Research Article

The Evaluation of Dynamic Airport Competitiveness Based on IDCQGA-BP Algorithm

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Aimed at the multidimensional and complex characteristic of airport competitiveness, a new algorithm is proposed in which BP neural network is optimized by improved double chains quantum genetic algorithm (IDCQGA-BP). The new algorithm is better than existing algorithms in convergence and the diversity of quantum chromosomes. The empirical data of eight airports in Yangtze River Delta in 2011 and 2012 is applied to verify the feasibility of the new algorithm, and then the competitiveness of the eight airports from 2013 to 2015 is gotten through the algorithm. The results show the following. (1) The new algorithm is better than the existing optimization algorithms in the aspects of error accuracy and run time. (2) The gaps of the airports in Yangtze River Delta are narrowing; the competition and cooperation are getting stronger and stronger. (3) The main increase reason of airport competitiveness is the increase of own investment.

1. Introduction

In recent years, with the rapid development of China and the improvement of household consumption level, aviation demand has increased enormously in China. Many cities are planning to invest on new airports or on airport extension, which can offer convenience to people's travel and promote the development of Chinese economy. However, what about the competitiveness of Chinese airports over the years? It has become the center of public concern.

For the past few years, the evaluation of airport competitiveness has been a popular research topic. Lieshout and Matsumoto [1] use route choose model to analyze the probable reconstructs competitiveness of Tokyo Haneda Airport. The results show that Haneda Airport's market share in Japan and Asia-Pacific region will increase signally with the help of Japanese government. Park [2] uses fuzzy linguistic approach to evaluate eight main airports in East Asia from the aspects of geographical characteristics, access system, environmental effects, operational conditions of lines, regional development, availability of planning implementation, socioeconomic effects, and airport charges. Lee

and Yang [3] analyze the strategy of Incheon Airport to be the logistic center of Northeast Asia; the results show that the key is whether Incheon Airport could attract sufficient global logistic service suppliers. Park [4] builds index system from the aspects of service, demand, management, facility and regional space, then evaluates the static competitiveness of the main airports in East Asia through multilayer decision model. Yeh et al. [5] build index system from the aspects of operational management, airport facility and consumer service quality, then analyze the static competitiveness of eleven Asia-Pacific airports through fuzzy multiple attribute evaluation method. Peng and Zhan [6] calculate the static airport competitiveness of Hangzhou airport and other Asia-Pacific airports through AHP model. X. Y. Wu and K. Y. Wu [7] establish AHP evaluation system and compare the advantages and disadvantages of five big airports in Asia-Pacific Ocean and then give out some improvement measures for Pudong airport in Shanghai.

The disadvantages of existing research are as follows.

(1) The existing research mainly focuses on the evaluation of static airport competitiveness; the airport competitiveness under competition and cooperation has not been

TABLE 1: The evaluation index system of dynamic airport competitiveness.

Index classification	First-class indices	Second-class indices
Index system of dynamic airport competitiveness	Regional influence	The proportion of business income divided by city third industry output V_1
		Paid tax V_2 (hundred million yuans)
		Flight zone level V_3^1
	Own strength	The proportion of staff with college degree or above V_4
		Total assets V_5 (hundred million yuans)
		Investment amount V_6 (hundred million yuans)
		The number of nonexclusive service desks V_7
	Market condition	City resident transportation expense V_8
		Average aircrafts movement in a day V_9 (sorties/day)
		Service radius V_{10}^2
		Freight throughput V_{11} (ten thousand tons)
		Passenger throughput V_{12} (ten thousand person-time)

evaluated, which leads to the difference between evaluated competitiveness and real competitiveness.

(2) Few pieces of literature have considered the error accuracy of evaluation method in the difference between evaluated competitiveness and real competitiveness. There are linear features and nonlinear features between airport competitiveness and its evaluation indices. However, few pieces of literature have considered nonlinear features, which may result in irrational results.

This paper is structured as follows: firstly, the evaluation index system of airport competitiveness is built; secondly, a new algorithm is proposed in which BP neural network is optimized by improved double chains quantum genetic algorithm (IDCQGA-BP); Thirdly, the real data of 8 Chinese airports in Yangtze River Delta region is applied to do the empirical study. Moreover, the advantages of the new algorithm over other evaluation methods are analyzed from the aspects of error precision and running time. Finally, the eight airports' dynamic competitiveness from 2013 to 2015 is calculated through the new algorithm. The results show that the new algorithm has good applicability.

