The Application of LM – BP Neural Network in the Prediction of Total Output Value of Agriculture

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Abstract  Gross agricultural product is an important indication to measure the agricultural development level of a region. It would be affected by many factors, having the characteristics of non-linearity. For this reason, LM – BP neural network was put forward as the model and method for predicting gross agricultural product. Taking the indications of the sown area of crop, the output of grain, sugarcane, cassava, tea, meat, aquatic products, turpentine and camellia seed, etc. as inputs, during 2000 to 2012 in Guangxi, the gross agricultural product data from the analysis of simulation experiment show that the prediction of LM – BP neural network fits well with actual results.

Key words  Total output value of agriculture, Artificial neural network, LM – BP neural network, Prediction

1 Introduction
The total output value of agriculture is an important indicator to measure the level of agricultural productivity and development in a region. The statistical mathematical modeling method is mainly used to predict the total output value of agriculture. Zhang Jiexia et al. use adaptive ARMA to establish the model for predicting the total output value of agriculture[1]. Chen Xianzhou et al. use the ARIMA time series model to predict China’s total output value of agriculture[2]. Liu Nan et al. use the gray theory and establish the gray prediction model to predict the agricultural economy[3-4]. The total output value of agriculture is affected by farming, animal husbandry, fishery, forestry and many other factors, so it has the nonlinear characteristics. There are flaws in using the statistical mathematical modeling method to predict the total output value of agriculture such as model selection difficulty and low prediction accuracy. In 1986, the American scholar Rumenlhart developed the error back propagation (BP) method[5], which is a common method of training artificial neural networks used in conjunction with an optimization method such as gradient descent. The method calculates the gradient of a loss function with respects to all the weights in the network. The gradient is fed to the optimization method which in turn uses it to update the weights, in an attempt to minimize the loss function. However, BP network shows some shortcomings such as slow convergence and poor generalization capability, limiting its application. LM – BP network is an improved BP network, and it uses the second derivative information to produce an ideal search direction when the function draws near the optimal value, thereby greatly improving the network convergence speed. This paper establishes the LM – BP neural network prediction model on total output value of agriculture, and uses the major agricultural production indicators in Guangxi as inputs to train the LM – BP neural network and predicts the total output value of agriculture. Compared with the standard BP network, LM – BP neural network has stronger fitting, higher efficiency and higher accuracy in predicting the total output value of agriculture, thereby providing an accurate and reliable method for predicting the total output value of agriculture.

2 BP neural network
2.1 BP algorithm  BP networks are necessarily multilayer perceptrons (usually with one input, one hidden, and one output layer). In order for the hidden layer to serve any useful function, multilayer networks must have non-linear activation functions for the multiple layers; a multilayer network using only linear activation functions is equivalent to some single layer, linear network. Non-linear activation functions that are commonly used include the logistic function, the softmax function, and the gaussian function. The BP algorithm for calculating a gradient has been rediscovered a number of times, and is a special case of a more general technique called automatic differentiation in the reverse accumulation mode. The result may converge to a local minimum. The "hill climbing" strategy of gradient descent is guaranteed to work if there is only one minimum. However, often the error surface has many local minima and maxima. If the starting point of the gradient descent happens to be somewhere between a local maximum and local minimum, then going down the direction with the most negative gradient will lead to the local minimum. There are limitations in the BP algorithm; gradient descent can find the local minimum instead of the global minimum; the convergence obtained from BP learning is very slow; the convergence in BP learning is not guaranteed; BP learning does not require normalization of input vectors. In order to accelerate the convergence of networks, some improved methods introduce the second derivative informa-
tion to improve BP algorithm, such as conjugate gradient method, Newton’s method and LM algorithm. The main idea of LM algorithm is to add a non-negative diagonal matrix to Gauss–Newton method, and use forced definite strategy.

2.2 LM-BP algorithm

LM (Levenberg-Marquardt) algorithm is the improved Gauss–Newton method. Using the Gauss-Newton method, it produces an ideal search direction when the function draws near the optimal value, and by the adjustment of network weights, it overcomes the shortcomings of blind searching of negative gradient descent method, thereby greatly improving the network convergence speed. Let \( w_i \) be the vectors consisting of the \( k \)-th iteration weights and thresholds, then the \( k+1 \)-th weights are updated as follows:

\[
 w_{k+1} = w_k + \Delta w
\]

(1)

For the error function \( E(w) \), there is:

\[
 E(w) = \frac{1}{2} \sum_{i=1}^{N} (t_i - o_i)^2
\]

where \( N \) is the dimension of the output vector; \( t_i \) is the target output of output neuron \( i \) in the output layer; \( o_i \) is the actual output of this neuron.

