Fault Prediction of CNC Machine Tools Based on Gutenberg-Richter Law and Fuzzy Neural Networks

Tiebin Wang[1], Jie Yu[1*], Yu Cao[1], Weidong Wang[1], Gege Zhao[1], Xinghe Sun[2]
[1]School of Mechanical and Resource Engineering, Wuzhou University, Wuzhou 543002, China
[2]Yanji Cigarette Factory, Jilin 133000, China
E-mail: binbinwenzhi@163.com (T.W.); 17678314998@163.com (J.Y.); 527871161@qq.com (Y.C.); 1463394922@qq.com (W.W.); 2568776317@qq.com (G.Z.); yu99jie99@sohu.com (X.S.)
[*]Corresponding author

Keywords: CNC machine tools, reliability, fuzzy neural network, fault prediction

Received: May 29, 2024

The magnitude-frequency relationship is one of the most cited empirical equations by seismologists for studying seismic activity, and it has been widely used in earthquake forecasting and earthquake hazard analysis. Applying this equation to fit and analyze a large amount of CNC machine failure data, similar conclusions to those of seismology were obtained. The adaptive neural network ANFIS model was used to predict the b-value as an output quantity, associated with the fault level and number of faults. The sample data were tested separately using the ANFIS toolbox of MATLAB software and the Neural Net Fitting APP function. The ANFIS model has better accuracy in b-value prediction, which shows that the ANFIS model has certain ability to predict the parameters of the G-R Law. b-value prediction reflects the stability of CNC machine operation to a certain extent, and the change of b-value can speculate the possibility of CNC machine failure in continuous operation, which has certain reference significance for the normal operation of production. The experimental data were obtained from the manufacturer of a series of CNC machine tools in use, covering a time span of up to seventeen years. The results show that the ANFIS model significantly outperforms the BP neural network in terms of accuracy.

Povzetek: Opisana je uporaba Gutenberg-Richterjevega zakona in adaptivnih nevronskih mrež za napovedovanje okvar CNC strojev.

1 Introduction

Gutenberg-Richter's Law (G-R Law) $\lg N = a - bM$ is a formula often used in earthquake studies. In general, the magnitude M and frequency N of earthquakes in different regions generally satisfy this statistical rule. Where a and b are constants, a characterizes the level of seismic activity in the region during the statistical time, and b represents the proportional relationship between the number of large and small earthquakes in the region.

The analogy between CNC machine failures and seismic activity shows validity and applicability in several ways. Firstly, the similarity of statistical characteristics, the statistical characteristics of seismic activity show that small earthquakes occur frequently and large earthquakes are rare, this law also applies to the failure data of CNC machine tools, in which small failures occur frequently and large failures are rare. Secondly, in terms of system complexity, earthquakes are complex system phenomena caused by crustal movement, and the frequency distribution of different levels of earthquakes reflects their complexity; similarly, CNC machine tools, as a complex mechanical and electronic system, involve multiple sub-systems and components, and the probability of failure and the severity of the different components also show similar distribution characteristics. Further, in terms of failure propagation mechanism, the energy propagation and accumulation mechanism of earthquakes determines the frequency and magnitude distribution of earthquakes, and small failures in CNC machine tools may accumulate and lead to more serious failures, and this failure accumulation and propagation mechanism is similar to the accumulation and release of earthquake energy. Finally, in terms of prediction and prevention, the frequency of small earthquakes can be monitored and analysed to predict the likelihood of large earthquakes, and similarly more serious failures can be predicted and prevented by monitoring small failures in CNC machine tools, e.g., by monitoring vibration, temperature, and other sensor data, potential problems can be detected in advance and preventive maintenance can be carried out. Taken together, these similarities suggest that applying the G-R law of seismic activity to the prediction of CNC machine tool failures is theoretically and practically sound.

The authors used seismic G-R curves to depict the relationship between the failure level and the frequency of failures of a series of CNC lathes, and came to some similar conclusions to those in seismology [1]. That is, during the period of frequent failures, the b-value is low, and with the implementation and improvement of reliability measures, the reliability of CNC machine tools is significantly improved and the failure rate stabilizes, and the b-value gradually increases in this period and finally approaches 1.0.

