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Research on Parameter Estimation of Reliability of CNC Machine Tool Based on BP Neural Network

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Abstract

In order to survive and develop, the manufacturers of CNC machine tools put forward urgent requirements for reliability prediction. In this paper, a classification prediction and two-parameter estimation method of NC machine tools based on BP neural network is proposed. A BP neural network model for classification prediction and two-parameter estimation of reliability of NC machine tools is established, and a specific algorithm is given.

Keywords

BP Neural Network; Classified Prediction; Parameter Estimation.

1. INTRODUCTION

CNC machine tool is an important basic equipment of modern manufacturing industry. The basic technical parameters of domestic machine tools can reach the international advanced level, but its reliability and accuracy stability are far from foreign countries. According to statistics, the average trouble-free working time (MTBF) of CNC machine tools in China is more than 900 hours, while the average trouble-free working time of famous brand CNC machine tools in the United States, Germany, Japan and other countries can be more than 1000 hours, or even more than 2500 hours, which makes the market share of CNC machine tools in China lower. Therefore, the most important thing is to improve the reliability of CNC machine tools in order to improve the manufacturing level of CNC machine tools and equipment manufacturing capacity in China. [1]

Machine reliability refers to the ability of a machine tool to perform specified functions under specified conditions and within specified time intervals. [2] How to improve the reliability of CNC machine tools is an urgent problem in China. Scholars at home and abroad have done a lot of research on improving the reliability of machine tools. British scholars manage the collected operation data by establishing a reliability database, and analyze and study the weak links and fault distribution rules of NC machine tools based on the collected data. Through on-site tracking and assessment of 35 CNC machine tools, Birmingham University found that the failure interval of CNC machine tools obeys the Weibull distribution of shape parameters ranging from 0.8 to 1.07 according to the average fault interval time detected. [3] Under the leadership of Jia Ya [4], Jilin University has accumulated a large number of failure data in the reliability research area of CNC lathes, punches, machining centers and CNC systems, and has achieved many results. Gao Ping, Tsinghua University, et al. [5] analyzed the reliability modeling and parameter estimation methods of complex systems. Zhang Genbao of Chongqing University and others [6] studied the reliability allocation of the system based on support vector machine. In Dai Yi [7], Tianjin Vocational and Technical Normal University analyzed the application of Bayes theory to the reliability evaluation of censored data.

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In recent years, with the development of neural network, artificial neural network has been widely used in pattern classification, clustering, regression and fitting, optimization calculation and so on, and its application prospect is broader [8]. Therefore, the neural network is used to analyze the time truncated data of the reliability of CNC machine tools. At present, the research on this topic is relatively few at home and abroad, so it is prospective.

2. NETWORK MODEL

The BP neural network model is shown in Figure 1. It consists of input layer, hidden layer and output layer. The number of hidden layer is not strictly required. Assuming that the input layer is M, i.e., there are M input signals, any of which is represented by m; the first hidden layer is I, i.e., there are I neurons, any of which is represented by i; the second hidden layer is J, i.e., there are J neurons, any of which is represented by j, and the output layer is P, i.e., there are P neurons, any of which is represented by P. The synaptic weights of the input layer and the first hidden layer are expressed by wmi; the output values of the p-th neuron of the input signal of the first hidden layer are wij, which is the connection weights between the j-th neuron of the hidden layer and the i-th neuron of the input layer, and Vjk, which is the connection weights between the k-th neuron of the output layer and the j-th neuron of the hidden layer. The BP neural network model is generally multi-layer, which is fully connected between layers, but there is no connection between the same layer. Multilayer network design enables BP neural network to mine more information from input. However, too many neurons will affect the accuracy of the results and appear over-fitting phenomenon. BP neural network uses error back propagation algorithm to learn. In BP Neural Network, the input data propagates backward from the input layer through the hidden layer, and in training the weights of the network, the connection weights of the network are corrected forward from the output layer through the middle hidden layer along the direction of reducing errors. With the continuous training and learning, the final error is getting smaller and smaller. [9]

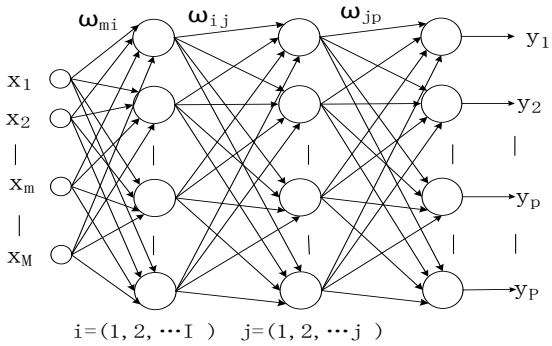

Fig. 1 BP Neural Network Model

3. ALGORITHM PRINCIPLE

Let an input vector be [x1, x2,... xn], the objective function value is [d1, d2,... dm], the output vector of the hidden layer of the network is [y1, y2,... yj], the output vector of the network is [y1, y2,... yn], there are:

$$v_i^I = f\left(\sum_{m=1}^{M} \omega_{mi}\, x_{km}\right)$$

$$v_j^J = f\left(\sum_{i=1}^{I} \omega_{ij}\, v_i^I\right)$$

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$$v_p^P = f\left(\sum_{j=1}^{J} \omega_{jp}\, v_j^J\right)$$

$$y_{kp} = f\left(\sum_{j=1}^{J} \omega_{jp}\, v_j^J\right)$$

The error signal of the p-th neuron in the output layer is

$$e_{kp}(n) = d_{kp}(n) - y_{kp}(n)$$

If the error energy of neuron P is $\frac{1}{2}e_{kp}^{2}(n)$ defined as, then the sum of error energy of all neurons in the output layer is $E(\mathrm{n})$

$$\mathrm{E}(n) = \frac{1}{2}\sum_{p=1}^{P} e_{kp}^2(n)$$

4. EXPERIMENTAL RESULTS AND ANALYSIS

4.1. Input Data

The quality and quantity of reliability data itself have a great influence on the results of reliability data analysis, but there are great difficulties in data collection. So MATLAB software can generate a large number of data. After a lot of research, it is found that the failure of CNC machine tools mostly obeys Weibull distribution, so the time truncated random numbers obeying Weibull distribution are generated by using MATLAB statements. When considering Weibull distribution, three parameters (m, η,δ) are often involved. The significance of these three parameters is described in detail below.

4.1.1 Shape Parameter m

The density of failure probability curve, cumulative failure probability curve, reliability curve and the shape of failure rate curve of Weibull distribution vary with m value, so m is called shape parameter.

4.1.2 Position Parameter δ

The position parameter delta determines the starting point of the distribution. It should be noted that when delta is less than 0, the product will fail at the beginning of operation, that is, these components have failed during the storage period; when delta is equal to 0, the failure probability density function curve is a two-parameter Weibull distribution, and what has been discussed in this paper is the two-parameter classification.

4.1.3 Scale Parameter η

Scale parameter determines the height and width of the failure probability density curve of Weibull distribution. When η increases, the height and width of the failure probability density curve decrease, and vice versa.

In this paper, four groups of data are generated by using MATLAB. Four kinds of Weibull distribution (shape parameter m = 1.2, 0.8, scale parameter 1200, 1500 hours) are selected to test the four distribution with 4,000 truncation time corresponding to a certain truncation time for 12,000 times. Data with dimension of input vector [30,200] are selected from each group, and a set of input vectors [30,800] is formed. In order to make the data adapt to the transfer function better, reduce the error rate in the calculation process, and accelerate the calculation speed and convergence, it is necessary to standardize the data in the neural network algorithm,

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and convert the input variables linearly. The results of the conversion calculation are between [-1, 1].

4.2. Output Date

Network output corresponds to four states, so the expected output is four, that is, which state the output produces is 1, otherwise the result is 0. So the output of the network is as follows:

shape parameter m = 1.2, scale parameter 1500 hours (1, 0, 0, 0)

(2) Shape parameter m = 0.8, scale parameter 1500 hours (0, 1, 0, 0)

(3) Shape parameter m = 1.2, scale parameter 1200 hours (0, 0, 1, 0)

(4) Shape parameter m = 0.8, scale parameter 1200 hours (0, 0, 0, 1)

4.3. Network Parameters

4.3.1 Initialization of Weights and Thresholds

Initialization of weights and thresholds has a certain impact on the convergence of the network. If the network is selected well and converges quickly, the network may be saturated and difficult to converge, or the network is limited to local minima. At present, there is no optimal initialization method, but the best values are not the same. Generally, they are chosen between - 1 and 1. In this algorithm, the random number between - 1 and 1 is used as the initial value of the weight according to the actual situation.

4.3.2 Determination of Learning Factor and Potential Factor

Learning factor is large, convergence speed is fast, conversely slow, if too large, easy to cause network oscillation, divergence and other phenomena. The effect of potential factors is to make learning factors large enough without oscillation. Reasonable learning factors and potential factors can improve the efficiency of network learning. In order to shorten the convergence time of the algorithm, variable learning factor can be used. The value of learning factor is very large at the beginning. With the increase of iterations, the value of learning factor can be reduced appropriately, and this can also improve the progressiveness of the algorithm.

