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Reliability Prediction of CNC Machine Tool Spindle Based on Optimized Cascade Feedforward Neural Network

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ABSTRACT Aiming at the large error of traditional reliability prediction method, and the defects of BP neural network prediction method, a new method of optimized cascade feedforward neural network was proposed based on Adam algorithm to predict the reliability of CNC machine tool spindles. A three-layer optimized cascade feedforward neural network model for reliability prediction was established based on the first n^{th} reliability value and the mean time between failure corresponding to the $(n+1)^{th}$ reliability value as the input variables of the neural network. Besides, error comparison analysis was performed on the test set data using the existing relevant reliability data for simulation training. As per the research results, the absolute value of the maximum relative error of the reliability prediction value obtained by this method is 2.53% which is less than 3%, and the prediction method shows high accuracy. Compared with BP neural network, it has the advantages of faster learning speed and better nonlinear fitting ability. Therefore, this method is feasible to be utilized for the prediction of the reliability of CNC machine tool spindles, and provides a reference for improving the accuracy of CNC machine tool reliability prediction.

INDEX TERMS Optimized cascade feedforward neural network, CNC machine tool spindle, predict, reliability.

I. INTRODUCTION

As a key component of CNC machine tools, the failure rate of machine tool spindle presents an important factor affecting the reliability of machine tools [1], [2], and accounts for about 20% of the overall failure rate of machine tools. Reliability prediction research on the spindles of CNC machine tools can help managers take necessary measures in time before the occurrence of failure, thereby ensuring the maintenance and avoiding the failure [3]. This is conducive to the improvement of the reliability of the CNC machine tool spindle, and the reliability of the entire CNC machine tool eventually. However, the traditional reliability prediction methods are not accurate enough when dealing with some reliability data with time-ordered characteristics and high nonlinearity [4]. Based on the statistics, the relative error between the predicted value and the true value ranges from tens of percent to several thousand percent [5]. At present, there are few studies on the reliability prediction of machine tool spindles at home and abroad. Liu *et al.* [6] proposed to use Monte Carlo method for the reliability prediction of machine tool spindle. Although the correctness of the resulted data was verified, this method is complicated and not accurate enough. Artificial neural network can approximate arbitrary nonlinear mapping through training and learning, thereby making the breakthrough based on the above-mentioned traditional reliability prediction methods [4], [7]. Moreover, the neural network has its unique advantages thanks to their ability to process reliability data with time-ordered characteristics [4]. Specifically, when facing the thorny problems, such as lack of physical understanding, statistical changes in observed data, and generation of data by nonlinear mechanism, the neural networks are often available for relatively effective solutions [8]. Therefore, the artificial neural network is highly valued by the academic community, and widely used in the field of reliability prediction at present. Pratik *et al.* [9] applied the

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optimized new neural network to software reliability prediction. Its neural network model shows better fitting and prediction ability, and can release software faster; Wang *et al.* [10] followed BP neural network method to achieve the reliability prediction of power distribution system with higher prediction accuracy; Tian *et al.* [11] applied BP neural network method to the reliability prediction of coal shearer, thereby achieving relatively high precision prediction, and satisfying the requirements of accuracy; Wang *et al.* [12] predicted the optimal power allocation using the artificial neural network method to enhance the security-reliability tradeoff, and verified the feasibility of the method. At present, BP neural network method in neural network is increasingly used for reliability research [13]. However, it still shows certain limitations, for example, its learning speed is slow, and it is easy to fall into the local minimum point of the objective function [14], which makes it difficult to calculate. Therefore, an optimized cascade feedforward neural network model based on the Adam algorithm is established to study the reliability prediction of CNC machine tool spindle by taking the advantages of the cascade feedforward neural network method compared with the traditional method and the BP network, and combining the timing characteristics of the data. The after-sale failure data of the spindle of a certain type of CNC machine tool is planned to be used for training neural network modeling, completing the scientific prediction, and testing the effectiveness and feasibility of the model for reliability value prediction.

