# COMPETITIVE PRICING BETWEEN HIGH-SPEED RAILWAY AND CIVIL AVIATION BASED ON THE CELLULAR AUTOMATON

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## Abstract

China has seen constant improvement and expansion in the high-speed railway network and the civil aviation transportation network due to the persistent contribution towards the construction of the transportation infrastructure. However, transportation products by high-speed railway and civil aviation are replaceable. This makes the two transport modes fall into fierce competition. Therefore, it is significantly essential to examine the gaming rivalry in passenger transport by high-speed railway and civil aviation. It is also necessary to formulate proper competition strategies to increase transportation revenues, optimize resources, and promote the orderly competition between the two. By studying both China's and international cases, this paper provides the competitive pricing nested bi-level programming model for high-speed railway and civil aviation passenger transport on the basis of the principles of profit maximization and generalized cost minimization. The Cellular Automaton is utilized as part of the adjusted passenger flow. In addition, the hierarchical particle swarm optimization is utilized for modelling the solution. The balanced competitive pricing for high-speed rail and civil aviation is acquired by the sample calculation. Moreover, to verify the precision of the model developed in this paper, the comparative analysis is done on the basis of swarm evolution and change in passenger flow by logit separation.



## Key Words

Cellular automation, competitive pricing, swarm evolution, hierarchical particle swarm


## 1. Introduction

China's high-speed railway has accomplished a rapid development within a short time due to the vast investment on the high-speed railway infrastructure. It inevitably brings the fierce competitions between the high-speed railway and civil aviation regarding the market share and capacity benefits. The high-speed railway has comparative advantages in the safety, accuracy, and convenient transfer compared with civil aviation transport. For example, all flights between Zhengzhou and Xi'an were reluctant to terminate within only 48 days after the operation of the high-speed railway between the places. The competition has been very intense from the beginning of high-speed railway development. This research discusses mainly the competitive prices for the high-speed railway and civil aviation transport to guarantee better operating profits while satisfying the demands of the medium and long distances. With rapid economic growth, China's transportation industry has been developing rapidly and people's demands for travel are growing rapidly. As such, China's high-speed rail network structure has been continuously improving and the civil aviation transport network has been expanding. However, vicious competition between the two transport modes is still existing due to the attribute of replaceable transportation products. Such improper competition not only harms the interests of both sides but also causes a series of social problems. Therefore, research on game and competition is of great significance to enhance the transportation benefits between high-speed railway and civil aviation passenger transport. It also develops the suitable competition strategy. Furthermore, it optimizes the allocation of resources and promotes orderly competition.

Foreign transport decision-making departments and relevant experts and scholars are very concerned about the reform in high-speed passenger transport fare system and fare setting. Jeroslow theoretically identified the price adjustment range utilizing the demand function and demand elasticity coefficient in economic principles. He evaluated the related factors influencing the fare setting, such as the competitor's business capacity and traveller's fare affordability. Furthermore, by utilizing the experience and knowledge of experts or decision-makers, he modified the parameters of the price adjustment model and verified


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it with actual cases [1]. Marcotte and Marquis regarded the transport enterprise and consignor as an internally non-cooperative whole, utilized Balachandran's discussion about consistency between overall interests and individual interests as the theoretical basis, and built an optimal system profit model to maximize the profits of transport enterprise and consignor [2]. By utilizing a combination of sensitivity analysis and cases, Yang and Yagar built a bi-level programming model for fare setting under multi-mode traffic conditions to minimize the passengers' travel costs and maximize the transport department's profit by taking interests of passengers and transport department into full account [3]. On the grounds of principle of urban traffic balanced flow, Ferrari built a bi-level programming pricing model for railway passenger tickets when demands changed under multi-mode conditions and solved it utilizing the sensitivity analysis [4].