For the Newton’s method, there is:

\[
 \Delta w = -H^{-1}g
\]

(3)

where \( H \) is the Hessian matrix of error function \( E(w) \); \( g \) is the gradient.

\[
 g = J^T e(w)
\]

(4)

\[
 H = J^T w J(w) e(w) + S(w)
\]

(5)

\[
 S(W) = \sum_{i=1}^{k} e_i(W) \nabla^2 e_i(w)
\]

(6)

where \( e(w) = [e_1(w), e_2(w), \ldots, e_N(w)]^T \) is the Jacobian matrix.

\[
 J = \begin{bmatrix}
 \frac{\partial e_1(w)}{\partial w_1} & \frac{\partial e_2(w)}{\partial w_1} & \cdots & \frac{\partial e_N(w)}{\partial w_1} \\
 \frac{\partial e_1(w)}{\partial w_2} & \frac{\partial e_2(w)}{\partial w_2} & \cdots & \frac{\partial e_N(w)}{\partial w_2} \\
 \vdots & \vdots & \ddots & \vdots \\
 \frac{\partial e_1(w)}{\partial w_n} & \frac{\partial e_2(w)}{\partial w_n} & \cdots & \frac{\partial e_N(w)}{\partial w_n}
\end{bmatrix}
\]

(7)

Hessian matrix approximates;

\[
 H_{approx} = J^T w J(w)
\]

(8)

\[
 S_0 \Delta w = [-J^T w J(w)]^{-1} J^T w e(w)
\]

(9)

Using LM algorithm, formula (8) is modified;

\[
 H = J^T w + u I
\]

(10)

where \( u \) is a small number; \( I \) is the \( N \times N \) unit matrix.

So the network weight using LM method is updated as follows:

\[
 w(k+1) = w(k) - [J^T w J(w) + u I]^{-1} J^T w e(w)
\]

(11)

When \( u = 0 \), it is the Gauss–Newton method; when \( u \) is very large, LM approximates the steepest descent gradient method. In the actual operation, \( u \) value is tentatively and dynamically adjusted. When makes the error function \( E(w) \) decrease, then \( u \) value increases; otherwise, \( u \) value decreases. When using formula (11) to modify the weight, there is a need to calculate the \( n \)-order algebraic equations, and the time complexity of LM algorithm is \( O(n^3/6) \). If \( n \) is large, then the amount of computation and storage is very large, but the efficiency of each iteration is significantly improved, which can greatly improve the overall performance, especially when in need of high precision. LM – BP algorithm is described as follows;

(i) Given \( \varepsilon > 0 \), initialize \( w \) and set the network learning efficiency and \( u \) parameter;

(ii) Calculate the network output, and if the difference between the actual output and the target value is less than, then turn to step (v), or else perform step (iii);

(iii) Use formula (7) to calculate the Jacobian matrix \( J \);

(iv) Use formula (9) to achieve the update of network weights, jump to step (ii);

(v) End.

3 LM – BP neural network predictive model for the total output value of agriculture

3.1 LM – BP neural network

LM – BP neural network consists of three networks (input layer, hidden layer and output layer). The input layer is the factor variable related to output expectation, and its nodes are determined by the relevant factors to solve the problem; the output layer is the expected target output; the hidden layer node is normally achieved by the empirical formula. Guangxi is located in subtropical China, and it is the major province of producing subtropical crops. By the analysis, it is found that the major indicators affecting the total output value of agriculture in Guangxi include crop growing area \( x_1 \); grain production \( x_2 \); sugarcane production \( x_3 \); cassava production \( x_4 \); tea production \( x_5 \); meat production \( x_6 \); output of aquatic products \( x_7 \); camellia seed production \( x_8 \); turpentine production \( x_9 \). The total output value of agriculture in the year is as the output of the network. Therefore, we can determine the number of input nodes of LM – BP neural network at 9, and output nodes at 1. The middle hidden layer is obtained by formula (12);

\[
 l_i = \sqrt{m+n+c}
\]

(12)

where \( l_i \) is the hidden layer node; \( m \) is the network input node; \( n \) is the network output node; \( c \) takes the between 1 and 10. In this paper, \( m \) is 9, \( n \) is 1, and \( c \) is 5. Based on formula (9), we get 8 hidden layer nodes, thereby constituting the LM – BP neural network predictive model for total output value of agriculture. The model structure is shown in Fig. 1.

