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Urbanization Level Forecast Based on BP Neural Network

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***Abstract*—Urbanization is the general trend and tide of the current world development and also one of the most remarkable social and economical phenomena in the world. Urbanization level becomes an important symbol of the economic strength and modernization level in a region and thus how to improve the local urbanization level has become a priority for economic development. With the increasing urbanization level, a series of adverse effects have been brought about. It is a very important task to make a scientific forecast for the urbanization of a region. Take Zhejiang Province as an example; only considering the present economic development factors, the currently most popular BP network (Back-Propagation Network) in the neural network is adopted to establish the forecast model; and the urbanization level of Zhejiang Province in 2000-2004 is forecasted. For the forecast result, the maximum relative error is 2.51%, the minimum relative error is 0.23% and the mean absolute percent error is 1.05%. Thus, the result indicates that the model has high forecast precision and therefore can be used to forecast the urbanization level of Zhejiang Province in the future.**

Keywords-BP neural network; urbanization level; forecast

I. INTRODUCTION

Urbanization is the historical process of human life forms transformed from rural type to urban type, manifesting the transformation from rural to urban population and the urban economic, social, spatial and cultural multi-directional transformation, and also the continuous development and perfection process[1]. Urbanization is the general trend and tide of the current world development and also recognized as one of the most remarkable social and economic phenomena in the whole world[2-4]. In recent years, the urbanization level has become an important symbol of the economic strength and modernization level in a region and an important indicator to judge the development level of a city. Various regions consider the local urbanization level improvement as the priority of the current economic development[5]. However, with the increasing urbanization level, the urbanization process has more and more obvious effects on water resources and urban environment indispensable to human existence and development. There are 400 cities lacking water among above 600 cities in China. Because the surface water is in short supply, people depend on the groundwater more and more frequently, causing the exploitation and supplement imbalance of the groundwater and the continuous water level drop and thus triggering a series of serious effects: groundwater depletion, land subsidence, land collapse, ground fissure, building collapse, groundwater intruded by sea water, vegetation died from shrivelling, etc. The urbanization process has also brought about the Urban Heat Island Effect, the Urban Condensation Nuclei Effect and the Urban Hindrance Effect so as to make the underlying surface change and cause water disasters[6]. Lots of various gases and granular substances exhausted by cities can adversely affect human bodies, creatures and objects and have damaged the biological environment so as to change the formation and structure of such environment and break the balance between producer organisms and consumer organisms. In addition, the urbanization process leads to noise and electromagnetic wave pollution.Therefore, undoubtedly, it is fairly significant to make a scientific forecast to the urbanization level in a region.

Urbanization level is indicated with the globally common urbanization ratio, which refers to the ratio of the population of cities and towns to the total population (including agricultural and non-agricultural population). At present, the common methods used in urbanization level forecast mainly include grey forecast, time-series forecast, neural network forecast, economic factor related analysis forecast, etc. Among them, the economic factor related analysis method is widely used because it sufficiently considers the effect of economic development on urbanization level[1,2,4,7,8]. In respect of the economic factor related analysis method, the scholars at home and abroad, for purpose of their own researches, classify the relationship between the economic development level of a country and the urbanization level of such country into the following types: linear relationship, logarithmic curve relationship, logistic curve relationship[2,9,10]. However, urbanization expansion is a dynamic, non-linear and multi-feedback-loop complicated system, so it is very difficult for the traditional linear and non-linear system in both theoretical research and practical application. As a neural network has the ability to approximate to any non-linear mapping through learning, it is remarkably advantageous to apply the neural network in the modeling and forecast of a non-linear system[11]. This thesis attempts to take Zhejiang Province as study object, and in consideration of only the factor of the current economic development, utilizes the most popular Back-Propagation Network(BP network) in the neural network to establish the forecast model and accordingly forecast the urbanization level of Zhejiang Province.

II. PRINCIPLE OF BP NEURAL NETWORK ALGORITHM

A. Network Structure

In 1974, in his thesis for doctor degree, P. Werbos brought forward the first learning algorithm applicable for multi-layer networks; however, this algorithm had not been recognized sufficiently and applied widely until the mid of the 1980s the PDP (Parallel Distributed Procession) Panel published the book called as Parallel Distributed Processing in 1986 and applied in the research of neural network. Since then, this algorithm has been the most famous multi-layer network learning algorithm, i.e. BP algorithm, by now. The neural network trained with this algorithm is called as BP neural network [12].

