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A Simulate Prediction and Analysis of Jilin Province Rural Tourism Development Based on BP Neural Network

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The BP neural network is the most mature and widely used artificial neural network model. It has the simple structure, strong operability and good self learning ability. This paper first introduce the neural network in general. This paper choose the BP neural network as a method of simulated prediction of 2014 to 2023 Jilin Province rural tourism revenue and scenic area. Then this paper identify the prediction indicators of the neural network, complete the network training. The results shows the BP neural network has a good simulation ability of arbitrary complex nonlinear system and a strong fitting ability. The simulation process also indicates the BP neural network has many deficiencies, including difficulty in initial learning rate selection and low convergence speed.
Keywords: Pearman correlation method, Rural tourism, BP Neural Network

1. Introduction

Neural network, also known as artificial Neural network is composed of a large number of neurons in a certain topology of the interconnection network, it can reflect the basic characteristic of the human brain, it is the abstract and simplify simulation of the human brain. Neural network involves neural science, physics, mathematics, statistics and computer science, etc. The neural network can study the intelligent behavior through simulate the human brain’s physiologic structure and function. In recent years, although there have been many kinds of artificial neural network (ANN) model have been proposed and studied in depth, but consider for all the existing neural network model, back propagation (BP) learning algorithm neural network model or its improved version have a proportion of 80% to 90%, Yin, F. et al(2011) reported. Theoretically, three layer BP neural network can simulate any complex nonlinear system as long as it has enough hidden layer nodes. Therefore, the BP neural network is widely used in pattern recognition, signal processing, automatic control and forecasting.
The application of BP neural network have to determine the network structure in advance, and the network structure optimization has always been the hot spot for researchers around the world, Cui Dongwen (2013) reported. BP neural network structure includes the number of input layer neurons, the number of output layer neurons, the number of hidden layer neurons.
The key of Network structure design lies in the design of the hidden layer structure, specifically refers to the number of hidden layer and number of neurons in hidden layer. The number of the hidden layer determine the network's memory capacity, generalization ability, training speed and quality of the output response. A small number of hidden layer will produce non-convergence learning, low recognition ability and low generalization ability of the network.
Since the reform and opening up, China’s national economy has achieved rapid development, people's living standard and life quality have greatly improve, from now on the economic development of our country goes into the stage of industrialization, the non-agricultural industries become the leading industry of the national economy. The traditional agricultural industry development falls behind in recent years, it become a bottleneck of our country’s society's development, Boskovic, T. et al(2013) and Komppula, R. (2014) reported . With the guidance of national policies, driven by the local governments, rural tourism is the revitalization of regional economic and effective means to increase farmers' income, the rural tourism just nourish in a short span of 20 years in the vigorous and rapid development of our country.

2. Modeling Method

The topology structure of the BP neural network is shown in figure 1.

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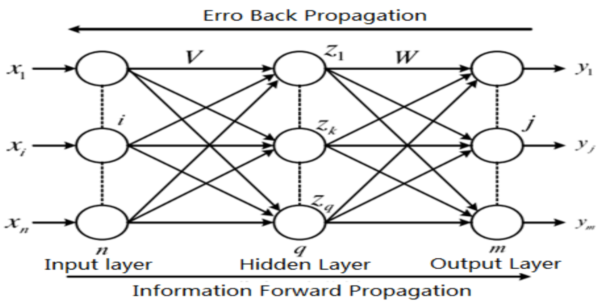

Figure 1. The topology structure of the neural netwok

3. Prediction model of Jilin province rural tourism industry development

3.1 Prediction indicators' raw data

Rural tourism as a new type of tourism, it's still in the development in Jilin province. The statistics about rural tourism first began at 2006. This paper select the historical data from year 2009 to 2013, shown in table 1 and figure 2. The data all come from the provincial statistical yearbook, other national economic and social development statistic comes from the provincial bulletin and government report.