3.2 Modeling realization of LM – BP neural network using MATLAB

MATLAB \(^{(9)} \) is used to realize modeling of the above LM – BP neural network, including the setting of some parameters such as the network input layer, hidden layer and output layer nodes, network transfer function and training function. Based on the above analysis, this paper uses the \( 9 \times 8 \times 1 \) network structure (9 input layer nodes, 8 hidden layer nodes and 1 output layer node). The hidden layer transfer function uses the logsig func-
Fig. 1 The LM – BP neural network predictive model for total output value of agriculture

Table 1 The major indicators of agricultural production in Guangxi during 2000 – 2012

<table>
<thead>
<tr>
<th>Year</th>
<th>Total output value of farming, forestry, animal husbandry and fishery 10^4 yuan</th>
<th>Total crop growing area 10^4 ha</th>
<th>Grain production 10^4 t</th>
<th>Sugarcane production 10^4 t</th>
<th>Cassava production 10^4 t</th>
<th>Tea production 10^4 t</th>
<th>Meat production 10^4 t</th>
<th>Output of aquatic products 10^4 t</th>
<th>Camellia seed production 10^4 t</th>
<th>Turpentine production 10^4 t</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000</td>
<td>828.97</td>
<td>6 258.6</td>
<td>1 667.24</td>
<td>2 937.87</td>
<td>132.56</td>
<td>1.79</td>
<td>287.26</td>
<td>239.86</td>
<td>11.86</td>
<td>21.60</td>
</tr>
<tr>
<td>2001</td>
<td>872.90</td>
<td>6 196.7</td>
<td>1 607.35</td>
<td>3 653.33</td>
<td>128.02</td>
<td>1.89</td>
<td>306.98</td>
<td>247.77</td>
<td>13.46</td>
<td>21.67</td>
</tr>
<tr>
<td>2002</td>
<td>916.50</td>
<td>6 164.4</td>
<td>1 549.38</td>
<td>4 393.38</td>
<td>149.21</td>
<td>1.96</td>
<td>329.67</td>
<td>255.14</td>
<td>10.85</td>
<td>22.53</td>
</tr>
<tr>
<td>2003</td>
<td>1 030.89</td>
<td>6 107.4</td>
<td>1 484.82</td>
<td>4 861.84</td>
<td>139.73</td>
<td>2.13</td>
<td>353.52</td>
<td>264.61</td>
<td>9.27</td>
<td>25.21</td>
</tr>
<tr>
<td>2004</td>
<td>1 294.53</td>
<td>6 172.9</td>
<td>1 473.19</td>
<td>5 003.87</td>
<td>152.47</td>
<td>2.24</td>
<td>383.05</td>
<td>274.31</td>
<td>11.54</td>
<td>28.24</td>
</tr>
<tr>
<td>2005</td>
<td>1 448.37</td>
<td>6 343.9</td>
<td>1 516.29</td>
<td>5 154.69</td>
<td>173.61</td>
<td>2.62</td>
<td>418.60</td>
<td>284.19</td>
<td>11.74</td>
<td>30.19</td>
</tr>
<tr>
<td>2006</td>
<td>1 622.22</td>
<td>5 557.3</td>
<td>1 538.99</td>
<td>5 924.83</td>
<td>197.59</td>
<td>2.85</td>
<td>445.35</td>
<td>294.61</td>
<td>12.72</td>
<td>34.25</td>
</tr>
<tr>
<td>2007</td>
<td>2 026.22</td>
<td>5 896.9</td>
<td>1 463.20</td>
<td>7 509.44</td>
<td>164.12</td>
<td>3.66</td>
<td>371.00</td>
<td>288.82</td>
<td>15.10</td>
<td>53.29</td>
</tr>
<tr>
<td>2008</td>
<td>3 232.37</td>
<td>5 996.5</td>
<td>1 429.93</td>
<td>7 269.96</td>
<td>180.33</td>
<td>4.44</td>
<td>410.99</td>
<td>303.47</td>
<td>16.39</td>
<td>55.71</td>
</tr>
</tbody>
</table>

3.3 BP network training

This paper selects the major indicators\(^{[10]}\) of agricultural production in Guangxi during 2000 – 2012 to test the LM – BP neural network predictive model for total output value of agriculture in Guangxi. The data are taken from Guangxi Statistical Yearbook (2001 – 2013). Table 1 shows the data concerning total output value of agriculture and related indicators in Guangxi during 2000 – 2012.

In this paper, we use one-year time lag to predict the total output value of agriculture, namely taking the production indicators in the previous year as the input data for the current total output value, the current total output value as training output target. Thus we can construct Table 1 into the following training and testing sample, as shown in Table 2.