Zheng et al. [2] used fuzzy information theory to derive the probability of occurrence of a certain magnitude gear at different b values. CNC machine tool faults are fuzzy in description and adaptive fuzzy neural network is used as a fault prediction method. The adaptive neuro-fuzzy inference system is based on Takagi-Sugeno model, ANFIS integrates neural network and fuzzy logic principles with the ability to learn from nonlinear functions. Bart Kosko first combined fuzzy theory and neural network to promote the development of fuzzy neural network and Jang proposed a fuzzy inference model based on network structure [3-6].

The ANFIS model can be used to solve some more complex problems effectively. Neural networks are used to implement the three basic processes of fuzzification, fuzzy inference and anti-fuzzification of fuzzy control, and the adaptive and learning mechanisms of neural networks are used to extract rules from the input and output samples, and offline training and online learning algorithms are used to continuously self-tune the inference rules [7-11].

2 G-R law analysis of a series of CNC machines

Our research team has been working on the reliability of CNC machine tools for many years. In order to improve the reliability of CNC machine tools, there has been cooperation with manufacturers of CNC machine tools. The manufacturers of CNC machine tools are responsible for the collection of CNC machine tool failure data, we analyze the data and propose corresponding improvement programs and measures, and the reliability of CNC machine tools has been improved year by year.

The collected failure data of a series of CNC machine tools from 2004-2021 were analyzed, and the failure data were divided into six stages with three years as a stage. As shown in Table 1.

Table 1: A series of CNC machine tool failure data statistics for each stage

Stage	Time interval	Failure data
Stage 1	January 2004 to December 2006	1927
Stage 2	January 2007 to December 2019	1385
Stage 3	January 2010 to December 2012	726
Stage 4	January 2013 to December 2015	453
Stage 5	January 2016 to December 2018	394
Stage 6	January 2019 to December 202	421

The failure data of the first, third and sixth stages were classified into classes to obtain the data in Tables 2-4.

Table 2: Fault data of stage 1

Failure level	M	N	lgN
1	1	1927	3.2900
2	1.5	1274	3.1051
3	2	724	2.8597
4	2.5	326	2.5132
5	3	188	2.2741
6	3.5	126	2.1003
7	4	71	1.8512
8	4.5	34	1.5314
9	5	18	1.2552
10	5.5	12	1.0791
11	6	5	0.6989

Table 3: Fault data of stage 3

Failure level	M	N	lgN
1	1	726	2.8609
2	1.5	314	2.4969
3	2	127	2.1038
4	2.5	45	1.6532
5	3	17	1.2304
6	3.5	6	0.7856
7	4	3	0.3706
8	4.5	2	0.2050

Table 4: Fault data of stage 6

Failure level	M	N	lgN
1	1	421	2.6242
2	1.5	122	2.0863
3	2	36	1.5563
4	2.5	12	1.0791
5	3	4	0.6020
6	3.5	1	0.0572

By fitting the G-R curve to all the fault data of each stage, the obtained b-value is plotted as a curve. The collected data are for reference, and it is found that with the growth of time, high-grade faults basically do not appear in the middle and late stages, so the level 3 faults are used as the boundary, and the level 11 faults are divided into two parts, above level 3 is the big faults, and below level 3 is the small faults, making a line graph of the ratio of small and big faults, as shown in Figure 1. From the graph, it can be seen that the b value is gradually increasing, and the ratio of small and large faults is gradually approaching 0, which indicates that the proportion of large faults is getting smaller and smaller as the b value increases. The results can be concluded that the b value can be used as a prediction indicator to judge the CNC machine tool fault prediction, and the numerical size of the b value can determine whether the CNC machine tool is faulty or not.

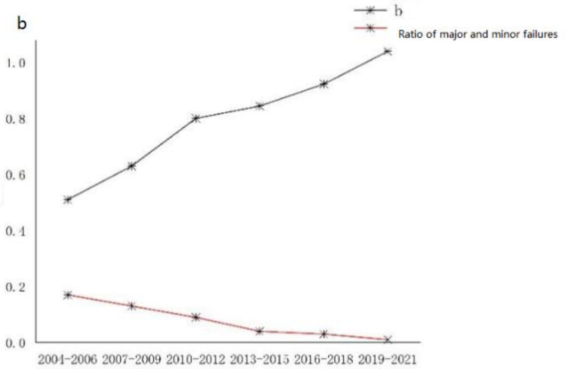

Figure 1: Change chart of b value and ratio of major and minor failures

The data were fitted to the three stages to derive the parameters a and b for each stage, as shown in Table 5.

