Tourism Environment Carrying Capacity Prediction based on Improved BP Neural Network

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Abstract **- China has experienced a rapid economic and social growth, and tourism now has become one of the key components and strategic pillar industries in the national economy exactly after 2010. Tourism environment carrying capacity is important to the sustainable development of tourism. BP neural network based on improved particle swarm optimization is proposed. The improved tourism environment carrying capacity prediction is used to predict tourism environment carrying capacity of some city in China. The result shows that prediction accuracy of proposed scheme is higher than traditional BP neural network.**

Keywords - tourism environment; carrying capacity prediction; BP neural network; particle swarm optimization

I. INTRODUCTION

For the short-term tendency, the urban tourism environment problems become increasingly prominent. For example, ecological environment system destruction, tourism resources over development, scenic areas continuous overload etc. As the magnitude for describing the natural environment, the economic environment and the social environment system, which can withstand the tourism activities intensity, the tourism environment carrying capacity is not only the important tool of tourism plan, development and management, but also is the key indicator which weighs the degrees of tourism sustainable development, thus studying the present situation and future development countermeasure of urban tourism environment carrying capacity is an inevitable tendency.

The management of beach carrying capacity was proposed by SILVA[1]. A strategy for sustainable tourism economic development in cross river state was proposed by Akpan[2]. Exploring sustainable tourism in Niger ia for developmental growth was proposed by Ayeni[3]. An evaluation of the performance of a national tourism organization was proposed by Ajadi[4]. Xiu-hong Zhang[5] introduced the connotation of tourism environmental bearing capacity, analyzed the relationship between the coordinated development of tourism economy and ecological environment resources protection, introduced the calculation modes and evaluation indexes of the tourism environmental carrying capacity in the aspects of ecological environment carrying capacity, tourism resources carrying capacity, and the carrying capacity of tourist facilities, calculated the thresholds of carrying capacity, and provided the early-warning data for the ecological tourism system. Research on tourist environment bearing capacity assessment and ecological security warning system of scenic spots in Tibet was proposed by Yunpin[6]. Mapping Landscape values and development preferences-a method for tourism and residential development planning was proposed by Brown[7]. Harnessing tourism potentials for sustainable development was proposed by Tunde[8]. Research and prospect on theoretical framework of water environmental bearing capacity was given by Li Q[9]. Establishing the social tourism carrying capacity for the tourist resorts of the east coast of the republic of cyprus was given by Alexis Saveriades[10]. Proactive monitoring and adaptive management of social carrying capacity in arches national park was proposed by Steven[11]. Fuzzy adaptive management of social and ecological carrying capacities for protected areas was proposed by Tony[12]. Research on the competitiveness of China's tourism trade in service with uncertain linguistic information was given by Xuehua Liu[13]. Suitability evaluation of traditional sports tourism development with uncertain linguistic information was given by Rongwei Li[14].

In the next section, principle of BP neural network is investigated. In Section 3, BP neural network based on improved particle swarm optimization and the improved tourism environment carrying capacity prediction is given. In section 4, empirical analysis is given. Finally, some conclusions are given in section 5.

II. PRINCIPLE OF BP NEURAL NETWORK

Artificial neural network is a network composed of widely interconnected neurons, which is abstract, simplification and simulation of the human brain and reflects the basic characteristic of the human brain. Artificial neural network studies human intelligent behaviour from the physiological structure of the brain and simulate information processing function of the human brain. It is a kind of technology rooted in neuroscience, mathematics, statistics, physics, computer science and engineering.

At present, a lot of artificial neural network models have been put forward and a variety of learning algorithms have been developed. Multilayer forward feedback neural network model of the BP algorithm is most widely used and the most mature. BP algorithm is also called the back propagation algorithm and is a kind of artificial neural network suitable for nonlinear pattern recognition and classification prediction problem, the structure of it is shown in figure 1.

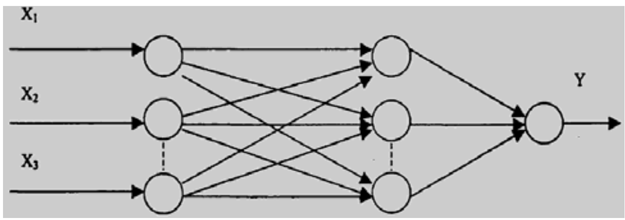

Fig. (1). Structure of artificial neural network

Multilayer forward network can be seen as a black box, input and output data obtained by actual measurement is taken as sample for black box learning. make the study in the "black box", the effects of each input variable on output variable is recorded by the black box in the learning process of sample automatically. Because transfer function of node neuron is nonlinear, the black box also is nonlinear. The whole learning process is the process of establishment of prediction model. As long as the number of nodes and the training samples is enough, black box can realize output prediction of arbitrary input.

