

Forecasting the Rural Per Capita Living Consumption Based on Matlab BP Neural Network

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Abstract

Resident consumption is the important for the rapid and sustainable economic growth in China, and the number of rural residents is almost half of the total number, and forecasting the rural residents per capita living consumption accurately and reliably provide important basis for the government to establish new development strategies. Therefore, prediction of rural per capita living consumption is one of the important contents of the analysis of Chinese economy development in the future. In recent years, there are many prediction methods about the consumption, but some is low accuracy. In this paper, the BP neural network based on Matlab simulates the rural residents per capita living consumption, and forecasts the consumption expenditure in future three years through the actual data test and empirical analysis. Prediction results show that this method has high prediction accuracy; the model is feasible and effective in the application of forecast residents living consumption.

Key Words: BP Neural Network; per capita living consumption; forecasting model; empirical analysis

1. Introduction

The government has been committed to expanding the domestic demand, and the residents living consumption is an important factor affecting domestic demand. According to the 2012 census, the proportion of the number of rural residents relative to total population was 51.66% (2009), 50.05% (2010), 48.73% (2011). The consumer is the final consumption expenditure for various goods and services in a certain period. In addition to directly in the form of currency to buy the goods and services, including other forms of consumption for goods and services, namely virtual expenditure. Slow growth in consumption has become an important factor for restricting the sustainable economy development in China.

Accurately predicting rural per capita living consumption has important significance to increase the income of peasants, improve the rural consumption level, reasonably promote the development of rural consumer market. Scientific prediction for the rural per capita living expenditure can provide an important basis for the government to formulate new strategy of economic development, more reasonably to increase the income of rural residents and to ensure the whole economic and social develop stably and sustainably.

Residents consumption system is a complex system, which determines the instability of consumption forecasting effect. Common prediction models are ARIMA model, GM (1, 1) model, combination forecasting and neural network prediction, and so on. At present, some domestic scholars used different methods and prediction model to research the per capita living consumption, but the adoption of the method and the basic data are different, forecasting results are also different, and sometimes the prediction precision is low. Thus, there are still some problems in prediction method choice, so we need to find a more accurate, more scientific and more effective forecasting model.

2. Literature review

2.1 Living consumption prediction models

Li Dongsheng, Zhu Zhonggui (2009) establish the grey dynamic model GM (1, 1), and predict the rural residents living consumption in Hubei through accuracy test and model correction[1]. Bai Lichi, Wu Xianbin (2006) use the basic theory and method of the grey model GM (1, 1) and predict the peasants consumption based on 2000-2005 per capita net income and the per capita consumption index in Zhejiang[2]. Zhan Jinhua (2009) forecasts Chinese 2008-2015 annual disposable income and living consumption according to 2000-2007 China urban per capita disposable income and per capita consumption data, using the basic GM (1,1)[3]. Han Xinghuan, Wang Xia (2013) according to 1992-2010 rural residents consumption statistics in Jilin Province, take the consumption statistics in 2001-2010 as the sample interval for prediction and use GM (1,1) model to predict the rural consumption level in Jilin Province in 2011-2020. These predictions use relatively little data information, the methods are also very simple, but the degree of models fitting is low.

Gao Xiaohua (2013) selects 1990-2012 annual income of rural residents in Shandong Province and consumption data to establish the linear regression model and predict the rural living consumption in future 3 years[5]. Liu Yourui (2011) establishes the multiple regression model, basing on the 1990-2010 living consumption data, to predict the urban living consumption level in future three years in Nanchong, Sichuan. He has proved the level increases year by year and the residents' disposable income level and market consumption price level have a great influence on the urban residents living consumption level[6].

Lu Xiaoli (2012) predicts the future growth rate of living consumption level by Markov model and ARIMA model, according to per capita rural residents consumption in 1978-2009 in Sichuan, show that the rural residents living consumption growth rate is 10%-20% in next few years[7]. Ma Wenjing (2012) selects the rural residents per capita consumption expenditure in 1990-2011 and establishes four ARIMA (P, D, q) (P, D, Q) s models by using Eviews differential operators. Through evaluation of the four models, she selects the most appropriate model to forecast the future rural living consumption expenditure [8].

