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Construction and Simulation of Failure Distribution Model for Cycloidal Gears Grinding Machine

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ABSTRACT To increase reliability, reduce machine tool failure, and shorten maintenance time, serval failure distribution models are discussed based on the cycloidal gears form grinding. A fault data expansion algorithm model based on the radial basis function (RBF) neural network is proposed to accurately evaluate the reliability of cycloidal gears form grinding machines. The model uses a self-organizing clustering learning algorithm to determine the RBF centers and expansion constants of the neural network. It trains the neural network using the learning algorithm's output and imports the randomly generated cumulative failure distribution function to obtain simulation data. A numerical example of researching failure distribution is presented which shows that the estimated value of mean time between failures (MTBF) is 909.20h, and the estimated value of reliability is 0.4874. Finally, the fault tree analysis-analytic hierarchy process (FTA-AHP) is used to analyze the fault tree of the cycloidal gear grinding machine. The reliability evaluation indexes are obtained by analyzing the corresponding reliability characteristic function, which proves the failure distribution model is valid. It has important guiding significance in evaluating the reliability and performance of large computer numerical control (CNC) form gear grinding machines.

INDEX TERMS Failure distribution model, cycloidal gears, gear form grinding machine, reliability evaluation, simulation.

I. INTRODUCTION

The manufacturing industry's top priorities include lower production costs, on-time delivery, and high-quality products. Breakdowns in manufacturing gear or machine tools have an impact on a manufacturer's ability to satisfy Cost, Time, and Quality objectives (CTQ). Reliability engineering as a subject matter is developed vastly in the last few decades. In the high-speed development stage of national industrial modernization, computer numerical control machine tools, as the key basic equipment of the modern manufacturing industry, have been widely used in modern industrial industries such as new energy automobile manufacturing, rail transit, aerospace, and wind power generation. Cycloidal gears form grinding machine tools play an important role in aerospace, automobile, wind power, and other mechanical product manufacturing. The heart of each production system is its machine tools. To meet client demand, manufacturing industries rely on machine tools. Failure of a machine tool reduces productivity and increases uncertainty in shop floor operations, resulting in large financial losses. In addition, by entering into long-term maintenance or availability contracts, users of such systems are also sharing the risk of failure with machine tool manufacturers. Machine tool manufacturers now have a new business opportunity to service their traditionally product-focused business. Machine tool makers can combine effective life cycle maintenance services with their hardware goods, such as machine tools. As a result, machine tool manufacturers and users alike must concentrate on the heart of reliability. As a key index of the overall performance of machine tools,

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the reliability level directly reflects the development level of a country's industrial modernization [1]. Therefore, how to improve the reliability level of cycloidal gears form grinding machines has always been a research hot spot. To improve the reliability of cycloidal gears form grinding machines, the modeling and simulation of machine tools are applied to the form grinding machine to increase trouble-free working time and enhance machining efficiency.

In the reliability analysis of machine tools, the determination of the fault distribution model of the whole machine system is the basis of the follow-up research work. At present, the commonly used research methods are as follows: firstly, the scatter diagram of fault data is used to preliminarily assume that it conforms to a certain distribution type, then the least square method is used to estimate the parameters of the distribution function, and finally, the method to test whether the fault data conform to the original hypothesis model is performed [2], [3]. However, there are several problems in the practical application of the above methods. Although the least square method is simple and convenient to estimate the parameters of the distribution function, the accuracy of the calculation results is slightly poor and the parameter interval estimation can not be carried out. When more than two distribution models are selected from the same group of data through a hypothesis test, the optimal fault distribution model not be able to be selected through quantitative analysis. Given the above problems, experts and scholars in the field of reliability research in machine tools have carried out relevant research work [4]–[6]. In recent years, modern method theory has gradually become the frontier and hot spot in the field of reliability research. Because of their excellent data analysis ability, a neural network has been widely used in intelligent fault diagnosis, reliability design, and evaluation. Alawad *et al.* [7] used a convolution neural network to accurately realize fault feature extraction and pattern recognition in huge fault signals. Ben *et al.* [8] applied a neural network model to realize life prediction and reliability evaluation. Jia *et al.* [9] used the linear learning algorithm of RBF neural network to complete the work previously handled by the nonlinear learning algorithm and maintain the high precision of the nonlinear algorithm, which was further generalized in the few-shot classification algorithm. The reliability theory of multi-state systems is suitable for complex electromechanical systems. This reliability theory has been developed by experts and scholars at home and abroad, which has formed a series of method systems, such as the structural function method, generating function method, and Monte Carlo method [10]–[13]. An intelligent optimization algorithm can get the optimal solution of the model, which is mainly used for fault data fitting and distribution function parameter estimation in reliability. Park *et al.* [14] used an optimization algorithm and Fisher matrix in parameters interval estimation of correlated reliability distribution. Mi *et al.* [15] proposed a network of evidence method for reliability analysis of the Servo Feed Control System of CNC Heavy-Duty Horizontal Lathes (HDHLs), which showed that the common cause failure had a considerable impact on system reliability and verified the computational accuracy of the method. Zhang *et al.* [16] proposed a self-adjusting opposite adjustment algorithm (SRPSA) to solve the problems existing in reliability modeling, and it can provide excellent initial solutions for other local optimization algorithms.