A given network input is propagated to the hidden layer through the pre-set connection weight, then incentive value is outputted to the output layer node by hidden layer node and the output value is given at last. Through the comparison of output value and expected value, the connection weights are modified from output layer to hidden layer and input layer. The learning process is stopped and the specific parameters are outputted. The positive propagation and reverse correction alternates, eventually mean square error of the output value and expected value is minimized, the network tends to converge and the network connection weight does not change.

The most basic BP network is three layer feed forward network composed of input layer, hidden layer and output layer. Each layer has a number of neuron nodes and adjacent two layers of nodes are connected by weights. Supposing there is n number of input $x_1, x_2, \dots, x_n$. $w_1, w_2, \dots, w_n$ represents the weights corresponding to the input, which represents connection intensity between input neuron and output neuron. A represents the input sum of neurons, which is called activation function. Y represents output of neuron. θ represents threshold of neuron.

$$Y = f(A)$$

$$A = \sum_{i=1}^{n} W_i X_i - \theta$$

III. THE IMPROVED TOURISM ENVIRONMENT CARRYING CAPACITY PREDICTION

A D-dimension searching space is set and the total number of particles in the swarm is n. The position of the i-th particle is represented by

$$X_i = (x_{i1}, x_{i2}, \cdots, x_{iD}).$$

The optimal position of the i-th particle is:

$$P_i = (p_{i1}, p_{i2}, \cdots, p_{iD}).$$

The optimal value of:

$P_i(i = 1, 2, \dots, n)$ is P_g . $V_i = (v_{i1}, v_{i2}, \cdots, v_{iD})$

represents speed of the i-th particle. The position of the particle is changed by the following formula.

$$V^{k+1} = wV^k + c_1 r_1 (P_i^k - X^k) + c_2 r_2 (P_g^k - X^k)$$
$$X^{k+1} = X^k + V^{k+1}$$

c_1 and c_2 are positive constants, r_1 and r_2 are random numbers uniformly distributed between 0 and 1. w represents internal inertia weight. Clerc redesigned the velocity updating formula in 2002 when compression factor is used to study the convergence behaviour of PSO algorithm. PSO algorithm with compression factor is called CPSO[15].

$$V^{k+1} = \lambda(V^k + c_1 r_1 (P_i^k - X^k) + c_2 r_2 (P_g^k - X^k))$$

$$\lambda = \frac{2}{\left|2 - \varphi + \sqrt{\varphi^2 - 4\varphi}\right|}$$

The improved particle swarm optimization algorithm is called IMPSO. The particles in the swarm are composed of two initial population, one is a parasitic swarm, and the other is the host swarm. When biological parasitic behavior occurs, parasitic creatures absorb nutrient from the host swarm. When parasites invade the host, the host will produce acquired immune. In the algorithm, a parasitic behavior happens in parasitic swarm and the host swarm in a certain number of iterations t. According to the size of the fitness value, two species of particles will be ordered. One half of particles with the high fitness value belong to parasitic swarm and the remaining half of the particles belong to the host population. When the fitness value of host swarm is worse than the optimal fitness value of parasitic swarm, particles of host swarm is set to learn from individual optimal particle of host population, optimal particle of host population and optimal particle of parasitic population at the same time. Otherwise the population evolves independently.

In order to assist the elite particle jump out of local extremum point, avoid the whole swarm falling into local extremum point, elite learning mechanism is used for the parasitic population. The velocity update formula is as follows.

$$V^{k+1} = w\,\mathrm{sgn}V^k + c_1 r_1 (P_i^k - X^k) + c_2 r_2 (P_g^k - X^k)$$
$$+ c_3 Gauss(0,1)(X^k - P_i^{kd})$$

w represents internal inertia weight. sgn represents symbol function, which controls change of flight direction according to the value of random number r . c_3 represents random number between 0 and 1. $Gauss(0,1)$ represents Gaussian distribution function. P_i^{kd} represents position of the d-th dimension of optimal particle in the k-th iteration. The mutation formula is as follows.

$$\eta(t) = 1 - a^{[1-\frac{t}{T}]^b}$$

a represents random number between 0 and 1, t represents the current iteration times, T represents the total iteration times and the value of b is 2.