2. Index System

According to the existing literature [8, 9], the evaluation index system comes from three aspects: regional influence, own strength, and market condition. The index system is shown in Table 1.

Notes. (1) Flight zone level is defined as the biggest aircraft that the facilities of airport flight zone can support; it has two measurement indicators: the length of runway and the distance between the wingspan of the biggest supported airplane and the felly of main landing gear. In China, flight zone level is divided into several grades: 4F, 4E · 60, 4E · 45, 4D, and 4C, and their measurable values are 5, 4.5, 4, 3, and 2, respectively [9].

(2) Service radius is officially defined by Civil Aviation Administration of China as people amount within 100 km from airport or within 1.5 hours driving range. Service

FIGURE 1: The structure of BP neural network.

radius is defined as people amount of the directly controlled municipalities and prefecture level cities in China [9].

According to the results of famous scholars and institutes [10, 11], the result-type measurement indices of competitiveness are market share and resource usage rate. So this paper defines main business income and return on asset as the ideal outputs.

3. The Model

3.1. BP Neural Network. The basic structure of BP neural network [12] is shown in Figure 1.

If the non-linear smooth activation function is defined as $g : R^1 \rightarrow R^1$, the weight matrixes are defined as $W^0 = \{W_{mp}^0\}_{M \times P}$ and $\omega^0 = \{\omega_{pn}^0\}_{1 \leq p \leq P, 1 \leq n \leq N}$; for any input $\xi = (\xi_1, \dots, \xi_N) \in R^N$, the real output is

$$\zeta_m^0 = g(W_m^0 \cdot \tau^0) = g\left(\sum_{p=1}^P W_{mp}^0 \cdot \tau_p^0\right), \quad m = 1, 2, \dots, M. \quad (1)$$

The output of hidden layer is

$$\tau_p^0 = g(\omega_p^0 \cdot \xi) = g\left(\sum_{n=1}^N \omega_{pn}^0 \cdot \xi_n\right), \quad p = 1, 2, \dots, P. \quad (2)$$

If the input is $\{\xi_j\}_{j=1}^J \subset R^N$, its ideal output is $\{o_m\}_{m=1}^M \subset R^M$ and its real output of BP neural network is $\{c_m\}_{m=1}^M \subset R^M$; the error function can be defined as

$$E(W, \omega) = \frac{1}{2} \sum_{m=1}^M \|o_m - c_m\|^2. \quad (3)$$

$\|\cdot\|$ is European Norm.

Gradient descent algorithm (GDA) is the common method to train BP neural network. However, traditional gradient descent algorithm has some disadvantages in converging slowly and falling into the local minimum point easily [13]. Two methods are applied to improve GDA. (1) Gradient descent algorithm with momentums and adaptive variable rate: adaptive variable rate can accelerate the algorithm convergence, and momentums can reduce the shock and seek global optimum. (2) Some intelligent optimization algorithms can optimize the weights and threshold of BP neural network, which can accelerate the algorithm convergence and seek global optimum. The intelligent optimization algorithms contain genetic algorithm, particle swarm optimization, and so on.

3.2. The Evaluation Algorithm of Dynamic Airport Competitiveness Based on IDCQGA-BP. Quantum genetic algorithm (QGA) [14, 15] is a probability optimization algorithm based on the principle of quantum computing. It has been widely applied in combination optimization and function optimization. Double chains quantum genetic algorithm (DCQGA) is one kind of QGA and has been a popular research topic [16]. In DCQGA, the initial value of θ_{ij} of the quantum bit's probability amplitude $[\cos \theta_{ij}, \sin \theta_{ij}]^T$ is generated randomly in $(0, 2\pi)$, $i = 1, 2, \dots, n$, $j = 1, 2, \dots, m$. n stands for population size; m stands for the number of quantum bits in each quantum chromosome. The phase is updated by quantum rotation gate and chromosomal mutation is realized by quantum nongate, which can enlarge the search space of quantum chromosome and accelerate the algorithm convergence.