Table 5: Failure data fitting results

stage	G-R LAW	b value	a value	MTBF
stage1	lgN=3.847-0.51M	0.51	3.847	379
stage3	lgN=3.663-0.80M	0.80	3.663	1024
stage6	lgN=3.637-1.04M	1.01	3.637	1922

As can be seen from Table 5, the b-values are gradually increasing with the implementation of the improvement measures. Along with the implementation of reliability improvement measures, the b-value has increased, and the higher-grade failures are gradually decreasing until they no longer appear. At a later stage, the value of b-value is around 1.0 and the failure rate is gradually stabilized. The reliability of CNC machine tools at this time has been greatly improved and the MTBF value can reach about 2000 hours.

It can be concluded from the results that the b-value can be used as a prediction indicator for the prediction of CNC machine failures, and the magnitude of the b-value value can be used to determine whether the CNC machine has a failure.

3 Fault prediction of CNC machine tools based on G-R law parameters and fuzzy neural networks

3.1. Data samples

In this part, according to the statistics of a series of CNC machine tools in machine tool factory from 2008 to 2021, the respective b-values were calculated, the failure level M was divided, and 100 sets of sample data were compiled. The data samples are shown in Table 6.

Table 6. Data samples

b	N	M	b	N	M
0.49	132	2	0.92	110	3
0.51	67	2.5	0.93	105	3
0.52	115	2	0.92	107	3
0.48	137	2	0.92	36	3.5
0.49	75	2.5	0.94	33	3.5
0.53	58	2.5	0.94	34	3.5
0.5	126	2	0.93	34	3.5
0.49	75	2.5	0.92	107	3
0.45	157	2	0.92	108	3
0.48	77	2.5	0.91	115	3
0.47	146	2	0.99	68	3.5
0.53	58	2.5	0.98	77	3.5
0.53	107	2	0.95	35	4
0.53	66	2.5	0.97	23	4
0.52	76	2.5	0.98	24	4
0.49	130	2	1.02	55	3.5
0.51	122	2	1.01	58	3.5
0.52	116	2	1	64	3.5
0.51	67	2.5	1	19	4
0.5	71	2.5	0.99	20	4
0.85	176	3	0.98	25	4
0.8	253	2.5	1	19	4
0.79	105	3	1.02	16	4
0.86	68	3	1.03	47	3.5
0.84	197	2.5	1.03	49	3.5
0.85	187	2.5	1.02	55	3.5
0.8	102	3	1.02	55	3.5
0.88	155	2.5	1.02	17	4
0.87	63	3	1.02	17	4
0.84	198	2.5	1.01	18	4
0.84	76	3	1	19	4
0.85	187	2.5	1.02	17	4
0.83	83	3	0.99	23	4
0.86	175	2.5	0.98	7	4.5
0.86	177	2.5	0.97	5	4.5
0.84	74	3	0.96	8	4
0.87	63	3	0.99	7	4.5
0.85	71	3	0.97	27	4
0.85	188	2.5	1.01	19	4
0.85	188	2.5	1.02	16	4
0.93	35	3.5	1	20	4
0.92	38	3.5	1.01	19	4
0.9	126	3	1.02	5	4.5
0.94	95	3	1.01	6	4.5
0.93	105	3	0.99	7	4.5
0.94	33	3.5	0.98	26	4
0.93	35	3.5	0.97	27	4
0.94	31	3.5	0.98	24	4
0.92	109	3	0.99	22	4
0.92	109	3	1	20	4

3.1 ANFIS model prediction based on fuzzy neural network

In the above analysis, the b-values were calculated from the fault data of each stage, and the b-values were used as the target to make a judgment on the CNC machine tool fault prediction. Here, the ANFIS model was used as a tool, which was implemented by opening the toolbox with the anfisedit command in MATLAB, and the goal of the work was to predict the sample b-values to verify the feasibility of the b-values on the CNC machine tool prediction. The number of faults and fault levels in 100 sets of sample data are used as inputs, 80 sets of data are trained, and the output is the predicted b-value. An initial ANFIS model is built, and the initial ANFIS model structure contains 5 fuzzy subsets for each input quantity, and each subset in turn contains 5 different rules that translate the different results into 1 output quantity.

