# Fuzzy Reasoning based Reliability Fault Prediction of CNC Machine Tools

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***Abstract*—CNC machine tools are the infrastructure of the manufacturing industry, and many fields cannot do without them. This paper studies the fault data of a series of CNC machine tools, and predicts the fault level based on the activity parameters of Gutenberg Richter curve and fuzzy information theory. Apply the Gutenberg Richter curve model to the reliability analysis of CNC machine tools, and use this model to fit the curves separately. Fit the activity parameters of each stage with curves, and the results show that the b value can reflect the fault activity frequency of CNC machine tools. Due to the correlation and fuzziness between system faults, it is more appropriate to use a fuzzy neural network with strong adaptability and good learning ability, which can easily adjust parameters, and can express a more complex, high-dimensional nonlinear system through fewer conditions. The use of fuzzy reasoning can link the nonlinear relationship between fault level, b-value, and N-value. Analyze the error between the predicted fault level and the original level, and the small error indicates that the model has good predictive ability. Applying this predictive ability to the reliability research of CNC machine tools will yield good results.**

***Keywords—CNC machine tools; reliability; fuzzy inference; fault prediction***

## I. Preface

The failure of the CNC machine tool is recorded in real time, and the surrounding environment, the quality of its own components, and the operation of the controller all have a certain impact. Once a CNC machine tool has a high-impact failure it can bring great losses, not only affects the processing process, but also consumes personnel to detect and repair and time. In the reliability study of CNC machine tools, the quality of each component is tested and predicted to reduce the possibility of failure and reduce the loss caused by failure. If you can better predict the failure of CNC machine tools, it will reduce a lot of unnecessary trouble and loss. There will be some connection between some subsystem failures of CNC machine tools, and the failure of one system may cause the failure of another system as well, a phenomenon called system fault correlation [1]. The fault generation may be spontaneous or may be caused by other system correlations, and because of this uncertain relationship, fuzzy reasoning is used to study the method. Currently, there are many ways of fault prediction, statistical prediction techniques, mathematical prediction techniques, intelligent prediction techniques, and information fusion techniques, and it is very important to study fault prediction techniques to improve the maintenance and security of equipment [2].

Gutenberg and Richter proposed the famous earthquake magnitude relationship lgN = a-bM by studying the activity characteristics of the California earthquake. This relationship is one of the important properties of seismic activity research and has been widely used in the study of earthquake related issues. In this relation, M is the magnitude, and N represents the number of earthquakes in the area with a magnitude greater than or equal to M in a certain period of time. The values of a and b are constants, a-values reflect the average level of seismic activity in the area, and b-values reflect the proportional relationship between large and small earthquakes. Jie Yu proposed to use Gutenberg–Richter (G-R) curve analysis method to analyze the relationship between the failure level and the occurrence frequency of a series of CNC lathes. This is a useful attempt in the reliability analysis method research of CNC lathes, and some conclusions have been drawn.

Zheng et al. [3] and Wang et al. [4] proposed to use fuzzy information theory to analyze the relationship between the precursor anomalous elements and seismic elements of earthquakes, and to take the b value of 0.65 as the anomaly indicator based on the fuzzy matrix of b values calculated by different parameters with corresponding magnitude and the fuzzy information inference results. Wang et al. [4] proposed to use the beta value of the frequency of the magnitude of the gamma distribution also as an earthquake prediction indicator. Fuzzy theory is also used for CNC machine tool fault diagnosis, and the fuzzy diagnosis model is easy and simple to use and widely applied through its strong structural knowledge expression and ability to handle incomplete information. Fuzzy neural networks have been widely used in various fields and fuzzy systems have good superiority in dealing with complex nonlinear systems.

The whole paper is divided into four sections. The first section talks about the research background of the article, the second section talks about the research method fuzzy inference method used in this paper, the third section talks about the reliability fault prediction of CNC machine tools based on fuzzy inference, and the last section summarizes the paper, the shortcomings of the current research and the outlook for future research.

