International Journal of Multimedia and Ubiquitous Engineering
Vol.9, No.4 (2014), pp.51-62
http://dx.doi.org/10.14257/ijmue.2014.9.4.06

Regional GDP Prediction Based on Improved BP Neural Network Model

Zhikun Xu [1], Xiaodong Wang[2] and Yingying Jin[3]

College of Finance, Hebei Normal University of Science & Technology, Qinhuangdao, Hebei, P.R.China,066004

[1]xuvikp@126.com, [2]jmxwxd@126.com,[3]695735043@qq.com

Abstract

In this paper, an improved BP neural network model is proposed. In the model, the momentum factor can improve the training speed and avoid falling into local minimum. Steepness factor and adaptive learning rate can improve the convergence speed. The genetic algorithm is used to solve the problem of low training speed, low accuracy of prediction and easy to fall into local minimum of BP neural network. Then the improved BP neural network model is established to predict GDP of Anhui province. The result shows that it is better than the other models which are presented in this paper on forecasting GDP of Anhui province.

Keywords: *Prediction, GDP, BP neural network, GA, momentum, steepness, adaptive learning rate*

1. Introduction

The gross domestic product (GDP) is the main index to measure the economic development of country and region. It is also the main basis for the economic development strategy, planning, and a variety of macroeconomic policy. GDP can reflect the comprehensive development level of a country. So it is very important to predict GDP in a scientific method and forecast GDP precisely.

At present, there are lots of methods to predict GDP. The main methods are time series prediction method [1-3], markov prediction method [4-6], regression method [7-9], gray theory method [10-12], and neural network method [13-15], etc. In front of the four methods are the traditional forecasting methods. They mostly analyze the causal relationship between variables. Some problems which are multicollinearity and serial correlation exist in the practical application.

Artificial neural network is referred to as the neural network. It is a highly complex nonlinear network system composed of many neurons that connecting to each other. This complex network system can reflect many basic characteristics of brain function. In 1986, Rumelhart and McCelland [16] first proposed the back prorogations neural network. And the BP neural network is the most widely used artificial neural network model at present. BP neural network which has strong nonlinear mapping ability is the most representative neural network model. It also has some shortcomings such as long convergence time and easy to fall into local minimum point. Lots of scholars and researches study the neural network. Bao and Ren [17] compared BP neural network classification and maximum likelihood classification by using TM remote sensing data and the results showed that BP neural network based on LM algorithm is better than the maximum likelihood method for classify to remote sensing image Higher accuracy. Savich [18] *et al.* proposed a novel architecture for implementing multi-layer perceptron (MLP) neural networks on field programmable gate arrays (FPGA) and results showed that a minimum performance boost of three orders of magnitude (O^3) over software

ISSN: 1975-0080 IJMUE

implementation is regularly achieved. Jing [19] *et al.* proposed an improved BP neural network to predict separation percent (SP). And due to changing with increasing ratios of learning rates and weights properly, the improved BP neural network is better than BP algorithm. Zhang [20] applied BP Neural Network to predict gas content of coal seam. The results showed its prediction accuracy and feasibility are better than the multiple-regression model. Gao [21] *et al.* studied sparse algorithms for training Random Weight Networks (RWN). The paper compared with the traditional back-propagation (BP) and RWN algorithms, the experimental results show that the proposed RWN algorithms have effective performances on the accuracy or time. Bai [22] added a suitable momentum term to BP algorithm to accelerate the convergence speed and used the BP neural networks to SARS epidemic prediction. Han [23] proposed an automatic axon–neural network (AANN). In the algorithm the weights are adjusted by using a feed forward computation (FC) to obtain the information for the gradient during learning computation. There are also many fields which the neural network applied in and pretty of researcher tried to improve the neural network algorithm [24-27].

In this paper, the overall structure of the study is as follows: In Section 2, firstly, the principle of BP neural network is introduced. Secondly, the improved BP neural network is introduced with momentum factor, steepness factor, and adaptive learning rate and optimized genetic algorithm. In Section 3, we establish the improved BP neural network model to predict GDP of Anhui province. And in the last section, the conclusion is given and some improvement efforts are pointed out.