The main idea of the Gaussian affiliation function is to use a synthetic, uniform and variable function to describe the relationship between a series of observations. It helps to correctly express the associations in a given data set and gives reliable conclusions. The Gaussian affiliation function is chosen for the experimental model, and the name and parameters of the affiliation function can be edited in MATLAB.

By simulating training on 80 training sets, the final error was controlled within 0.02, and the number of updates of ANFIS weights was improved under 20 iteration cycles to achieve a high level of accuracy. Figure 2 shows the graph of training error versus the number of iterations.

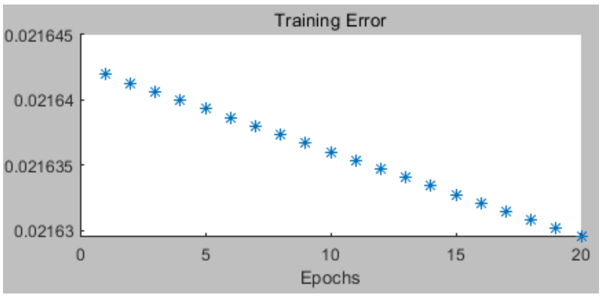

Figure 2: Training error and iteration numbers (80 training sets.20 iterative cycles)

After training, the overlap between the training and validation samples is viewed, and it can be seen from Figure 3 that the predicted samples almost overlap with those of the original samples, the model reaches stability, and the prediction effect meets the prior expectation.

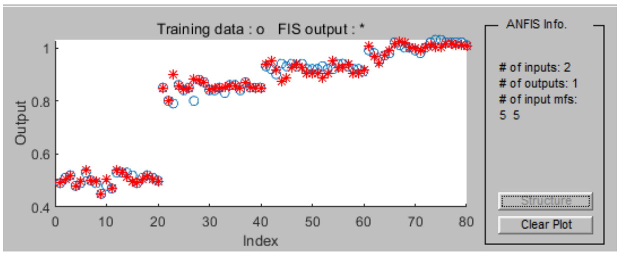

Figure 3: Test set and validation set overlap (after training)

3.2. Prediction data validation

The predicted data from the ANFIS model output, the original b-value data and the absolute errors between them are collated in the following Table 7.

Table 7: Prediction error table

Original b value	Predicted b value	Absolute error	Original b value	Predicted value	Absolute error
0.49	0.50	-0.01	0.92	0.94	-0.02
0.51	0.51	0	0.93	0.94	-0.01
0.52	0.52	0	0.92	0.92	0
0.48	0.50	-0.02	0.92	0.92	0
0.49	0.50	-0.01	0.94	0.92	0.02
0.53	0.52	0.01	0.94	0.94	0
0.5	0.51	-0.01	0.93	0.94	-0.01
0.49	0.49	0	0.92	0.92	0
0.45	0.45	0	0.92	0.92	0
0.48	0.48	0	0.91	0.92	-0.01
0.47	0.48	-0.01	0.99	0.98	0.01
0.53	0.53	0	0.98	0.98	0
0.53	0.53	0	0.95	0.96	-0.01
0.53	0.53	0	0.97	0.97	0
0.52	0.53	-0.01	0.98	0.98	0
0.49	0.50	-0.01	1.02	1	0.02
0.51	0.50	0.01	1.01	1	0.01
0.52	0.52	0	1	1	0
0.51	0.50	0.01	1	1	0
0.5	0.50	0	0.99	1	-0.01
0.85	0.83	0.02	0.98	1	-0.02
0.8	0.8	0	1	1	0
0.79	0.80	-0.01	1.02	1.02	0
0.86	0.85	0.01	1.03	1.02	0.01
0.84	0.85	-0.01	1.03	1.02	0.01
0.85	0.85	0	1.02	1.02	0
0.8	0.80	0	1.02	1.03	-0.01
0.88	0.88	0	1.02	1.03	-0.01
0.87	0.88	-0.01	1.02	1.02	0
0.84	0.85	-0.01	1.01	1.02	-0.01
0.84	0.85	-0.01	1	1	0
0.85	0.85	0	1.02	1	0.02
0.83	0.85	-0.02	0.99	1	-0.01
0.86	0.85	0.01	0.98	0.98	0
0.86	0.86	0	0.97	0.98	-0.01
0.84	0.85	-0.01	0.96	0.96	0
0.87	0.85	0.02	0.99	0.98	0.01
0.85	0.85	0	0.97	0.98	-0.01
0.85	0.85	0	1.01	1	0.01
0.85	0.85	0	1.02	1	0.02
0.93	0.94	-0.01	1	1	0
0.92	0.92	0	1.01	1	0.01
0.9	0.90	0	1.02	1.02	0
0.94	0.94	0	1.01	1	1.01
0.93	0.94	-0.01	0.99	0.98	0.01
0.94	0.94	0	0.98	0.98	0
0.93	0.94	-0.01	0.97	0.98	-0.01
0.94	0.94	0	0.98	0.98	0
0.92	0.94	-0.02	0.99	0.98	0.01
0.92	0.94	-0.02	1	1	0