According to literature [16–18], this paper proposes a new algorithm in which BP neural network is optimized by improved double chains quantum genetic algorithm (IDCQGA-BP). The new algorithm calculates the selective probability and the expectation reproduction rate of quantum chromosome through vector distance. The new algorithm can evaluate the dynamic airport competitiveness under competition and cooperation. Its principle is that IDCQGA-BP algorithm calculates the existing airport competitiveness through existing data, and then the influence of existing competitiveness on the future competitiveness's evaluation indices is analyzed from the aspects of competition and cooperation. The future value of evaluation indices is gotten according to the influence, and then IDCQGA-BP is used to calculate the future airport competitiveness based on the future value of evaluation indices.

The steps of the algorithm are as follows.

(1) Initialize the quantum population. Choose n quantum chromosomes with m quantum bits in $(0, \pi/2)$, which form

the initial quantum population $X = \{x_1, x_2, \dots, x_n\}$. The probability amplitude of each quantum bit is considered as two paratactic genes and each chromosome contains two paratactic gene chains; each gene chain stands for an optimal solution:

$$x_i = \begin{bmatrix} \cos \theta_{i1} \\ \sin \theta_{i1} \end{bmatrix} \begin{bmatrix} \cos \theta_{i2} \\ \sin \theta_{i2} \end{bmatrix} \dots \begin{bmatrix} \cos \theta_{im} \\ \sin \theta_{im} \end{bmatrix}, \quad (4)$$

$\theta_{ij} = \pi/2 * \text{rand}$, where rand is the random number in $(0, 1)$.

(2) Transform the solution space. In initial population, each quantum chromosome contains $2m$ quantum bits probability amplitude. In this step, linear transformation is applied to map the $2m$ quantum bits probability amplitude in $(0, \pi/2)^m$ to the weight value space of BP neural network. According to literature [19], the initial value of the weights in BP neural network should be the random value in $[a, b]$. If the j th quantum bit of quantum chromosome x_i is $[\alpha_j^i, \beta_j^i]^T$, its corresponding value space vector is

$$\begin{aligned} X_{jc}^i &= a + (b - a) * \alpha_j^i, \\ X_{js}^i &= a + (b - a) * \beta_j^i, \end{aligned} \quad (5)$$

where X_{jc}^i is the cosine solution of the j th quantum bit of quantum chromosome x_i , X_{js}^i is the sine solution of the j th quantum bit of quantum chromosome x_i , α_j^i is the probability amplitude of X_{jc}^i corresponding to quantum state $|0\rangle$, and β_j^i is the probability amplitude of X_{js}^i corresponding to quantum state $|1\rangle$.

(3) Calculate the vector distance and calculate the selective probability and the expectation reproduction rate of population X based on vector distance concentration.

The vector distance of chromosome x_i is

$$\text{dis}(x_i) = \sum_{k=1}^n |F(x_i) - F(x_k)|. \quad (6)$$

The vector distance concentration is

$$C(x_i) = \frac{1}{\text{dis}(x_i)} = \frac{1}{\sum_{k=1}^n |F(x_i) - F(x_k)|}. \quad (7)$$

The selective probability is

$$P(x_i) = \frac{\text{dis}(x_i)}{\sum_{i=1}^n \text{dis}(x_i)} = \frac{\sum_{k=1}^n |F(x_i) - F(x_k)|}{\sum_{i=1}^n \sum_{k=1}^n |F(x_i) - F(x_k)|}. \quad (8)$$

The expectation reproduction rate is

$$e(x_i) = \frac{F(x_i)}{C(x_i)} = F(x_i) \sum_{k=1}^n |F(x_i) - F(x_k)|. \quad (9)$$

(4) Sort the initial population X according to the selective probability P and the expectation reproduction rate e . The top ten quantum chromosomes that are high in expectation reproduction rate enter into new population X_{new} and the h quantum chromosomes whose selective probability is bigger

than certain value P_r ($P_r = 0.6 * \max(P)$) enter into new population X_{new} . Then $n - 10 - h$ quantum chromosomes generated randomly in $(0, \pi/2)$ enter into new population X_{new} .

(5) Update the quantum phase.

