中交通管制部门和乘客三方演化博弈模型。
2. 将拥堵收费、乘客共享率、途中费用和广义出行成本纳入空铁联运主体收益分析。
3. 以京沪、京广和京昆走廊为案例，揭示不同运输距离下企业引入空铁联运策略的差异。
4. 发现企业策略对关键参数变化最为敏感，是推动空铁联运系统演化的重要主体。