Foreign experts and scholars were the first to carry out reliability research on computer numerical control machine tools based on the theoretical basis of modern mathematics, such as probability statistics and engineering. They used parameter modeling and the Monte Carlo method to predict their reliability and this method is also the basic theory for future research. In the subsequent research, some scholars in the United States began to emphasize the concept of maintainability. Gupta *et al.* [17] proposed the theory of fault transfer function, which provided theoretical guidance for the maintenance strategy of machine tools. Then Rawat [18] proposed a simulation-based genetic algorithm to address the time-dependent failure rate of machine components, the partial recovery of components or systems due to imperfect maintenance, and the randomness of model parameters. In the research of the reliability model, Kumar *et al.* [19] proposed a method theory based on a genetic algorithm to solve the optimal solution problem of the reliability model in complex mechanical equipment of machine tools. Ansell *et al.* [20] systematically introduced the statistical principles and analysis methods of machine tool failure data based on machine tool operation data and carried out example verification under three different objects. Boral *et al.* [21] proposed a risk analysis method based on a modified Failure Mode and Effects Analysis (FMEA) to identify the main human errors and their causes and effects during CNC machining operations. Yalcinkaya *et al.* [22] studied the Weibull Bayesian parameter estimation and interval estimation methods in the case of small samples, and the Monte Carlo simulation showed that the Weibull Bayesian parameter estimation was more effective when the sample size was reduced. Yin *et al.* [23] discussed the application of fuzzy probability and statistics methods in reliability accelerated life tests. To provide robustness between different stress levels, the paper also considered the introduction of parameter power Weibull into the parameter interval estimation model. To speed up the life test speed of the CNC machine tool unit execution system, an optimal cost test design model with unknown parameter estimation was established for the Weibull distribution double-truncated life test [24]. Esmail *et al.* [25] used the Tsai-Hill failure criterion as a limit state function and estimation theory for analytical reliability to estimate the statistical parameters of effective stress. Boukhalfa *et al.* [26] applied a genetic algorithm and particle swarm optimization algorithm, using a fuzzy particle swarm algorithm can reduce the large torque fluctuation, speed up the advantage of the rise time, and reduce the interference to the experimental results. Soori *et al.* [27] proposed that a genetic algorithm-based optimization technique was used to determine optimized machining parameters to minimize machining errors and to compare the free-form