2. Optimized BP neural network

2.1. The principle of BP neural network

Neural network model needs to provide samples before training. The samples contain the input vector P and the corresponding expected output vector T. The training process should continue to adjust the weights and thresholds in order to make the error function of neural network achieve the minimum. The guiding ideology of the BP neural network is to modify the network weight and threshold values along the fastest decline in direction (*i.e.*, the negative gradient direction). The training process is composed of two parts: Information forward propagation and error back propagation [28-29].The architecture of three layer back propagation artificial neural networks is shown in Figure 1. The output of any neurons from input layer is the weighted sum of input mode components. The input of any neurons from hidden layer and output layer is equal to the weighted sum of its adjacent previous layer neurons.

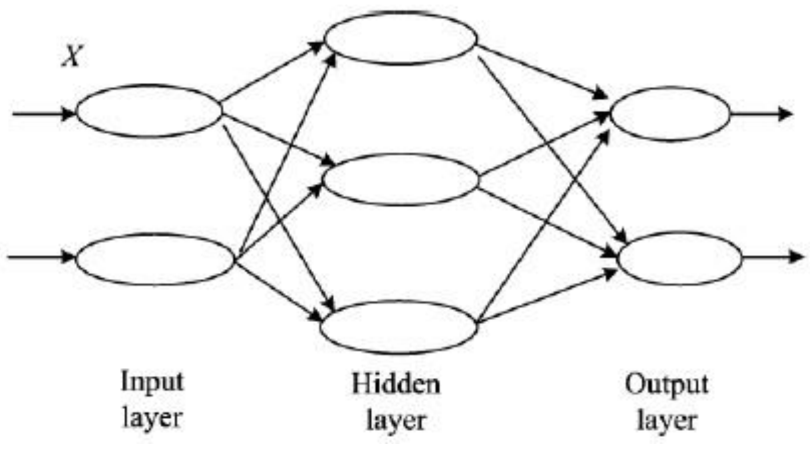

Figure 1. The architecture of three layer back propagation artificial neural networks

Assume that a neuron from a layer is set to be j and its input is set to be net_j and its output is set to be O_j. The output of any neurons of previous layer is O_i. Then we have following equation

$$net_j = \sum_i w_{ij} O_i \tag{1}$$

$$O_j = f(net_j) \tag{2}$$

Where w_{ij} is connection weight of neuron i and neuron j. The output function $f(net_j)$ is sigmoid function.

$$O_j = f(net_j) = \frac{1}{1+\exp(-net_j - \theta_j)} \tag{3}$$

Where θ_j is threshold value.

If the actual output of kth neuron in output layer is O_k and its input is set to be as net_k. And the output of jth neuron in hidden layer which next to output layer is O_j. Then we have

$$net_k = \sum_j w_{kj} O_j \tag{4}$$

$$O_k = f(net_k) \tag{5}$$

If there are N input samples, the expected output of kthneuron in the input layer is D_{pk}, and actual output is Y_{pk}. Then the mean square error of neural network system is

$$E = \frac{1}{2N} \sum_p \sum_k (D_{pk} - Y_{pk})^2 \tag{6}$$

When the network was trained, the neuron output error of output layer back propagates to the hidden layer and the input layer. And the weights between each layer are constantly revised in order to make the mean square error of neural system become minmum.

2.2. Improved BP neural network

The traditional BP neural network is easy to fall into local minimum and has the shortcoming of slow convergence speed etc. According to the shortcomings, improved BP neural network is proposed by introducing momentum factor, steepness factor, adaptive learning rate and optimized genetic algorithm. The momentum factor can improve the training speed and avoid falling into local minimum. Steepness factor and adaptive learning rate can improve the convergence speed. The introduction of optimized genetic algorithm is to solve the problem of low training speed, low accuracy of prediction and easy to fall into local minimum of BP neural network.

