The prediction on Residential real estate price Based on BPNN

Hongbin Xue

Department of City Management, Hunan City University, Yiyang, Hunan, 413000 ,China 2293780231@qq.com

Abstract—The paper brings up a mixed optimizing model based on IPSO-BPNN. The model has used IPSO to optimize the definition of original weights and threshold value. We take the real estate market in Changsha as an example. This algorithm can be applied in the price prediction of residential property.

Keywords- prediction; price; real estate; BPNN

I. Introduction

So far, scholars home and abroad have done research on real estate market and price[1-13].Kiel and Zable[1] have analyzed the the influence of geological location on the price of real estate through 3L approach. Zhou and Sornette[2] have used the real estate data of America to do research on foam of America real estate market.Zhou and Sornette[3] analyze the status of Las Vegas real estate in America, and conduct a thorough research on the prediction of foam in real estate, season changing and CSW index. Rapach and Strauss[4] analyze the predictable difference among the different states in America real estate market.Cutts[5] and others use the data of 27 cities to do reversion to house price and room rate, and study the longterm relation between house price and room rate. The research suggest that house price and room rate can be explained by the common economic variable(per income,the increase of urban population). Pace and others [6] analyze and predict the trend of Baton Rouge real estate price based on panel data model. The scholars at home widely argue that the house price is determined by the supply and demand on the market[7-8]. However, other scholars hold that demand is the main element that determines the house price rather than supply[9-10]. Because the supply in short term lacks elasticity. Chai Qiang[11] classifies demand into real demand and false demand and points that the house price raise brought by false demand can not last for long time. Other scholars think that the unreasonable supply is the main reason that causes the high increase of house price[12]. Yan Yan and others [13]use TEI@I methodology to predict the house price in China, and analyze the influence of policy on house price. Hu Liuxing[14]use gray system theory to do prediction analysis of house price. Zhang Wei[15] use rough set theory-BP neural network to predict house price in China.

From what has been discussed above,we know that among all the existing documents, most of the documents talk about the elements that determine the house price. However,the documents about the prediction of house price are relative less [6,13]. Among the documents about the prediction of house price, some constitute panel data models that consider several elements related to house price; Some adopt many complicated technology to do prediction analysis. This text brings up a simple and feasible prediction model—a house price prediction model based on gray correlation theory and IPOS-BPNN. It digs main factors from several factors that influence the house price, and do scenario analysis of the main factors, then use IPOS-BPNN method to predict the trend of China house price.

II. THE BASIC PRINCIPLE OF PREDICTION MODEL

Nowadays ,there is a wide application of artificial network.It mainly consists of neural identification ,optimizing design and prediction control.We usually do house price prediction based on artificial neural and combine several theory. However, because the assignment of original weights is random, it is easy to fall into partial minimum value. If we combine IPSO algorithm with BP network, we can get the assignment of original weights and threshold value, and the extremum is easy to get out of the partial minimum, which optimize the structure of network. So, it has a striking effect on the prediction assessment of residential property.

This model adopts gray correlation theory to do selection from numerous evaluating indicator. We get the matrix of original weights and threshold value through IPSO algorithm and BP network. At last, we assign original weights and threshold value to BP network. After network training, the prediction outcome of output model is illustrated in picture 1.



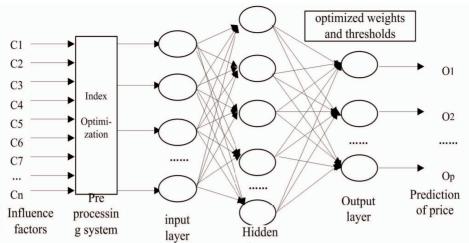


Figure 1. Optimization model of BP network

III. THE IMPROVED PARTICLE SWARM NEURAL NETWORK MODEL BASED ON THE ANALYSIS OF GRAY CORRELATION

A. Analysis of gray correlation

The basic idea of the GRA is to judge the correlation according to the similarity of the sequence curve geometric figure. The closer the curve is, the higher the relational grade is, otherwise, it smaller(deng Julong)[16]. The concrete calculation procedure of gray system analysis is as follows:

1. Establish the reference sequence and comparative sequence. The data sequence that reflect the behaviour of the system is called reference sequence. The one that influence the behaviour of the system is called comparative sequence,

Let the system action sequence be $X = \{\chi_i | i \in N, N = \{0,1,2,..., m\}, m \ge 2\}$

$$\chi_{i} = (\chi_{i}(1), \chi_{i}(2), ..., \chi_{i}(n))$$
 , $\chi_{i}(\kappa) \in \chi_{i}, \kappa \in K, K = \{1, 2, ..., n \}, n \ge 3 \}$

Where, the reference sequence is: $\chi_{0}(\kappa)$, $(\kappa = 1, 2, ..., n)$, and the comparative sequence, $\chi_{i}(\kappa)$, $(i = 1, 2, ..., m, \kappa = 1, 2, ..., n)$.

2. The reference sequence and comparative sequence were handled dimensionlessly. Since the physical meaning each factors are quite different in system, the data dimensions are not always the same. As a result, it is hard to make a comparison or difficult to draw a accurate conclusion. So, dimensionless is quite necessary in gray related analysis. The main methods are initial-value method, mean-value method, and interval relative value method, in this paper the mean-value process is mainly adopted, let:

$$\frac{\overline{\chi}_{0}}{\chi_{0}} = \frac{1}{n} \sum_{\kappa=1}^{n} \chi_{0}(\kappa) , \quad \chi_{0}' = \chi_{0}(\kappa) / \overline{\chi_{0}} , \quad \overline{\chi_{i}} = \frac{1}{n} \sum_{\kappa=1}^{n} \chi_{i}(\kappa) ,$$

$$\chi_{i}' = \chi_{i}(\kappa) / \overline{\chi_{i}} \qquad (\kappa = 1, 2, ..., n, i = 1, 2, ..., m_{0}) \qquad (2)$$

3. Calculating the gray relation coefficient between reference sequence and comparative sequence $\xi_{-0.1}(\kappa_-)$.

What is called the relational degree is substantively beyond x_i among the same parent sequence x_0 ,marked

means the geometric figure difference among curves. So the difference values can be take as the measuring scale of relational degree. A reference sequence x_0 has several comparative sequence $\chi_1, \chi_2, \dots, \chi_m$, and correlation coefficient of reference sequence and comparative sequence at each time (that is each point on curve) can be calculated as the following steps:

Step one: calculating the sequence difference. Let:

$$\Delta_{0i}(k) = |\chi_{0}' - \chi_{i}'|, i = 1, 2, ..., m$$
 (3)

Step two: calculating the maximum and minimum difference value between two poles. Let:

$$M = \max_{i} \max_{k} \Delta_{0i}(k), m = \min_{i} \min_{k} \Delta_{0i}(k)$$
(4)

Step three: calculating correlation coefficient.

$$\xi_{0i}(k) = \frac{m + \zeta M}{\Delta_{0i}(k) + \zeta M}$$

Where, distinguish factor ζ is $0 < \zeta < 1$; As to $\zeta \in (0,1)$, this paper adopts: $\zeta = 0.5$. $(\kappa = 1,2,...,n$, i = 1,2,...,m.)

4. Calculating correlation r_{0i} . Since correlation coefficient refers to the geometric figure difference among curves, it has more than one coefficient, however, the information is too much scattered to make a wholeness comparison. So , it is essential to centralize each time(each point on curve), namely the average value. As a amount expression of the reference sequence and comparative sequence, the formula of correlation r_{0i} is showed as follows:

$$r_{0i} = \frac{1}{n} \sum_{i=1}^{n} \xi_{0i}(k)$$
 (6)