In order to visualize the difference between the original sample data and the predicted data, the predicted data were plotted against the original data as a curve in Figure 4.

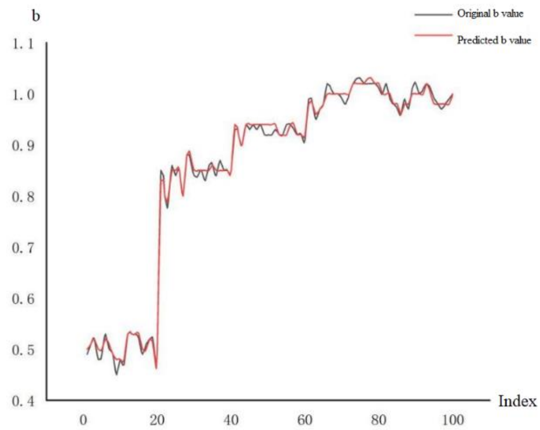

Figure 4: b-value prediction data and original b-value trend line graph (Data in table 7)

The absolute errors of the predicted b-value data and the original b-value data are plotted in Figure 5, from which it can be seen that the probability of the peak of the error decreases and basically stabilizes at 0 and 0.01, and the probability of 0.02 occurs less frequently in the whole set of samples.

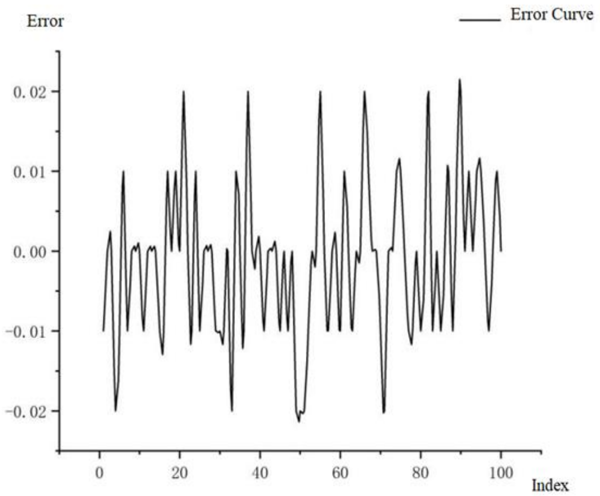

Figure 5: Error curve chart

From Figure 4, it can be seen that the prediction curve and the original curve have the same trend, and the two curves basically overlap, and from the error curve Figure 5, it can be seen that the maximum error of the predicted b-value does not exceed 0.02. Therefore, the fuzzy neural network model is applicable to the prediction of b-value in the G-R relationship equation, and the b-value is calculated and extracted by the existing fault data of CNC machine tools, and the data in the fuzzy neural network using fuzzy language rules Iterative calculation is carried out to reduce the error to within 0.02. The resulting predicted b-value is combined with the content of the previous chapter to grade the prediction results, which can determine the occurrence of major equipment failures in advance and is useful for CNC machine tool fault prediction.

4 BP neural network model prediction comparison

4.1. BP neural network prediction model

Artificial neural network model is an information processing system built with reference to the processing of information by neurons in the human brain [12-16]. The network consists of a series of interconnected artificial neurons with features such as nonlinear mapping, self-learning, and self-organizing adaptability, which can process massive amounts of data by multiple threads at the same time. ANNs are widely used in many fields such as medicine, economics, informatics, and engineering for their advantages of easy implementation in hardware and software. Neural networks are widely used in the fields of medicine, economics, and biology because of their easy implementation in hardware and software [4, 17-18].