The traditional BP neural network algorithm does not consider gradient direction in the adjustment of weights before the time t. Thus it makes the training oscillation and slow convergence speed. The additional momentum method considers the effect of error in the gradient as well as the changing trends in the error curve surface. The weight adjustment formula is shown in bellow.

$$\Delta W(t) = \eta \delta X + \alpha \Delta W(t-1) \tag{7}$$

The former part of a weight is added to the current weight adjustment by introducing momentum term. So when the error curve surface appears suddenly to fall, it can reduce the shock trend and improve the training speed. The flow chart of BP neural network with momentum term is shown in Figure 2.

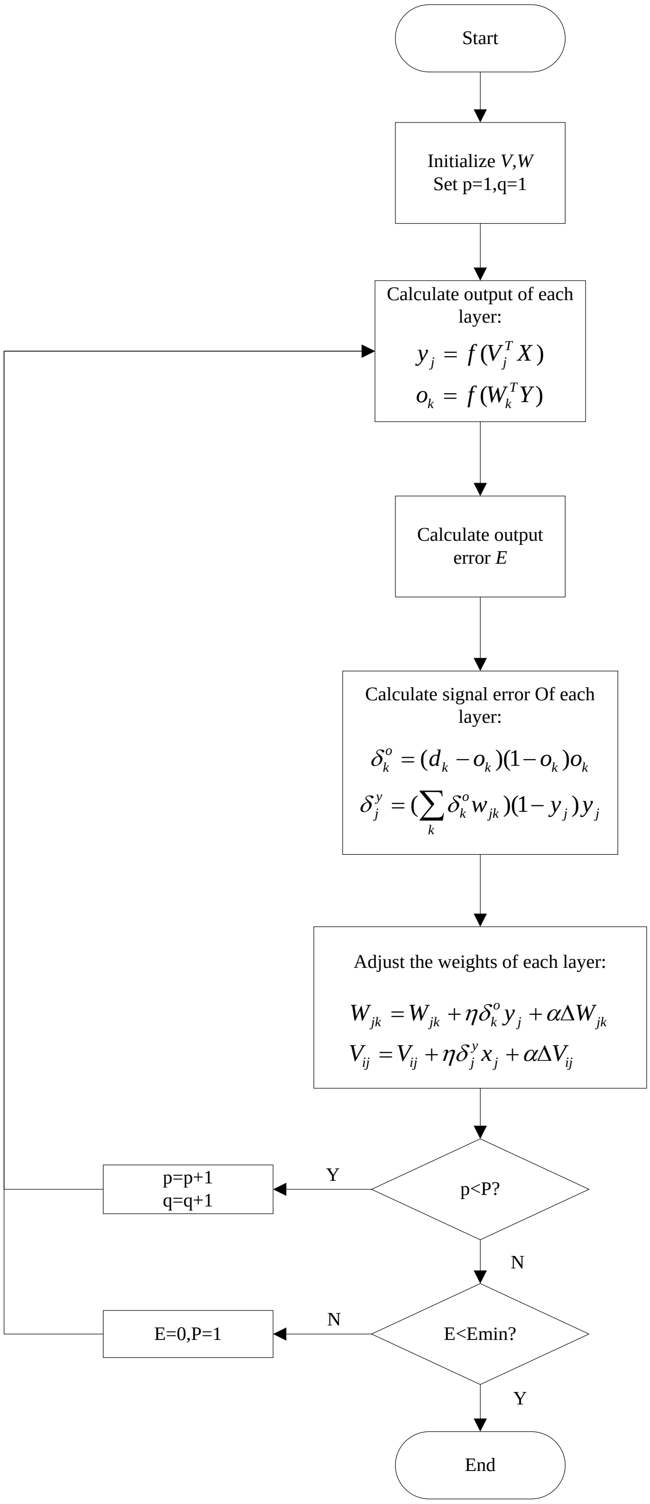

Figure 2. The flow chart of BP neural network with momentum term

The standard BP algorithm uses sigmoid function as activation function. The output range is $[0,1]$. Its derivative is $f' = f(1-f)$. But when the net input of neurons is too large or too small, the output will fall into the saturation region and the error can be significant, or even no convergence. Therefore after the neurons output enters the flat area, the net input of neurons needs to be compressed in order to make the output out of the saturated zone of transfer function.