## II. Fuzzy Inference

At the University of California, USA, Professor Zadeh introduced the concept of fuzzy sets in 1965 after years of research. Suppose the range U under study is the set, denoted as {u}, and U is called the theoretical domain, and the elements u inside the domain are denoted. $\mu_F : U \to [0,\ 1]$

$$u \to \mu_F(u) \tag{1}$$

$$0 < \mu_F(u) < 1 \tag{2}$$

The mapping $\mu_F$ denotes the affiliation function of a fuzzy set U. $\mu_F(u)$ is called the affiliation of u to the fuzzy set U. The value interval of the subordination is [0,1], when the subordination function is $\mu_F(u)=1$ , then the element u belongs to the domain U completely. When the subordination function is $\mu_F(u)=0$, then the element u does not belong to the domain U at all. When the subordination function is $0 < \mu_F(u) < 1$, then for the element u, it partially belongs to the theoretical domain U; the larger the value $\mu_F(u)$ of then, the greater the degree to which u belongs to the theoretical domain U; the smaller the value $\mu_F(u)$ of then, the smaller the degree to which u belongs to the theoretical domain U [5].

In classical set theory, the boundaries of the objects studied are clear; an element is affiliated with 1 if it belongs to a set, and 0 if it does not belong to a set.

$$f_A(x) = \begin{cases} 1, & x \in A \\ 0, & x \notin A \end{cases} \tag{3}$$

Reasoning is the process and way of thinking in which a new judgment is derived from a known judgment or judgments according to certain laws, and it is a thinking activity in which an unknown result is derived from known conditions [6]. Fuzzy reasoning is based on fuzzy set theory and fuzzy logic, and represents the probability that an event may occur by a likelihood value, which takes any number between 0 and 1 [7]. It is a process of converting input into output by fuzzy rules in an uncertainty inference method, and the result obtained is a fuzzy set or affiliation function. Fuzzy rules are the rules on which fuzzy inference is performed and can usually be expressed in natural language.

## III. Fuzzy Inference-based Reliability Fault Prediction of CNC Machine Tools

### A. Fault Data Sample Collation

The data comes from collaborative teams. The cooperation team has established a long-term cooperative relationship with machine tool manufacturers.

The collected fault data were stage-wise analyzed and integrated into a total of 100 sets of sample data. 70 sets of data were used for training and 30 sets of data were used for detection through ANFIS. The inputs were two nodes: the N value and the b value, and the output was the predicted rank M. The data samples were listed in Table I.