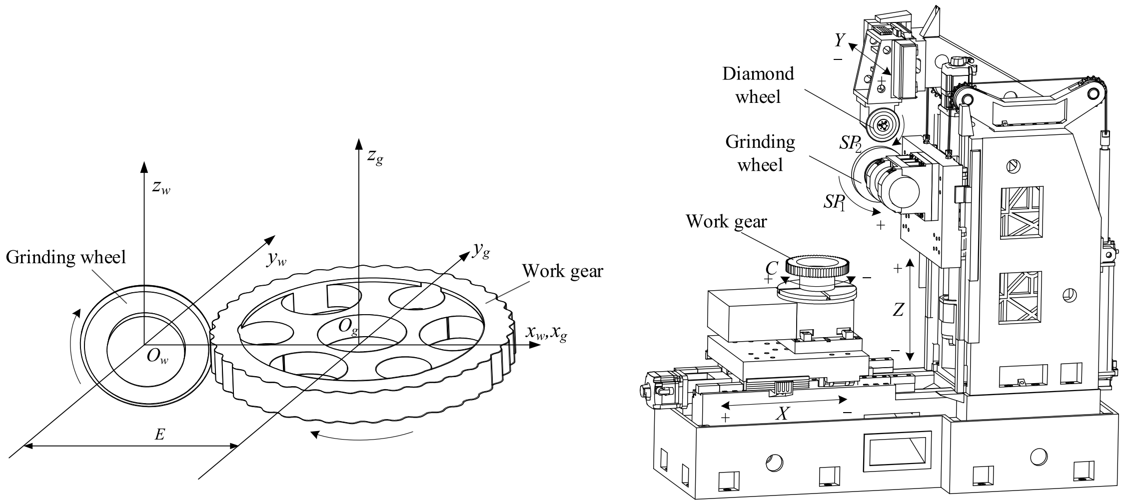


FIGURE 1. Schematic diagram of the structure and motion axis of the cycloidal gear grinding machine.

profiles of virtual and real machined parts with tool deflection errors to verify the reliability and accuracy of the software sex. Salonitis *et al.* [28] proposed a method for estimating the reliability of the remaining tool life based on the advanced approximation method and proved the reliability of the evaluation method by establishing a function model. At present, extensive research has been carried out on reliability analysis based on the surrogate model, which reduces the number of calls to real and complex performance functions while ensuring the accuracy of evaluation. To evaluate the failure probability more efficiently, an adaptive sampling method is proposed. Compared with Monte Carlo simulation or other active learning functions, this method has advantages in efficiency, convergence, and accuracy when dealing with complex problems [29]–[31].

From the perspective of the overall research trend at home and abroad, the research on the reliability of CNC machine tools focuses on the perspective of systems engineering, combined with multidisciplinary theory and modern analysis technology, and has carried out in-depth machine tool reliability design, modeling, evaluation, failure analysis, etc. In particular, the necessity and complexity of dynamic correlation between subsystems or components, reliability modeling method based on small samples, system reliability optimization simulation, fault factor identification, time index evaluation, and other issues are studied.

The structure of this study is presented as follows: conceptions and theories of fault distribution are briefly reviewed in Section 2. Different distribution functions are numerically calculated in Section 3. The reliability of cycloidal gears form grinding machines is evaluated in Section 4 and Section 5. Finally, Section 6 presents the conclusion, the research limitations, and directions for further research.

II. PARAMETER ESTIMATION

The main research is based on the cycloidal gears form grinding machine and the basic idea of the form grinding is the application of a modified wheel and the grinding path (Figure 1). This paper takes cycloidal gears form grinding machine tools as the research object, and according to the principle of reliability data collection, the fault data collection of the analysis object is carried out by the method of time cut-off. These axes applied for form grinding are including that axis one corresponds to the feed motion of the grinding wheel along the face width of the gear, and axis second, and third is the rotation of the grinding wheel and workpiece, respectively. And axis fourth corresponds to the longitudinal crowning motion of the grinding wheel along the radial direction of the work gear.

Although reliability is a crucial indicator of machine tool performance, it is difficult to quantify. Despite the importance of dependability, only a few corporate users, such as major automobile manufacturers, specifically stated their reliability needs in terms of MTBF. Compared with the traditional method for generating grinding, form grinding method not only requires wheel modification of high precision but also demands accurate position relative to the work gear and the grinding wheel in radial and tangential directions. Cycloidal gear form grinding is arranged based on the universal CNC gear form grinding machine, which has four digital servo closed-loop controlled axes: three rectilinear motions (X, Y, Z) and one rotational motion (C). SP_1 and SP_2 are spindles of the wheel and diamond wheel respectively. Coordinate systems $S_w(x_w, y_w, z_w)$ and $S_g(x_g, y_g, z_g)$ are rigidly connected to the grinding wheel and work gear, respectively. X is the radial motion for feeding the wheel down to tooth depth along with the vertical stroke motion Z. This machine is equipped with numerical control dressing devices which include motions of Y and Z. Parameter E is a machine installation coefficient that depends on the size of the grinding wheel and is measured immediately after tool alignment in machining.

A. DRAWING SCATTER DIAGRAM

The scatter plot of fault data can be determined by two different methods such as the equal time interval frequency method and the empirical distribution function method. This paper uses the empirical distribution function method to draw scatter plots. The statistical sample observation values are arranged in descending order, then the empirical distribution function $F_n(t_i)$ can be approximated by the median rank formula:

$$F_n(t_i) = \frac{i-0.3}{n+0.4}, \quad (t_1 \leq t_2 \leq \cdots \leq t_n) \tag{1}$$

where i is the fault serial number and n the total number of machine tool failures.