II. OPTIMIZED CASCADE FEEDFORWARD NEURAL NETWORK

A. CHARACTERISTICS OF CASCADE FEEDFORWARD NEURAL NETWORKS

The cascade feedforward neural network has a multi-hidden layer structure, which starts from a small network, automatically trains and adds hidden units, and finally forms a multi-layer structure. The level in the network is cascaded with each other [15], and the information is propagated from the input layer to the final output step by step [16]. This neural network uses the back propagation method to solve and keep updating the weights and biases. Compared with the non-cascaded standard BP neural network, the cascade feedforward neural network features a faster learning speed, and each layer of its neural network is connected to the input layer, which enables the cascade feedforward neural network to show a better nonlinear fitting ability in the test [17].

B. STRUCTURE OF CASCADE FEEDFORWARD NEURAL NETWORK

The structure of the cascade feedforward neural network is shown in Fig. 1, which includes one input layer, one hidden layer and one output layer. Its general mathematical expression is as follows:

$$\partial^n = f^n(W_1^n \partial^{n-1} + W_2^n p + b^n) \tag{1}$$

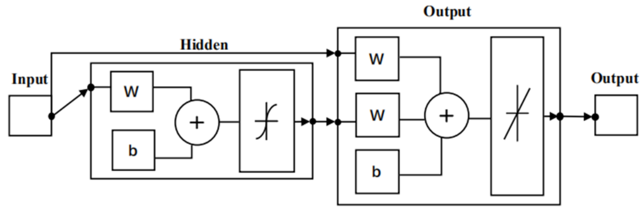

FIGURE 1. Basic structure of cascade feedforward neural network.

where n refers to the number of layers of neural network; and W represents the weight matrix of the hidden layer. The number of rows is equal to that of neurons in each layer, and the number of columns is equal to that of input individuals; b denotes the hidden layer bias column vector with the same number of rows as W; ∂ refers to the output vector of each layer; p is the input vector of each layer; and f represents the activation function.

C. OPTIMIZATION OF CASCADE FEEDFORWARD NEURAL NETWORK

The most direct purpose of cascade feedforward neural network optimization is to make the updating of the parameters more accurate. The optimization algorithm can minimize the value of the loss function, make the model closer to the real situation, and the prediction more accurate.

The Adam algorithm, namely Adaptive Moment Estimation, is used to optimize the cascade feedforward neural network, which combines RMSProp's heuristic algorithm with momentum optimization ideas. For each parameter, it not only has its own learning rate, but also its own Momentum. Compared with other adaptive learning rate algorithms, the Adam algorithm features a faster convergence speed and a more effective learning effect, which can improve the model training speed and training stability. The algorithm formula is as follows:

$$\begin{cases} v_t = \beta_1 v_{t-1} - (1-\beta_1) g_t \\ s_t = \beta_2 s_{t-1} - (1-\beta_2) g_t^2 \\ \Delta\omega_t^j = -\eta \dfrac{v_t}{\sqrt{s_t + \varepsilon}} g_t \\ \omega_{t+1}^j = \omega_t + \Delta\omega_t \end{cases} \tag{2}$$

where η refers to the initial learning rate; g_t represents the gradient at time t along ω^j; v_t denotes the exponential average of gradients along ω^j; s_t is the exponential average of squares of gradients along ω^j; and β_1, β_2 refer to the hyperparameters. Among them, β_1 is 0.9, β_2 is 0.999, and ε is defined as e^{-10}.

III. NEURAL NETWORK RELIABILITY PREDICTION

A. THEORETICAL BASIS OF NEURAL NETWORK PREDICTION MODEL

The optimized cascade feedforward neural network reliability prediction method combines the Adam optimization algorithm with the neural network prediction method. Based on a data-driven fault prediction technology, the cascade feedforward neural network reliability prediction method can realize data adaptation, learn from samples and try to capture the intrinsic functional relationship among sample data. It uses the feedback principle to correct the prediction model and prediction results through the feedback of prediction information, thereby improving the reliability of prediction. The training process first obtains the prediction error through the forward propagation of information, then obtains the gradient of each parameter through the error back propagation chain derivation, and finally updates each parameter. Repeat the above steps until the termination condition is reached before completing the training. The main formula is as follows:

$$\begin{cases} \text{From input layer to hidden layer}: O_j = \sum_i w_{ij} x_i + \theta_j \\ \text{From hidden layer to output layer}: O_k = \sum_j w_{jk} O_j + \theta_k \end{cases} \tag{3}$$

Formula (3) is summarized as

$$I_j = \sum_i w_{ij} O_i + \theta_j \tag{4}$$

where I_j refers to the unit value of the current layer; O_i represent the unit value of the previous layer; w_{ij} denotes the weight value connecting the two unit values between the two layers; and θ_j is the bias value of each layer.