The formula is

$$\begin{bmatrix} \cos(\Delta\theta) & -\sin(\Delta\theta) \\ \sin(\Delta\theta) & \cos(\Delta\theta) \end{bmatrix} \begin{bmatrix} \cos(\theta) \\ \sin(\theta) \end{bmatrix} = \begin{bmatrix} \cos(\theta + \Delta\theta) \\ \sin(\theta + \Delta\theta) \end{bmatrix}, \quad (10)$$

$\Delta\theta_i = -\text{sgn}(\sin(\theta_i - \theta_0)) * \Delta\theta_0 * \exp(-(\nabla F(x_i) - \nabla F_{\min})/(\nabla F_{\max} - \nabla F_{\min}))$, where ∇ is the gradient function; θ_0 is the iterative initial value.

(6) Calculate the mutation. Quantum nongate is used to calculate the mutation. Choose a chromosome randomly from the population according to the mutation probability; then choose several quantum bits randomly in the selected chromosome and use quantum nongate to process selected quantum bits, which can exchange the two probability amplitudes of the quantum bit and calculate the two gene chains' mutation.

(7) Calculate the relevance degrees of the chromosomes. The relevance degree function is based on the error function of BP neural network. It is

$$F(x_i) = \exp\left(-\frac{1}{2}\|\text{tar}(x_i) - g(W * g(\omega * x_i))\|^2\right), \quad (11)$$

where tar is the ideal output of BP neural network, W is the weight matrix between hidden layer and output layer, ω is the weight matrix between hidden layer and input layer, and g is activation function.

(8) Revise the algorithm. Sort the quantum bit angel θ of all quantum chromosomes in X_{new} and record the maximum $\theta_{\max}$ and minimum $\theta_{\min}$. If $|\theta_{\max} - \theta_{\min}| < \varepsilon$, then the value space should be reset as $(0, \pi/2)$.

(9) Return to step (2) and repeat the rest steps until either the convergence condition or the maximum iteration step is satisfied.

(10) Use the trained BP neural network and the data at t and $t - 1$ to calculate the airport competitiveness $\text{Com}(t)$ and $\text{Com}(t - 1)$.

(11) Normalize the main business income and return on assets at t and $t - 1$ and set their average value as the ideal output of BP neural network, which can be used to calculate the error accuracy of the algorithm.

(12) Analyze the influence of the airport competitiveness at t on the evaluation indices at $t + 1$ and estimate the value of the indices at $t + 1$. There are two aspects. (1) *Competition*. The key point is to analyze the influence of existing competitiveness on the future market shares of this airport and other airports. (2) *Cooperation*. The key point is to analyze the influence of the cooperation on international lines on the future market shares of this airport and other airports.

(1) *Competition*. According to literature [9], if airport A and airport B have direct competition (the service radiuses of the two airports have overlap), then the competitiveness of airport A will influence the future market conditions of airport A and airport B . In the same way, the competitiveness

of airport B will influence the future market conditions of airport A and airport B .

If there are N airports in a region whose service radiuses have overlap and the competitiveness of the N airports at t is $(\text{Com}_1(t), \text{Com}_2(t), \dots, \text{Com}_N(t))$ and the competitiveness of the N airports at $t - 1$ is $(\text{Com}_1(t - 1), \text{Com}_2(t - 1), \dots, \text{Com}_N(t - 1))$, the competitiveness change of airport i from $t - 1$ to t will influence the market share of airport i at $t + 1$. The change value 1 of passenger throughput V_{12} at $t + 1$ is

$$\left(\frac{\text{Com}_i(t)}{\sum_{i=1}^N \text{Com}_i(t)} - \frac{\text{Com}_i(t-1)}{\sum_{i=1}^N \text{Com}_i(t-1)} \right) * V_{12}(it). \quad (12)$$

Similarly, the change value 1 of freight throughput V_{11} , the change value 1 of average aircrafts movement in a day V_9 , the change value 1 of business income V_{01} , the change value 1 of paid tax V_2 , and the change value 1 of total assets V_5 are