Table 1 The factors affecting the rural tourism income and scenic area

indicator	Year 2009	2010	2011	2012	2013
GDP (billion)	271.9	324.1	397.5	475.3	573.4
Tertiary Industry production growth (billion)	82.8	95.4	209.8	246.8	269.1
Fiscal revenue (billion)	18.6	36.0	42.4	23.6	54.0
Fiscal spending (billion)	21.9	36.1	42.8	32.5	63.2
Investment in Fixed Assets (billion)	104.7	143.5	190.6	250.0	325.7
Agriculture, forestry, water conservancy and environmental expenditure (billion)	0.9	1.1	1.4	1.8	2.0
Urban disposable incomes (Yuan)	14006	15411	17797	20208	22275
The per capita net income of rural areas (Yuan)	5266	6237	7510	8598	9621
Reception capacity of scenic area (Million hectares)	52	85	100	450	550
Scenic area (Million hectares)	0.8	1.2	1.6	2.1	1.9
Number of scenic area	70	75	86	98	124
Number of tourism farmhouse	1560	2200	2780	2840	3210
Urban road total length (kilometer)	1480	1842	2115	2297	2482
Number of private cars	7928	75121	75623	76431	78145
Rural garden area (Million hectares)	6542	8670	10999	12453	15362

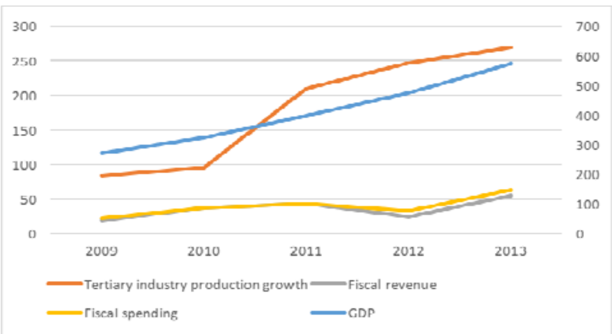

Figure 2. The factors affecting the rural tourism income and scenic area

3.2 The prediction indicators

Consider the large number of rural tourism income and rural tourism scenic area indicators, only a small number of indicators are included in this paper. The large number of indicators will increase the workload, not able to find the main factors, it is a necessary procedure to screen the indicators Fernandes, Teixeira, et al (2012) reported. Due to the indicators' different dimension, this paper use a normalized processing to get the unified dimensionless data, and then with the Spearman correlation analysis method to analyze each

indicator's correlation to the rural tourism income and rural tourism scenic area, then we get the main indicator of the prediction model. The result is shown in table 2 and 3.
From table 2, the GDP, Tertiary industry production growth, Investment in Fixed Assets, Agriculture, forestry, water conservancy and environmental expenditure, The per capita net income of rural areas, Reception capacity of scenic area, Number of scenic area, the 8 indicators has a close correlation to the rural tourism income with correlation coefficient greater than 0.8.
From table 3, the GDP, Tertiary industry production growth, fiscal spending, rural garden area, the 5 indicators have a close correlation to the rural tourism scenic area.

Table 2. The correlation of rural tourism income and all the indicators

indicator	Correlation	indicator	Correlation
GDP X1	0.901	The per capita net income of rural areas X8	0.925
Tertiary Industry production growth X2	0.845	Reception capacity of scenic area X9	0.891
Fiscal revenue X3	0.253	Scenic area X10	0.429
Fiscal spending X4	0.359	Number of scenic area X11	0.865
Investment in Fixed Assets X5	0.854	Number of tourism farmhouse X12	0.359
Agriculture, forestry, water conservancy and environmental expenditure X6	0.923	Urban road total length X13	0.341
Urban disposable incomes X7	0.865	Number of private cars X14	0.329

Table 3. The correlation of rural tourism scenic area and all the indicators

indicator	Correlation	indicator	Correlation
GDP X1	0.865	Fiscal spending X6	0.864
Primary Industry production growth X2	0.342	cultivated area X7	0.429
Tertiary Industry production growth X3	0.794	Agriculture, forestry, water conservancy and environmental expenditure X8	0.386
Reception capacity of scenic area X4	0.298	Rural garden area X9	0.684
Fiscal revenue X5	0.214	Rural tourism revenue X10	0.337

3.3 Simulation Prediction Model

Based on the BP neural network modeling analysis, the relationship of rural tourism income and impact indicators related to rural tourism income is:

$$T = \sum_{j=1}^{3}\sum_{i=1}^{6} V_j \left(W_{ji} P_i + B_{1j} \right) + B_2 \tag{1}$$