To provide a theoretical guidance for the pricing and adjustment of passenger transport management enterprises under market competitions, Crespi and Giorgi introduced game theory to the research process of transport pricing and established static and dynamic transport pricing models [5]. By explaining the attributes and estimating methodologies of civil aviation passenger transport, Sushama and Rajagopalan set up a total profit function of airline and presented conditions to maximize airline profits with or without discounts. They analysed profit, price, and output and proposed endogenous discount pricing by utilizing the Leontief's arbitrage model and Layson's model [6]. On the grounds of the bi-level programming model developed by related researchers, Su and Shi utilized a hybrid genetic algorithm & simulated annealing (GASA) optimization strategy, which combined genetic algorithm and simulated annealing algorithm to solve the model and analyse it with cases [7]. To throw light upon the functional relationship between expected revenue and price decision, Oysu and Bingul enhanced the traditional single flight dynamic fare setting model, utilized distinctive time points to switch price as decision variables, and rebuilt a dynamic fare setting model [8]. In competitive transport mode pricing, on the grounds of the complete analysis of economic benefits of railway passengers' fares and running speed of train, Shahanaghi and Rad utilized a bi-level programming model to demonstrate the passengers' fares and speed up policy under multiple traffic and transport modes between cities under elastic demands with cases [9].

With the development of logit work in transport studies, in view of the shift of competitive transport mode pricing from static to dynamic, aimed at maximizing profits, Si and Gao built an optimal bi-level programming model for railway passenger transport pricing under market competitions. On the grounds of logit shunt model, this proposed model described lower level programming of the passenger's choice between different service modes [10]. To amplify the benefits, Raturi *et al.* developed a competitive and cooperative game pricing model between high-speed railway and normal-speed railway and solved Nash equilibrium. In the modelling of passenger groups, he supposed that their behaviours were "always directly choosing a travel mode with low expenses" [11]. With a specific end goal to amplify the operating profits, Li *et al.* (2012) introduced the number of stations, density of stream of people, station spacing, path length, and other factors. He developed a rail transit operation and programming model and simulated the change of operating profits under two distinctive pricing methodologies "through ticket" and "mileage ticket" [12].

As an average complex social and financial framework, a transport framework is irregular and time varying. Particularly for enormous travel groups, influenced by the environment, travel information, subjective impression, and different factors, their travel decision must be a group decision-making process with limited judiciousness. However, to delineate passenger group's choice of travel mode, the vast majority of the above literary works simply utilize the customary logit shunt model. Practically, utilizing, logit cannot completely mirror the bounded rational group decision-making behaviour of passenger groups. It cannot reflect the self-organizational activities of passenger groups from the dimensions of time and space. Only a limited number of researchers have studied passenger transport organization and planning by delineating the passenger's subjective behaviours. With the reference to price, time, number of runs, distance, and other factors, Yuan and Huang developed an integrated multi-targeted optimization model for passenger's path choice in a railway network. Despite the fact that the introduction of passenger group's subjective activities made the decision-making activities reflected by the model more practical and improved the optimization results, there are few examinations presenting the spatial and worldly changes of passenger group shunting into fare optimization. To reflect the passenger's choice of transport in a more practical way, this article utilizes a 3D cellular genetic algorithm to shunt passenger groups in an equalized way based on their self-organizational evolution while shunting the passengers [13]. Li *et al.* (2012) developed a railway framework operation and optimization model by utilizing the passenger's place of residence as a variable and further introduced the concept of "agent" into this model. He developed a bi-level agent interaction mechanism. The upper agent was a railway operation department, which maximized profits, using fares, number of runs, *etc.* as variables. The lower agent was passengers, who maximized travel utility by choosing an address within their budget [14]. Hctrakul and Cirillo began from the actual behaviours of passengers in the process of travel and introduced the passenger's booking time and optimal distribution of seats into the railway fare optimization model [15].

## 2. Building a Competitive Pricing Model between High-Speed Railway and Civil Aviation

On the grounds of bi-level programming [16], this article builds a multi-level programming and collective pricing model. As the collaborative pricing between high-speed railway and civil aviation could be viewed as a dynamic gaming process and this process is composed of several static games [17], therefore, in this study, the author supposed that the fare of one high-speed passenger transport mode stayed the same and the fare of another high-speed passenger transport mode was reset.