$X^{k+1} = X^k + \eta \cdot X^k \cdot U(0,1)$, $r \geq rm$.

$X^{k+1} = X^k - \eta \cdot X^k \cdot U(0,1)$, $r < rm$.

r represents random number, $U(0,1)$ represents uniform random number, rm represents a constant number of 0.5.

The process of improved particle swarm optimization is as follows:

Step1: Set initialization range and initialize the speed and position of particle swarm randomly.

Step2: Calculate the fitness value, set the particle's individual historical optimal value and individual historical optimal position and the optimal position of all particles with the optimal fitness value is set as the global optimal position.

Step3: Update the particles, elite learning strategy is used to update the particle's velocity for the parasitic population and particle velocity of host population is updated by compression factor particle swarm optimization algorithm.

Step4: Calculate the fitness value, the result is compared with the individual optimal value in history. If the result is better, the individual optimal position is replaced by the position of this optimal value.

Step5: Determine the global optimal, compare individual particle optimal value with population optimal value. If it is better, it is set as the current global optimal position.

Step6: When the number of iterations satisfies the prescribed condition, the parasitic behaviour occurs.

Step7: Carry out mutation operation for the particles of host population with high frequency to acquire immunity ability.

Step8: Determine whether it meets the condition. If the algorithm meets the condition, the result is outputted. Otherwise go to step 3.
There are many weights adjustment method for BP learning algorithm based on gradient descent method and the gradient descent method is easy to fall into local minimum, has slow convergence speed, resulting in the convergence speed, training time and the global convergence of the BP neural network have serious deficiencies. So we can use other intelligent algorithm to optimize neural network optimization process. The improved PSO algorithm is used for neural network training to enhance the searching efficiency. In the neural network, there are m number of input vectors and k number of output vectors. The connection weighting matrix between input layer and hidden layer is $W = (w_{ij})_{m \times n}$ and the connection weighting matrix between hidden layer and output layer is $V = (v_{jp})_{n \times k}$. The threshold vector between input layer to hidden layer is $A_1 = (a_1, a_2, \cdots, a_n)^T$ and threshold vector between hidden layer to output layer is $A_2 = (a_1, a_2, \cdots, a_k)^T$. Output calculation formula of three-layer feed forward neural network is expressed as $Y = f(V[f(W^T X) + A_1] + A_2)$. In the improved particle swarm optimization, $D = m \times n + n \times k + n + k$. The connection weighting matrix between input layer and hidden layer is

$$IW = \begin{bmatrix} IW_{11} & IW_{12} & \cdots & IW_{1n} \\ IW_{21} & IW_{22} & \cdots & IW_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ IW_{m1} & IW_{m2} & \cdots & IW_{mn} \end{bmatrix}.$$

The connection weighting matrix between hidden layer and output layer is:

$$LV = \begin{bmatrix} LV_{11} & LV_{12} & \cdots & LV_{1k} \\ LV_{21} & LV_{22} & \cdots & LV_{2k} \\ \vdots & \vdots & \cdots & \vdots \\ LV_{n1} & LV_{n2} & \cdots & LV_{nk} \end{bmatrix}.$$

The threshold vector between input layer to hidden layer is:

$$A_1 = [a_{11}, a_{12}, \ldots, a_{1n}]^T.$$

The threshold vector between hidden layer to output layer is:

$$A_2 = [a_{21}, a_{22}, \ldots, a_{2k}]^T.$$

The particle code is:

$$x = [IW_{11} \cdots IW_{mn} LW_{11} \cdots LW_{nk} a_{11} \cdots a_{1n} a_{21} \cdots a_{2k}]$$

Training main steps of three-layer feed forward neural network based on improved particle swarm optimization are as follows:

Step1: Weights and thresholds of three-layer feed forward neural network are encoded, which corresponds to the individual of particle swarm optimization algorithm.

Step2: Set value range of the variable of the particle swarm optimization algorithm to initialize the position and speed of the particle swarm within the scope of initialization randomly.

Step3: In view of the optimization problem, set the neural network to determine neural network parameters and generate a new neural network model.

Step4. Dimension information in particle swarm is decoded to obtain weights and threshold parameters of network model. Calculate evaluation index of neural network as the fitness of algorithm.