The BP network is a neural network with three or above layers of neurons, including an input layer, a middle layer (hidden layer) and an output layer.

For any continuous function within closed intervals, the single-layer BP network can be adopted to approximate; therefore, a three-layer BP network can complete any mapping from n-dimension to m-dimension. This thesis adopts the three-layer BP network. The full connection between the upper and lower layer is achieved with no connection among neurons on every layer. After a pair of learning samples is provided for the network, activation values of neutrons spread from the input layer to the output layer through various middle layers and obtain the input response of the network at various neurons of the output layer. Subsequently, in the direction of reducing the error between target input and actual input, such activation values return to the input layer from the output layer through the middle layers so as to correct various connection weight values layer by layer. As the inverted spread and correction of such error is conducted continuously, the accuracy rate of the network response to the input mode is increasingly rising.

B. Network Learning Rules

Suppose the number of the nodes of the input layer, the hidden layer and the output layer of the BP neural network is n, p, q respectively; then the network input vector is $p_k = (a_1, a_2, \cdots, a_n)$; the network target vector is $T_k = (y_1, y_2, \cdots, y_q)$; the middle layer unit input vector is $S_k = (s_1, s_2, \cdots, s_p)$ and output vector is $B_k = (b_1, b_2, \cdots, b_p)$; the output layer single-layer input vector is $L_k = (l_1, l_2, \cdots, l_q)$ and output vector is $C_k = (c_1, c_2, \cdots, c_q)$; the connection weight from the input layer to the middle layer is $w_{ij} (i = 1,2,\cdots,n; j = 1,2,\cdots,p)$; the connection weight from the middle layer to the output layer is $v_{jt} (j = 1,2,\cdots,p; t = 1,2,\cdots,q)$; the output threshold value of every unit of the middle layer is $\theta_j (j = 1,2,\cdots p)$; the output threshold value of every unit of the output layer is $\gamma_t (t = 1,2,\cdots,q)$ and the parameter $k = 1,2,\cdots,m$.

(1) Initialization. Give a random value within the interval $(-1,1)$ for every connection weight value w_{ij} and v_{jt} and every threshold value θ_j and γ_t.

(2) Randomly select a set of input and target samples $p_k = (a_1^k, a_2^k, \cdots, a_n^k)$ or $T_k = (y_1^k, y_2^k, \cdots, y_q^k)$ and provide it for the network.

(3) Use the input sample $p_k = (a_1^k, a_2^k, \cdots, a_n^k)$, connection weight value w_{ij} and threshold value θ_j to calculate the input value of every unit of the middle layer s_j, and then use s_j to calculate the output value of every unit of the middle layer b_j through transfer function:

$$s_j = \sum_{i=1}^{n} w_{ij} a_j - \theta_j \quad j = 1,2,\cdots,p \tag{1}$$

$$b_j = f(s_j) \quad j = 1,2,\cdots,p \tag{2}$$

(4) Use the output b_j of the middle layer, the connection weight v_{jt} and threshold value γ_t to calculate the output of every unit of the output layer L_t, and then calculate the response of every unit of the output layer c_t:

$$L_t = \sum_{j=1}^{p} v_{jt} b_j - \gamma_t \quad t = 1,2,\cdots,q \tag{3}$$

$$c_t = f(L_t) \quad t = 1,2,\cdots,q \tag{4}$$

(5) Use the network target vector $T_k = (y_1^k, y_2^k, \cdots, y_q^k)$ and the network actual output c_t to calculate the common error of every unit of the output layer d_t^k:

$$d_t^k = (y_t^k - c_t) c_t (1 - c_t) \quad t = 1,2,\cdots,q \tag{5}$$

(6) Use the connection weight v_{jt} and the common error of every unit of the output layer d_t^k and the output of the middle layer b_j to calculate the common error of every unit of the middle layer e_j^k:

$$e_k^j = (\sum_{t=1}^{q} d_t v_{jt}) b_j (1 - b_j) \tag{6}$$

(7) Use the common error of every unit of the output layer d_t^k and the output of the middle layer b_j to correct the connection weight v_{jt} and the threshold valve γ_t:

$$v_{jt}(N+1) = v_{jt}(N) + \alpha d_t^k b_j \tag{7}$$

$$\gamma_t(N+1) = \gamma_t(N) + \alpha d_t^k \tag{8}$$

$$t = 1,2,\cdots,q \quad j = 1,2,\cdots,p \quad 0 < \alpha < 1$$

(8) Use the common error of every unit of the middle layer e_j^k and the input of every unit of the input layer $p_k = (a_1, a_2, \cdots, a_n)$ to correct the connection weight w_{ij} and the threshold value θ_j :

$$w_{ij}(N+1) = w_{ij}(N) + \beta e_j^k a_i^k \qquad (9)$$

$$\theta_j(N+1) = \theta_j(N) + \beta e_j^k \qquad (10)$$

$$t = 1,2,\cdots,q \quad j = 1,2,\cdots,p \quad 0 < \beta < 1$$

(9) Randomly select the next learning sample vector and provide it for the network, and then back to Step (3) until the training of m training samples is completed.

(10) Randomly select a set of input and target samples from m learning samples again and back to Step (3) until the global error of the network E is less than the preset minimum value, i.e. network convergence.

(11) The learning ends.

The network undergoing training shall have a performance test. The testing method is: select the test sample vector, provide it for the network and then check the correctness of its classification by the network[12].

III. Forecast of Zhejiang Province's Urbanization Level

A. Establishment of BP Network Forecast Model

Take the GDP per capita representing the current development factor as the input vector of the input layer, the urbanization ratios of the past years as target vector, the transfer function of the hidden layer of the network as , the transfer function of the output layer as and the training function as to establish a BP neural network model with one input node and one output node. The selection of the number of the neurons of the hidden layer involves a very complicated issue. By now, there have been no an ideal analysis formula to express the number of the neurons of the hidden layer, which, therefore, has to be confirmed according to the experience of the designer and many tests. This thesis attempts to use the formula to confirm the number of the neurons of the hidden layer, wherein, "m" is the number of the output neurons, "n" is the number of input units and "a" is a constant in the interval [1, 10]. Select the number of the neurons to be 3-6; under the specified precision , set the number of trainings as 5,000 and take the statistic data of 1980-1999 as training samples to train the model with the training results as shown in Figures1~4 and error comparison in Table Ⅰ.

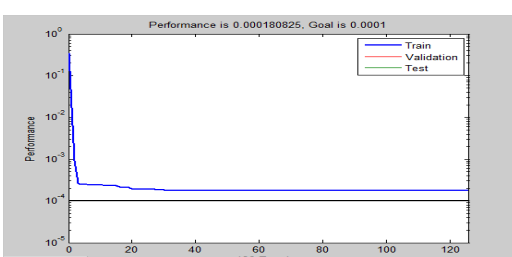

Figure 1. Training result of 3 neurons.

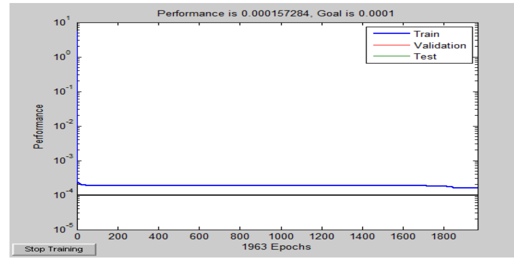

Figure 2. Training result of 4 neurons.

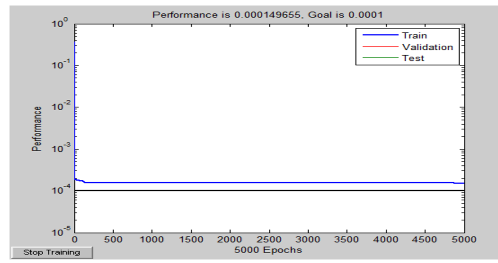

Figure 3. Training result of 5 neurons.

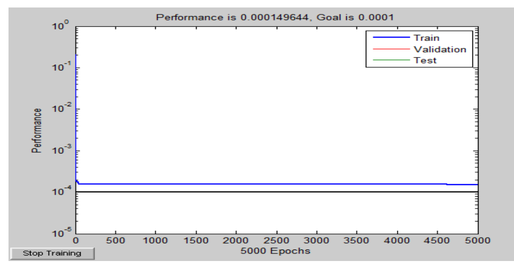

Figure 4. Training result of 6 neurons.