First of all, assume that the fare of one high-speed passenger transport mode $i^{-1}$ stayed the same, as a precondition. Let $Z$ as the objective function of upper programming, to represent the profit of high-speed passenger transport mode $i$. $x$ was the decision variable of upper programming (*i.e.*, the fare of high-speed passenger transport mode). Again, let $f$ as the objective function of lower programming, to represent the passenger's generalized travel cost. $y$ was the decision variable of lower programming (*i.e.*, the passenger capacity of each high-speed passenger transport mode). $y(x)$ was a decision variable function of upper programming.

The upper programming can be expressed as:

$$\begin{array}{c} \max Z = r_i(p_i, p_{i^{-1}}) \times (p_i - c_i) \\ \text{s.t. } p_i^{\min} \le p_i \le p_i^{\max} \end{array}, \tag{1}$$

where $i = 1, 2$ ($i = 1$ represents high-speed railway, $i = 2$ represents civil aviation), $i^{-1}$ represents a high-speed passenger transport mode competing with high-speed passenger transport mode $i$. $p_i$ is the fare set by high-speed passenger transport mode $i$, $c_i$ is the unit transport cost of high-speed passenger transport mode $i$, which was set as a constant in this article, $p_{i^{-1}}$ is the optimal fare for the competitor of high-speed passenger transport mode $i$, $r_i(p_i, p_{i^{-1}})$ is the passenger capacity of high-speed passenger transport mode $i$ when the fare was $p_i$, $p_i^{\min}$ is the minimum fare approved by a management department of high-speed passenger transport mode $i$, and $p_i^{\max}$ is the maximum fare approved by a management department of high-speed passenger transport mode $i$.

The lower programming can be expressed as

$$\begin{array}{c} \min F(r) = \sum\limits_{i=1}^{2} \int_0^{r_i} f_i(x)dx \\ \text{s.t. } \sum\limits_{i=1}^{2} r_i = Q, \quad r_i \ge 0 \end{array}, \tag{2}$$

where $r_i$ is the passenger flow of high-speed passenger transport mode $i$, $Q$ is the total passenger flow, and $f_i(x)$ is a generalized cost function of high-speed passenger transport mode $i$, expressed as a power function in this article in the following form:

$$f_i(r_i) = a(r_i)^b - V_i, \tag{3}$$

where $a$, $b$ are parameters, $V_i$ is the utility value observed in high-speed passenger transport mode $i$, expressed with the following equation:

$$V_i = \sum_{k=1}^{K} \alpha_i^k X_i^k + \beta_i, \tag{4}$$

where $\alpha_i^k$ is the passenger's emphasis on the $k$ attribute of high-speed passenger transport mode $i$, $X_i^k$ is the index value of the $k$ attribute of high-speed passenger transport mode $i$. Two affecting factors were selected in this article: fare and travel time and $\beta_i$ is the passenger's preference for high-speed passenger transport mode $i$.

Regarding the above mentioned statement, when the fare of civil aviation was fixed, a pricing optimization model for high-speed railway could be developed as follows:

$$\begin{cases} \max Z = r_1(p_1, p_{1^{-1}}) \times (p_1 - c_1) \\ \text{s.t. } p_1^{\min} \le p_1 \le p_1^{\max} \\ r_1(p_1, p_{1_{-1}}) \text{ is given by lower planning} \\ \min F(r) = \sum\limits_{i=1}^{2} \int_0^{r_i} f_i(x)dx \\ \text{s.t. } \sum\limits_{i=1}^{2} r_i = Q, \quad r_i \ge 0 \end{cases}. \tag{5}$$

Likewise, when the fare of high-speed railway was fixed, a pricing optimization model for civil aviation can be built as follows:

$$\begin{cases} \max Z = r_2(p_2, p_{2^{-1}}) \times (p_2 - c_2) \\ \text{s.t. } p_2^{\min} \le p_2 \le p_2^{\max} \\ r_2(p_2, p_{2_{-1}}) \text{ is given by lower planning} \\ \min F(r) = \sum\limits_{i=1}^{2} \int_0^{r_i} f_i(x)dx \\ \text{s.t. } \sum\limits_{i=1}^{2} r_i = Q, \quad r_i \ge 0 \end{cases}. \tag{6}$$