2.2 The application of neural network model

Li Guozhu (2007) combines the BP neural network model, the time variable model and grey prediction model organically and carries on the empirical analysis using the consumption data in 1986~2005 to predict the living consumption expenditure from 2007 to 2010[9]. He Qingbi (2007) establishes an improved BP network prediction model through an improved algorithm of BP neural network, and empirically analyzing this model with quarterly living consumption data in 1997.1-1998.8[10]. This model shows that the fitting degree of the predicted value and the actual value is high, which proves the BP neural network can improve the prediction accuracy and is a good prediction method.

For the neural network, it is currently used in the prediction of energy, such as oil, natural gas consumption and demand forecast, rarely its application in economics. For example, Xu Ping (2007) predicts oil demand in China based on BP neural network [11], Hu Xuemian, Zhang Qishan (2008) establish prediction model of BP neural network based on MATLAB to predict coal demand[12], Li Jianzhong (2010) research the security of energy supply and demand based on principal component analysis and BP neural network[13]. In the current study, Ma Fuyu, Yu Lean (2013) establish the consumption model to predict the quantity of annual pork consumption demand in China[14]. Sun Aobing (2005) establishes the neural network models of consumption function in China[15], as well as Wang Qingqing (2005) forecasts consumption based on artificial neural network combination[16].

Classic common forecasting methods such as exponential smoothing, gray model and regression analysis methods have a common limitation, which requires to know in advance prediction mathematical model of the object. But in practical application, many objects have complex uncertainty and variability, it is difficult to establish the prediction model. When using multiple factor for prediction, to predict the dependent variable factor, it often needs to predict every factor first, which increases the margin of prediction error. The neural network overcomes the difficulties in establishing model and estimating parameter, it does not need a specific mathematical model, less data, high precision, can be modified and can more precisely describe the mapping relationship between factors, so that it can reduce the difficulty of the prediction process, making up for some shortcomings in establishing models based on econometrics such as:

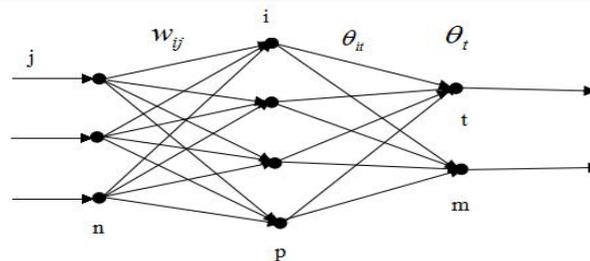
It's difficult for the current models to grasp the nonlinear phenomenon, the prediction value is relevantly low for the rising data based on exponential smoothing method, ARIMA model needs more data. Therefore, the research on the neural network prediction model has gradually become an important content of forecast method research.

3. BP neural network

3.1 Basic Principles

BP neural network is multiple-layer feedback network based on error Back-Propagation algorithm. The network model is proposed by Professor D. Rumelhart in Stanford University in 1985, called EBP (Error Back Propagation) algorithm. The BP algorithm solves the problem in the connection weights of containing layer in multilayer network model and improves the learning and memory function of neural network, especially the XOR problem; it has become one of the most typical models of neural network applications. BP neural network model is a forward connection model composed of input layer, hidden layer and output layer, neurons in same layer are independent of each other, not connected with each other, the adjacent layer neurons are connected by weight and interconnection structure, the structure of neural network is shown in figure 1:

Figure 1 Neural network structure



When a signal is input, it is spread forward to the nodes of the hidden layer first. The signal is spread by layer, and ultimately to the nodes of the output layer, and each layer has its own corresponding characteristic function to transform. Because the signal is propagated forward until the output layer, so the BP neural network model is a kind of feed-forward network. The learning process of BP neural network consists of forward spread and backward spread. When given an input pattern, the signal is spread from the input layer to the hidden layer and calculated, then the result is transferred to the next layer.