The solution is introducing a steepness factor λ in the original activation function. λ can better adjust weights out of the flat region and accelerate the convergence speed of BP neural network. The activation function with steepness factor is

$$f(x) = \frac{1}{1+e^{-x/\lambda}} \tag{8}$$

Specific approach is that let $\lambda > 1$ when the output reaches the flat region and let $\lambda = 1$ when the output out of the flat region. When $\lambda = 1$, the activation function is standard sigmoid function. This method can improve the convergence speed of BP algorithm.

Slow convergence speed of BP neural network learning is because of the fixed learning rate and inertia factor. In order to guarantee the convergence of the algorithm, the learning rate must be less than a certain upper bound, which determines the convergence rate of BP neural network can't be fast. The learning rate η is as the static input which belong to $(0,1)$, it has no change in the training process. If the initial η is too large, it will cause the training shock. If η is too small, the number of training times will increase and the training time is lengthened. So in the adaptive learning rate algorithm, if the network total error increases after a weight adjustment when the initial learning rate is set, this adjustment is invalid and $\eta = \beta \times \eta \ (0 < \beta < 1)$. If the network total error decreases, this adjustment is valid and $\eta = \alpha \times \eta \ (\alpha > 1)$.

The initial weights of BP neural network are calculated by improved Genetic Algorithm (GA). Genetic algorithm is good at global search, while the neural network is more effective.in the local search. So they can use their own characteristics. Firstly, the initial weights of neural networks are optimized by genetic algorithm, a better search space is found from the solution space. Then the BP algorithm is used in the small search space to find optimal solution. The flow chart of GA is shown in Figure 3.

Figure 3. The flow chat of GA

The general genetic algorithm always set a fixed number of populations. In view of this situation, an adaptive population genetic algorithm is put forward. The algorithm has a large number of initial populations in the early time. With the algorithm continues, the populations reduce. This ensures that the diversity of individuals and prevents the algorithm falls into local minimum. It also improves the convergence speed so that the algorithm can quickly find the optimal solution.
The specific steps of improved genetic algorithm are as follows:

Step 1: Randomly generate populations X with N individuals, which $X=(X_1,X_2,\cdots,X_n)^T$. Each individual in the population is $X_i=(X_1,X_2,\cdots,X_n)^T$. X_i represent the initial weight distribution of neural network. The value of each gene represents a connection weight of a neural network. The length of individual is the number of the weights of neural network. That is

$$n = r \times s_1 + s_1 \times s_2 + s_1 + s_2 \tag{9}$$

Where r is the number of input layer nodes. s_1 is the number of the hidden layer nodes. s_2 is the number of output layer nodes.

Considering the weight has the requirements of high accuracy. Therefore the floating point is chosen as coding method to encode the weight.

Step 2: In this step, the individual is evaluated according to the value of the fitness function. Each individual is decoded by the method and the BP neural network input samples are got then. The value of output error in neural network is calculated and is represented by E . The fitness function is

$$f = \frac{1}{1+E} \tag{10}$$

Then the fitness value of each individual according is calculated by the fitness function. The individuals in the population are descending sorted by the size of the fitness values. Judge whether the average fitness value of individuals of this generation in population is higher than the best average fitness value of individuals in previous evolution. If the average fitness value of individuals of this generation is higher, it means the average fitness value of population increases. Then we can reduce the size of population accordingly. The number of population size decreases from M to M'.

$$M' = M_{\min} + (\mathrm{M}_{\max} - \mathrm{M}_{\min})\mathrm{e}^{-\Delta} \tag{11}$$

Where $M_{\max}$ is the maximum size of population range. $M_{\min}$ is the minimum size of population range. Δ is the increment of average fitness value of population. In each generation, the current optimal solution is retained and it is taken to the next generation until the required accuracy is reached or the generation gets to the maximum iteration.