5.Put the correlation sequence in order $_{\circ}$ The correlation between factors are mainly described according to the size order, instead which of the relation degree .The correlation sequence is formed by arranging m subsequences and the same parent sequence according to the order from big to small, which is mark as $\{x\}$. It reflect the excellent and inferior of its subsequences. If $r_{0i} > r_{0j}$, then x_i has an advantage over x_j among the same parent sequence x_0 , marked as $\{x \mid |x_0\} > \{x \mid |x_0\} > \{x \mid |x_0\} > \{x \mid |x_0\} > x_0$, then x_i goes

as
$$\{\chi_{i}|\chi_{0}\}\langle\{\chi_{i}|\chi_{0}\}\rangle$$

B The improved particle swarm algorithm

1) Standard particle swarm algorithm

Particle Swarm Optimizer(PSO) is a algorithm based on swarm intelligence. It achieves optimizing searching under the guide of swarm intelligence produced through the cooperation and competition among the particles [17]. The algorithm is simple and flexible and easy to come true. The searching speed is fast in the first period. However, the speed becomes slower and slower in the later period. Particle Swarm perform strong homoplasy. It is easy to fall into partial optimum value.

The mathematical description of PSO is as follows:

$$v_{ij}^{k+1} = w \times v_{ij}^{k} + c_{1} \times r_{1} \times (pbest_{ij}^{k} - x_{ij}^{k}) + c_{2} \times r_{2}(gbest_{ij}^{k})$$
(7)
$$x_{ij}^{k+1} = x_{ij}^{k} + v_{ij}^{k+1}$$
(8)

Among them, v_{ij}^k and x_{ij}^k are velocity vector and position vector of particle I in the kth iteration. c_I and c_2 are learning factors; r_I and r_2 are random number among [0, 1; pbest_{ij} is the individual optimum value of particle; gbest_{ij} is the group optimum value of particle; w is inertia weights factor, which balance the partial optimum value and global optimum value.

2) The improved particle swarm algorithm

As to the value of w, most of the documents will adopt linear reduction method. The drawbacks of this method is that the value of w has high randomness, and the enlightenment of searching direction is weak. To solve this problem, this text studies adjusting the value of w based on the planeness of objective function, making w change with the evolutionary rate of particle. With the nonlinear changes of iteration times, this text brings up the evolutionary rate of particle $\varphi(t)$, which reflects the evolution degree of particle i in searching position and suggests the difference between present position and convergence position of particle.

$$\varphi(t) = \tan \beta = \alpha(t) / w(t-1)$$

When $\varphi(t) > 1$, this iteration diverges. It requires the searching step length to increase , thus strengthening the ability of searching optimum value globally . When $0 < \varphi(t) < 1$, this iteration converges. It requires the searching step length to decrease, thus speeding up the crowding level of particle and strengthening he ability of searching optimum value partially. After several iterations, the value of $\varphi(t)$ stays 0. It means that particle has found optimum value or the algorithm suspends . The improved inertia weight w change according to the following formula:

$$w(t+1) = c \times \alpha(t) / \alpha(t+1), \qquad c \in (0,1)$$

of network, \hat{y}_{t} is the actual output, w_{ji} is the network

(10)

$$\alpha(t) = \frac{1}{m} \sum_{i=1}^{m} |f(x_i(t)) - f(x_{best}(t))|, \qquad t = 1, 2, \dots, n$$
(11)

Among them, $f(x_i(t))$ is the function value of the ith particle in the tth time iteration:

 $f(x_i(t) = f(x_{i,1}(t), x_{i,2}(t), \dots, x_{i,k}(t), f(x_{best}(t))$ is the function value of the optimal particle in the tth time iteration:

$$f(x_{best}(t) = \min f(x_i(t)) \circ$$

C The principle and method of BPNN

BP neural network can achieve any input and out nonlinear mapping. It has high nonlinearity and self-adapting learning ability. Therefore, it has been widely used in approximation of function, model identification, data compression and other fields. The guiding theory of BP network learning principle is: the amendment of weights and threshold value have to follow the direction where performance function decreases fastest—negative gradient direction. The mathematical expression is as formula (6):

$$x_{k+1} = x_k - a_k g_k \tag{12}$$

Among them, x_k is the present matrix of weights and threshold value, g_k is the present grads of performance function, a_k is the learning rate.