Perform nonlinear conversion on the output of each layer, and f is the nonlinear conversion function, also known as the activation function, which is defined as

$$f(x) = \frac{1}{1 + e^{-x}} \tag{5}$$

then, the output of each layer is

$$O_j = \frac{1}{1 + e^{-I_j}} \tag{6}$$

in this way, the output value of each layer can be obtained in the positive direction of the input value.

According to the reverse transmission of the error, the formula is expressed as:

$$\begin{cases} \text{For the output layer}: Err_k = O_k(1 - O_k)(T_k - O_k) \\ \text{For the hidden layer}: Err_j = O_j(1 - O_j) \sum_k Err_k w_{jk} \end{cases} \tag{7}$$

where T_k refers to the true value; and O_k represents the predicted value. The weight update formula is:

$$\begin{cases} \Delta w_{ij} = (l) Err_j O_i \\ w_{ij} = w_{ij} + \Delta w_{ij} \end{cases} \tag{8}$$

where l represents the learning rate. The bias update formula is as follows:

$$\begin{cases} \Delta \theta_i = (l) Err_j \\ \theta_j = \theta_j + \Delta \theta_j \end{cases} \tag{9}$$

The training stops when any one of the following conditions is satisfied: The update of the eccentric weight is below a certain threshold, the predicted error rate is lower than a certain threshold, and the preset number of cycles is reached.

B. BASIC METHODS AND PROCEDURES OF NEURAL NETWORK PREDICTION

The basic process of the utilization of optimized cascade feedforward neural network to predict the reliability of CNC machine tool spindle is shown in Fig. 2. And the basic steps of reliability prediction are as follows:

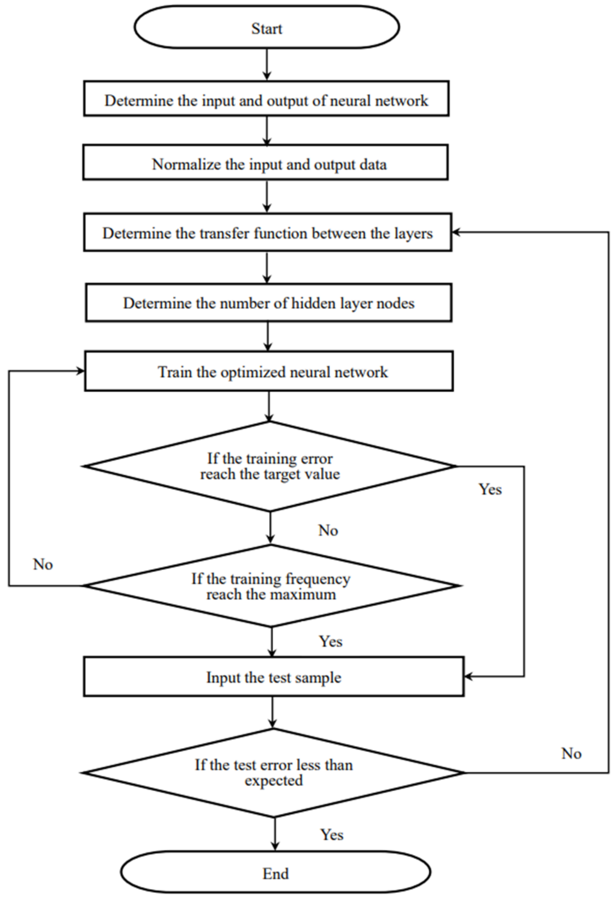

FIGURE 2. **Flow chart of reliability prediction of CNC machine tool spindle based on optimized neural network.**

(1) Determine the input and output variables of the neural network. The n reliability values $R_{i-1}, R_{i-2}, \ldots\ldots, R_{i-n}$ before the i^{th} reliability value R_i, and the $MTBF$ corresponding to R_i are taken as the input variables of the cascade feedforward neural network, and the i^{th} reliability value R_i is taken as the output variable of the neural network. Input and output variables are used for neural network modeling and training. Based on the practical engineering experience, when n is 5, the predicted effect is relatively good. To make the neural network training convergent, and save the training time, the input data was normalized, and placed in the interval [0,1] [4], [18]. The formula of data normalization processing is expressed as follows:

$$inputdata_i = \frac{MTBF_i - MTBF_{\min}}{MTBF_{\max} - MTBF_{\min}} \tag{10}$$

where $inputdata_i$ refers to the i^{th} input data; $MTBF_i$ represents the $MTBF$ value corresponding to the i^{th} input data; besides,

$MTBF_{\min}$ and $MTBF_{\max}$ are the minimum and maximum of all known $MTBF$ values, respectively.