$$\begin{aligned} & \left(\frac{\text{Com}_i(t)}{\sum_{i=1}^N \text{Com}_i(t)} - \frac{\text{Com}_i(t-1)}{\sum_{i=1}^N \text{Com}_i(t-1)} \right) * V_{11}(it), \\ & \left(\frac{\text{Com}_i(t)}{\sum_{i=1}^N \text{Com}_i(t)} - \frac{\text{Com}_i(t-1)}{\sum_{i=1}^N \text{Com}_i(t-1)} \right) * V_9(it), \\ & \left(\frac{\text{Com}_i(t)}{\sum_{i=1}^N \text{Com}_i(t)} - \frac{\text{Com}_i(t-1)}{\sum_{i=1}^N \text{Com}_i(t-1)} \right) * V_{01}(it), \\ & \left(\frac{\text{Com}_i(t)}{\sum_{i=1}^N \text{Com}_i(t)} - \frac{\text{Com}_i(t-1)}{\sum_{i=1}^N \text{Com}_i(t-1)} \right) * V_2(it), \\ & \left(\frac{\text{Com}_i(t)}{\sum_{i=1}^N \text{Com}_i(t)} - \frac{\text{Com}_i(t-1)}{\sum_{i=1}^N \text{Com}_i(t-1)} \right) * V_5(it). \end{aligned} \quad (13)$$

(2) *Cooperation*. In a region, some airports are international hub airports, and some are regional airports. The cooperation among the airports is embodied in the cooperation on international lines between international hub airports and regional airport. The international lines of the N airports at t are $\text{In } t_1(t), \text{In } t_2(t), \dots, \text{In } t_N(t)$; the bigger the proportion of airport i 's international lines is, the more cooperation benefits airport i can get. So the change value 2 of passenger throughput V_{12} at $t + 1$ is

$$\frac{\text{In } t_i}{\sum_{i=1}^N \text{In } t_i} * \sum_{i=1}^N V_{12}(it) * p_t * \theta_t, \quad (14)$$

where p_t is the proportion of the passenger throughput of international lines divided by the total passenger throughput and θ_t is the natural population growth rate of the region.

Similarly, the change value 2 of freight throughput V_{11} , the change value 2 of average aircrafts movement in a day V_9 ,

the change value 2 of business income V_{01} , the change value 2 of paid tax V_2 , and the change value 2 of total assets V_5 are

$$\begin{aligned}
& \frac{\ln t_i}{\sum_{i=1}^N \ln t_i} * \sum_{i=1}^N V_{11}(it) * p_t * \theta_t, \\
& \frac{\ln t_i}{\sum_{i=1}^N \ln t_i} * \sum_{i=1}^N V_9(it) * p_t * \theta_t, \\
& \frac{\ln t_i}{\sum_{i=1}^N \ln t_i} * \sum_{i=1}^N V_{01}(it) * p_t * \theta_t, \\
& \frac{\ln t_i}{\sum_{i=1}^N \ln t_i} * \sum_{i=1}^N V_2(it) * p_t * \theta_t, \\
& \frac{\ln t_i}{\sum_{i=1}^N \ln t_i} * \sum_{i=1}^N V_5(it) * p_t * \theta_t.
\end{aligned} \tag{15}$$

According to the results of competition and cooperation, the passenger throughput of airport i at $t + 1$ is

$$\begin{aligned}
& V_{12}(i(t+1)) \\
& = V_{12}(it) + \left(\frac{\text{Com}_i(t)}{\sum_{i=1}^N \text{Com}_i(t)} - \frac{\text{Com}_i(t-1)}{\sum_{i=1}^N \text{Com}_i(t-1)} \right) * V_{12}(it) \\
& + \frac{\ln t_i}{\sum_{i=1}^N \ln t_i} * \sum_{i=1}^N V_{12}(it) * p_t * \theta_t.
\end{aligned} \tag{16}$$

The freight throughput V_{11} , the average aircrafts movement in a day V_9 , the business income V_{01} , the paid tax V_2 , and the total assets V_5 at $t + 1$ are

$$\begin{aligned}
& V_{11}(i(t+1)) \\
& = V_{11}(it) + \left(\frac{\text{Com}_i(t)}{\sum_{i=1}^N \text{Com}_i(t)} - \frac{\text{Com}_i(t-1)}{\sum_{i=1}^N \text{Com}_i(t-1)} \right) \\
& * V_{11}(it) + \frac{\ln t_i}{\sum_{i=1}^N \ln t_i} * \sum_{i=1}^N V_{11}(it) * p_t * \theta_t, \\
& V_9(i(t+1)) \\
& = V_9(it) + \left(\frac{\text{Com}_i(t)}{\sum_{i=1}^N \text{Com}_i(t)} - \frac{\text{Com}_i(t-1)}{\sum_{i=1}^N \text{Com}_i(t-1)} \right) \\
& * V_9(it) + \frac{\ln t_i}{\sum_{i=1}^N \ln t_i} * \sum_{i=1}^N V_9(it) * p_t,
\end{aligned}$$

TABLE 2: The parameters of IDCQGA-BP.