Taken together, the competitive pricing process between high-speed railway and civil aviation was a dynamic gaming process of complete information. As a new entrant, high-speed railway sets the transport price as $p_1^0$, according to its own construction and operating conditions. Civil aviation observed $p_1^0$, combined with its own fare $p_2^0$ and substitutes it into (6). Then, civil aviation passenger transport identified a fare of civil aviation under $p_1^0$. In doing so, civil aviation passenger transport formed a pricing strategy $(p_1^0, p_2^1)$. Under civil aviation's new pricing strategy $(p_1^0, p_2^1)$, high-speed railway substituted it into (5) and identified the fare of high-speed railway $p_1^1$ under $p_2^1$. Similarly, high-speed railway also formed a new fare strategy $(p_1^1, p_2^1)$. After a round of game, civil aviation and high-speed railway formed a new fare strategy $(p_1^1, p_2^1)$. By analogy, after $n$ rounds of games, civil aviation and high-speed railway formed a set of fare strategies $\{(p_1^1, p_2^1), (p_1^2, p_2^2), \ldots, (p_1^n, p_2^n)\}$. Through these fare games, the final fare tended to be equalized and formed an optimal fare strategy.

## 3. Analysing a Self-Organizational Evolution and Equalized Shunting Process of Passenger Groups

### 3.1 The Setting of Cellular Automaton

In the form of probabilistic combinations, the shunting mode for all passengers in (2) was discretized into individual passengers' travel decisions. This article adopted a 3D cellular automaton to build a passenger group evolution and shunting model [18], because the existing research

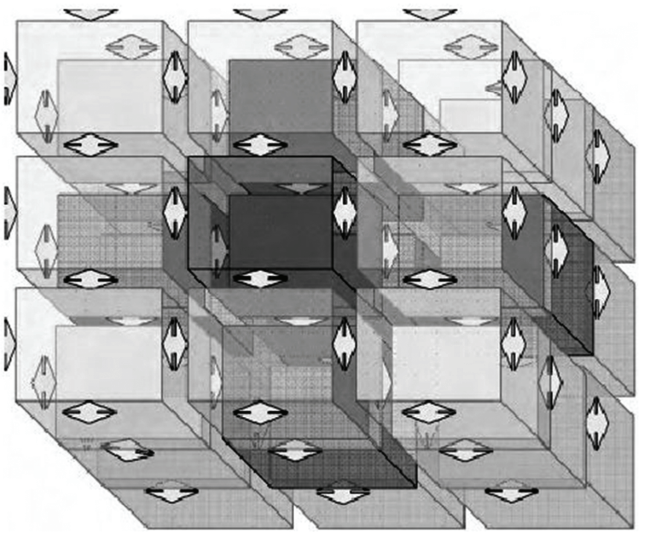

Figure 1. Cellular neighbours in 3D space.

demonstrated that a 3D cellular automaton had good properties in information transmission speed [19].

1. Cellular space: an $m \times m \times m$ grid. Every cube represented a passenger, whose 3D coordinates were $(x, y, z)$.
2. Cellular neighbour: As described in Fig. 1, regarding spatial distribution, every central cell had six neighbours in space.
3. Cellular state.

The probabilistic combination of passenger's choices for high-speed railway and civil aviation is expressed as $\mu_i^{(x,y,z)}$ $(i = 1, 2)$, where $\sum_{i=1}^{2} \mu_i^{(x,y,z)} = 1$.

The perception of generalized travel cost: From (2) and (3), an individual passenger's judgement of generalized travel cost is as follows:

$$f^{(x,y,z)} = \sum_{i=1}^{2} \int_0^{\mu_i^{(x,y,z)}Q} [a(\mu_i^{(x,y,z)}Q)^b - V_i]dx. \quad (7)$$

Thus it can be seen that (6) was the discretization of (2).

High-speed passenger transport mode: Each passenger chose high-speed passenger transport mode $i$ at the probability of $\mu^{(x,y,z)}$.

*Evolution rule*: The passenger group in cellular space updated the probabilistic combination of their travel mode choices through both time and space on the basis of the concept of cellular genetic algorithm. The particular strategy is demonstrated in Section 2.