(2) Group the data. The data samples with small sample size can be grouped based on the leave-one-out method [19]. n known reliability data were divided into $(n-m)$ groups, and each group contains $(m + 1)$ values. Among them, the first m values were used as the input samples for neural network training and learning, while the $(m + 1)^{\text{th}}$ value was taken as the expected mapping value [20]. The value of m should be neither too large nor too small. In the case that the value of m is too large, the calculation will be complicated due to the excessive unnecessary information; in contrast, if the value is too small, the prediction accuracy of the neural network may be reduced. Therefore, to make the prediction more accurate, the value range of m is generally set from 6 to 12 [4].

(3) Determine the activation function. In the cascade feedforward neural network, the activation function connected among different layers is the *sigmoid* function, and the activation function connected to the output is linear function [17].

(4) Determine the number of hidden layer nodes. The selection of the number of nodes in the hidden layer has a great influence on the performance of the neural network [21]. In another word, too less nodes will lead to poor fitting of network, and the decrease of the accuracy of prediction results; in contrast, too many nodes will increase the training time, result in the phenomenon of "over fitting", consequently, the generalization ability of neural network will decrease, affecting the accuracy of neural network prediction [22], [23]. Formula (11) is utilized to calculate the optimal number of hidden layer nodes [24].

$$l = \sqrt{n+m} + a \tag{11}$$

where l refers to the number of hidden layer nodes; n represents the number of input layer nodes; m denotes the number of output layer nodes; and a is the constant between 1 and 10.

(5) Use MATLAB software to program the optimized cascade feedforward neural network, and train the neural network.

(6) Input the validation set data into the trained neural network to adjust the model parameters, and initially evaluate the model. Then, input the test set data into this neural network for reliability value error comparison, and evaluation of its predictive ability. In the case that the neural network meets the requirements of accuracy or cycle times, the prediction results will be output to complete the reliability prediction; otherwise, the structure of the neural network will be readjusted to continue the training [25].

IV. RELIABILITY PREDICTION OF CNC MACHINE TOOL SPINDLE BASED ON NEURAL NETWORK

The reliability of CNC machine tools refers to the ability of the machine tool to achieve the functions in the entire operating life cycle under the product use environment and working conditions defined in the design determined during the design. In general, it is related to failures. The index to measure reliability includes the mean time between failure ($MTBF$) which refers to the average time between two failures of a CNC machine tool in operation.

The failure mechanism refers to the internal causes for physical, chemical, and biological, etc. changes that result in the malfunction of product, which is the essential cause of failure. The stress acting on the components causes damage to the components, and ultimately leads to system failure. In the case that the mechanical parts lose the ability to achieve the specified functions due to various reasons, such as design, material, process, and assembly, they are out of function, in another word, they fail. The failure of the key components of mechanical equipment means that the equipment is in a faulty state. The failure mechanism of mechanical parts is generally indicated by wear, deformation, fracture, corrosion and material aging, etc. Accordingly, preventive measures and design improvement methods can be developed based on the failure mechanism analysis.

Totally 221 spindle reliability-related data were selected from more than 5000 production practice data of a certain model of CNC lathe in a machine tool factory, among which 27 groups of data were analyzed and collated. The mean time between failure $MTBF$ corresponding to the i^{th} reliability value R_i in the data, and the preceding n reliability values are taken as the inputs of the neural network. In the meantime, R_i corresponding to $MTBF$ is taken as the output of the neural network. And the input and output data are normalized. Due to the fact that the reliability data are within the range from 0 to 1, normalization processing is not required. The specific data are shown in I.