Step5: Speed of particles in the parasitic population is updated using elite learning strategies. The speed of the particles of host population is updated using compression factor particle swarm optimization algorithm.

Step6: Calculate the fitness value of each particle and the result is compared with the individual optimal value in history. If it is better, this position is set as individual optimal value in history.

Step7: Compare individual optimal value of each particle in history with the position of the optimal value in the swarm. If it is better, the particle is set as the global optimal point.

Step8: When the number of iterations satisfies condition, parasitic behaviour occurs. Carry out mutation operation for the particles of host population with high frequency to acquire immunity ability.

Step9: Determine whether the algorithm meets the condition. If it meets the condition, output the result. Otherwise go to step 3.

IV. EMPIRICAL ANALYSIS

Six commonly used standard test functions are used for simulation experiment. The initialization range of function 1, function 2, function 3, function 4, function 5 and function 6 is:

$(50,100)^D$, $(10,30)^D$, $(2.56,5.12)^D$, $(10,20)^D$, $(300,600)^D$, $(200,500)^D$. $D=30$,

the number of particle is:

$n=40$, $w=0.729$, $c_1=c_2=2.05$.

$$f_1(x)=\sum_{i=1}^{n}(\sum_{j=1}^{i}x_j)^2,$$

$$f_2(x)=\sum_{i=1}^{n}(100(x_{i+1}-x_i)^2+(x_i-1)^2),$$

$$f_3(x)=\sum_{i=1}^{n}(x_i^2-10\cos(2\pi x_i)+10),$$

$$f_4(x)=-20\exp(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n}x_i^2})$$
$$-\exp(\frac{1}{n}\sum_{i=1}^{n}\cos 2\pi x_i)+20+e,$$

$$f_5(x)=\frac{1}{4000}\sum_{i=1}^{D}x_i^2-\prod_{i=1}^{D}\cos\left(\frac{x_i}{\sqrt{i}}\right)+1,$$

$$f_6(x)=418.9828n-\sum_{i=1}^{n}(x_i\sin(\sqrt{|x_i|})).$$

The software is Matlab 7.0, the maximum iteration number is 1000 and each experiment runs 50 times. The change curve of optimal value in optimization process from function 1 to function 6 is shown in figure 2 to figure 7. The blue line represents CPSO algorithm[15] and the green line represents the proposed algorithm. IMPSO is compared with CPSO algorithm, showing that it has a faster convergence speed and better precision in the testing of unimodal functions and multi-peak functions.

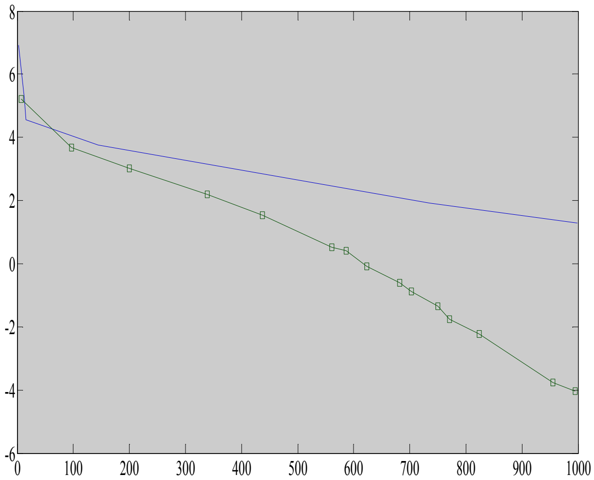

Fig. (2). The curve of average optimal value of function 1.

Data from 1992 to 2004 is taken as the training sample, related parameters of tourism environment carrying capacity are taken as the input data, including land accumulative total investment cost, annual cost of land investment, catering, wholesale and retail assets investment, society assets investment of social service, tourism revenue and the number of tourists. Maturely-trained BP neural network is used to predict tourism environmental carrying capacity calculation results from 1994 to 2005 of some city in China. The result is shown in figure 8. The blue line represents the actual value, the yellow line represents the prediction result based on BP neural network and the red line represents prediction result based on proposed algorithm. It can be seen that prediction accuracy based on improved BP neural network is higher than BP neural network based on CPSO.