TABLE I. Table of Output Prediction Levels M

| Serial number | N | b | M | Serial number | N | b | M |
|---|---|---|---|---|---|---|---|
| 1 | 131 | 0.49 | 2 | 51 | 109 | 0.92 | 3 |
| 2 | 66 | 0.51 | 2.5 | 52 | 102 | 0.93 | 3 |
| 3 | 114 | 0.52 | 2 | 53 | 109 | 0.92 | 3 |
| 4 | 138 | 0.48 | 2 | 54 | 38 | 0.92 | 3.5 |
| 5 | 74 | 0.49 | 2.5 | 55 | 32 | 0.94 | 3.5 |
| 6 | 59 | 0.53 | 2.5 | 56 | 32 | 0.94 | 3.5 |
| 7 | 125 | 0.5 | 2 | 57 | 35 | 0.93 | 3.5 |
| 8 | 74 | 0.49 | 2.5 | 58 | 109 | 0.92 | 3 |
| 9 | 158 | 0.45 | 2 | 59 | 109 | 0.92 | 3 |
| 10 | 79 | 0.48 | 2.5 | 60 | 117 | 0.91 | 3 |
| 11 | 144 | 0.47 | 2 | 61 | 68 | 0.99 | 3.5 |
| 12 | 59 | 0.53 | 2.5 | 62 | 74 | 0.98 | 3.5 |
| 13 | 109 | 0.53 | 2 | 63 | 31 | 0.95 | 4 |
| 14 | 63 | 0.53 | 2.5 | 64 | 26 | 0.97 | 4 |
| 15 | 74 | 0.52 | 2.5 | 65 | 23 | 0.98 | 4 |
| 16 | 131 | 0.49 | 2 | 66 | 53 | 1.02 | 3.5 |
| 17 | 120 | 0.51 | 2 | 67 | 58 | 1.01 | 3.5 |
| 18 | 114 | 0.52 | 2 | 68 | 63 | 1 | 3.5 |
| 19 | 66 | 0.51 | 2.5 | 69 | 19 | 1 | 4 |
| 20 | 70 | 0.5 | 2.5 | 70 | 21 | 0.99 | 4 |
| 21 | 177 | 0.85 | 3 | 71 | 23 | 0.98 | 4 |
| 22 | 251 | 0.8 | 2.5 | 72 | 19 | 1 | 4 |
| 23 | 107 | 0.79 | 3 | 73 | 16 | 1.02 | 4 |
| 24 | 66 | 0.86 | 3 | 74 | 49 | 1.03 | 3.5 |
| 25 | 199 | 0.84 | 2.5 | 75 | 49 | 1.03 | 3.5 |
| 26 | 188 | 0.85 | 2.5 | 76 | 53 | 1.02 | 3.5 |
| 27 | 100 | 0.8 | 3 | 77 | 53 | 1.02 | 3.5 |
| 28 | 158 | 0.88 | 2.5 | 78 | 16 | 1.02 | 4 |
| 29 | 61 | 0.87 | 3 | 79 | 16 | 1.02 | 4 |
| 30 | 199 | 0.84 | 2.5 | 80 | 18 | 1.01 | 4 |
| 31 | 75 | 0.84 | 3 | 81 | 19 | 1 | 4 |
| 32 | 188 | 0.85 | 2.5 | 82 | 16 | 1.02 | 4 |
| 33 | 81 | 0.83 | 3 | 83 | 21 | 0.99 | 4 |
| 34 | 177 | 0.86 | 2.5 | 84 | 7 | 0.98 | 4.5 |
| 35 | 177 | 0.86 | 2.5 | 85 | 8 | 0.97 | 4.5 |
| 36 | 75 | 0.84 | 3 | 86 | 9 | 0.96 | 4 |
| 37 | 61 | 0.87 | 3 | 87 | 7 | 0.99 | 4.5 |
| 38 | 70 | 0.85 | 3 | 88 | 26 | 97 | 4 |
| 39 | 188 | 0.85 | 2.5 | 89 | 18 | 1.01 | 4 |
| 40 | 188 | 0.85 | 2.5 | 90 | 16 | 1.02 | 4 |
| 41 | 35 | 0.93 | 3.5 | 91 | 20 | 1 | 4 |
| 42 | 38 | 0.92 | 3.5 | 92 | 18 | 1.01 | 4 |
| 43 | 125 | 0.9 | 3 | 93 | 5 | 1.02 | 4.5 |
| 44 | 95 | 0.94 | 3 | 94 | 6 | 1.01 | 4.5 |
| 45 | 102 | 0.93 | 3 | 95 | 7 | 0.99 | 4.5 |
| 46 | 32 | 0.94 | 3.5 | 96 | 24 | 0.98 | 4 |
| 47 | 35 | 0.93 | 3.5 | 97 | 26 | 0.97 | 4 |
| 48 | 32 | 0.94 | 3.5 | 98 | 24 | 0.98 | 4 |
| 49 | 109 | 0.92 | 3 | 99 | 22 | 0.99 | 4 |
| 50 | 109 | 0.92 | 3 | 100 | 20 | 1 | 4 |

a. N: falut numbers; M: fault levels.

b. The b-value is the slope of a straight line, indicating the degree of activity of the fault occurrence.