Table 2 LB – BP network training sample

<table>
<thead>
<tr>
<th>Sample number</th>
<th>Target output y</th>
<th>Sample input x</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>x₁</td>
<td>x₂</td>
</tr>
<tr>
<td>1</td>
<td>872.90</td>
<td>6 258.6</td>
</tr>
<tr>
<td>2</td>
<td>916.50</td>
<td>6 196.7</td>
</tr>
<tr>
<td>3</td>
<td>1 030.89</td>
<td>6 164.4</td>
</tr>
<tr>
<td>4</td>
<td>1 294.53</td>
<td>6 172.9</td>
</tr>
<tr>
<td>5</td>
<td>1 448.37</td>
<td>6 343.9</td>
</tr>
<tr>
<td>6</td>
<td>1 622.22</td>
<td>5 557.3</td>
</tr>
<tr>
<td>7</td>
<td>2 026.22</td>
<td>5 896.9</td>
</tr>
<tr>
<td>8</td>
<td>3 232.37</td>
<td>5 996.5</td>
</tr>
<tr>
<td>9</td>
<td>4 490.72</td>
<td>5 996.5</td>
</tr>
</tbody>
</table>

First, we normalize the learning sample using the minmax function to make the data fall within \([-1, 1]\), and take the pretreated samples as the input training network. Fig. 2 (a) and (b) show the LM – BP and standard BP network training error curves. From Fig. 2 (a), it is found that after four iterations of LM – BP network, the network learning reaches the predetermined error requirements, while the standard BP network can reach the predetermined error requirements after 6875 iterations. The convergence rate of LM – BP network is much faster than that of the standard BP network, indicating that LM – BP has higher efficiency in predicting total output value of agriculture.
4 Results and analysis

We input the samples into LM – BP neural network and standard BP neural network respectively for prediction, and the results are shown in Table 3. As can be seen from Table 3, the average error of prediction of LM – BP network model on total output value of agriculture is small, with the maximum error of 0.08% and minimum error of 0.00%. The predicted value is very close to the actual value, indicating that LM – BP neural network shows good generalization and fitting property for the total output value of agriculture. As to the predicted results of standard BP, the maximum error is 2.95% and the minimum error is 0.07%, with the average error of 1.14%. The predicted value greatly deviates from the actual value, indicating that the standard BP network shows poor fitting property in predicting total output value of agriculture, and the predictive result is not good. The trained LM – BP neural network is used to predict the total output value of agriculture. The main indicators of agricultural production in Guangxi in 2012 are regarded as the BP network input to predict the total output value of agriculture in Guangxi in 2013. The predictive result of model is 358.783 billion yuan, and the total output value of agriculture in Guangxi in 2014 was 371.696 billion yuan.

<table>
<thead>
<tr>
<th>Year</th>
<th>The actual value</th>
<th>LM – BP neural network</th>
<th>Standard BP network</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Predictive value</td>
<td>Error</td>
<td>Predictive value</td>
</tr>
<tr>
<td>2001</td>
<td>872.90</td>
<td>873.78</td>
<td>0.10</td>
</tr>
<tr>
<td>2002</td>
<td>916.50</td>
<td>916.86</td>
<td>0.04</td>
</tr>
<tr>
<td>2003</td>
<td>1 030.89</td>
<td>1 031.30</td>
<td>0.04</td>
</tr>
<tr>
<td>2004</td>
<td>1 294.53</td>
<td>1 294.10</td>
<td>0.03</td>
</tr>
<tr>
<td>2005</td>
<td>1 448.37</td>
<td>1 448.50</td>
<td>0.01</td>
</tr>
<tr>
<td>2006</td>
<td>1 622.22</td>
<td>1 623.50</td>
<td>0.08</td>
</tr>
<tr>
<td>2007</td>
<td>2 026.22</td>
<td>2 025.90</td>
<td>0.01</td>
</tr>
<tr>
<td>2008</td>
<td>2 389.79</td>
<td>2 390.80</td>
<td>0.04</td>
</tr>
<tr>
<td>2009</td>
<td>2 380.51</td>
<td>2 381.40</td>
<td>0.04</td>
</tr>
<tr>
<td>2010</td>
<td>2 720.99</td>
<td>2 721.90</td>
<td>0.03</td>
</tr>
<tr>
<td>2011</td>
<td>3 323.37</td>
<td>3 323.30</td>
<td>0</td>
</tr>
<tr>
<td>2012</td>
<td>3 490.72</td>
<td>3 489.40</td>
<td>0.04</td>
</tr>
</tbody>
</table>

The average error 0.04 1.41

5 Conclusions

Owing to the self-learning, nonlinearity and reliability advantages, BP neural network provides a new way to predict total output value of agriculture. However, the standard BP algorithm uses the steepest descent method. The method is simple but the convergence is slow, easily leading to misconvergence and overfitting. LM – BP network utilizes Gauss – Newton method to produce an ideal search direction when the function draws near the optimal value, and by the adjustment of network weights, it overcomes the shortcomings of blind searching of negative gradient descent method, thereby greatly improving the network convergence speed. Due to the nonlinear fitting advantages and strong generalization ability, it provides an efficient, accurate and reliable method to predict the total output value of agriculture.

References


Fig. 2 Training error curves

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