Such calculating and transferring to the output layer finally produce an output mode, This is a process of state updating layer by layer, which is called the forward propagation. If the error between the actual output pattern and the expected output patterns is large, the error signal will be returned from the output layer to the input layer through the hidden layer along the original path, and connection weights of each layer will be modified according to the error values to reduce the error. This process can not stop until the result can meet the conditions, which is called the backward propagation. Once all the training patterns are satisfied, BP network learning is in a good state, when using BP network, we just need forward propagation, no backward propagation.

3.2 Learning Algorithm

- (1) Initializing the weights and residual error of each neuron, usually taking random numbers are close to zero.
- (2) For a given data sample, as the input of neural network model, we will set the expected output value; We set the input mode vector as: $X = \{x_1, x_2, \dots, x_n\}$, and the corresponding the desired output mode vector as: $d = \{d_1, d_2, \dots, d_m\}$.
- (3) Calculating the actual output values of nodes in each layer through the forward propagation in network, we set the calculation formula of the neurons data u_i in the hidden layer as:

$$u_i = \sum_{j=1}^n w_{ji} - \theta_i, \quad i = 1, 2, \dots, p.$$

Among them, w_{ji} is the connection weight between the neuron j in the input layer and the neuron i in the hidden layer; θ_i is threshold value of the neuron i in the hidden layer; p is the number of hidden layer neurons.

To simulate the no-phenomenon characteristics of biological neuron, we set u_i as an independent variable to Sigmoid function, and calculate the output value y_i of hidden layer neurons. The Sigmoid function as:

$$y_i = f(u_i) = \frac{1}{1 + e^{-u_i}}, i = 1, 2, \dots, p.$$

Similarly, we calculate the output value y_t and the input value u_t of neurons in each layer:

$$u_t = \sum_{i=1}^p w_{it} - \theta_t, t = 1, 2, \dots, m$$

$$y_t = f(u_t) = \frac{1}{1 + e^{-u_t}}, t = 1, 2, \dots, m$$

w_{it} is the connection weight between the neuron i in hidden layer and the neuron t in output layer; θ_t is the threshold value of the neuron t ; m is the number of the neurons in output layer.

4. The model construction based on Matlab BP neural network

4.1 Select samples

We collect 1991-2011 national rural residents per capita living consumption statistics from China Statistical Yearbook. In order to improve the data distribution, to improve the training speed and sensitivity, and to increase the model accuracy and effectively to avoid the saturated zone of the Sigmoid activation function in hidden layer, we request input values between the (0, 1). First we should normalize all the input data.

The normalized formula as:

$$b = \frac{a - a_{min}}{a_{max} - a_{min}}$$

Among them, a is the primitive data of rural per capita consumption, b is the normalized variable. We input the processed data to consumption prediction mode and train the data, then we can obtain the predictive value. In order to make the data correspond to the real data we should anti-normalize the predictive value. The anti-normalization formula as:

$$a_f = b_f (a_{fmax} - a_{fmin}) + a_{fmin}$$

a_f is the anti-normalized variable, b_f is output variable of the model.

The maximum value is 10000, the minimum value is 500, the standardization data as the following table 1:

Table 1 1991-2011, rural per capita living consumption data and normalized data

Year	1991	1992	1993	1994	1995	1996	1997
Original data	619.80	659.00	769.60	1016.80	1310.26	1572.08	1617.15
Standardization data	0.01261	0.01674	0.02838	0.05440	0.08529	0.11285	0.11759
Year	1998	1999	2000	2001	2002	2003	2004
Original data	1590.33	1577.42	1670.13	1741.09	1834.30	1943.30	2184.65
Standardization data	0.11477	0.11341	0.12317	0.13064	0.14045	0.15193	0.17733
Year	2005	2006	2007	2008	2009	2010	2011
Original data	2555.40	2829.02	3223.85	3660.68	3993.45	4381.82	5221.13
Standardization data	0.21636	0.24516	0.28672	0.33270	0.36773	0.40861	0.49696

Data from: China Statistical Yearbook

4.2 Select the network structure

BP neural network based on Matlab includes the input layer, hidden layer and output layer. Through a lot of simulation training, we determine the number of nodes in the input layer and the hidden layer, and select the optimal network structure to predict consumption more accurately.