### B. Predictive Model Modeling

We applied the seismic G-R curve model to the CNC machine tool and analyzed the fault activity parameters of the CNC machine tool. Since the fault signs and faults of CNC machine tools are also fuzzy in nature, and fuzzy neural networks have good fuzzy reasoning and adaptive learning capabilities [8-11]. Nonlinear relationships can be well modeled.

The model has only two rules, as follows.

Rule 1:

$if$ $x$ is $A_1$ and $y$ is $B_1$ then $f_1 = p_1x + q_1y + r_1$;

Rule 2:

$if$ $x$ is $A_2$ and $y$ is $B_2$ then $f_2 = p_2x + q_2y + r_2$;

Final output: $f = f_1 + f_2$

For any input variable $[x, y]$, the output of this inference system, f is the weighted average of the two rule outputs, and then we get:

$$f = \frac{\omega_1 f_1 + \omega_2 f_2}{\omega_1 + \omega_2} = \bar{\omega}_1 f_1 + \bar{\omega}_2 f_2 \tag{4}$$

$$\bar{\omega}_1 = \frac{\omega_1}{\omega_1 + \omega_2} \tag{5}$$

$$\bar{\omega}_2 = \frac{\omega_2}{\omega_1 + \omega_2} \tag{6}$$

$\omega_1$, $\omega_2$ are the product of the values of the affiliation functions in general.

The network structure is shown in the figure below (see Fig. 1).

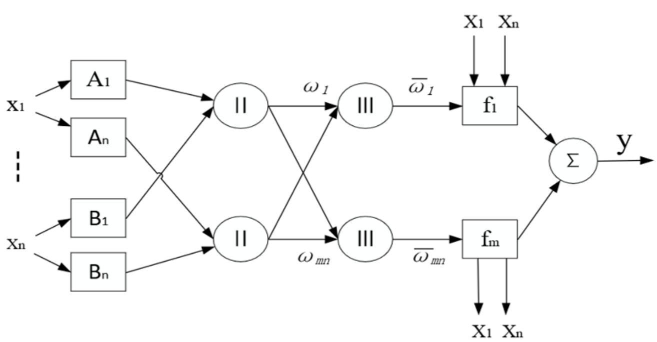


Fig. 1. Takagi-Sugeno fuzzy neural network model structure diagram.

Takagi-Sugeno fuzzy neural network model is divided into five layers: input layer, fuzzification layer, rule layer, defuzzification layer, and output layer. The fuzzy rule front piece is the first three layers, and the rule back piece is the last two layers. The square shape indicates the untrainable nodes and the circle indicates the trainable nodes.

Layer 1: Input layer. The n nodes in this layer are connected to the input vector $X = \{X_1, X_2, \cdots, X_n\}$ and transmit the input value X to the next layer, A and B are the fuzzy linguistic variables of the input X.

Second layer: fuzzification layer. This layer has $n \times m$ nodes, m is the number of fuzzy sets of each variable, each node represents a linguistic variable value, the input of the i group of m nodes is $X_i$, the output is the affiliation function of each input variable belongs to the fuzzy set of each linguistic variable value $\mu_i^j(X_i)$, $\mu_i^j(X_i)$ is the j fuzzy set of $X_i$.

Layer 3: Rule layer. Each node represents a fuzzy rule, and the specific role is to match each input variable to the corresponding fuzzy rule, and to calculate the fitness of the input value to each rule. The mathematical equation is calculated as follows.

$$\omega_j = \mu_1^{i_1} \mu_2^{i_2} \cdots \mu_i^{i_n} \tag{7}$$

Layer 4: Normalization layer. This normalizes the incoming model data from the previous layer for calculation.

$$\bar{\omega}_j = \frac{\omega_j}{\sum_{i=1}^{m} \omega_j} \tag{8}$$

Layer 5: Output layer, output layer y is the weighted sum of the network results after the rule.

$$y = \sum_{j=1}^{m} \bar{\omega}_j y_j \tag{9}$$

$y_j$ is the weighted sum of the posterior pieces of each rule.