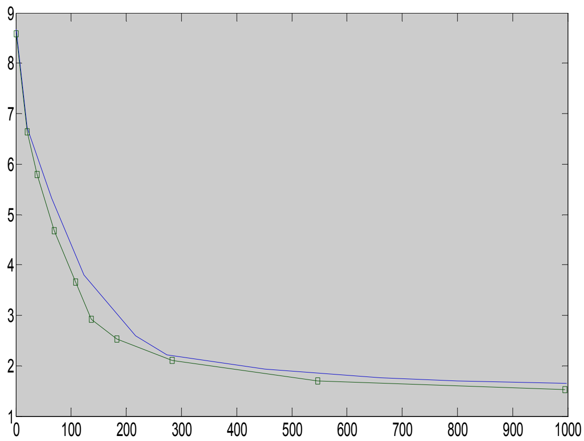

Fig. (3). The curve of average optimal value of function 2.

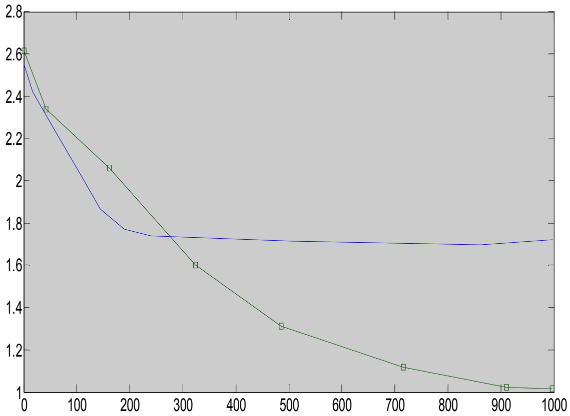

Fig. (4). The curve of average optimal value of function 3.

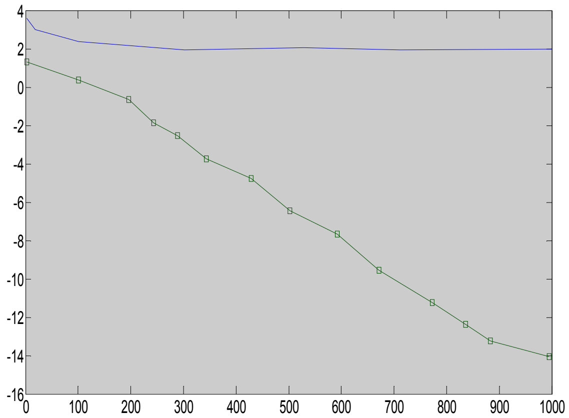

Fig. (5). The curve of average optimal value of function 4.

V. CONCLUSIONS

Tourism environment carrying capacity prediction is important to the sustainable development of tourism. Principle of BP neural network is investigated. Then BP neural network based on improved particle swarm optimization is proposed. At last, the improved BP neural network is used to predict tourism environment carrying capacity of some city in China. The result shows that prediction accuracy of proposed scheme is higher than traditional BP neural network, which can provide reference for tourism sustainable development.

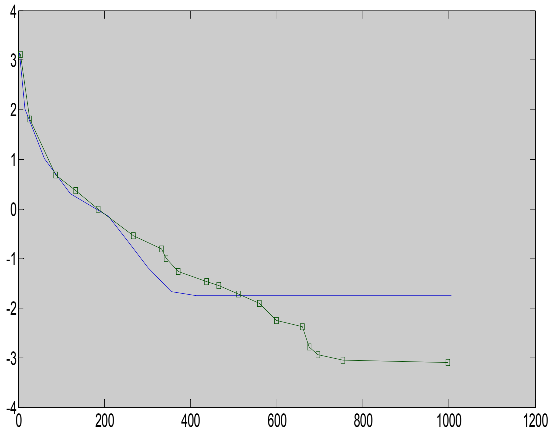

Fig. (6). The curve of average optimal value of function 5

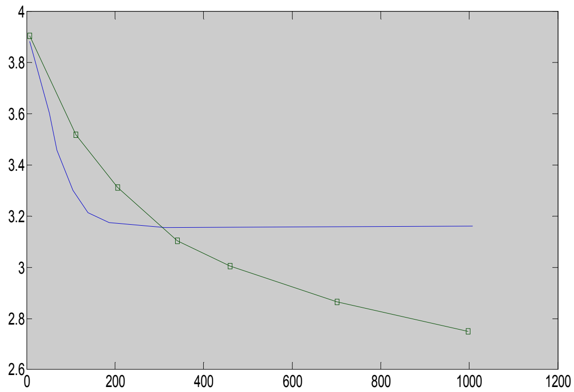

Fig. (7). The curve of average optimal value of function 6

Fig. (8). The curve of average optimal value of function 6.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflicts of interest.

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