### 3.2 Evolution Rule Based on Cellular Genetic Algorithm

From the previous examination, a passenger's travel mode choice based on the cellular automaton diffused his/her individual subjective behaviour to the group decision-making process [20]. The customary logit mostly mirrored passenger shunting at distinctive administration levels and the procedure to accomplish general equilibrium. Initially, this equilibrium procedure was composed of partial equilibrium of a passenger group. The equilibrium procedure described by logit, from partial equilibrium to overall equilibrium, would definitely disturb the price balance in upper programming.

This article utilized the development idea of cellular genetic algorithm to depict the procedure from partial equilibrium to overall equilibrium.

The development steps were as follows:

1. Calculate an individual passenger's adaptability ($\Omega$ represented cellular space):

$$F^{(x,y,z)} = \frac{\max\limits_{x,y,z\in\Omega}[f^{(x,y,z)}] - \min\limits_{x,y,z\in\Omega}[f^{(x,y,z)}]}{f^{(x,y,z)} - \min\limits_{x,y,z\in\Omega}[f^{(x,y,z)}]}. \quad (8)$$

Equation (8) shows the lower generalized travel cost for each passenger, the higher adaptability he/she had.

2. Screened by the rule that an individual traveller's flexibility to encompass neighbours ought to be more noteworthy than or equivalent to his/her own cell (represented with $\Omega$), to ascertain the likelihood of his/her decision:

$$\mathrm{Fit}^{(x',y',z')} = \frac{\mathrm{eval}^{(x',y',z')}}{\sum_{x',y',z'\in\Omega'} \mathrm{eval}^{(x',y',z')}}, \quad (9)$$

where $\mathrm{Fit}^{(x',y',z')}$ represents the probability that a central cell $(x, y, z)$ learned from its neighbours. The cell $(x, y, z)$ would choose an excellent individual from its neighbours.

3. Evolved. Set the learning evolution probability as $\delta$. Perform a crossover operation between the cell $(x, y, z)$ and selected excellent individual $(x^*, y^*, z^*)$, to adjust the probabilistic combination of its own travel mode choice. The algorithm is as follows:

$$\mu_i'^{(x,y,z)} = (1-\delta) \times \mu_i^{(x,y,z)} + \delta \times \mu_i^{(x^*,y^*,z^*)}, \quad i = 1, 2. \quad (10)$$

After the above steps, the proportion of passengers selecting travel mode $i$ in cellular space can be expressed as

$$\mu_i = \frac{\sum_{x,y,z\in\Omega} \mu_i'^{(x,y,z)}}{m^3}. \quad (11)$$

In each iteration, the passenger flow of high-speed passenger travel mode $i$ in the variation process of fare can be calculated.

## 4. Designing a Solution Algorithm for Hierarchical Particle Swarm Model

Particle swarm optimization (PSO) algorithm was a global self-adaptive random search technique based on swarm intelligence. The velocity and position of the particle swarm in the proposed algorithm was updated as follows:

$$\begin{aligned} v_i(t+1) = {} & \omega * v_i(t) + c_1 * \mathrm{rand}\,1 * (p_i - x_i(t)) \\ & + c_2 * \mathrm{rand}\,2 * (p_g - x_i(t)), \end{aligned} \quad (12)$$

$$x_i(t+1) = x_i(t) + v_i(t+1), \tag{13}$$

where $x_i(t), v_i(t)$ are the position and velocity of a particle. rand 1, rand 2 are random numbers within $[0, 1]$. $p_i, p_g$ are the optimal position traversed by particle $i$ and the global optimal position traversed by particle swarm, $\omega$ is an inertia weight, mainly used to strike a balance between the global exploration and local development of the particle swarm. Their numerical values can be determined according to specific optimization problems.

The focused pricing process between high-speed railway and civil aviation depicted in this article was a developmental gaming process between two decision-makers. In a developmental diversion, a game player could develop another system by a previous choice. Hierarchical PSO algorithm was just an iterative and nested optimization algorithm designed with the evolutionary game between two decision-makers. A game player can generate an existing strategy through historical strategies in an evolutionary game. We can simulate a game player's strategy choice process using PSO algorithm, because a PSO algorithm had good function approximation ability.