The more the antecedents are satisfied, the stronger the rule is and the more it guides the output. The learning algorithm mainly adjusts the parameters to make the final output have better results.

The following figure shows the structure of the Sugeno fuzzy system model (see Fig. 2).

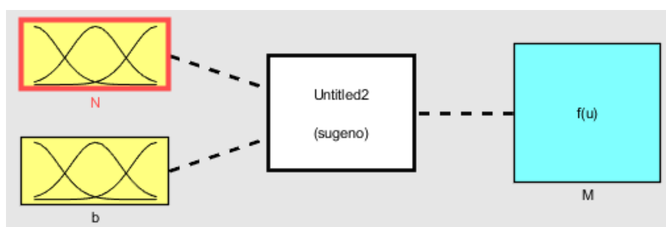


Fig. 2. Sugeno fuzzy system model.

The advantages of this model, which is a nonlinear model, is very adaptable, can easily adjust parameters, can express more complex, high-dimensional nonlinear systems with fewer conditions, and is insensitive to parameter changes [12-17]. Its output variables are constants or linear functions and the output is an exact quantity.

### C. Model Matlab Simulation

The adaptive neuro-fuzzy inference system can be implemented in Matlab using a toolbox or an editor [17-21]. The goal is to make predictions about fault levels, based on the number of faults and the value of the active parameter b as input. 100 sets of data are input, 70 sets of data are used for training and 30 sets of data are used for detection. The inputs are two nodes: N values and b values, and the outputs are the predicted levels M. The initial FIS is formed with two variables as inputs, four fuzzy subsets for each input quantity, and four regular outputs for each subset, for a total of 16, and finally these subsets are clarified to produce 1 output quantity. The network structure is illustrated below (Fig. 3).

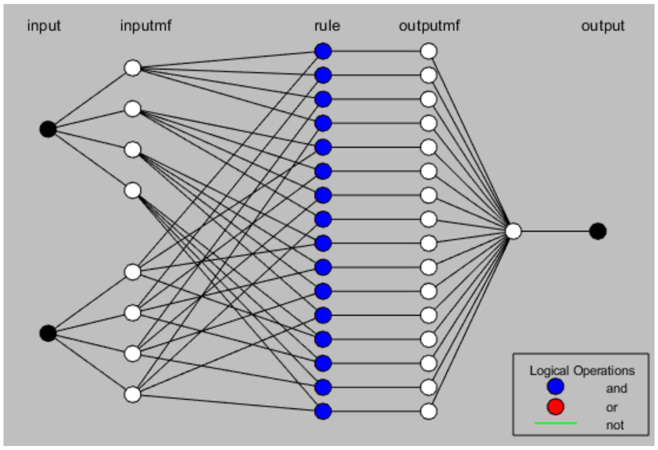


Fig. 3. Model system structure diagram.

Training on 70 sample data, the training error of the model can reach 0.142 after 9 training sessions, which can obtain good prediction results. The following figure shows the training error curve (from Fig. 4 to Fig. 8).

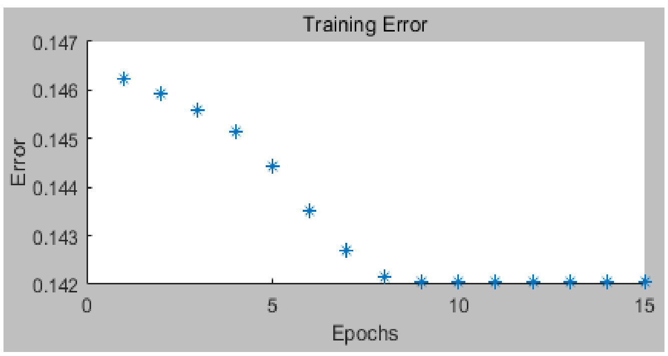


Fig. 4. Training error diagram.