The the basic principle and computing process of three layers BP neural network are simply explained as follows:

As to
$$N$$
 sample set $\{(x_k, y_k) | x \in R^m, y \in R^n\}, (k = 1, 2, \dots, N)$, two discrete temporal series, we classify the general sample into training sample φ_1 and testing sample φ_2 .

Firstly, we use training sample to establish mapping relation through error training, and then we use testing sample test whether network can give us right input and output relations. We adopt the three-layer BP neural network whose input node number is m, output node number is n, the number of node in hidden layer is P. We take sigmoid type as activation function between input layer and hidden layer, and take linear function as activation function between hidden layer and output layer. Then we come to the relation between network input and output:

$$y_{k}(t) = \sum_{j=1}^{p} v_{jk} \cdot f[\sum_{i=1}^{m} w_{ij} \cdot x_{i}(t) + \theta_{j}] + r_{k}$$
 (13)
In the formula ,
$$f(x) = \frac{1}{1 + e^{-x}}, k = 1, 2, \dots, n, t = 1, 2, \dots, N_{1}$$
, x_{i} is

the input of network, $y_k(t)$ is the expectation output weights between input node and the node in hidden layer, v_{ij} is the network weights between output node and the

node in hidden layer, θ_j is the threshold value of the layer node, r_k is the threshold value of output node. We define the overall error of the network is less than \mathcal{E}_1 , then the error of the output node is:

$$E_{1} = \frac{1}{2} \sum_{k=1}^{N_{1}} \sum_{t=1}^{n} [y_{k}(t) - \hat{y_{k}}(t)]^{2} \le \varepsilon_{1}$$

If the error of average mean square error of the testing sample is less than \mathcal{E}_1 , then we come to:

$$E_{2} = \frac{1}{N - N_{1}} \sum_{K=N_{1}}^{N} \sum_{t=1}^{n} [y_{k}(t) - \hat{y_{k}}(t)]^{2} \le \varepsilon_{2}$$
15)

In the practical application, the E_1 is usually too small, but E_2 can not satisfy the requirement, this is the so-called over-fitting phenomena. It is only when both E1 and E2 satisfy the requirement, BP neural network can have utility value.

D IPSO algorithm optimizes BP neural network prediction algorithm

The basic steps that IPSO algorithm optimizes BP neural network prediction algorithm are as follows:

Step 1 Initialize the parameter, including group scale, iteration times, learning factors and the value range of position and speed .Among them, the initialization of particle and speed assign random value to the position and speed of particle.

Step 2 According to the number of input and output parameter of temporal series,we constitute topological structure of BP neural network. A particle swarm was produced randomly, $W_i = (w_{i1}, w_{i2}, ..., w_{is})^T$, i = 1, 2, ..., n presents the original value of BP neural network, among them.

$$S=RS_1+S_1S_2+S_1+S_2$$
 (16)

In the formula, R,S1 and S_2 are the node number of input layer ,hidden layer, and output layer of BP neural network respectively.:

Step 3 Define a evaluation function of particle and give an evolutionary parameter of BP neural network. Then use the particle W_i gained in Step 2 to assign value to the weights and threshold value of BP neural network, and input training sample to do neural network training. When it reaches the set precision ,we can get a output value of

network training $\hat{y_i}$. Then the fitness value of individual W_i from group W can be defined as:

$$fit_{i} = \sum_{j=1}^{M-1} (\hat{y}_{j} - y_{j})^{2}, i = 1, 2, \dots, n$$
 (17)

In the formula, \hat{y}_j is the training output value; y_j is the training output expectation value; M is the phase number of phase space reconstruction; n is the scale of the group;

higher education lever (x_{13}) .From the data of

Step 4 According to the input and output samples, we figure out the fitness value corresponding to the position of every particle. Then we define individual extremum and group extremum according to the fitness value of original particle, and take the best position of every particle as its the best position in the history.

