Research on the influence of hidden layers on the prediction accuracy of GA-BP neural network

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Abstract. In order to improve the prediction accuracy of GA-BP neural network, the effect of hidden layer neurons number on the prediction accuracy of algorithm was considered and an improved GA-BP neural network was proposed. Taking 60 equipment maintenance time of a photovoltaic charging station as the specimens, the high prediction accuracy of improved GA-BP neural network has been proved. Results indicate that the GA-BP neural network has the highest prediction accuracy when the number of hidden layer neurons is 5. The average relative error of improved GA-BP neural network between the predicted values and the expected values is 6.1%, decreasing 57% compared with BP neural network. The prediction accuracy of improved GA-BP neural network is much higher than that of BP neural network, and the predicted time can provide a basis for personnel scheduling.

1. Introduction
At present, the models used for data prediction mainly include time series model[1], linear regression model[2], grey model[3, 4], neural network[5-8] and so on. Because neural network has good nonlinearity and flexibility, can learn and store a lot of mapping relations of input and output modes and needn’t to describe the mathematical equation of the mapping relation, it is widely used as prediction model. In reference[9], BP neural network is used to predict the generation power of photovoltaic charging station, but the result shows that the prediction error is large. In reference[10], BP neural network is used to predict the residual power of electric vehicles, but the maximum prediction error is 57%, which can’t accurately predict the expected value. In reference[11], BP neural network is used to predict the photovoltaic power generation, but the relative error of prediction is 25%~30%. Because of the difference of the initial weight and threshold value of BP neural network, it’s easy to cause the calculation not to converge or fall into the local extreme point, so that the prediction error is large. By optimizing the initial weight and threshold value of BP neural network with genetic algorithm[12-14], the algorithm can effectively avoid falling into local extreme points, and achieve the purpose of improving the calculation accuracy. However, when GA-BP algorithm is used for prediction, the different number of neurons in hidden layer will lead to different prediction accuracy. That is to say, for different neural network structures, the optimal number of neurons in hidden layer is not the same. When GA-BP algorithm is used, it is necessary to know the optimal number of neurons in hidden layer. At present, there is no clear calculation formula for determining the number of hidden layer neurons in GA-BP neural network, usually empirical formula is used to determine the number of hidden layer neurons[15-19]. Because the formula is based on experience, there are certain limitations between different neural network structures, so it is particularly important to find the best number of hidden layer neurons to improve the prediction accuracy.
In order to obtain the optimal hidden layer neuron number of GA-BP neural network, this paper takes the equipment maintenance of a photovoltaic charging station as the research object, takes the maintenance time under different maintenance personnel skills and different maintenance equipment difficulties as samples, determines the optimal hidden layer neuron number by experimental simulation method, and explains the advantages of GA-BP neural network by comparing BP and GA-BP neural network. The maintenance time prediction of photovoltaic charging station equipment provides useful guidance.

2. Improved GA-BP Neural Network

2.1 BP Neural Network

As shown in Figure 1, the structure chart of BP neural network prediction of maintenance time takes the skills of maintenance personnel and the difficulty of maintenance equipment as the input layer and the maintenance time as the output layer.

![Figure 1. Structure diagram of neural network maintenance time prediction](image)

In the BP neural network, the number of neurons in the input layer \( n_1 = 2 \), and the number of neurons in the output layer \( n_3 = 1 \). The number of hidden layers is usually determined by the empirical formula (1), and the expression is as follows:

\[
    n_2 = \sqrt{n_1 + n_3} + a
\]

(1)

Where \( a \) is an integer between 1 and 100. Because formula (1) is an empirical formula, it can not explain the problem accurately. In this paper, combined with the neural network structure of maintenance time prediction, the influence of the number of hidden layer neurons on the prediction accuracy of neural network is studied, and the optimal number of hidden layer neurons is found, so as to improve the neural network algorithm.