4.2.1 Determine the number of nodes in the input layer

The number of nodes of time series data in input layer is, generally among 2~6. When the number of nodes in input layer is too large, the network learning times are too large.

The number is too small, the neural network can not reflect the prediction accuracy. We design the node number from small to large by trial. The network error is not significantly reduced, with the number of the nodes in input layer increasing, at this time, the number of nodes in input layer is the optimal for the BP network.

4.2.2 Determine the number of nodes in the hidden layer

In general, the number of nodes in hidden layer is too small, BP neural network will not be able to build complex mapping relations, so that the training of BP neural network cannot effectively produce results; But the number of nodes in hidden layer is excessive, the error is not necessarily minimal, so that the BP neural network learning may be too long, also the phenomenon of data "over-fitting" may appear, which reduce the stable performance of the BP network. In 1989, Hecht-Nielsen proved that the BP network with hidden layer can be used to approximate to any continuous function. Thus a three-layer neural network can complete the mapping from n dimension to m dimension.

Therefore, the principle of determining the number of nodes in hidden layer is: in the experiment, the primary node number in hidden layer can be determined the range according to the type $h = \sqrt{n+m+a}$ or type $h = \log_2 n + a$ (h is the number of nodes in hidden layer, n as the number of nodes in input layer, m as the number of nodes in output layer, a is an integer among $0 \sim 10$). In order to meet the accuracy requirements, we take as small as possible number of nodes. According to the Kolmogorov theorem, usually the optimal number of nodes in hidden layer is $2n-1, 2n$, or $2n+1$ (n as the number of nodes in input layer), BP network has convergence effect.

4.2.3 Determine the number of nodes in the output layer

In this paper, the output layer is only one dimension, the rural per capita living consumption. So the next, we only need to determine the number of nodes in input layer and in hidden layer. In this paper, the number of nodes in input layer and in hidden layer is determined by trial, to train and test the network. Based on the empirical formula of the number of nodes in hidden layer, we train the network with different numbers of nodes in input layer and hidden layer, and choose the number of nodes with minimum error as the optimal number of nodes in hidden layer and in input layer.

5. Consumption Forecast

5.1 BP network training based on the Matlab

When training the network, the data input is the normalized data during 1991-2006, output data is normalized data during 1994-2009. After training the network, we select the data from 2010 and 2011 as the test samples and analyze the testing error. In this paper, The learning algorithm of BP network is LM (Levenberg-Marquardt) algorithm, which is the fast algorithm proposed to train the BP network. Respectively we set the network training relative error as 0.001, 0.0001, the maximum training times as 500, 1000, 1500, 2000, 2500, the number of iterations 25, 50, the learning rate is 0.05. Under such condition, we train the network structure on different numbers of nodes in input layer and hidden layer and get the minimum relative error rate of network with different numbers of nodes, the average relative error rate are shown in table 2:

Table 2 Network structure training error value with different numbers of nodes

node number in input layer \ node number in output layer	3	4	5	6	7	8	9	10	11	12
2	0.018	0.027	0.057	0.007	0.029	0.017	—	—	—	—
3	—	0.046	0.03	0.025	0.012	0.079	0.020	0.030	0.013	0.036
4	—	—	0.016	0.045	0.009	0.018	0.035	0.016	0.010	0.038
5	—	—	—	0.008	0.027	0.020	0.005	0.017	0.006	0.080
6	—	—	—	0.092	0.007	0.010	0.046	0.016	0.012	0.006

When the the number of nodes in hidden layer is 2, the number of nodes in hidden layer is greater than 8, network over-fits the data and network structure is not stable. Under normal circumstances, the number of node in hidden layer should be greater than in input layer, network structure has good stability, therefore in this table, we don't list the relative error rates of the above two cases.