Input neurons	12
Hidden neurons	20
Output neurons	1
Weights	260
Population size	1000
Mutation rate	0.1
Initial phase	0.01π
Target error	0.01
Max iterations	5000
$[a, b]$	$[0, 0.38]$
ε	0.0001

$$\begin{aligned}
& V_{01}(i(t+1)) \\
& = V_{01}(it) + \left(\frac{\text{Com}_i(t)}{\sum_{i=1}^N \text{Com}_i(t)} - \frac{\text{Com}_i(t-1)}{\sum_{i=1}^N \text{Com}_i(t-1)} \right) \\
& * V_{01}(it) + \frac{\ln t_i}{\sum_{i=1}^N \ln t_i} * \sum_{i=1}^N V_{01}(it) * p_t * \theta_t, \\
& V_2(i(t+1)) \\
& = V_2(it) + \left(\frac{\text{Com}_i(t)}{\sum_{i=1}^N \text{Com}_i(t)} - \frac{\text{Com}_i(t-1)}{\sum_{i=1}^N \text{Com}_i(t-1)} \right) \\
& * V_2(it) + \frac{\ln t_i}{\sum_{i=1}^N \ln t_i} * \sum_{i=1}^N V_2(it) * p_t * \theta_t, \\
& V_5(i(t+1)) \\
& = V_5(it) + \left(\frac{\text{Com}_i(t)}{\sum_{i=1}^N \text{Com}_i(t)} - \frac{\text{Com}_i(t-1)}{\sum_{i=1}^N \text{Com}_i(t-1)} \right) \\
& * V_5(it) + \frac{\ln t_i}{\sum_{i=1}^N \ln t_i} * \sum_{i=1}^N V_5(it) * p_t * \theta_t.
\end{aligned} \tag{17}$$

Then, according to their historical growth rates, this paper predicts the future value of flight zone level, the proportion of staff with college degree or above, investment amount, the number of nonexclusive service desks, city resident transportation expense, service radius, and city third industry output.

(13) Set the indices calculated in step (12) as the network inputs, and then use the BP neural network trained in step (10) to calculate the dynamic airport competitiveness under competition and cooperation at $t + 1$.

The main improvements are embodied in the following. (1) The initial value of phase is randomly selected in $(0, \pi/2)$ instead of $(0, 2\pi)$ and the value space of θ is revised at step (8). It can reduce the search space of the algorithm signally and assure the algorithm's faster convergence. (2) The selective probability and expectation reproduction rate calculated by vector distance can increase the diversity of

TABLE 3: The results in 2011.

Airports	Shanghai Pudong	Shanghai Hongqiao	Ningbo	Hefei	Hangzhou	Nanjing	Wenzhou	Wuxi
Target value	0.5513	0.3404	0.0667	0.0585	0.2329	0.1739	0.0745	0.0391
BP	0.6207	0.4898	0.1237	0.0954	0.3615	0.2044	0.1011	0.0594
QGA-BP	0.5090	0.4310	0.0882	0.0472	0.2448	0.1855	0.0909	0.0532
DCQGA-BP	0.5409	0.3930	0.0678	0.0496	0.2945	0.1818	0.0891	0.0498
IDCQGA-BP	0.5622	0.3641	0.0732	0.0597	0.2116	0.1691	0.0727	0.0367

TABLE 4: The results in 2012.

Airports	Shanghai Pudong	Shanghai Hongqiao	Ningbo	Hefei	Hangzhou	Nanjing	Wenzhou	Wuxi
Target value	0.5745	0.3631	0.1183	0.0735	0.2625	0.1847	0.0858	0.0395
BP	0.6386	0.4098	0.1398	0.0996	0.3115	0.2052	0.1062	0.0602
QGA-BP	0.5370	0.3910	0.1088	0.0868	0.3048	0.1955	0.1003	0.0578
DCQGA-BP	0.6109	0.3830	0.1278	0.0696	0.2813	0.1618	0.0991	0.0502
IDCQGA-BP	0.5922	0.3741	0.1032	0.0697	0.2416	0.1791	0.0827	0.0387

quantum chromosomes and can reduce the search space of θ . Then, according to literature [19], this paper sets the initial weight's value range of BP neural network as $[a, b]$ (in the numerical computation, it is $[0, 0.38]$), which can accelerate the convergence.