A game player's technique decision procedure could be recreated utilizing PSO calculation. During the time spent in swarm optimization, a game player could be viewed as an agent. This calculation can emphasize and take care of two advanced issues associated with bi-level programming. Contrarily, the optimal solution $y^{**}$ of lower programming was solved based on the optimal solution $x^*$ of upper programming. After that, $y^{**}$ was delivered to the upper programming model, as the basis to optimize upper solution. This calculation applied a multi-swarm operator self-authoritative dynamic model to understand the gaming and enhancement amongst upper and lower swarms. With the emphasis of swarms, the multi-swarm operator framework can display a progressively stable state from various starting states in a self-hierarchical manner, *i.e.*, Stackelberg balance, accordingly getting the ideal arrangement of a bi-level programming issue. The duplicated flow condition is as per the following:

$$\begin{aligned} x_i(t+1) &= x_i(t) + x_i(t)((AX(T))_i - X(t)^T AX(t)), \\ i &= 1, 2, \ldots, n, \end{aligned} \tag{14}$$

$$\begin{aligned} y_i(t+1) &= y_i(t) + y_i(t)((AY(T))_j - Y(t)^T AY(t)), \\ i &= 1, 2, \ldots, n, \end{aligned} \tag{15}$$

where $x_i(t), X(t), AX(t)_i$ are the proportions of upper swarms which adopted strategy $i$.

The way to explain the model was to utilize 3D cell hereditary calculation to refresh the determination possibility of initial high-speed travel mode and circulate the passenger flow reasonably. The principle steps of calculation were as follows:

As a matter of first importance, when the fares of high-speed railway and civil aviation are $(p_1^t, p_2^t)$, where $t = 0, 1, \ldots, n$, the selection probability of initial high-speed travel mode was updated utilizing a 3D cellular genetic algorithm and the passenger flow $(r_1^t, r_2^t)$ was equalized. Assume that the fare of high-speed railway $p_1^t$ stayed the same. The optimal solution $p_2^{t+1}$ of the fare of civil aviation in (6) was solved using hierarchical particle swarm algorithm. From that point onwards, when the fares of high-speed railway and civil aviation were $(p_1^t, p_2^{t+1})$, again the selection probability of initial high-speed travel mode was refreshed utilizing a 3D cellular genetic algorithm. Assume that the fare of civil aviation $p_2^{t+1}$ remains the same. The optimal solution $p_1^{t+1}$ of the fare of high-speed railway in (5) was solved utilizing the hierarchical particle swarm algorithm. Finally, convergence was determined. If $|p_i^{t+1} - p_i^t| \le \xi$, the fares of high-speed railway and civil aviation were equalized. Otherwise, $t = t + 1$. Proceeding with the above procedure until the point that the judgement condition was satisfied.

The particular strides of calculation were as follows:

*Step 1.* Set the initial fares of high-speed railway and civil aviation as $(p_1^t, p_2^t)$. Let $t = 0$. A swarm $X_1, X_2$ was initialized in the upper programming in (5) and (6).

*Step 2.* When the fare was $(p_1^t, p_2^t)$, perform the cellular automaton evolution rule once. Let the passenger group complete an evolution cycle, update the selection probability of high-speed travel mode, and obtain an equalized passenger flow solution $(r_1^t, r_2^t)$.

*Step 3.* Let the fare of high-speed railway stay the same on the basis of the selection probability of high-speed travel mode updated in Step 2, and obtain swarm $Y_1$ for the lower programming in (6). Utilize $Y_2$ as the premise to perform the upper programming in (6). Finally, solve the optimal individual of swarm $X_2$ and obtain an optimal solution $p_2^{t+1}$ for the fare of civil aviation in (6).

*Step 4.* When the fare was $(p_1^t, p_2^{t+1})$, execute the cellular automaton evolution rule again. Let the passenger group complete an evolutionary cycle and update the selection probability of high-speed travel mode.

*Step 5.* Based on the selection probability of high-speed travel mode updated in Step 2, let the fare of civil aviation stay the same. According to the initialized swarm $X_1$, obtain swarm $Y_1$ for the lower programming in (5). Use $Y_1$ as the basis to execute the upper programming in (5). Finally, solve the optimal individual of swarm $X_1$ and obtain an optimal solution $p_1^{t+1}$ for the fare of high-speed railway in (5).