The transfer function between the input layer and the hidden layer is sigmoid function, the expression is shown in formula (2), and the linear transfer function purelin function is used between the hidden layer and the output layer[20].

\[
    f(x) = \frac{1}{1 + e^{-x}}
\]

(2)

The input layer, the hidden layer and the output layer are represented by \( I, J \) and \( K \) respectively, the corresponding neurons are represented by \( i, j \) and \( k \) respectively, the weights of the input layer and the hidden layer are represented by \( W_{ij} \), the weights of the hidden layer and the output layer are represented by \( W_{jk} \), the inputs of the neurons are represented by \( u \), and the excitation outputs are represented by \( v \). Suppose the training sample set \( X = [X_1, X_2, ..., X_N] \), if the predicted value of any training sample \( X_m = [x_1, x_2] \) in \( X \) is \( y_m \) and the expected value is \( z_m \), then there are:
The X_m error of the m training sample is:

$$E_m = \frac{1}{2} \sum_{i=1}^{N} (y_m - z_m)^2$$

(4)

For N samples, the total average error is:

$$E(N) = \frac{1}{N} \sum_{m=1}^{N} E_m$$

(5)

2.2 The realization of GA-BP neural network

The specific steps of GA-BP neural network are as follows:

Step-1: chromosome coding. In this paper, real coding is used to encode chromosomes. The coding length is:

$$S = I \times J + J \times K + J + K$$

(6)

Step-2: fitness function. The reciprocal of the square sum of the absolute error between the predicted value and the expected value of the neural network is taken as the fitness function, and the expression is as follows:

$$F_m = \frac{1}{1 + \frac{1}{2} \sum_{m=1}^{N} (y_m - z_m)^2}$$

(7)

Step-3: choice. The proportion selection method is adopted, and the selection probability is:

$$p_m = \frac{F_m}{\sum_{m=1}^{P} F_m}$$

(8)

Step-4: crossover. Using the real crossing method, the crossing process of the k Gene g_k and the l gene g_l at the j position are as follows:

$$g_{kj} = g_{kj}(1-b) + g_{lj}b$$

$$g_{lj} = g_{lj}(1-b) + g_{kj}b$$

(9)

Where b is the random number between 0 and 1.

Step-5: variation. The j gene g_j of the i individual was selected to mutate with a relatively small mutation probability, and the variation equation was as follows:

$$g_{ij} = g_{ij}r_1 + (g_{ij} - g_{\text{max}})f(g), r_1 \geq 0.5$$

$$g_{ij} = g_{ij}r_1 + (g_{\text{min}} - g_{ij})f(g), r_1 \leq 0.5$$

(10)

$$f(g) = r_2(1 - \frac{s}{s_{\text{max}}})$$

Among them, r_1 is the random number between [0,1], r_2 is the random number, g_{\text{max}} and g_{\text{min}} are the upper and lower limits of g_j, s and s_{\text{max}} are the current iteration times and the maximum evolution times.

Step-6: calculate the fitness function. If the pre-set end condition of the algorithm is met, the weight and threshold of the optimized neural network will be output. Otherwise, return to Step-3 to
continue the iteration until the end condition is met.

Step 7: the optimal weights and thresholds of genetic algorithm are taken as the initial weights and thresholds of neural network, and the maintenance time prediction model is obtained.

3. Prediction samples and determination of neural network parameters

3.1 Collection of sample data
Taking a photovoltaic charging station as the research object, there are 15 maintenance personnel in the photovoltaic charging station \(A_1, A_2, A_3, \ldots, A_{15}\) for maintenance of four types of common faults (photovoltaic array fault, battery fault, photovoltaic controller fault, inverter fault) of photovoltaic charging station. As the maintenance time is related to the skill of maintenance personnel and the difficulty of fault type, the control variable method is used in data collection, and the sample data obtained is shown in Table 1.