4. The Case

4.1. The Data. The basic data in this paper comes from eight airports in Yangtze River Delta in 2011 and 2012. The eight airports are Shanghai Pudong airport, Shanghai Hongqiao airport, Ningbo Lishe airport, Hefei Luogang airport, Hangzhou Xiaoshan airport, Nanjing Lukou airport, Wenzhou Yongqiang airport, and Wuxi Shuofang airport. The data of service radius comes from the definition. Because Shanghai Pudong airport is listed airport, its "proportion of staff with college degree or above," "total assets," "investment amount," "return on asset," "freight throughput," "passenger throughput," "aircraft movements," and "main business income" come from annual report. The data of other airports comes from research report and network data. Other data comes from the statistical yearbook of the city.

4.2. The Advantages and Disadvantages of the Algorithms. The activation function is $1/(1 + \exp(-2x))$; other parameters of IDCQGA-BP are shown in Table 2.

In order to analyze the advantages and disadvantages of IDCQGA-BP, this paper uses BP neural network [12], BP neural network optimized by quantum genetic algorithm (QGA-BP) [20–22], BP neural network optimized by double chains quantum genetic algorithm (DCQGA-BP) [16] and BP neural network optimized by improved double chains quantum genetic algorithm (IDCQGA-BP) to evaluate the airport competitiveness. The ideal output is defined as the average value of normalized main business income and normalized return on asset. This paper runs the four algorithms ten times based on the real data in 2011 and 2012. The results are the average value of the ten results, as shown in Tables 3 and 4.

From Tables 3 and 4, we can get the following conclusions. (1) In Yangtze River Delta, Shanghai Pudong airport is an international hub airport, Shanghai Hongqiao airport, Hangzhou Xiaoshan airport, and Nanjing Lukou airport are regional hub airports, and Ningbo Lishe airport, Hefei Luogang airport, Wenzhou Yongqiang airport, and Wuxi Shuofang airport are feeder airports. These conclusions are the same as those in literature [23]. (2) All the eight airports' competitiveness has increased from 2011 to 2012, but the increase rates are different. Ningbo Lishe airport's increase rate is the biggest (41%); the main increase reason is the increase of market condition. Then the medial ones are those of Hefei Luogang airport (16.75%), Hangzhou Xiaoshan airport (14.18%), and Wenzhou Yongqiang airport (13.76%). Their main increase reason is the improvement of regional influence. The smaller ones are those of Shanghai Pudong airport (5.34%), Shanghai Hongqiao airport (2.75%), and Wuxi Shuofang airport (5.45%). Their main increase reason is the improvement of own strength, especially the increase of own investment.

The errors and running times are shown in Table 5.

From Table 5, it can be concluded that IDCQGA-BP is better than the existing optimization algorithms in the aspects of error accuracy and run time.

4.3. Dynamic Airport Competitiveness. In this paper, the airport competitiveness in 2011 and 2012 is the initial value to analyze the dynamic airport competitiveness of the eight airports in Yangtze River Delta from 2013 to 2015. This paper supposes that the flight zone levels of the eight airports from 2013 to 2015 are the same as those in 2012. The average increase rate of "the proportion of staff with college degree or above" is 15.2% based on the historical data from 2008 to 2012. The average increase rate of "investment amount" is 13.2%; the number of nonexclusive service desks remains unchanged. The average increase rate of "city resident transportation expense" is 11.08% based on the city statistical yearbook. The average increase rate of "service radius" is 2.8% and the average increase rate of "third industry output" is 17.7%.

TABLE 5: The errors and running times of the four algorithms.

Algorithms	Maximum error	Minimum error	Average error	Average running time (s)
BP	1.156	0.560	0.714	11.539
QGA-BP	0.784	0.425	0.592	7.891
DCQGA-BP	0.629	0.162	0.301	6.560
IDCQGA-BP	0.627	0.146	0.287	6.195

TABLE 6: The overlap conditions of the eight airports' service radius.