Step 5 During the every iteration process, according to formula(6) and formula(7),the speed and position of particle are renewed by individual extremum and group extremum; Then introduce simple self-adapting variant particle, and reinitialize the particle at a certain probability after renewal of particle every time; At last, figure out the fitness value of the new particle, and renew the individual extremum and group extremum according to the fitness value of the new group particle;

Step 6 After meeting the maximum iteration times, we use the optimizing particle produced by improved particle swarm to assign value to the connection weights and threshold value of BP neural network. After BP neural network prediction model is trained, the optimizing solution predicted by temporal series is put out.

IV. THE APPLICATION OF GRAY CORRELATION AND NEURAL NETWORK MODEL BASED ON IMPROVED PARTICLE SWARM IN RESIDENTIAL PROPERTY EVALUATION MODEL

A The preference of factors that influence residential property price

The factors that influence real estate price are mainly as follows. Firstly, the factors that influence price under real estate demand system, it mainly includes 13 data index. They are (1) Basic need and paying capacity (2) Paying capacity provided by government policy (3) Leasing market of real estate; Second, the factors that influence price under real estate supply system. Under the supply system of residential property, the supply cost is the basic factors that determines house price. It determines price changes to some extend; Thirdly, the factors that influence house price brought by government policy. The house price and cost constitution suggest that, there exists unreasonable profit in real estate market. How to execute effective price control to real estate market, and keep reasonable profit level for the explorer, thus making real estate market return to be reasonable? It needs our control over price. According to the research findings, this text selects the following main factors: Commercial residential building sales area ten thousand m^2 (x_1) 、 GDP per capita/yuan (x_2) , general money supply (M2) (trillion) (x_3) , Consumer Price Index (CPI) (x_4) , Average lending rate per year (R) (x_5) . Exchange rate (EX) (x_6) . Urbanization rate (x_7) , Size of population who want houses (x_8) . Land transaction price index (x_9) . Building material sales price index (x_{10}) , Residents' saving (x_{11}) , Room rate level(x_{12} , using house rent index to represent).

Changsha, Hunan , we can come to the degree of association between the factors and house price as the table 1 shows .

TABLE 1 RESULT OF DEGREE OF GRAY ASSOCIATION

Factor	X1	X2	Х3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13
Degree of association	0.66	0.88	0.82	0.62	0.84	0.77	0.90	0.89	0.54	087	0.45	0.35	0.42
Association order	8	3	6	9	5	7	1	2	10	4	11	13	12

Generally, when the degree of association is larger than 0.8, there is a perfect association between subsequence and parent sequence; when the degree is between 0.6 and 0.8, there is a good association; when the degree is less than 0.5, there is no association between them [18]. This text selects several factors who have degree of association over 0.6 with residential property price. They are :Commercial residential building sales area GDP per capita general money supply Consumer Price Index Average lending rate per year Room rate Urbanization rate Size of population who want houses Building material sales price index 9 factors as the input neure of neural network.

B The collection of evaluation data of real estate

We take the real estate market in Changsha, Hunan as an example. We adopt temporal series data from 2000 to 2010 and analyze them. All the data come from ${\rm \center{data}}$ Changsha Statistics Almanac ${\rm \center{data}}$, ${\rm \center{data}}$ Chinese Real Estate Market Almanac ${\rm \center{data}}$ during 2000 and 2010.

C The definition of network structure and training parameter

BP neural network adopts three-layer topological structure. We assume the number of neure in input layer and output layer are all 9, he number of neure in output layer is 1.We adopt sigmoid type function as activation function between input layer and hidden layer, and linear function as activation function between hidden layer and

output layer. The learning factor is 0.7, factor of momentum is 0.9. The scale of particle swarm is 20, learning factor $c_1 = c_2 = 2.0$, the original value of inertia weights $\omega_0 = 0.9$, the range of r_1 , r_2 is [0,1], the maximum iteration times is 2000.