Step 3: Selection operation. In this algorithm, the proportional selection operator is chosen. If the fitness value of ith individual of the population is f_i, and the probability of the individual that be selected is

$$p_i = \frac{f_i}{\sum_{i=1}^{M} f_i} \tag{12}$$

Step 4: Crossover operation. Since the individuals use float encoding method, the arithmetic crossover method is chosen as the crossover operation method. The probability of crossover is P_c, then we do crossover operation according to crossover probability.

$$X_1(\mathrm{t+1}) = \alpha X_1(\mathrm{t}) + (1-\alpha) X_2(\mathrm{t}) \tag{13}$$

$$X_2(\mathrm{t+1}) = \alpha X_2(\mathrm{t}) + (1-\alpha) X_1(\mathrm{t}) \tag{14}$$

Step 5: Mutation operation. Here, a uniform mutation operator is used as the mutation operation. For each value of gene locus in every individual, it is change to a random number according to the mutation probability P_m. By the way, the random number should not go out of the range.

$$X_k = U_{\min}^k + r(U_{\max}^k - U_{\min}^k) \tag{15}$$

Where $U_{\max}^k$ is the maximum number of kth locus of gene. $U_{\min}^k$ is the minimum number of kth locus of gene.

Step 6: Termination condition. Judge whether the algorithm reaches termination conditions. If the algorithm doesn't reach termination conditions, then turn to Step 2. Otherwise, turn to Step 7. Here, the termination conditions are maximum iteration number and minimum error bound.

Step 7: Output the best individual of the population which is the optimal initial weight.

3. Model construct and prediction

The improved BP neural network model is applied to predict GDP of Anhui province in this paper. There are many factors that can affect GDP. In this paper, the index system which has influence on GDP is concluded in Table 1.

Because different indexes data and GDP data have different units. The units will have influence on the performance of the model. This paper the function shown in Eq.(16) is used to standardize.

$$x^{*}=\frac{(x-x_{\min})}{(x_{\max}-x_{\min})} \tag{16}$$

Table 1. Index system

Variable	Index
X1	The proportion of first industrial population
X2	Total investment in fixed assets
X3	Fiscal expenditure
X4	Loan balance at the end of year
X5	Electricity consumption of whole society
X6	Turnover of freight traffic
X7	Business volume of post and telecommunications
X8	Total retail sales of social consumer goods
X9	CPI
X10	Urbanization rate
X11	Total population
X12	The RMB exchange rate against the dollar
X13	Steel production
X14	Chemical fiber production
X15	Grain production
X16	Pork production
X17	The per capita net income of rural residents
X18	The per capita real income of city residents
X19	Industrial added value
X20	High school students
X21	Total import and export volume
X22	The completed investment in real estate development

Then we use standardized data from the index system and GDP data to establish the improved BP neural network model proposed in this paper. The model is used to predict the GDP of Anhui province.

The Regression curve of improved BP neural network model is shown in Figure 4. From Figure 4, we can find intuitively that the model proposed in this paper has a good performance on the regression and forecasting.