When useful information is stored in the weight matrix, the learning ability of ANN is improved by adjusting the weights and thresholds of the neural network. Early neural networks were a single-layer perceptual model with simple patterns, clear structure, and small computational effort. In recent years, the traditional neural network model cannot be adapted to the current scientific research needs due to the intensive research in the field of neural networks. The proposed multilayer feed forward network has solved this problem by making the trainability of neural networks significantly improved.

The flowchart of CNC machine tool fault prediction based on G-R curve parameters and fuzzy neural network is shown in Figure 6.

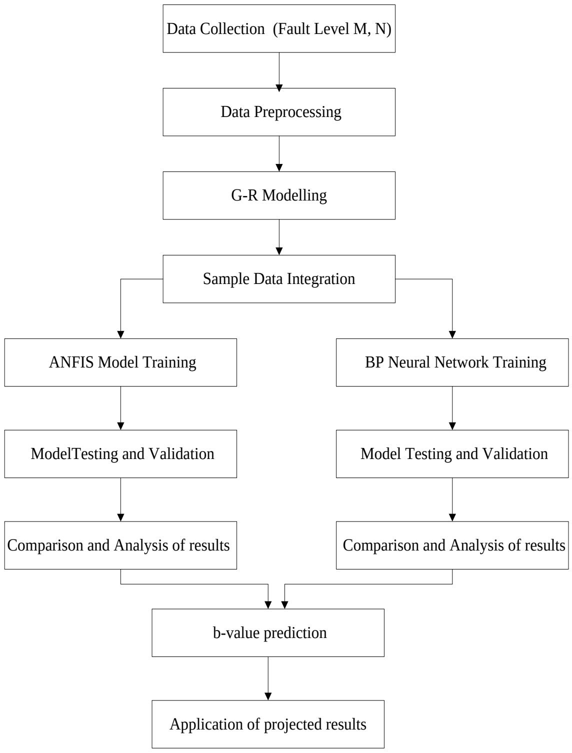

Figure 6: Flowchart of failure prediction for CNC machine tools

4.2. Model output

The Neural Net Fitting APP function of MATLAB is used to allocate 80 sets of training set, 10 sets of validation set, and 10 sets of tests set as shown in Figure 7. The number of faults N and fault level M are used as input data, the b-value is used as output data, and the number of implied layers is determined as 5 layers after several debuggings.

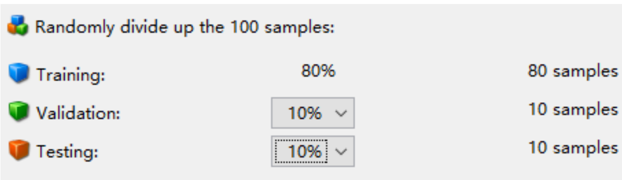

Figure 7: Data segmentation

After BP neural network training, it can be concluded that the training set and validation set are optimal at 5 iterations, and the error reaches an accuracy within 0.01, as shown in Figure8.

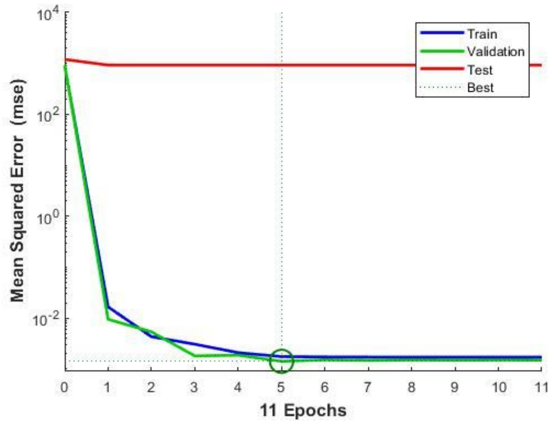

Figure 8: Neural network error transformation visualization diagram

By looking at the visualization graph of the regression ability of the training network (Figure 9), it is found that the regression ability of the training and validation sets is better and the fitting effect is better, but the regression ability of the test set is poor, which makes the regression ability of the overall data cannot achieve better results and the correlation is lower, and the desired requirement for the prediction effect is not achieved, so compared with the fuzzy neural network, the ANFIS model prediction results are chosen as the judgment of the prediction ability in this paper.