From the above, when the number of nodes in input layer is 5, the number of nodes in hidden layer is 9, the network relative error rate is minimum, as 0.005. At this time, the target error rate we set is 0.01 and the training relative error square is 0.0001, the maximum training times is 1000, the number of iterations is 25, the learning rate is 0.05, the BP neural network model has good stability and can obtain better results, so the optimal network structure is 5-9-1. We save the weights and threshold value of trained 5-9-1 BP network preservation to forecast next consumption. The training results as shown in figure 2:

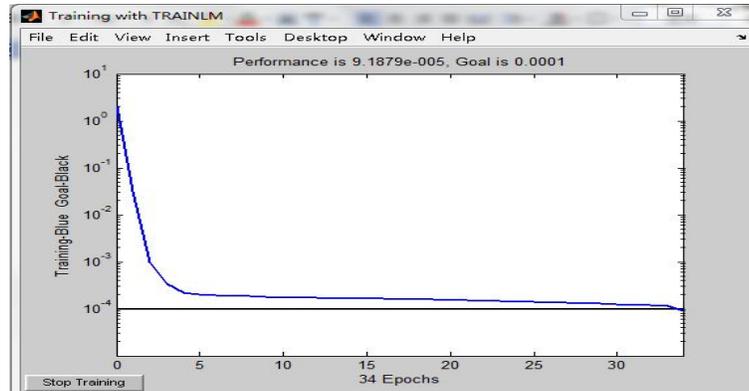


Figure 2 Network training results

The figure2 shows that the network performance function value is 9.78×10^{-5} , the mean square error of network output and target output is 9.78×10^{-5} , close to the target error as 0.0001.

5.2 Error Analysis

For the fitting effect between observation value of test sample and the prediction value of the BP neural network as shown in figure3:

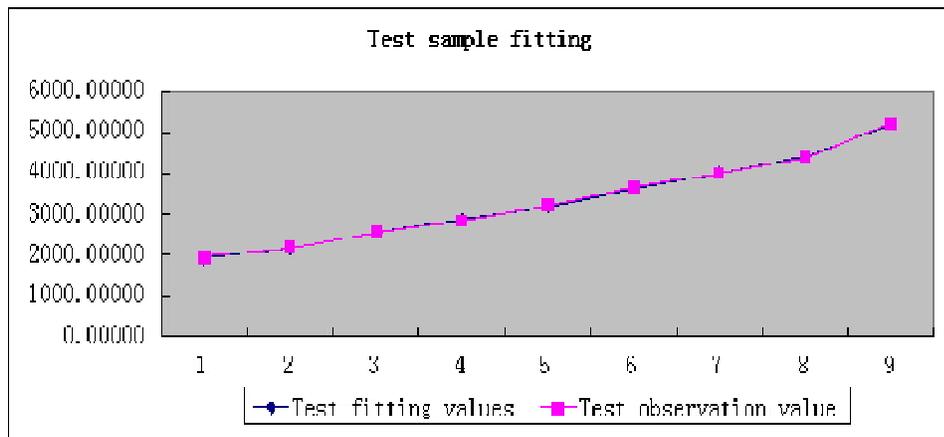


Figure3 Test sample fitting

An important standard to measure a model is the relative error between the sample observation value and model prediction value, the relative error is less, the stability of the model is better. This graph shows, the model is of high accuracy and good fitting effect.

We compare the predicted rural living consumption data with the actual consumption data during 2010-2011 and analyze the error, shown in table 3:

Table 3 the error rate between the actual data and the predicted data

Year	The actual data	The normalized data	The predicted data	The anti-normalized data	The error rate
2010	4381.82	0.40861	0.41209	4414.85	0.00754
2011	5221.13	0.49696	0.49444	5197.18	-0.00459

From the table we can found, each error rate of the test sample is less than 0.01, the target error rate, and the average error rate is 0.00606, lower than the target error 0.01, too. The accuracy of the model is high, therefore, can forecast rural per capita living consumption in future three years.