The 27 sets of data listed in I are converted into sample values and grouped. According to the data in I and the corresponding grouping method, m is 6, which can be converted into 21 groups of sample data, as shown in II, with 7 input values and 1 output value for each group. The first 13 sets of sample data shown in II were taken as the training set samples of the neural network. The next 4 sets of data were taken as validation set samples. And the last 4 sets of data were taken as test set samples for error analysis of prediction results.

Based on the sample data of each group listed in II, MATLAB software was used for optimized cascade feedforward neural network programming. Among them, the neural network input layer contains 7 nodes, and the output layer contains 1 node. According to Formula (11), the number of nodes in the hidden layer is chosen as 6. The activation function of the hidden layer is the $\log - sigmoid$ function, and that of the output layer is the linear function. In addition, the maximum training number of the neural network is set at 1000. The structure diagram of the neural network after training is shown in Fig. 3.

Input the training sample data listed in II into the neural network for training. After 7 iterations, the training is completed, as shown in Fig. 4, it refers to the data-point comparison between the reliability prediction results of the training set data after optimized neural network operation and the actual results in the training set data. As shown in the figure, the optimized cascade feedforward neural network's

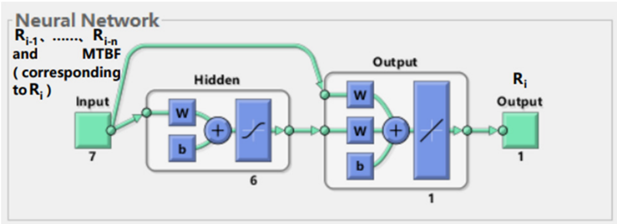

FIGURE 3. Structure diagram of the trained neural network.

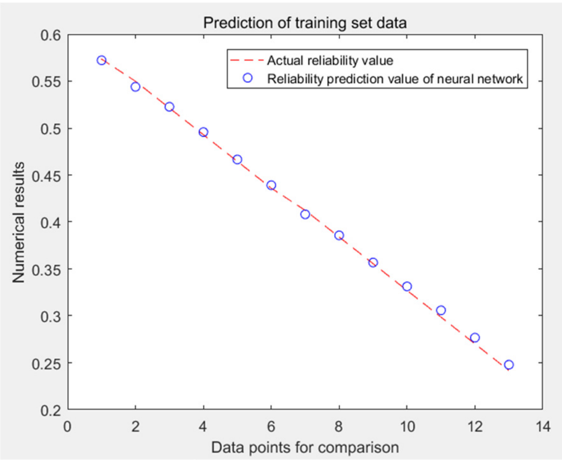

FIGURE 4. Comparison of prediction results of training set data.

prediction of the training set data is very close to the real value. As per the training result graph of the neural network after operation in MATLAB, the mean square error of the training reaches 1.96×10^{-19}. The neural network performance curves of the three sample sets are shown in Fig. 5. And the best verification performance is 5.7891×10^{-6} when the number of training times is 2.

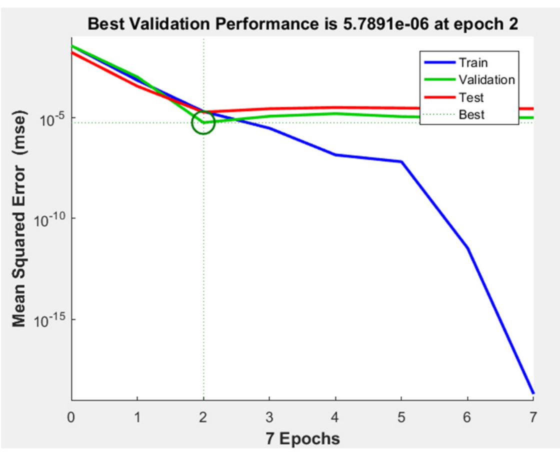

FIGURE 5. Neural network performance curves of three sample sets.

For the neural network that has been trained and verified, the test set data is employed for error comparative analysis. The input data of the test set samples are input into the trained

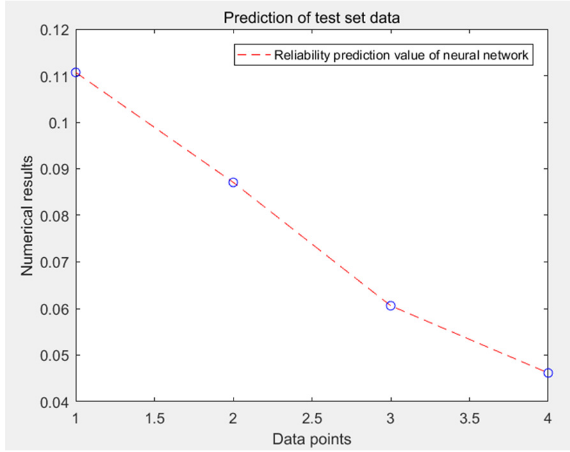

FIGURE 6. Predicted value of neural network.