Overlap or not	Pudong	Hongqiao	Ningbo	Hefei	Hangzhou	Nanjing	Wenzhou	Wuxi
Pudong	—	1	1	0	1	0	0	1
Hongqiao	1	—	1	0	1	0	0	1
Ningbo	1	1	—	0	1	0	0	0
Hefei	0	0	0	—	0	1	0	0
Hangzhou	1	1	1	0	—	0	0	1
Nanjing	0	0	0	1	0	—	0	1
Wenzhou	0	0	0	0	0	0	—	0
Wuxi	1	1	0	0	1	1	0	—

Note. 1 stands for overlap, 0 stands for no overlap.

The overlap conditions of the eight airports' service radius are shown in Table 6.

The international lines of the eight airports in 2012 are shown in Table 7.

The proportion of the passenger throughput in international lines divided by the total passenger throughput is $p_i = 20.2\%$. Based on the increase rate analysis, this paper uses IDCQGA-BP algorithm to calculate the airport competitiveness of the eight airports in Yangtze River Delta from 2013 to 2015, as shown in Table 8.

As shown in Table 8, the eight airports' competitiveness has increased from 2013 to 2015, but the increase rates are different. The average increase rate of Wuxi Shuofang airport is the biggest; then the medial ones are those of Hefei Luogang airport and Ningbo Lishe airport. The smaller ones are those of Hangzhou Xiaoshan airport, Nanjing Lukou airport, and Wenzhou Yongqiang airport. The smallest ones are those of Shanghai Pudong airport and Shanghai Hongqiao airport. The competitiveness of feeder airports increases signally, whose average increase rate (17.44%) is bigger than international hub airport (3.32%) and regional hub airports (6.94%). The average increase rate of regional hub airports is bigger than international hub airport. The gaps of the airports in Yangtze River Delta are narrowing; the competition and cooperation are getting stronger and stronger. The main increase reason of Wuxi airport is the increase of own investment. More investment could lead to software and hardware conditions upgrade and help attract more airlines, especially international flights. More investment could assure more open aero policies. However, blind extension should be avoided and more measures should be taken from the aspects of improving resource usage efficiency such as the efficiency of capital, flights, and human resources.

5. Conclusion

In this paper, the airport competitiveness when airports are facing competition and cooperation is studied. The empirical study is based on the data of eight airports in Yangtze River Delta in 2011 and 2012, and the eight airports' dynamic competitiveness under competition and cooperation from 2013 to 2015 is calculated. The average increase rate of feeder airports is bigger than international hub airport and regional hub airports. The average increase rate of regional hub airports is bigger than international hub airport. The gaps of the airports in Yangtze River Delta are narrowing; the competition and cooperation are getting stronger and stronger.

On the whole, the contribution of this paper to the literature is embodied in two aspects. Firstly, a new algorithm—IDCQGA-BP algorithm—is proposed. From the results, it can be concluded that IDCQGA-BP is better than the existing optimization algorithms in the aspects of error accuracy and run time. IDCQGA-BP has satisfactory imitative effect and high accuracy; its applicability has been verified. Secondly, The paper simulates the influence of competition and cooperation on airports' market share and calculates the dynamic airport competitiveness when airports are facing competition and cooperation. It fills the gap of the existing literature in which only static airport competitiveness has been evaluated and lays good foundation for evaluating dynamic airport competitiveness reasonably.

However, it should be noted that the parameter selection process has certain randomness. This paper runs the algorithm ten times to minimize the effect caused by this randomness, but this will increase the workload. Future research could focus on avoiding the randomness to reduce the workload.

TABLE 7: The international lines of the eight airports in 2012.

Airports	Shanghai Pudong	Shanghai Hongqiao	Ningbo	Hefei	Hangzhou	Nanjing	Wenzhou	Wuxi
Number	93	10	13	8	27	18	7	7

TABLE 8: The dynamic airport competitiveness of the eight airports from 2013 to 2015.

Airports	Shanghai Pudong	Shanghai Hongqiao	Ningbo	Hefei	Hangzhou	Nanjing	Wenzhou	Wuxi
2013	0.6254	0.3905	0.1204	0.0965	0.2535	0.1847	0.0993	0.0547
2014	0.6544	0.4197	0.1449	0.1172	0.2703	0.1951	0.1025	0.0666
2015	0.6675	0.4252	0.1637	0.1362	0.2913	0.2201	0.1138	0.0883
Average increase rate (%)	3.3194	4.3940	16.6617	18.8312	7.1982	9.2223	7.1235	27.1688

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