5.3 Forecasting consumption

We predict the per capita consumption in 2012, 2013, 2014 in rural area by using the trained BP neural network, the results shown in table 4:

Table 4: Predicting results (unit: yuan)

Year	2012	2013	2014
The predicted data	0.56981	0.66398	0.76232
The anti-normalized data	5913.19	6807.810	7742.04

6. Conclusion

(1)The predicted results show that Chinese rural per capita living consumption rises steadily nearly 3 years, with the living level increasing, the spiritual consumption as well as the material consumption will also increase, the government and the relevant departments should do a good job to meet rural material and spiritual demand. This prediction also provides an important basis for the government to formulate national economic development strategies.

(2)We adopt BP neural network based on Matlab to forecast the per capita living consumption , the efficiency of operating computer program is high , the error is less than 0.01, the prediction accuracy is high, so the prediction through BP neural network based on Matlab has certain practical application value. The error analysis shows that, the prediction error is very small, the existence of the error is mainly because the quantity of data is limited and there are some errors during training process, if the amount of training data increases, prediction results will be more accurate .

7. References

- Li Dongsheng, Zhu Zhonggui. *Application of GM(1,1) model in prediction the rural consumption*[J]. Journal of Hubei Agricultural College. 2009, 19(3):266-268
- Peng Liquan. *The research on development tendency of rural living consumption structure*[J]. Chinese rural observation. 2006, (5) :30-36
- Liu Youduan. *The regression analysis and prediction of urban residents' Life Level of consumption*[J]. Journal of Linyi University. 2011, 33(6):10-13
- Han Xinghuan, Wang Sha. *Analysis of status and trend of rural consumption in Jilin Province*[J]. Journal of Jilin Agricultural University. 2013 , 35(1):111-120
- Lu Xiaoli. *Analysis and forecast of the living expenditure increase of rural residents in Sichuan Province based on forecast and ARIMA model*[J]. Journal of Anhui Agriculture. 2012, 40(21): 90-94
- Ma Wenjing. *Prediction of rural per capita living consumption cash spending* [J]. Journal of Oriental Culture. 2012 , (9):143-144
- Zhan Jinhua. *Grey Prediction for China's urban resident income and consumption*[J]. Journal of Chongqing Technology and Business University. 2009, 26(2):42-46
- He Bingqing. *Application of BP neural network to city consume prediction*[J]. Journal of Chongqing Jiaotong University 2007, 26(1):155-157
- Li Guozhu. *The combined forecasting model of residential consumption in China*[J]. Contemporary Economy & Management. 2007, 29(6):7-10
- Xu Ping, Wang Ben. *Forecasting oil demand in China based on BP neural network*[J]. Journal of Daqing Petroleum Institute. 2007. 4, 31(2):82-84.
- Hu Xuemian , Zhao Guohao. *Forecasting model of coal demand based on matlab BP neural network*[J]. Chinese Journal of Management Science. 2008, 10(16):521-525.
- Li Jianzhong, Xie Wei. *Study on security of energy supply and demand based on principal component analysis and BP neural network*[J]. Water Resources and Power. 2010, 28(5):169-171.
- Ma Fuyu, Yu Lean. *Prediction study on pork annual consumption demand in China based on neural network*[J]. Journal of Science & Mathematics Science. 2013, 33(1):67-75.
- Sun Aobing, Zhang Annian. *Artificial neural network model directly applicable in consumption forecast* [J]. Journal of Henan University of Science and Technology. 2005, 26(1):44-47.
- Han Liquan. *The Theory, design and application of the artificial neural network*[M]. Beijing Chemical Industry Press, 2005:1-51.
- Zhou Pin. *The design and application Matlab neural network* [M]. Tsinghua university press, 2013.