D Simulation test

We adopt the data of Changsha from 2000 to 2010, and take that of a quarter as statistics. There are 44 samples in all. We take 38 samples of them as training sample, 6 samples as testing samples. We use two groups of sample to do training and simulation test to standard BP neural network and IPSO-BP neural network respectively. The training and simulation results are as follows.

The training error curve of this model is explained in picture2. When Iteration times is 383, the error meet the requirement, and the speed of convergence is faster. The comparison of sample's data before and after the definition of input variable of neural network through gray correlation analysis are illustrated in table 2. We can learn from the table that: before the definition of input variable of neural network, it takes 10 minutes for BPNN training to reach the error of $\pm 5\%$, among them, there are two testing samples whose error is more than ±5%; It takes IPSO-BPNN9 minutes, and there is a sample whose error is more than ±5%. After we define the input variable of neural network through gray correlation analysis, it takes BPNN training 6 minutes to let the error be $\pm 5\%$, among them, there is a testing sample whose error is over $\pm 5\%$. It takes IPSO-BPNN 4 minutes, and all the testing samples meet the error requirement.

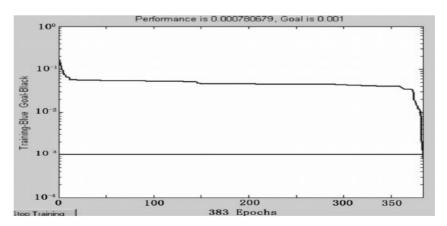


Figure 2. Error curves in training process

TABLE 2 THE COMPARISON OF SAMPLE'S DATA BEFORE AND AFTER THE DEFINITION OF INPUT VARIABLE OF NEURAL NETWORK THROUGH GRAY CORRELATION ANALYSIS

code	True price		Before inpu	itting variable		After inputting variable				
	yuan/m²	BPN	NN	IPSO-	-BPNN	В	PNN	IPSO-BPNN		
		Simulation value	error (%)	Simulation value	error (%)	Simulation value	error (%)	Simulation value	error (%)	
39	2468	2356	4.54	2394	2.99	2378	3.65	2408	2.43	
40	2738	2651	3.18	2678	2.52	2684	1.97	2759	0.77	
41	3030	2896	4.42	2903	4.19	2910	3.96	2956	2.44	
42	2991	2731	8.69	2806	6.19	2785	6.89	2921	2.34	
43	3411	3212	5.83	3315	2.81	3359	1.52	3388	0.67	
44	4417	4215	4.57	4301	2.63	4258	3.60	4356	1.38	

V. CONCLUSION

(1)We optimize the evaluation index based on gray correlation theory, and combine IPSO with BPNN. According to degree of group prematurity convergence and the inertia weights adjusted by self-adapting value, we renew the speed and position of particle. We let the improved particle swarm algorithm replace BP neural network's grads reduction method, and use it to train the connection weights and threshold value of neural network.We have achieved reasonable assignment of original weights of BP neural network and established prediction model for residential property 's price. We take a case in Changsha, Hunan as an example. We predict the residential property price influenced by several evaluation index. The result shows that the prediction result brought up by using this model is in accordance with the residential property market price in Changsha .So ,the evaluation result brought up by model is reliable.

(2)This model avoid drawbacks of previous index's inadequacy and the partial minimality of function extremum, which ensures the rationality of BP neural network original weights's assignment. It has both theoretical and practical significance in the research on the prediction of real estate price.

(3)The prediction method for residential property price based on improved particle swarm IPSO-BPNN model has advantages of good output stability, high speed of convergence, high precision of prediction. It can control a average percentage error of price prediction not more than 2.5%, which improves the precision of prediction. Compared with traditional BP neural network and traditional IPSO-BPNN method, this method is superior to them in reducing iteration times, output stability, convergence and precision of prediction.

(4) The IPSO-BPNN algorithm based on gray correlation brought up in this text provides a scientific and feasible way for the prediction of residential property price.

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