*Step 6.* Judge convergence. Stop if $|p_i^{t+1} - p_i^t| \le \xi$. Otherwise, $t = t + 1$. Go to Step 2. Through the above steps, an equalized fare between high-speed railway and civil aviation could be computed.

## 5. Case Study

During the time spent on model operation, for simplicity of computation, the running time of vehicles ought to be the normal running time per 100 km. In the meantime, drawing on investigations of important researchers, a few parameters were guessed on the premise of applicable information measurements.

Table 1
Model Parameter Setting

| Parameter | Meaning | Numerical Value | Parameter | Meaning | Numerical Value |
|---|---|---|---|---|---|
| $m \times m \times m$ | Size of cellular space | $10 \times 10 \times 10$ | $\beta_1$ | Passenger's preference for high-speed railway | 1.0326 |
| $\alpha_1$ | Passenger's emphasis on fare | $-1.8355$ | $\beta_2$ | Passenger's preference for civil aviation | 1.0079 |
| $\alpha_2$ | Passenger's emphasis on running time | $-0.2552$ | $p_1^0$ | Initial fare of high-speed railway | 45 |
| $h_1$ | High-speed railway's running time per 100 km | 0.4 | $p_2^0$ | Initial fare of civil aviation | 55 |
| $h_2$ | Civil aviation's running time per 100 km | 0.12 | $p_1^{\min}$ | The minimum fare of high-speed railway | 30 |
| $c_1$ | High-speed railway's operating cost (10,000 yuan) per 100 km | 6 | $p_1^{\max}$ | The maximum fare of high-speed railway | 50 |
| $c_2$ | Civil aviation's operating cost (10,000 yuan) per 100 km | 10 | $p_2^{\min}$ | The minimum fare of civil aviation | 50 |
| $a$ | A parameter in the generalized cost equation | 1.2 | $p_2^{\max}$ | The maximum fare of civil aviation | 80 |
| $b$ | A parameter in the generalized cost equation | 0.4 | $\delta$ | Evolution degree | 0.4 |

### 5.1 The Setting of Basic Parameters

Drawing on studies of relevant scholars [21], [22], the setting of model parameters is given in Table 1.

### 5.2 Competitive Pricing Analysis

The initial price of civil aviation was set as 55 yuan because currently the average fare of civil aviation was 25% off. The fares of high-speed railway and civil aviation [45 yuan, 55 yuan] were used as initial values. Through calculation, parameters in the process of iteration and final results are given in Table 2.

It is evident from Fig. 1 that after nine iterations of fares of high-speed railway and civil aviation, the operation results were converged. The synergistic pricing between high-speed railway and civil aviation accomplished balance and dependability. The outcomes of the evaluation figured that an equalized price interval for high-speed railway was [36.5 yuan, 37 yuan]. An equalized price interval for civil aviation was [55 yuan, 55.5 yuan].

After the analysis of information in Table 2, it is evident that the passenger flow, profit, and iterative fare of both high-speed railway and civil aviation passenger transport changed in every iteration in the first nine iterations. Meanwhile, with the gaming between high-speed railway and civil aviation, the passenger flow and profit of both parties did not change linearly, however, it fluctuated. After the ninth iteration and games, changes in the passenger flow, profit, and iterative fare between both parties tended to be stable. The consequences of fare collaboration were balanced. After rehashed price games, the passenger flow and profit of both parties reached an equalized state. The working benefit was inside an adequate range for both high-speed railway and civil aviation passenger transport. The pricing games between both parties were over.

### 5.3 Comparative Analysis between Swarm Evolution and Logit Separation

Through calculation, the passenger flow based on swarm evolution and logit separation is given in Table 3.