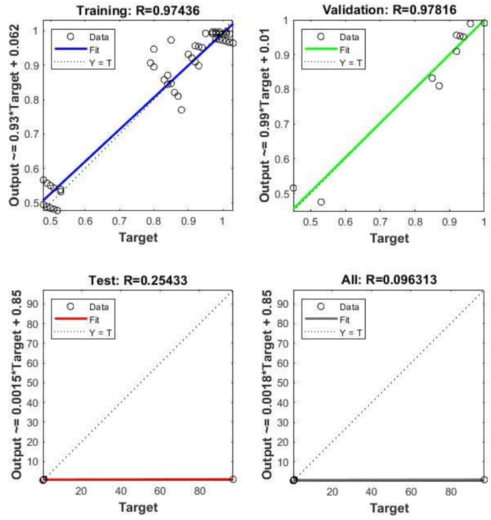

Figure 9: Neural network regression capability visualization chart

Table 8: Comparison to ANFIS predictive model and BP neural network prediction model

ANFIS predictive model			BP neural network prediction model		
Original b-value	Predictive b-value	Absolute value of error in percent	Original b-value	Predictive b-value	Absolute value of error in percent
0.85	0.83	2.35%	0.85	0.89	4.70%
0.8	0.8	0	0.8	0.84	5%
0.79	0.80	1.26%	0.79	0.85	7.59%
0.86	0.85	1.16%	0.86	0.80	6.97%
0.84	0.85	1.19%	0.84	0.89	5.95%
0.93	0.94	1.06%	0.93	0.89	4.49%
0.94	0.94	0	0.94	0.90	4.44%
0.93	0.94	1.06%	0.93	0.98	5.26%
0.94	0.94	0	0.94	0.89	5.61%
0.92	0.94	2.12%	0.92	0.96	4.17%

From the results in Table 8 we can see that: the BP neural network predicts poorly with a large error. And the ANFIS model predicts better results, indicating that the ANFIS model is credible in predicting the parameters of the G-R relational equation.

5 Conclusion

CNC machine tool faults are extremely uncertain, and these occurring faults within the whole machine system may be closely related. The connection between fault level and b-value is established using the G-R model, because the fuzzy neural network has a better adaptive capability to solve the problem that the sample data is nonlinear, so ANFIS in fuzzy inference is used to associate the b-value as the output quantity with the fault level M and the number of faults N up to achieve the prediction of parameter b value. Using the two toolboxes in MATLAB, the ANFIS model is tested and compared based on the integrated sample data, and the number of iterations and error of the ANFIS model is smaller, while the BP neural network is poorly fitted, with lower correlation and larger error. And the b-value predicted by the ANFIS model is within 0.02 of the original b-value, indicating that the ANFIS model can predict the parameters of the G-R relational equation as expected.

The innovative nature of this study is reflected in the following aspects:

Combining G-R curve and ANFIS model: by combining G-R curve and ANFIS model, the relationship between failure level, number of failures and b-value is successfully established, and the high-precision prediction of b-value of parameter is achieved. This method is novel in dealing with the fault prediction of complex systems. High-precision prediction: By comparing the experimental data, it proves the significant advantage of ANFIS model in prediction accuracy, which provides a more reliable tool for CNC machine tool fault prediction. Wide applicability: The application of ANFIS model is not only limited to CNC machine tool fault prediction, but also can be extended to other industrial fields for fault diagnosis and prediction, which has a wide application prospect.

The results of this paper are more reasonable and will provide a basis for the future studies.

Funding Statement

This work was sponsored by Wuzhou University Level Project (2023B007); This work was sponsored by Wuzhou University Research Foundation for Advanced Talents (WZUQDJJ21088).

Data availability statement

The datasets generated or analyzed during this study are available from the corresponding author on reasonable request.

References

[1] J. Yu and Y. L. Shi. Failure rate analysis of CNC machine tools based on G-R curve. Machine Tools and Hydraulics, 37(10): 257-258, 2009. https://doi.org/10.1109/ICMTMA.2011.329.