In (1):
T - rural tourism income target output
P - rural tourism income indicator actual input or rural tourism scenic area indicator actual input
V - the weights of the network layer
W - the weights of input layer
B1 - input layer threshold

4. Network training and simulation prediction

4.1 Network Training

After the BP neural network is generated and initialized, we can use the existing "input - target" sample vector data for the network training.
(1) Data Pre-processing. In order to improve the efficiency of neural network training, use premnmx function on "input - target" sample to standardize the data as pre-processing, which will make the data falls into interval [-1,1]. Assume SX as the standardized influential indicator on rural tourism income and rural tourism scenic area, SY as the standardized rural tourism income and rural tourism scenic area, as shown in table 4 and 5.

Table 4. Standardized Rural Tourism Income Data

Year	Input P								Output T
	SX1	SX2	SX5	SX6	SX7	SX8	SX9	SX11	SY
2009	-0.7168	-0.8492	-0.8082	-0.9987	1.0000	-0.3017	-0.9805	-0.9864	-1.0000
2010	-0.7560	-0.8751	-0.8143	-0.9787	0.6214	-0.4332	-0.9865	-0.9912	-0.7725
2011	-0.9432	-0.9716	-0.9511	-0.9995	-0.6147	-0.8623	-0.9963	-0.9987	0.4240
2012	-0.9266	-0.9603	-0.9317	-0.9986	-0.4878	-0.8216	-0.9879	-0.9967	0.4340
2013	-0.9156	-0.9621	-0.9153	-0.9989	-0.4264	-0.8001	-0.9859	-0.9967	1.0000

Table 5. Standardized Rural Tourism Scenic Area Data

Year	Input P				Output T
	SX1	SX3	SX6	SX9	SY
2009	-0.7487	-0.6801	1.0000	-1.0000	-1.0000
2010	-0.7800	-0.6691	1.0000	-1.0000	-0.5823
2011	-0.8004	-0.6536	1.0000	-1.0000	-0.2352
2012	-0.7644	-0.5987	1.0000	-1.0000	0.3863
2013	-0.7799	-0.5760	1.0000	-1.0000	1.0000

(2) Network Training. With the newff function of Matlab, we can create a forward BP neural network. This paper will set up a three layers BP neural network. After the processing of sample data, the BP neural network can be trained with Traingdm algorithm as follow:

$$|net, tr| = train(net, P, T) \tag{2}$$

In (2), the P is Input sample vector set, T is the corresponding target sample vector set, net on each side of the equal sign is the neural network object before and after training, tr stores the erros and logs of the training process.
Network simulation. The simulation is achieved through sim function with the trained neural network, the sim function is:

$$A = sim(net, P) \tag{3}$$

In (3), *P* is the input sample vector set, *T* is the corresponding target sample vector set, *net* on each side of the equal sign is the neural network object before and after training, *tr* stores the erros and logs of the training process, *A* is the simulation result. The simulation error degree is shown in figure 3 and figure 4.

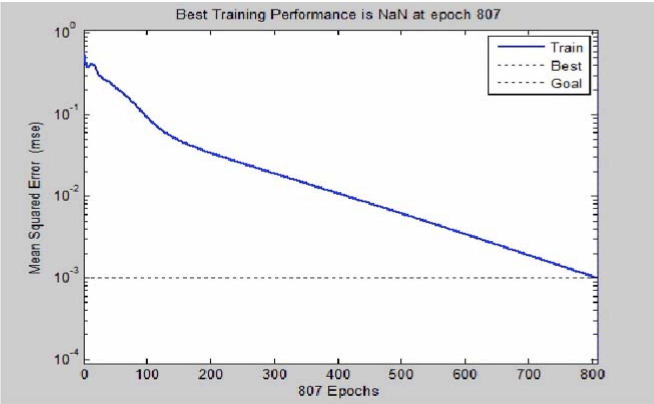

Figure 3. Rural Tourism Income Neural Network Simulation Error Degree

The figure 3 of rural tourism income network training error curves shows that the network iteration 807 times to complete the training, and error reach the minimal error target. Therefore, the simulation effect is good, the neural network model is acceptable.
The figure 4 of rural tourism scenic area network training error curves shows that the network iteration 3715 times to complete the training, and error reach the minimal error target. Therefore, the simulation effect is good, the neural network model is acceptable.