TABLE 1. Input and output data of neural network.

The serial number	MTBF	Normalized results	The actual value of R_i
1	42	0	0.7440
2	47	0.0168	0.7156
3	49	0.0235	0.6872
4	54	0.0403	0.6588
5	60	0.0604	0.6256
6	65	0.0772	0.6019
7	69	0.0906	0.5735
8	76	0.1141	0.5498
9	81	0.1309	0.5213
10	90	0.1611	0.4929
11	99	0.1913	0.4645
12	109	0.2248	0.4360
13	115	0.2450	0.4123
14	122	0.2685	0.3839
15	129	0.2919	0.3555
16	147	0.3523	0.3270
17	155	0.3792	0.2986
18	174	0.4430	0.2701
19	181	0.4664	0.2417
20	194	0.5101	0.2133
21	206	0.5503	0.1848
22	217	0.5872	0.1564
23	221	0.6007	0.1280
24	254	0.7114	0.1090
25	272	0.7718	0.0853
26	299	0.8624	0.0616
27	340	1	0.0474

neural network, and the reliability prediction value of the CNC machine tool spindle corresponding to different *MTBF* values based on the optimized cascade feedforward neural

TABLE 2. Sample values of neural network.

S/N	Input values: R(t)	Input values: MTBF	Output value
1	0.7440 0.7156 0.6872 0.6588 0.6256 0.6019	0.0906	0.5735
2	0.7156 0.6872 0.6588 0.6256 0.6019 0.5735	0.1141	0.5498
3	0.6872 0.6588 0.6256 0.6019 0.5735 0.5498	0.1309	0.5213
4	0.6588 0.6256 0.6019 0.5735 0.5498 0.5213	0.1611	0.4929
5	0.6256 0.6019 0.5735 0.5498 0.5213 0.4929	0.1913	0.4645
6	0.6019 0.5735 0.5498 0.5213 0.4929 0.4645	0.2248	0.4360
7	0.5735 0.5498 0.5213 0.4929 0.4645 0.4360	0.2450	0.4123
8	0.5498 0.5213 0.4929 0.4645 0.4360 0.4123	0.2685	0.3839
9	0.5213 0.4929 0.4645 0.4360 0.4123 0.3839	0.2919	0.3555
10	0.4929 0.4645 0.4360 0.4123 0.3839 0.3555	0.3523	0.3270
11	0.4645 0.4360 0.4123 0.3839 0.3555 0.3270	0.3792	0.2986
12	0.4360 0.4123 0.3839 0.3555 0.3270 0.2986	0.4430	0.2701
13	0.4123 0.3839 0.3555 0.3270 0.2986 0.2701	0.4664	0.2417
14	0.3839 0.3555 0.3270 0.2986 0.2701 0.2417	0.5101	0.2133
15	0.3555 0.3270 0.2986 0.2701 0.2417 0.2133	0.5503	0.1848
16	0.3270 0.2986 0.2701 0.2417 0.2133 0.1848	0.5872	0.1564
17	0.2986 0.2701 0.2417 0.2133 0.1848 0.1564	0.6007	0.1280
18	0.2701 0.2417 0.2133 0.1848 0.1564 0.1280	0.7114	0.1090
19	0.2417 0.2133 0.1848 0.1564 0.1280 0.1090	0.7718	0.0853
20	0.2133 0.1848 0.1564 0.1280 0.1090 0.0853	0.8624	0.0616
21	0.1848 0.1564 0.1280 0.1090 0.0853 0.0616	1	0.0474

network method can be obtained. As shown in Fig. 6, the predicted values are 0.1107, 0.0871, 0.0606, 0.0462, respectively. Comparison with the actual value of the corresponding reliability was made, and the prediction error value of the neural network was shown in III. The absolute value of the absolute error of the prediction results is 0.0017, 0.0018, 0.0010, and 0.0012, respectively. Compared with the traditional mathematical model prediction method, the error is rather small, and the prediction accuracy is improved largely. Besides, the absolute value of relative error is 1.56%, 2.11%, 1.62%, and 2.53%, respectively. All these values are less than 3%, indicating that the optimized cascade feedforward neural network prediction method shows a high prediction accuracy, and is acceptable in engineering [26]. It is feasible to use this neural network for the prediction of the reliability of CNC machine tool spindle, which can make the prediction result more accurate, and provide certain effective references for the improvement of the reliability of CNC machine tool.