| maintenance personnel | Failure Type                 |               |               |               |
|------------------------|------------------------------|---------------|---------------|---------------|
|                        | Photovoltaic array failure   | Battery failure| Photovoltaic controller failure | Inverter failure |
| \(A_1\)                | 85.5                         | 91.3          | 71.9          | 62.2          |
| \(A_2\)                | 228.0                        | 245.1         | 193.3         | 161.6         |
| \(A_3\)                | 171.0                        | 183.1         | 145.1         | 121.5         |
| \(A_4\)                | 38.0                         | 41.8          | 33.4          | 26.2          |
| \(A_5\)                | 114.0                        | 123.8         | 98.2          | 80.9          |
| \(A_6\)                | 133.0                        | 143.1         | 114.3         | 94.7          |
| \(A_7\)                | 247.0                        | 266.6         | 210.9         | 174.9         |
| \(A_8\)                | 361.0                        | 389.2         | 307.1         | 255.3         |
| \(A_9\)                | 209.0                        | 226.6         | 178.8         | 146.2         |
| \(A_{10}\)             | 133.0                        | 142.6         | 113.8         | 93.3          |
| \(A_{11}\)             | 104.5                        | 115.8         | 89.5          | 72.6          |
| \(A_{12}\)             | 66.5                         | 71.1          | 56.0          | 46.1          |
| \(A_{13}\)             | 95.0                         | 104.6         | 81.8          | 65.9          |
| \(A_{14}\)             | 142.5                        | 151.8         | 122.4         | 101.3         |
| \(A_{15}\)             | 180.5                        | 193.9         | 152.8         | 128.1         |

According to the time for different maintenance personnel to maintain different equipment in Table 1, the skills of maintenance personnel and the difficulty of maintenance equipment can be normalized through the control variable method. The PV array fault, battery fault, PV controller fault and inverter fault are numbered \(X_1, X_2, X_3\) and \(X_4\) in sequence. For the expression of maintenance personnel skills and maintenance equipment difficulty, see formula (11) and formula (12).

\[
T_{Am} = \frac{1}{4} \sum_{n=1}^{4} \left( 1 - \frac{t_{Am,X_n}}{\sum_{m=1}^{15} t_{Am,X_m}} \right) 
\]  
(11)

\[
d_n = \frac{1}{15} \sum_{m=1}^{15} \frac{t_{Am,X_m}}{t_{Am,X_n}} d_1 
\]  
(12)

Among them, \(T_{Am}\) is the skill of maintenance personnel \(A_m\), \(t_{Am,X_n}\) are the time taken by maintenance personnel \(A_m\) to repair fault \(X_n\), and \(d_n\) is the difficulty of repairing fault \(X_n\).

The skills of maintenance personnel and the difficulty of maintenance equipment can be obtained,
as shown in Table 2 and table 3. It can be seen that the maintenance time of maintenance personnel is directly proportional to the difficulty of maintenance equipment.

| Maintenance personnel | A1 | A2 | A3 | A4 | A5 | A6 | A7 | A8 |
|-----------------------|----|----|----|----|----|----|----|----|
| Skill                 | 0.91| 0.76| 0.82| 0.96| 0.88| 0.86| 0.74| 0.62|

| Maintenance personnel | A9 | A10 | A11 | A12 | A13 | A14 | A15 |
|-----------------------|----|-----|-----|-----|-----|-----|-----|
| Skill                 | 0.78| 0.86| 0.89| 0.93| 0.9  | 0.85| 0.81|

Table 3. Difficulty of maintenance service

| Maintenance failure | X1 | X2 | X3 | X4 |
|---------------------|----|----|----|----|
| Difficulty          | 0.88| 0.95| 0.75| 0.62|

3.2 Parameter setting of GA-BP neural network

In this paper, 80% (48) of the total sample set is used as the training sample set, and the remaining 20% (12) are used as the test sample set to verify the accuracy of the model. The maximum number of training steps of neural network is 2000, the learning rate is 0.01, the momentum factor is 0.95, and the training target error is 0.0005. The initial population number of genetic algorithm is 50 and the maximum evolution number is 200. The crossing probability is 0.5, and the mutation probability is 0.03. According to formula (8), the chromosome length is 21.

4. Analysis of prediction results

4.1 The influence of number of hidden layer neurons on the prediction accuracy

The number of neurons in the hidden layer $n_2=3, 5, 10, 15, 20, 30$ were simulated respectively. Figure 2 shows the prediction curve of GA-BP neural network for 12 samples under different number of neurons in hidden layer. When $n_2=5$, the predicted curve is the closest to the expected curve, while in other cases, the deviation between the predicted curve and the expected curve is large.
In order to quantitatively analyze the influence of the number of neurons in the hidden layer on the prediction accuracy, the influence diagram of the number of neurons in the hidden layer on the prediction accuracy and calculation time of GA-BP neural network is drawn according to the simulation results, as shown in Figure 3.