TABLE I. Network Training Errors

Hidden Layer Neuron Numbers	Error /%
3	0.1589
4	0.1432
5	0.1338
6	0.1337

Table Ⅰ indicates that small difference exists among the network training errors while the training times differ greatly when the numbers of neurons in the hidden layer are 3-6 respectively. When the number of the neurons in the hidden layer is 3, the trainings are 126; when such number is 6, such trainings reach maximum 5,000. After the overall consideration, the number of the neurons in the hidden layer is set as 3. Table Ⅱ indicates that the target error of the network is not satisfied after 126 trainings; through the observation of the network training curves, the training process of the network does not converge, because too small is set. In such event, reset , train the model and then training result will be as shown in Figure 5.

Figure5 indicates that the network target error has been satisfied and the training process of the network converges quickly, appearing linear. The weight value of the network hidden layer is IW1=[-16.8004 16.5646 -16.8174] and the threshold value of such layer is b1=[16.7994 -8.1575 -0.0801]; the weight value of the output layer is LW2=[-0.0159 0.1871 -

0.3899] and the threshold value of such layer is b2=0.3573. This model is adopted to forecast the urbanization of Zhejiang Province in 2000-2004.

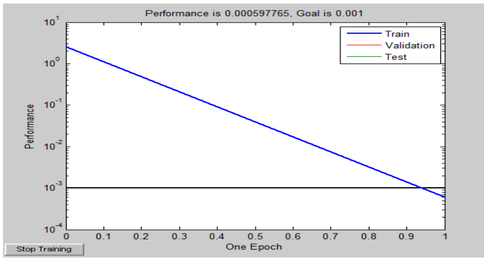

Figure 5. Training result with $\varepsilon = 0.001$.

B. Forecast Results and Analysis

According to the statistics yearbook of Zhejiang Province, the GDP per capita of 2000-2004 is RMB13,309, RMB14,655, RMB16,838, RMB20,147 and RMB23,942. If the trained model is adopted to forecast the urbanization level of Zhejiang Province in 2000-2004, the forecast result will be as shown in Table II below.

TABLE II. FORECAST RESULT OF URBANIZATION LEVEL

Year	Actual Value /%	Predicted Value /%	Relative Error /%
2000	48.67	47.45	2.51
2001	50.90	50.31	1.16
2002	51.90	52.25	−0.67
2003	53.00	52.88	0.23
2004	54.00	53.64	0.67

Table II indicates that the forecast precision of the BP network is very ideal. All relative errors of the forecast results are less than 5%, maximum relative error is 2.51%, minimum relative error is 0.23% and mean absolute percent error is 1.05%. According to the results, the forecast performance of the BP network obtained through training is rather good with forecast values very close to actual values. However, this model has some disadvantages: firstly, it considers too few influencing factors; and secondly, the confirmation of the hidden layer mainly relies on the empirical method and the trial method.

Typically, the urbanization level below 30% indicates the preliminary development stage, the urbanization level between 30%-70% indicates the metaphase speeding stage and above 70% the anaphase mature development stage. The urbanization level of Zhejiang Province in 2000 was 48.67% and 54% in 2004. This indicates that the urbanization level of Zhejiang Province is increasing gradually and on the metaphase speeding stage.

IV. CONCLUSION

The BP network is the core part of the forwarding network and it represents the most essential and perfect content of the neural network[12]. As the BP network has very strong self-adaptation and self-organization learning capacity, very excellent error tolerance, distribution and parallel processing feature as well as very powerful extrapolation and interpolation and astringency, together with its simple network architecture and easily programmed and realized algorithm, it can approximate the random non-linear mapping relation provided that sufficient hidden layers and hidden nodes are available[2,12]; therefore, this model can be adopted to forecast the urbanization level of Zhejiang Province. Although the BP network has been used widely, it has some inborn disadvantages and deficiencies. For example, as the learning speed is constant, the network is slow in convergence and thus needs very long training time. The BP algorithm can make the weight value converge to one value, but it cannot ensure it is the global minimum value of the error plane and it can be easily run into a local minimum value; in addition, the selection of the number of the layers and units of the hidden layer has been short of theoretical direction and generally is based on experience and repeated tests [12]. Such disadvantages and deficiencies will become the targets of the improvement of the BP neural network in the future. Therefore, more advantages will be available if the BP network is used for urbanization forecast.

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