TABLE 3. Comparison error between predicted value and actual value.

MTBF	Actual value of reliability	Reliability prediction value of neural network	Absolute value of absolute error	Absolute value of relative error
254	0.1090	0.1107	0.0017	1.56%
272	0.0853	0.0871	0.0018	2.11%
299	0.0616	0.0606	0.0010	1.62%
340	0.0474	0.0462	0.0012	2.53%

V. CONCLUSION

(1) The cascade feedforward neural network avoids the disadvantages of BP network, such as slow convergence speed and strong tendency to fall into local minimum. Meanwhile, compared with other machine learning prediction methods, it shows low computational complexity and strong fitting ability. Adam optimization algorithm is widely used, which has better effect in practical application than other adaptive technologies, and can realize the fast and efficient optimization of neural network.

(2) The absolute value of the relative error of the reliability prediction value obtained based on the optimized cascade feedforward neural network method is less than 3%, indicating that the prediction accuracy of this method is high. And this method is practical in engineering due to its obvious advantages compared with other reliability prediction methods. Moreover, it can better solve the problem of reliability prediction of CNC machine tool spindle, and provide a new method for reliability prediction of CNC machine tool.

(3) For reliability prediction, optimized cascade feedforward neural network method also shows some limitations. For example, it has a low ability to solve reliability data with mutation. To prevent mutation data from affecting the accuracy of neural network prediction, it is necessary to analyze the key factors affecting reliability before the implementation of prediction to determine whether there are inherent characteristics affecting product reliability.

REFERENCES

[1] Y. Li, "Compilation and application of load spectrum of machine tool spindle reliability test program based on Lamikiz model," Dept. Mech. Manuf. Automat., Jilin Univ., Changchun, China, Tech. Rep., 2019.
[2] W. Tong, "Reliability analysis and simulation of CNC machine tool spindle system," Dept. Mech. Des. Theory, Northeastern Univ., Shenyang, China, Tech. Rep., 2015.
[3] G. L. Li, "Research on the state monitoring of ship main engine driven by data," Dept. Nav. Archit. Ocean Eng., Dalian Maritime Univ., Dalian, China, Tech. Rep., 2019.
[4] R. Y. Li and R. Kang, "Prediction method of failure rate based on neural network," *Acta Aeronautica Sinica*, no. 2, pp. 357–363, 2008.
[5] M. J. Cushing, D. E. Mortin, T. J. Stadterman, and A. Malhotra, "Comparison of electronics-reliability assessment approaches," *IEEE Trans. Rel.*, vol. 42, no. 4, pp. 542–546, Dec. 1993.
[6] Z. J. Liu, B. L. Liu, and Y. B. Hu, "Reliability prediction of machine tool spindle based on Monte Carlo method," *Modular Mach. Tools Automated Process. Technol.*, no. 2, pp. 34–36 and 42, 2018.
[7] J. J. Guo *et al.*, "Reliability calculation method of electromechanical system by stochastic fault injection combined with neural network method," *J. Mech. Eng.*, vol. 53, no. 6, pp. 195–202, 2017.