It can be seen from the figure that the calculation error of GA-BP neural network is low when $n_2 = 3$–6, and the calculation accuracy of neural network is the highest when $n_2 = 5$, the average calculation error is only 6.1%. With the increase of the number of neurons in the hidden layer, the calculation error increases rapidly. When $n_2 = 11$, the average calculation error is as high as 73%. Then with the increase of $n_2$, the average calculation error decreases gradually, reaching the minimum value when $n_2 = 20$ (about 19%). After that, with the increase of the number of neurons in the hidden layer, the average calculation error increased again. However, with the increase of the number of neurons in the hidden layer, the calculation time of GA-BP neural network increases gradually. Considering synthetically, for the GA-BP neural network with this structure, the number of hidden layer neurons is the best with $n_2 = 5$.

4.2 Comparison of BP and GA-BP neural networks
When the number of hidden layer neurons is 5, the prediction results of BP and GA-BP neural network are compared. Figure 4 shows the curve of the predicted value of BP neural network and GA-BP neural network in the same period of training. It can be seen from the figure that the predicted value of GA-BP neural network is closer to the expected value than that of BP neural network.
**Figure 4.** Comparison of predicted value and expected value when training

Table 4 shows the prediction of 12 test samples by two prediction algorithms. For the test samples, the prediction accuracy of GA-BP neural network is significantly higher than that of BP neural network. The average relative error of BP neural network is 63%, that of improved GA-BP neural network is only 6.1%, which is 57% lower than BP neural network. The error of the improved GA-BP neural network is controllable, which can meet the accuracy requirements of the maintenance time prediction of the photovoltaic charging station.

Table 4. Comparison of predicted and expected values of the two algorithms

| Test samples | Expected value/min | BP neural network | GA-BP neural network |
|--------------|--------------------|-------------------|----------------------|
|              |                    | Predicted value/min | Absolute error/min | Relative error/% | Predicted value/min | Absolute error/min | Relative error/% |
| 1            | 38.0               | 121.1              | 83.1                | 218.6            | 42.8              | 4.8                | 12.6              |
| 2            | 123.8              | 194.0              | 70.2                | 56.7             | 129.2             | 5.4                | 4.4                |
| 3            | 114.3              | 167.5              | 53.2                | 46.5             | 122.4             | 8.1                | 7.1                |
| 4            | 174.9              | 230.5              | 55.6                | 31.8             | 185.8             | 10.9               | 6.2                |
| 5            | 361.0              | 381.7              | 20.7                | 5.7              | 336.8             | -24.               | -6.7               |
| 6            | 226.6              | 270.6              | 44.0                | 19.4             | 226.0             | -0.6               | -0.28              |
| 7            | 113.8              | 167.5              | 53.7                | 47.2             | 122.4             | 8.6                | 7.5                |
| 8            | 72.6               | 119.6              | 47.0                | 64.8             | 73.7              | 1.1                | 1.5                |
| 9            | 66.5               | 142.7              | 76.2                | 114.6            | 74.3              | 7.8                | 11.7               |
| 10           | 104.6              | 179.1              | 74.5                | 71.2             | 111.2             | 6.6                | 6.3                |
| 11           | 122.4              | 174.9              | 52.5                | 42.9             | 129.8             | 7.4                | 6.0                |
| 12           | 128.1              | 177.78             | 49.7                | 38.8             | 132.7             | 4.6                | 3.6                |

5. Conclusion
In this paper, the influence of the number of neurons in the hidden layer on the prediction accuracy of neural network is analyzed, and an improved GA-BP neural network prediction model is established. By using the control variable method, the time spent by the maintenance personnel with different skills to maintain the equipment with different difficulties was investigated. The optimal number of hidden layer neurons of the GA-BP neural network was 5 through experimental simulation. Compared with BP neural network, the improved GA-BP neural network has higher prediction accuracy. From the prediction value of 12 test samples, the average relative error with the expected value is about 6.1%, which is 57% lower than that of BP neural network. The improved GA-BP neural network can meet the accuracy requirements of the maintenance time prediction and can be used for the maintenance time prediction of the photovoltaic charging station.

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