By observing data in Table 3, it is evident that while utilizing 3D cellular genetic algorithm to shun the passenger group, in every iteration, high-speed railway's passenger flow was extremely higher than the civil aviation. However, while utilizing logit separation, in every iteration, high-speed railway's passenger flow was significantly lesser than the civil aviation. In reality, high-speed railway's passenger flow was generally higher than the civil aviation. It shows that the affecting factors considered by passenger shunting based on 3D cellular genetic algorithm might be more extensive than that of logit separation. Based on either 3D cellular genetic algorithm or logit separation, the overall variation trend of the passenger flow of high-speed railway and civil aviation was roughly the same. The distinction was that the variety scope of 3D cellular genetic algorithm was greater than logit separation. It showed that compared with logit separation, utilizing a 3D cellular genetic algorithm, the effect of fare variation on the difference of passenger flow was more noticeable. The above

Table 2
High-Speed Rail and Civil Aviation Competitive Pricing Results

| Initial Fare | Number of Iterations | High-Speed Railway Passenger Flow | Civil Aviation Passenger Flow | High-Speed Railway Profit | Civil Aviation Profit | High-Speed Railway's Next Iterative Fare | Civil Aviation's Next Iterative Fare |
|---|---|---|---|---|---|---|---|
| High-speed railway −45 Civil aviation −55 | 1 | 524 | 476 | 20,436 | 21,420 | 45 | 55 |
| | 2 | 566 | 434 | 20,205.84 | 26,547.56 | 41.6993 | 71.1695 |
| | 3 | 536 | 465 | 18,265.004 | 23,476.03 | 40.0765 | 60.5949 |
| | 4 | 535 | 460 | 17,655.749 | 22,726.73 | 39.0014 | 58.8747 |
| | 5 | 540 | 463 | 17,240.202 | 21,691.11 | 37.9263 | 57.1546 |
| | 6 | 537 | 463 | 16,873.292 | 21,346.43 | 37.4214 | 56.1046 |
| | 7 | 536 | 464 | 15,522.057 | 21,267.20 | 37.0113 | 55.8345 |
| | 8 | 537 | 463 | 16,604.684 | 21,104.74 | 36.9212 | 55.5826 |
| | 9 | 536 | 464 | 16,536.94 | 21,083.04 | 36.8525 | 55.4376 |
| | 10 | 536 | 464 | 16,536.297 | 21,081.60 | 36.8513 | 55.4345 |
| | 11 | 536 | 4,464 | 16,536.297 | 21,081.60 | 36.8513 | 55.4345 |

Table 3
Passenger Flow Based on Swarm Evolution and Logit Separation

| Number of Iterations | High-Speed Railway's Passenger Flow Based on Logit Shunt | High-Speed Railway's Passenger Flow Based on Swarm Evolution | Civil Aviation's Passenger Flow Based on Logit Shunt | Civil Aviation's Passenger Flow Based on Swarm Evolution |
|---|---|---|---|---|
| 1 | 483 | 524 | 517 | 476 |
| 2 | 502 | 566 | 498 | 434 |
| 3 | 495 | 536 | 505 | 464 |
| 4 | 495 | 535 | 505 | 465 |
| 5 | 495 | 540 | 505 | 460 |
| 6 | 495 | 537 | 505 | 463 |
| 7 | 495 | 536 | 505 | 464 |
| 8 | 495 | 537 | 505 | 463 |
| 9 | 495 | 536 | 505 | 464 |
| 10 | 495 | 536 | 505 | 464 |
| 11 | 495 | 536 | 505 | 464 |

investigation demonstrated that a 3D cellular genetic algorithm based on passenger group evolution was more applicable to passenger group shunting in the proposed model in this article than logit separation.

## 6. Conclusion

This paper develops a bi-level programming model for collaborative pricing between high-speed railway and civil aviation to maximize profits and minimize the generalized cost. Then it investigates thoroughly the structure of the bi-level programming model. In addition, it executes the self-organizational equalized shunting on the passenger group utilizing a 3D cellular genetic algorithm. The empirical analysis confirms the appropriateness of hierarchical PSO calculation to the bi-level programming model. Utilizing a contextual analysis pricing of high-speed railway and civil aviation per 100 km at different fares, this paper concludes that the high-speed railway's passenger transport fare per 100 km should be 36.8513 yuan and the civil aviation's fare should be 55.4345 yuan. This is a reasonable collaborative pricing scheme for the high-speed passenger transport. This research avoids the vicious competition between high-speed railway and civil aviation. When the high-speed railway is put into operation, it may refer to the current ticket price of civil aviation to compete more vigorously for the passenger transport market and gain greater economic benefits.

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