4.3.3 Judgment of the Endpoint of Iterative Computing

When the network converges, the iterative calculation can be stopped, and then the simulation and prediction can be carried out. There are three methods to determine the end point of iteration. One is that the total error is less than the specified error, the other is that the number of iterations reaches the predetermined number, and the third is that the error of monitoring sample set increases. In this paper, the second method is adopted to specify the number of iterations in advance, and the size of iterations should be selected according to the actual situation.

5. RESULT

5.1. Experimental Result

After determining the input, output and transfer functions of the BP network, the method of selecting different hidden layers, different hidden layer nodes and different training networks can be used to iterate continuously until the global optimal solution is found. The input data are 200, 400, 600 and 800 groups respectively. Twelve of them are selected as test data and the rest are training sets. After distinguishing the training set from the test set, the training set model is used to predict the test set. The results are shown in the following table:

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Table 1. Input is the result output of 200 groups

0.999977	0.011254404	-2.14E-05	-0.00097	0.999979	0.006903	-5.46E-05	-0.00074	0.99998	0.003923	-7.44E-05	-0.00053
4.48E-05	0.989510767	0.00849812	0.000581	4.18E-05	0.993672	0.0046124	0.000427	3.89E-05	0.996481	0.0021627	0.000292
-0.00013	-0.000999766	0.99154311	0.011243	-0.00011	-0.00074	0.9954275	0.006764	-0.0001	-0.00052	0.9978685	0.003748
8.16E-05	0.000269642	-0.0001687	0.989377	7.26E-05	0.000178	-0.000123	0.993721	6.39E-05	0.000104	-8.21E-05	0.996615

Table 2. Input is the result output of 400 groups

1.00005	0.00688	0.00089713	0.000285	1.000042	0.003964	0.000656	0.000201	1.000034	0.002012	0.0004449	0.000129
-0.00016	0.997058	0.00642802	0.00169	-0.00014	0.998609	0.0037013	0.001145	-0.00012	0.999491	0.0018832	0.0007
3.80E-05	-0.00174	0.99306723	0.004898	3.53E-05	-0.00113	0.9959845	0.002694	3.27E-05	-0.00065	0.9979563	0.001291
0.000141	-0.0013	0.00039978	0.993942	0.000128	-0.00085	0.0002788	0.996531	0.000115	-0.00049	0.0001809	0.998242

Table 3. Input is the result output of 600 groups

1.000028	0.012008	0.00030147	0.000586	1.0000256	0.007198	0.0002085	0.000357	1.0000233	0.003961	0.0001314	0.0001917
2.56E-05	0.988664	0.00719112	-0.00033	2.52E-05	0.993318	0.0038628	-0.00016	2.47E-05	0.996416	0.0017419	-5.68E-05
8.48E-05	-0.00031	0.99242054	0.0106	7.78E-05	-0.00022	0.9958629	0.005637	7.10E-05	-0.00015	0.998078	0.0024858
-2.94E-05	0.000563	-0.000257	0.989006	-2.53E-05	0.000417	-0.000191	0.994094	-2.14E-05	0.00029	-0.000133	0.997351

Table 4. Input is the result output of 800 groups

0.999774	0.005273	0.00024377	-0.00056	0.999825	0.003037	0.0001907	-0.00041	0.9998694	0.00158	0.0001431	-0.000273
-1.62E-04	0.994914	0.00470139	0.00041	-1.48E-04	0.99711	0.0028438	0.000298	-1.35E-04	0.998532	0.0015759	2.02E-04
1.13E-04	-0.00062	0.99522739	0.00919	8.86E-05	-0.00045	0.9971097	0.005078	6.72E-05	-0.00031	0.9983998	0.002392
3.19E-05	0.000465	-0.0001024	0.990782	3.37E-05	0.000322	-7.10E-05	0.994915	3.47E-05	0.000202	-4.35E-05	0.9976193

Table 5. Target output results

1	0	0	0	1	0	0	0	1	0	0	0
0	1	0	0	0	1	0	0	0	1	0	0
0	0	1	0	0	0	1	0	0	0	1	0
0	0	0	1	0	0	0	1	0	0	0	1

5.2. Result Analysis

In the above table, the comparison error between Table 1-Table 4 and Table 5 is very small, and the classification calculation of time censored data can be realized. Comparing the results of Table 1-Table 4, setting errors can be achieved by adjusting the neurons of different hidden layers and hidden layers in different inputs. When training data of the same setting errors are more, more neurons are needed to achieve it.

6. CONCLUDING REMARKS

Based on the characteristics of reliability prediction of NC machine tools, a BP neural network model and algorithm for reliability classification of NC machine tools are established in this paper. The principle and steps of the algorithm and the methods to deal with the problems encountered in the algorithm are described systematically. Compared with the traditional mathematical model prediction method, the reliability prediction method proposed in this paper is more accurate and reliable than the traditional mathematical model prediction method.

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