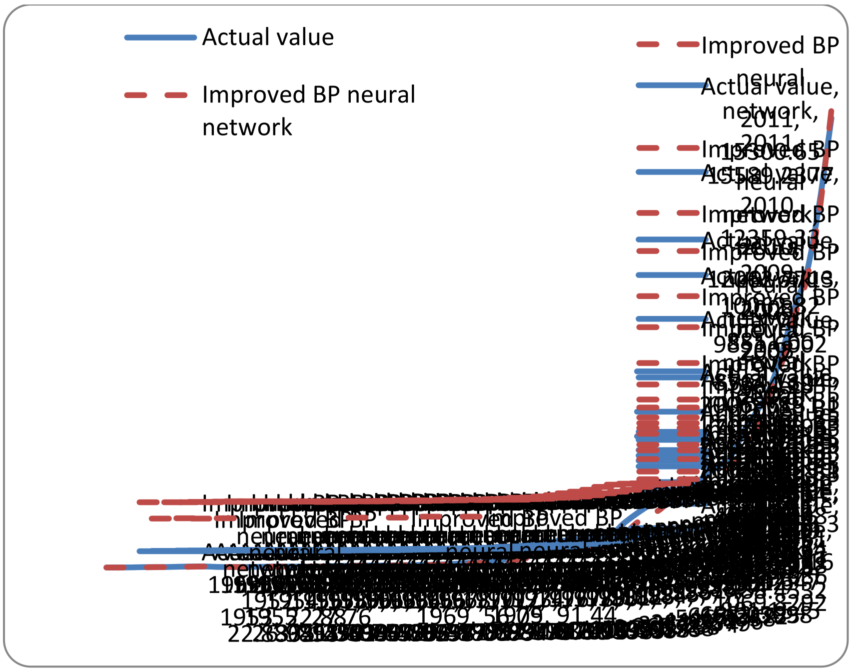

Figure 4. Regression curve of improved BP neural network

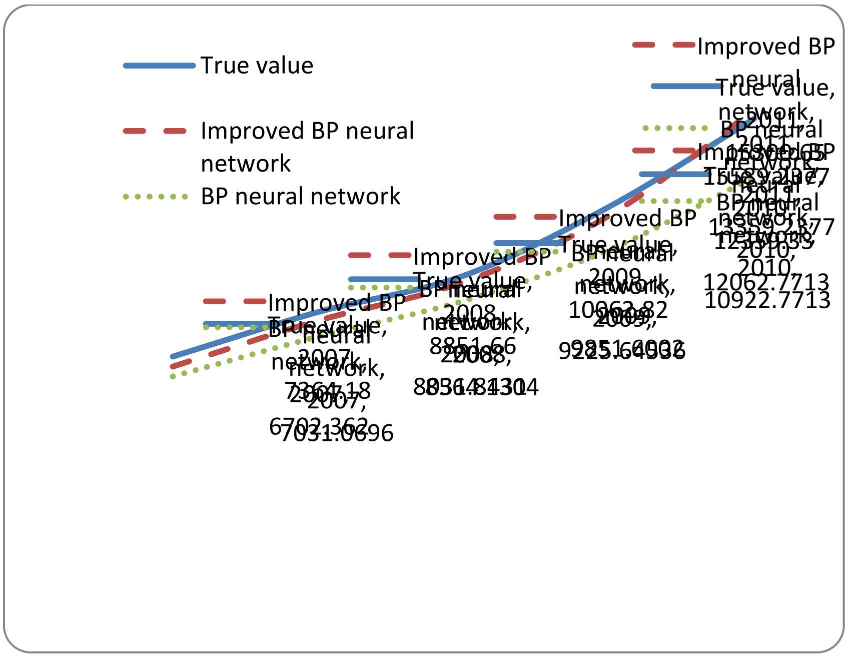

Figure 5. The prediction results of different models

In Figure 5, the prediction performance of improved BP neural network model is compared with standard BP neural network. From Fig 5, it is obviously that the model proposed in this paper is better than standard BP neural network.

In addition, the improved BP neural network model is also compared with other models, such as ARMA and SVR model. The results are shown in Table 2 and Table 3.

Table 2. Comparison of different prediction results

	Improved BP neural network	ARMA	standard SVR	BP neural network
MAPE	0.0731	0.1291	0.0943	0.1835
RMSE	36.2485	45.0271	40.5982	58.6424

From Table 2, we can find that the improved BP neural network model has the best performance on both MAPE and RMSE. It shows that the model proposed in this paper has good predictive ability. The relative errors of different models are shown in Table 3. We can find that the improved BP neural network model has the best prediction accuracy while the standard BP neural network model has the worst prediction accuracy of all these models from the years of 2007 to 2011. It also indicates that the momentum factor, steepness factor, adaptive learning rate and optimized genetic algorithm can enhance the prediction accuracy. In Figure 6, the prediction results of different models is shown obviously and the model proposed in this paper has the smallest absolute value of relative error from 2007 to 2011.