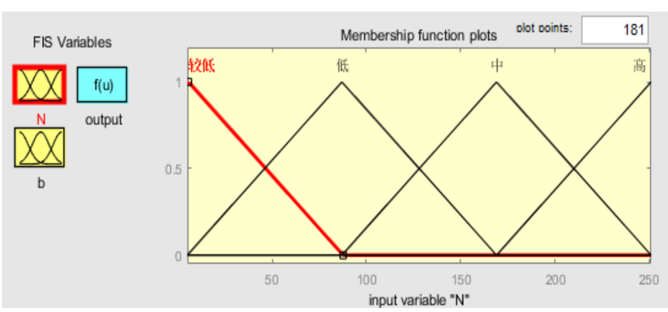


Fig. 5. Plot of the affiliation function of the input variable N.

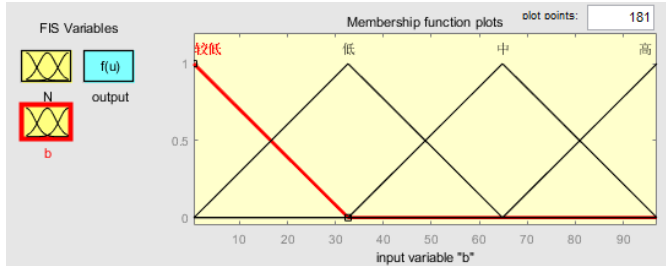


Fig. 6. Plot of the affiliation function of input variable b.

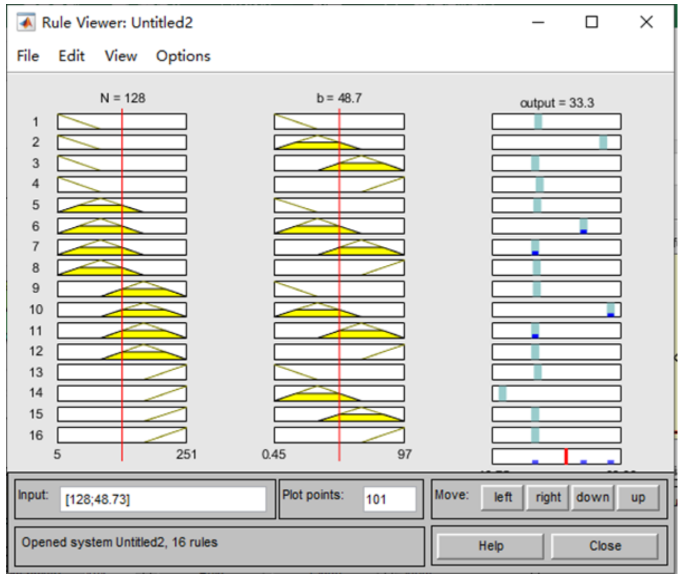


Fig. 7. Fuzzy rule observation chart.

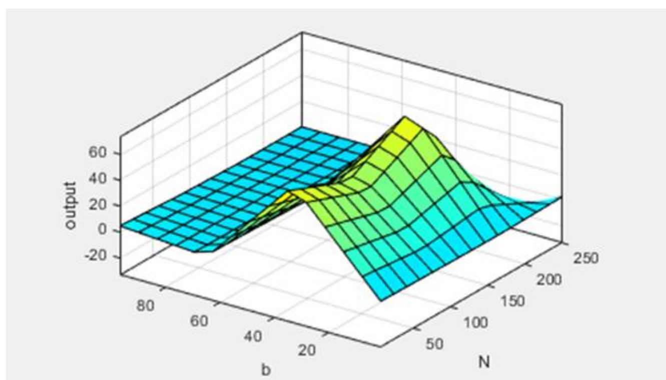


Fig. 8. 3D surface plot of input variables and output variables.

## *D. Model Validation and Analysis of Data*

The output predicted data, original data and error data are organized in the following Table II.