B. PROBABILITY DISTRIBUTIONS FUNCTIONS

After initially determining the distribution type, it is necessary to use sample data to estimate the parameters of the model. The commonly used parameter estimation methods in statistics include a graphical method, least square method, maximum likelihood method, etc. Compared with the previous two methods, the maximum likelihood method has high calculation accuracy and the estimation result does not depend on the empirical distribution function. On the other hand, the parameter point estimate and the confidence interval can be effectively evaluated. The large likelihood method estimates the parameters of the hypothetical distribution model.

The time it takes for a unit to fail is not constant; rather, it is a random variable. This variable is usually continuous and non-negative. Various functions completely specify the random variable's distribution. In the next paragraphs, these functions are briefly explored.

The Probability Density Function (PDF) of the time to failures distribution $f(t)$ has the following features if T (T > 0) is a continuous random variable reflecting the time to failures of a system (component).

$$f(t) \geq 0 \quad \text{and} \quad \int_0^\infty f(t)dt = 1 \tag{2}$$

The Cumulative Distribution Function (CDF) of the failure distribution can be written as:

$$F(t) = \int_0^t f(t')dt' = 1 \tag{3}$$

$F(t)$ has the following property:

$$0 \leq F(t) \leq 1 \tag{4}$$

$$F(0) = 0 \quad \text{and} \quad \lim_{t\to\infty} F(t) = 1 \tag{5}$$

In terms of the probability density function, R(t) can be written as:

$$R(t) = \int_t^\infty f(t')dt' = 1 \tag{6}$$

$R(t)$ has the following property:

$$0 \leq R(t) \leq 1 \tag{7}$$

$$R(0) = 1 \quad \text{and} \quad \lim_{t\to\infty} R(t) = 0 \tag{8}$$

It can be seen from Equations 3 and 6 that:

$$R(t) = \int_t^\infty f(t')dt' = 1 \tag{9}$$

The Failure Rate is another significant function in reliability research $\lambda(t)$. It can be represented as the conditional probability of failure per unit of time and is the instantaneous rate of failure. It can be written as:

$$\lambda(t) = \lim_{\Delta t\to 0} \frac{P_r\{t \leq T \leq t+\Delta t \,|T \geq t\}}{\Delta t} \tag{10}$$

This can be easily reduced to:

$$\lambda(t) = \frac{f(t)}{R(t)} \tag{11}$$

1) WEIBULL DISTRIBUTION

Weibull distribution is a widely used distribution to model failure process which includes three parameters, shape parameter β, scale parameter η, and location parameter t_0. The value of the shape parameter β provides insight into the behavior of the failure process. The second parameter, i.e., the scale parameter η represents the time corresponding to the cumulative probability of failure. In reliability analysis, it is usually assumed that the location parameter t_0 is equal to zero. so it is normally characterized by two parameters, shape and scale parameters. At this time, the Distribution Function $F(t)$, Probability Density Function $f(t)$, Reliability Function $R(t)$, and Failure Rate Function $\lambda(t)$ can be expressed as:

$$\begin{cases} f(t) = \dfrac{\beta}{\eta}\left(\dfrac{t}{\eta}\right)^{\beta-1} e^{-(t/\eta)^\beta}, & t \geq 0 \\ R(t) = e^{-(t/\eta)^\beta} \end{cases} \tag{12}$$

2) EXPONENTIAL DISTRIBUTION

In reliability theory, the exponential distribution is the most basic, single-parameter distribution function. This distribution will be followed by failures caused by purely random or chance events. In the case of a time-to-failure distribution, it is usually defined by a single parameter known as the failure rate λ. The following are the functions for exponential distribution that were mentioned in the preceding section:

$$\begin{cases} f(t) = \lambda e^{-\lambda t}, & t \geq 0 \\ R(t) = e^{-\lambda t} \end{cases} \tag{13}$$

3) NORMAL DISTRIBUTION

The normal distribution has a sensitive responsivity to phenomena that occur in a concentration of failures around the mean life. The normal distribution can be characterized by two parameters, mean μ and variance σ^2. The distribution is symmetric about its mean, with the spread of the distribution determined by the standard deviation σ. Let the random variable $T \in N(\mu, \sigma^2)$, then reliability functions can be expressed as

$$\begin{cases} f(t) = \dfrac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{t-\mu}{\sigma}\right)^2}, & -\infty < t < \infty \\ R(t) = 1 - \Phi\left(\dfrac{t-\mu}{\sigma}\right) = \displaystyle\int_{-\infty}^{\frac{t-u}{\sigma}} \dfrac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} dz \end{cases} \tag{14}$$