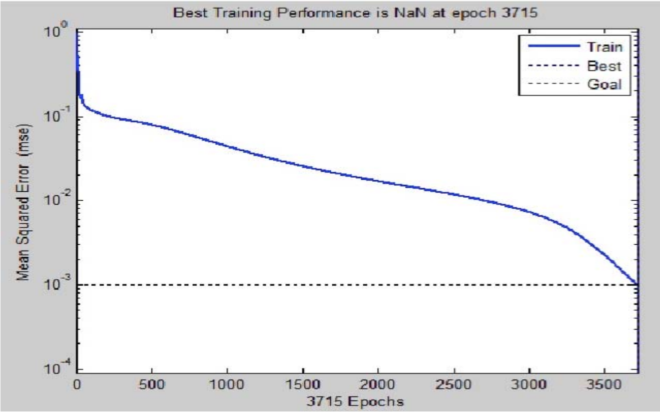

Figure 4. Rural Tourism Scenic Area Neural Network Simulation Error Degree

4.2 The Prediction Result

With the model and trained neural network in this paper, the simulation of rural tourism income and scenic area in the following 10 years can be predicted, as shown in table 6,7 and figure 5.

Table 6. The prediction of 2014 to 2023 rural tourism income

Year	2014	2015	2016	2017	2018
Predicted Income (Billion)	1.03	1.39	1.6	1.73	1.84
Year	2019	2020	2021	2022	2023
Predicted Income (Billion)	2.07	2.15	2.37	2.51	2.63

Table 7. The prediction of 2014 to 2023 rural tourism scenic area

Year	2014	2015	2016	2017	2018
Predicted Area (Million hectares)	2.4	2.8	3.2	3.7	4.1
Year	2019	2020	2021	2022	2023
Predicted Area (Million hectares)	4.9	5.6	6.5	7.4	8.6

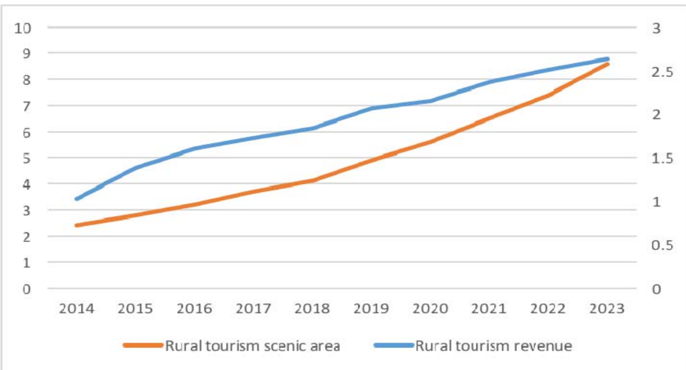

Figure 5. The 2014 to 2023 rural tourism revenue and scenic area

5. Conclusions

This paper use rural tourism income and rural tourism scenic area as prediction objects. Based on 2009 to 2013 rural tourism data, this paper builds a simulation prediction model and predicts the future 10 years rural tourism income and scenic area. The prediction results shows that the rural tourism industry in Jilin province is rapidly developing, and in the year of 2014 to 2023, the rural tourism industry will continue growth greatly.

The simulation process also indicates the BP neural network has many deficiencies, including difficulty in initial learning rate selection and low convergence rate. The fixed and variable vector algorithm in BP neural network have a very low convergence speed, which is shown in this paper, the initial training take 3715 epochs. Thus the variable vector algorithm in BP neural network need to be improved to reduce the initial learning epochs. And also the BP neural network has a poor predict extrapolation effect. When processing of a small interval training, the forecast period and the training period tends to be inconsistent, when processing of a large interval training, the predict extrapolation effect will get worse. To improve the BP neural network in future research, the improvement can focus on the time series algorithm and unipolar Sigmoid function algorithm

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