TABLE II. PREDICTION GRADE ERROR TABLE

| Original Grade | Prediction Level | Error | Original Grade | Prediction Level | Error |
|---|---|---|---|---|---|
| 2 | 2.0 | 0.0 | 3 | 2.7 | 0.3 |
| 2.5 | 2.5 | 0.0 | 3 | 2.8 | 0.2 |
| 2 | 2.1 | -0.1 | 3 | 2.7 | 0.3 |
| 2 | 2.0 | 0.0 | 3.5 | 3.6 | -0.1 |
| 2.5 | 2.5 | 0.0 | 3.5 | 3.8 | -0.3 |
| 2.5 | 2.6 | -0.1 | 3.5 | 3.8 | -0.3 |
| 2 | 2.0 | 0.0 | 3.5 | 3.7 | -0.2 |
| 2.5 | 2.5 | 0.0 | 3 | 2.7 | 0.3 |
| 2 | 2.0 | 0.0 | 3 | 2.7 | 0.3 |
| 2.5 | 2.4 | 0.1 | 3 | 2.6 | 0.4 |
| 2 | 2.0 | 0.0 | 3.5 | 3.4 | 0.1 |
| 2.5 | 2.6 | -0.1 | 3.5 | 3.3 | 0.2 |
| 2 | 2.2 | -0.2 | 4 | 3.8 | 0.2 |
| 2.5 | 2.6 | -0.1 | 4 | 3.9 | 0.1 |
| 2.5 | 2.5 | 0.0 | 4 | 4.0 | 0.0 |
| 2 | 2.0 | 0.0 | 3.5 | 3.6 | -0.1 |
| 2 | 2.0 | 0.0 | 3.5 | 3.6 | -0.1 |
| 2 | 2.1 | -0.1 | 3.5 | 3.5 | 0.0 |
| 2.5 | 2.5 | 0.0 | 4 | 4.1 | -0.1 |
| 2.5 | 2.5 | 0.0 | 4 | 4.0 | 0.0 |
| 3 | 2.5 | 0.5 | 4 | 4.0 | 0.0 |
| 2.5 | 2.6 | -0.1 | 4 | 4.1 | -0.1 |
| 3 | 2.6 | 0.4 | 4 | 4.1 | -0.1 |
| 3 | 3.2 | -0.2 | 3.5 | 3.7 | -0.2 |
| 2.5 | 2.5 | 0.0 | 3.5 | 3.7 | -0.2 |
| 2.5 | 2.5 | 0.0 | 3.5 | 3.6 | -0.1 |
| 3 | 2.7 | 0.3 | 3.5 | 3.6 | -0.1 |
| 2.5 | 2.5 | 0.0 | 4 | 4.1 | -0.1 |
| 3 | 3.2 | -0.2 | 4 | 4.1 | -0.1 |
| 2.5 | 2.5 | 0.0 | 4 | 4.1 | -0.1 |
| 3 | 3.0 | 0.0 | 4 | 4.1 | -0.1 |
| 2.5 | 2.5 | 0.0 | 4 | 4.1 | -0.1 |
| 3 | 2.9 | 0.1 | 4 | 4.0 | 0.0 |
| 2.5 | 2.5 | 0.0 | 4.5 | 4.2 | 0.3 |
| 2.5 | 2.5 | 0.0 | 4.5 | 4.1 | 0.4 |
| 3 | 3.0 | 0.0 | 4 | 4.1 | -0.1 |
| 3 | 3.2 | -0.2 | 4.5 | 4.2 | 0.3 |
| 3 | 3.1 | -0.1 | 4 | 4.0 | 0.0 |
| 2.5 | 2.5 | 0.0 | 4 | 4.1 | -0.1 |
| 2.5 | 2.5 | 0.0 | 4 | 4.1 | -0.1 |
| 3.5 | 3.7 | -0.2 | 4 | 4.0 | 0.0 |
| 3.5 | 3.6 | -0.1 | 4 | 4.1 | -0.1 |
| 3 | 2.5 | 0.5 | 4.5 | 4.3 | 0.2 |
| 3 | 2.9 | 0.1 | 4.5 | 4.3 | 0.2 |
| 3 | 2.8 | 0.2 | 4.5 | 4.2 | 0.3 |
| 3.5 | 3.8 | -0.3 | 4 | 3.9 | 0.1 |
| 3.5 | 3.7 | -0.2 | 4 | 3.9 | 0.1 |
| 3.5 | 3.8 | -0.3 | 4 | 3.9 | 0.1 |
| 3 | 2.7 | 0.3 | 4 | 4.0 | 0.0 |
| 3 | 2.7 | 0.3 | 4 | 4.0 | 0.0 |