4) LOGNORMAL DISTRIBUTION

If T is the random variable representing the lognormal time to failure, the logarithm of T has a normal distribution with mean μ and standard deviation σ. The logarithm $\ln t$ of the non-negative random variable t is set to obey the normal distribution, then the variable t obeys the lognormal distribution, namely $\ln t \in N\left(\mu, \sigma^2\right)$, and f reliability functions can be expressed as

$$\begin{cases} f(t) = \dfrac{1}{\sigma t\sqrt{2\pi}} e^{-\left(\frac{\ln t-\mu}{2\sigma^2}\right)^2}, & t > 0 \\ R(t) = 1 - \Phi\left(\dfrac{\ln t-\mu}{\sigma}\right) = \displaystyle\int_{0}^{\frac{\ln t-u}{\sigma}} \dfrac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} dz \end{cases} \tag{15}$$

III. FAULT DATA DISTRIBUTION MODEL

This paper takes cycloidal gears form grinding machine as the research object, and analyzes the used failure interval time from the machine tool field operation records of the internship cooperation unit. According to the total fault time, they are arranged as shown in Table 1. These data represent the running status of the machine tool under the actual working environment and maintenance conditions, so it can truly reflect the reliability level of the cycloidal gears form grinding machine.

TABLE 1. The time between failures of cycloidal gears form grinding machine.

Time series between failures (h)
58, 123, 215, 370, 489, 584, 672, 750, 833, 896, 925, 975, 1042, 1240, 1375, 1574, 1688, 1788, 1896, 1988

A. SOLVING FAULT DISTRIBUTION MODEL

Before solving the distribution model, the time between failures needs to be preprocessed, and the preprocessing is mainly to draw a function scatter plot.

First, the failure interval time $t_i \in [58, 1988]$ is grouped according to formula (16), and the number of groups k is set as

$$k = 1 + 3.32 \ln n_f \tag{16}$$

where n_f is the total number of faults; the number of groups k can be rounded appropriately.

The group spacing $\Delta\tau$ after grouping is:

$$\Delta\tau = \frac{\tau_l - \tau_s}{k} \tag{17}$$

where τ_l is the upper limit and τ_s is the lower limit, respectively.

The frequency ω_i of each group falling into the data is

$$\omega_i = \frac{\Delta n_i}{n_f} \tag{18}$$

where Δn_i is the frequency of each group falling into the data.

Then the probability density observation value $\hat{f}_n(t_i)$ of each group can be expressed as

$$\hat{f}_n(t_i) = \frac{\omega_i}{\Delta\tau} \tag{19}$$

According to the above process, the data are substituted into and calculated in turn: $k = 10$; $\Delta\tau = 193$, and the other calculated values are shown in Table 2.

TABLE 2. Data of fault probability density function plot.

Group	Upper limit	Lower limit	Group median	Δn_i	ω_i	$\hat{f}_n(t_i)$
1	58	251	154.5	3	0.15	7.772×10^{-4}
2	251	444	347.5	1	0.05	2.591×10^{-4}
3	444	637	540.5	2	0.1	5.181×10^{-4}
4	637	830	733.5	2	0.1	5.181×10^{-4}
5	830	1023	926.5	4	0.2	1.036×10^{-3}
6	1023	1216	1119.5	1	0.05	2.591×10^{-4}
7	1216	1409	1312.5	2	0.1	5.181×10^{-4}
8	1409	1602	1505.5	1	0.05	2.591×10^{-4}
9	1602	1795	1698.5	2	0.1	5.181×10^{-4}
10	1795	1988	1891.5	2	0.1	5.181×10^{-4}

Use the group median value in Table 2 as the abscissa and $\hat{f}_n(t_i)$ as the ordinate to draw a scatter plot of the probability of failure, and fit the function curve by polynomial curve fitting, as shown in Figure 2.

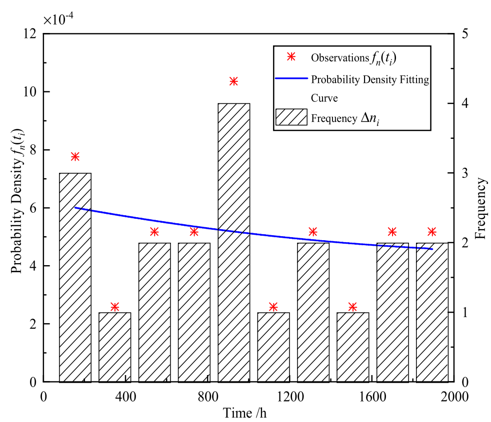


FIGURE 2. Scatter diagram of fault probability density function.