[8] L. Lu *et al.*, "Research on character recognition of vehicle license plate based on convolutional neural network," in *Proc. 12th Nat. Academic Conf. Image Graph.* Shanghai, China: Chinese Society Image Graphics: Chinese Society of Image Graphics, 2005, p. 4.
[9] P. Roy, G. S. Mahapatra, and K. N. Dey, "Forecasting of software reliability using neighborhood fuzzy particle swarm optimization based novel neural network," *IEEE/CAA J. Automatica Sinica*, vol. 6, no. 6, pp. 1365–1383, Nov. 2019.
[10] H. G. Wang, H. X. Tian, and H. S. Li, "Reliability prediction method of BP neural network distribution system considering small sample statistics," *J. Power Sci. Technol.*, vol. 34, no. 2, pp. 40–46, 2019.
[11] Z. Tian, S. X. Jing, and L. J. Zhao, "Reliability prediction of coal shearer based on particle swarm optimization BP neural network," *J. Henan Polytech. Univ. (Natural Sci. Ed.)*, vol. 39, no. 1, pp. 68–74, 2020.
[12] X. Y. Wang, Y. Gao, G. Zhang, and M. Guo, "Prediction of optimal power allocation for enhancing security-reliability tradeoff with the application of artificial neural networks," in *Proc. 2nd Int. Conf. Adv. Comput. Technol., Inf. Sci. Commun. (CTISC)*, Mar. 2020, pp. 40–45.
[13] S. Ke, "Fatigue life prediction and fatigue reliability analysis of aero-engine turboshaft," Dept. Mech. Eng., Univ. Electron. Sci. Technol. China, Chengdu, China, Tech. Rep., 2020.
[14] A. D. Xu, H. F. Li, and L. F. Cheng, "Power supply reliability prediction model of PCA-PSO-ELM distribution network," *J. Harbin Eng. Univ.*, vol. 39, no. 6, pp. 1116–1122, 2018.
[15] A. S. Zimmermann and S. Mattedi, "Density and speed of sound prediction for binary mixtures of water and ammonium-based ionic liquids using feed-forward and cascade forward neural networks," *J. Mol. Liquids*, vol. 311, Aug. 2020, Art. no. 113212.
[16] X. W. Zhang, Y. Zheng, and B. W. Yang, "Optimization design of airfoil based on cascaded forward network," *J. Zhejiang Univ. (Eng. Sci. Ed.)*, vol. 51, no. 7, pp. 1405–1411, 2017.
[17] X. W. Zhang, "Research on airfoil optimization algorithm based on cascade feedforward neural network," Dept. Aircr. Des., Zhejiang Univ., Hangzhou, China, Tech. Rep. V224, 2017.
[18] X. Xia, X. F. Chen, and L. Ye, "Dynamic prediction of the reliability of friction torque performance of satellite momentum wheel bearings," *China Mech. Eng.*, vol. 30, no. 11, pp. 1268–1275, 2019.
[19] M. Abas, K. Naeem, T. Habib, I. Khan, U. Farooq, Q. S. Khalid, and K. Rahman, "Development of prediction model for conductive pattern lines generated through positive displacement microdispensing system using artificial neural network," *Arabian J. Sci. Eng.*, vol. 46, no. 3, pp. 2429–2442, Mar. 2021.
[20] F. Belotti and F. Peracchi, "Fast leave-one-out methods for inference, model selection, and diagnostic checking," *Stata J., Promoting Commun. Statist. Stata*, vol. 20, no. 4, pp. 785–804, Dec. 2020.
[21] S. K. Hou, Y. R. Liu, and K. Zhang, "Prediction of TBM tunnelling parameters based on IPSO-BP hybrid model," *Chin. J. Rock Mech. Eng.*, vol. 39, no. 8, pp. 1648–1657, 2020.
[22] Z. Fan, W. Y. Fu, and X. N. Zhao, "Prediction of multiphase dynamic pipeline corrosion rate based on wavelet neural network," *Chem. Ind. Prog.*, vol. 37, no. 8, pp. 2904–2911, 2018.
[23] J. P. Jiao, S. Y. Li, and Y. Chang, "Research on the method of identifying the surface defects of the weld in the header pipe joint," *Chin. J. Sci. Instrum.*, vol. 38, no. 12, pp. 3044–3052, 2017.
[24] C. K. Wen, B. Xie, and R. C. Li, "Design of tractor operating load data platform and quality prediction of rotary tillage operation," *J. Agricult. Machinery*, vol. 51, no. 8, pp. 372–381, 2020.
[25] Y. Jin and S. J. Liu, "Fatigue reliability analysis of aviation bearing based on artificial neural network," *J. Northeastern Univ. (Natural Sci.)*, vol. 39, no. 6, pp. 850–855, 2018.
[26] J. Y. Shi, "Reliability prediction method and application of large generator sets," *Chin. J. Mech. Eng.*, vol. 47, no. 18, pp. 165–172, 2011.

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