The fault level prediction curve has the same trend as the original curve (shown in Fig. 9), and the maximum error from the predicted fault level does not exceed 0.5 (shown in Fig. 10), indicating that this fuzzy model is suitable for predicting the fault level in this way.

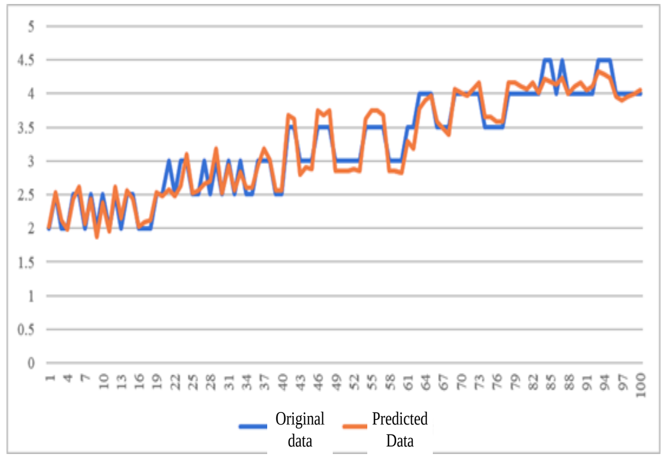


Fig. 9. Fault level prediction data and original data trend line graph.

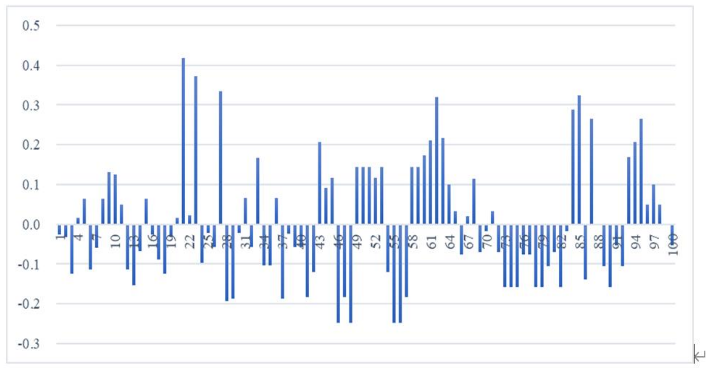

Fig. 10. Fault error cluster bar chart.

## IV. CONCLUSION

The fault data of CNC machine tools have been collected and analyzed, and then the Gutenberg–Richter (G-R) curve relationship in the earthquake has been applied to CNC machine tools. The physical meaning of the parameters is studied to describe the failure grade of the CNC machine tools. By comparing the b-value and the ratio of large failure to small failure with time, it is proved that b-value can reflect the ratio of large failure to small fault over a period of time.

CNC machine tool faults are random and fuzzy in nature, but there may actually be close relationships linked internally, as fuzzy neural networks have good adaptability and can solve nonlinear fuzzy system capabilities. The non-linear relationship between fault level and b-value and N-value can be linked by using fuzzy inference. With 100 data samples, 70 samples were used for model training, and the training error did not exceed 0.15. 30 samples were then used for model testing, and the predicted fault levels were analyzed for error with the original levels, and the error was not significant indicating that the model has good prediction capability.

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

When using fuzzy reasoning method for fault prediction, the influence of various other factors on the prediction is not considered, and only the relationship between activity parameters and earthquake magnitude is predicted. Explore other influencing factors during later research.

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