B. SCATTER PLOT OF EMPIRICAL DISTRIBUTION FUNCTION

In reliability assessment, formula (20) is often used to approximate the empirical distribution function value $F_n(t_i)$.

$$F_n(t) = \begin{cases} 0 & t < t_1 \\ \dfrac{i-0.3}{n+0.4} & t_i \le t < t_{i+1} \\ 1 & t \ge t_n \end{cases} \tag{20}$$

The final calculation results are shown in Table 3.

TABLE 3. Data of empirical distribution function plot.

i	t_i / h	$F_n(t_i)$	i	t_i / h	$F_n(t_i)$
1	58	0.034313	11	925	0.524509
2	123	0.083333	12	975	0.573529
3	215	0.132352	13	1042	0.622549
4	370	0.181372	14	1240	0.671568
5	489	0.230392	15	1375	0.720588
6	584	0.279411	16	1574	0.769607
7	672	0.328431	17	1688	0.818627
8	750	0.377450	18	1788	0.867647
9	833	0.426470	19	1896	0.916666
10	896	0.475490	20	1988	0.965686

Take t_i as the abscissa and $F_n(t_i)$ as the ordinate to draw a scatter plot of the empirical distribution function, as shown in Figure 3.

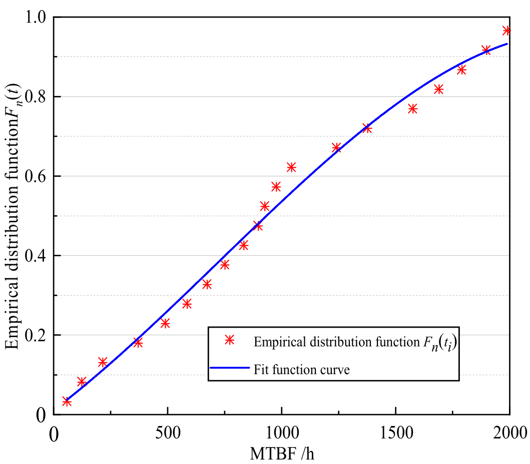


FIGURE 3. Scatter diagram of the empirical distribution function.

Synthesize Figure 2 and Figure 3, and compare and analyze the image properties of the four types of reliability distribution model functions analyzed. It is found that the current fitting curve shape cannot pre-select the possible distribution. In the face of the four distribution models, the null hypothesis H_0 is made, and the MLE parameter estimation solution is performed. The MLE parameters are solved and the estimated parameters are $\hat{\mu} = 6.5903, \hat{\sigma} = 0.9159$. Therefore, the lognormal fitting cumulative distribution function is:

$$F(t) = \Phi\left(\frac{\ln t - 6.5903}{0.9159}\right) \tag{21}$$

Figure 4 shows the curve fitting situation of the fitted distribution function and the empirical distribution function solved by the original data.

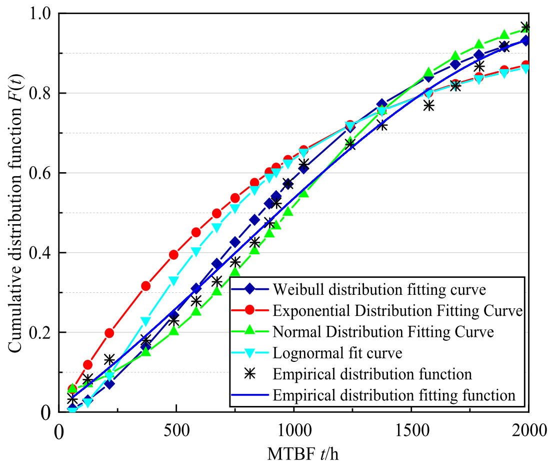


FIGURE 4. Original data curve fitting situation diagram.

It is difficult to determine which distribution model to reject or accept based on the curve fitting situation in Figure 8 alone. Therefore, it is necessary to perform statistical hypothesis testing on the four hypothetical distributions made above. The method is to use the Mann test for the Weibull distribution and use the Mann test for the other distributions. Three distributions use the K-S test.