Table 3. The relative error of different models

	Improved BP neural network	ARMA	standard SVR	BP neural network
2007	-0.0532	-0.0884	-0.0832	-0.1021
2008	-0.0413	-0.0716	-0.0721	-0.0938
2009	-0.0237	-0.0727	-0.0623	-0.0826
2010	-0.0240	-0.0792	-0.0450	-0.1235
2011	0.0189	-0.0945	-0.0528	-0.1297

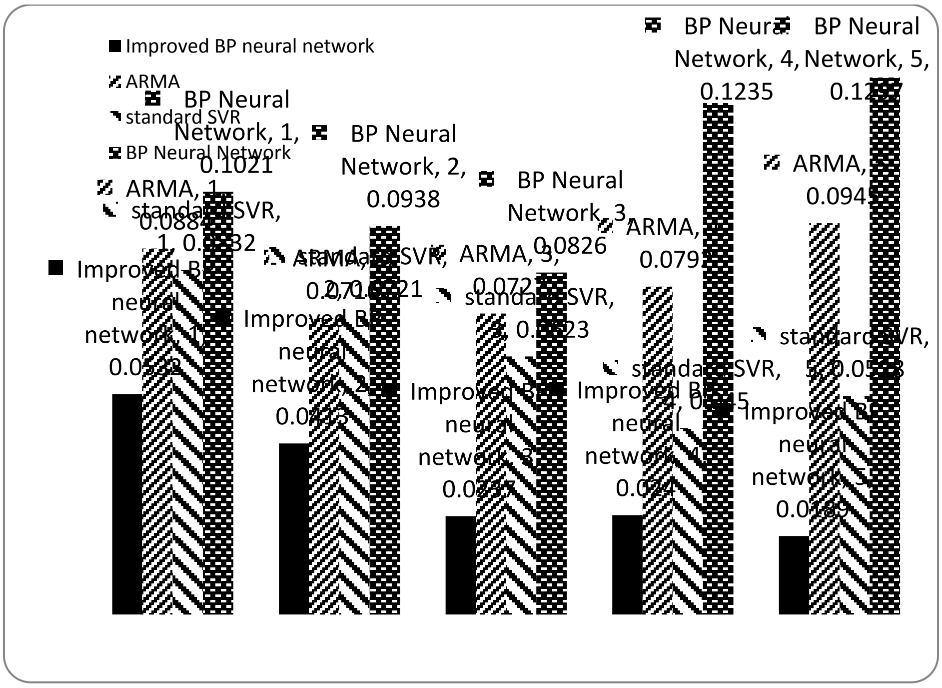

Figure 6.The absolute value of relative error of different models

4. Conclusion

In this paper, an improved BP neural network model is proposed in order to enhance the prediction accuracy. The momentum factor is adopted to improve the training speed and avoid falling into local minimum. Steepness factor and adaptive learning rate can improve the convergence speed. The optimized genetic algorithm is used to solve the problem of low training speed and low accuracy of prediction. It also prevents the BP neural network from falling into local minimum easily. Prediction results show that the proposed model is superior to other alternatives in GDP forecasting of Anhui province.

By the way, this study still has many improvements. For example, the index system may be not comprehensive enough and there are other advanced optimization algorithms that can be used in BP neural network or there are also some other methods that can be combined into BP neural network.

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Authors

Zhikun Xu

He received his bachelor's degree of Economics in Inner Mongolia Agricultural University, (1993) and master's degree of management in North china Electric Power University, (2010). Now he works in hebei normal university of science and technology institute of finance and economics, Qinhuangdao, Hebei. He is a Master's Supervisor . Her major fields of study are practical economics.

Xiaodong Wang

He received his bachelor's degree of Management in Hebei Normal University of Science and Technology, Qinhuangdao, Hebei. (2003) and master's degree of economics in Yunnan University of Nationalities (2006) , Now he is a lecturer in Hebei Normal University of Science and Technology, Qinhuangdao, Hebei. His major fields of study are economics and accounting.

Yingying Jin

She received her bachelor's degree of education inHebei Normal University, Baoding, Hebei. (2001) and master's degree of education in Hebei Normal University, Baoding, Hebei. (2005), Now she is a lecturer in Hebei Normal University of Science and Technology, Qinhuangdao, Hebei. Her major fields of study are practical economics.