[2] Z. B. Zheng, D. W. Liu, X. Q. Shen, and X. Q. Wang. Reliability of b-value full time scan results and correlation with earthquakes in North China. Earthquake, (3): 8-14, 2001. https://doi.org/10.3969/j.issn.1000-3274.2001.03.002

[3] Y. L. Li. Research on load forecasting problem of power system based on neural network. Shenyang University of Technology, 2014.

[4] X. J. Zhang. Adaptive neuro-fuzzy inference system (ANFIS) and its simulation. Electronic Design Engineering, 20(5): 11-13, 2012. https://doi.org/10.14022/j.cnki.dzsjgc.2012.05.054

[5] Y. Zhang, R. Zheng, G. Shen, and B. K. Chen. Reliability analysis for CNC machine tool based on failure interaction. Intelligent Computing and Information Science, 134: 489-496, 2011. https://doi.org/10.1007/978-3-642-18129-0_76

[6] Z. Yang, B. Xu, F. Chen, Q. Hao, X. Zhu, and Y. Jia. A new failure mode and effects analysis model of CNC machine tool using fuzzy theory. Harbin, China: The 2010 IEEE International Conference on Information and Automation, 582-587, 2010. https://doi.org/10.1109/ICINFA.2010.5512403.

[7] G. B. Zhang, L. Zhang, and Y. Ran. Reliability and failure analysis of CNC machine based on element action. Applied Mechanics and Materials, 494-495: 354-357, 2014. https://doi.org/10.4028/www.scientific.net/AMM.494-495.354

[8] B. K. Lad and M. S. Kulkarni. A parameter estimation method for machine tool reliability analysis using expert judgment. International Journal of Data Analysis Techniques and Strategies, 2(2): 155-169, 2010. https://doi.org/10.1504/IJDATS.2010.032455.

[9] D. Z. You and H. Pham. Reliability analysis of the CNC system based on field failure data in operating environments. Quality and Reliability Engineering International, 32(5): 1955-1963, 2015. https://doi.org/10.1002/qre.1926.

[10] C. R. Vishnu and V. Regikumar. Reliability based maintenance strategy selection in process plants: A case study. Procedia Technology, 25: 1080-1087, 2016. https://doi.org/10.1016/j.protcy.2016.08.211

[11] T. Gulavane. Reliability analysis of CNC turning centre machine: A case study from Indian industry. Third National Conference on Reliability and Safety Engineering, 2016. https://www.researchgate.net/publication/311693390_Reliability_Analysis_of_CNC_Turning_Centre_Machine_A_Case_Study_from_Indian_Industry

[12] R. B. Patil, B. S. Kothavale, L. Y. Waghmode, and S.G. Joshi. Reliability analysis of CNC turning center based on the assessment of trends in maintenance data: A case study. International Journal of Quality and Reliability Management, 34(9): 1616-1638, 2017. https://doi.org/10.1108/IJQRM-08-2016-0126.

[13] R. B. Patil, D. A. Mhamane, P. B. Kothavale, and B. Kothavale. Fault tree analysis: A case study from machine tool industry. Proceedings of TRIBOINDIA-2018 An International Conference on Tribology, 2018. https://doi.org/10.2139/ssrn.3382241.

[14] A. H. Moghaddam, M. H. Moghaddam, and M. Esfandyari. Stock market index prediction using artificial neural network. Journal of Economics, Finance and Administrative Science, 21(41): 89-93, 2016. https://doi.org/10.1016/j.jefas.2016.07.002.

[15] J. Tang, F. Liu, W. Zhang, R. Ke, and Y. Zou. Lane-changes prediction based on adaptive fuzzy neural network. Expert Systems with Applications, 91: 452-463, 2018. https://doi.org/10.1016/j.eswa.2017.09.025.

[16] S. Yu, H. B. Zou, F. Yu, C. L. Fu, and N. Han. Application of fuzzy neural network in short-term load forecasting of power system. Smart Power, 46(11): 88-91+97, 2018. https://doi.org/10.3969/j.issn.1673-7598.2018.11.015

[17] J. H. He, B. Y. Zhang, and J. H. Luo. Fuzzy neural network model based on high fill foundation in charcoal rock area of Guangxi Settlement prediction research. Western Transportation Science and Technology, 2: 60-63, 2020. https://doi.org/CNKI:SUN:XBJT.0.2020-02-020

[18] Y. Zhang. Stock data analysis based on BP neural network multi-portfolio model. Fuyang Normal University, 2022.