First, determine the critical value $F_\alpha(2k_1, 2k_2)$ of Mann's test: $n = 20, k_1 = 10, k_2 = 9$, by formulas (22) and (23).

$$M = \frac{k_1 \sum_{i=k_1+1}^{n-1} (\ln t_{i+1} - \ln t_i)/M_i}{k_2 \sum_{i=1}^{k_1} (\ln t_{i+1} - \ln t_i)/M_i} \tag{22}$$

$$\begin{cases} k_1 = \left\lfloor \dfrac{n}{2} \right\rfloor, k_2 = \left\lceil \dfrac{n-1}{2} \right\rceil \\ M_i = Z_{i+1} - Z_i \\ Z_i = \ln\left[-\ln\left(1 - \dfrac{i-0.5}{n+0.25}\right)\right] \end{cases} \tag{23}$$

Then a given significant level $\alpha = 0.1$, $F_{0.1}(20, 18) = 1.84$ can be obtained by checking the F distribution table. Then determine the critical value $D_{n,\alpha}$ of K-S test: also take the significant level $\alpha = 0.1$, then when $n = 20$, $D_{20,0.1} = 0.174$ can be obtained by checking the critical value table of

K-S the test. Finally, the test statistics of each fitted distribution function are calculated respectively. For comparative analysis, all the calculation results of the hypothesis test are calculated as shown in Table 4.

TABLE 4. Original data fitting distribution hypothesis test.

Distribution type	Test statistics	Critical value	Judgment hypothesis
Weibull	0.7485	1.84	Accept
Exponential	0.1715	0.174	Accept
Normal	0.0803	0.174	Accept
Lognormal	0.1369	0.174	Accept

Analyzing Figure 4 and Table 4, it is found that based on the existing small sample fault data, the reliability distribution model of the CNC forming gear grinding machine cannot be determined through the conventional statistical distribution theory. The four theoretical distributions of the original hypothesis are all Therefore, the accurate fitting of the reliability distribution model of the machine tool has become a necessary prerequisite for evaluating its reliability level.

IV. RBF NEURAL NETWORK ALGORITHM

RBF neural network is a type of forwarding neural network, and its network structure includes an input layer, hidden layer, and output layer. The basic idea is to use radial basis functions to form the hidden layer space, and the hidden layer transforms the input quantity and converts it to a high-dimensional space so that it is linearly separable in the high-dimensional space. In reliability data analysis, the function approximation function of the RBF network is mainly used to generate simulation data with the same distribution type as the original data, to achieve the purpose of large sample data analysis.

A. RBF METHOD STEPS

RBF neural network has a variety of learning strategies according to the selection method of the radial basis function center. In this paper, the self-organizing clustering learning algorithm is used as the learning method of the RBF neural network. The method mainly includes the following two parts: one is to determine the basis function center and extended constant spread of the neural network through the output of the learning algorithm; the other is to determine the weights from the hidden layer to the output layer through supervised learning training. The specific algorithm steps are as follows:

Assuming k is the number of centers, n is the total number of samples, and the central domain of the m-th iteration is $c_1(m), c_2(m), \cdots, c_k(m)$, then $\omega_1(m), \omega_2(m), \cdots, \omega_k(m)$ is the corresponding analysis domain.

Initialization. Take the empirical distribution function $F_n(t_i)$ and fault data t_i in Table 1 as the sample input, and randomly select k original data as the initial central domain. Clustering. Calculate the geometric distance of all inputs to the specified center, and cluster the data according to the principle of minimum spacing.

$$D_{i,j}(m)=\left\|x_j-c_i(m)\right\|, \quad j=1,2,\cdots,n;\; i=1,2,\cdots,k \tag{24}$$

where x_j is the jth sample.

Update the central domain.

$$c_i(m+1)=\frac{1}{n_i}\sum_{x\in\omega_i(t)} x, \quad i=1,2,\cdots,k \tag{25}$$

where n_i is the number of samples contained in the ith analysis domain.

Judge. If $c_i(m+1) \neq c_i(m)$, go to the second step to continue the iteration; if the center domain has been uniquely determined, determine the center of the basis function, and the iteration terminates.

Train a neural network. Design the RBF neural network structure and train it with the output of the above steps, where the spread value of the network is determined by the minimum spacing between the central domains:

$$\begin{cases} \delta_i = pd_i \\ d_i = \min\left\|c_j - c_i\right\| \end{cases} \tag{26}$$

where p is the overlap coefficient, generally take $p = 1.0$.

Data augmentation. Taking the randomly generated cumulative distribution function value $F(t)$ as the input value, the output of the network is the expanded fault data.

Parameter estimation and testing. The augmented data are subject to maximum likelihood parameter estimation and the test is used to determine the type of distribution fitted.

B. GENERATION AUGMENTED DATA

The simulation and verification are carried out according to the above modeling steps. To eliminate the calculation deviation caused by random parameter intervention, set the number of iterations to 500 times, randomly select 14 sample data as the initial center domain, and import all the sample data into the algorithm program to obtain the basis function center and spread value; then establish the neural network structure is trained based on the cluster analysis results. After the training is completed, the overall performance of the network is tested with the original data and the data fitting error is calculated. The fitting curve of the RBF neural network is shown in Figure 5, and the fitting error is shown in Figure 6.

It can be seen from Figure 5 and Figure 6 that the trained RBF neural network model fits the original data well, and the average absolute error of training reaches 11.02. Therefore, the simulated data generated by this algorithm can reflect the function distribution law between the original data. Then, 100 randomly generated cumulative failure distribution function values were imported into the RBF neural network model to

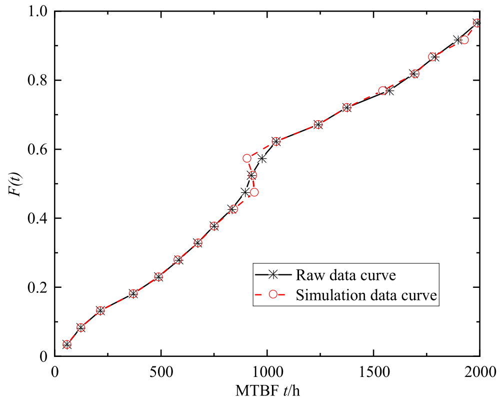


FIGURE 5. RBF neural network fitting curve to the original data.

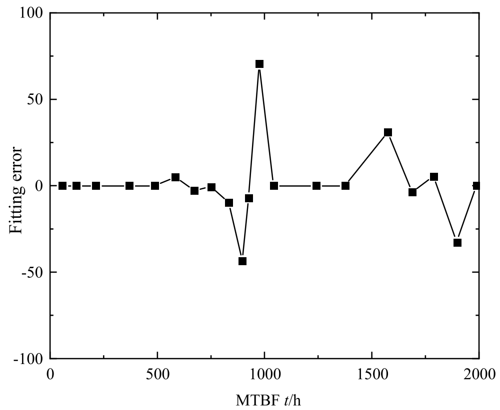


FIGURE 6. Fitting error diagram.

obtain the expanded failure data. The parameter maximum likelihood estimation is performed on the expanded data, and the cumulative distribution function of each distribution type is obtained. The fitting function is shown in Figure 7.

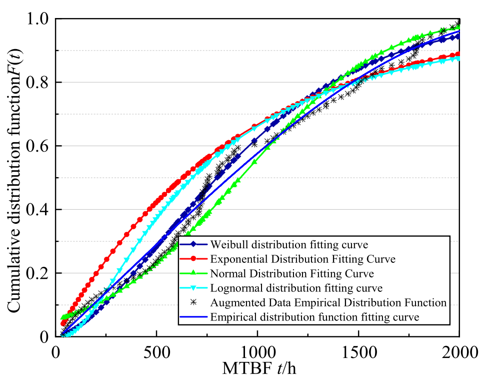


FIGURE 7. Expansion data curve fitting situation diagram.

Here, the calculation process is omitted, and the functional form of each distribution model after understanding is given directly. Each distribution function is computed as follows.

Weibull distribution ($\hat{\beta} = 1.5621$, $\hat{\eta} = 1011.7242$):

$$F(t) = 1 - \exp\left[-\left(\frac{t}{1011.7242}\right)^{1.5621}\right] \tag{27}$$

Exponential distribution ($\hat{\lambda} = 0.0011$):

$$F(t) = 1 - \exp(-0.0011t) \tag{28}$$

A normal distribution ($\hat{\mu} = 915.7423$, $\hat{\sigma} = 562.1382$):

$$F(t) = \Phi\left(\frac{t - 915.7423}{562.1382}\right) \tag{29}$$

Lognormal distribution ($\hat{\mu} = 6.5168$, $\hat{\sigma} = 0.9344$):

$$F(t) = \Phi\left(\frac{\ln t - 6.5168}{0.9344}\right) \tag{30}$$

The fitted distribution under the expanded data is tested for the statistical hypothesis. Given the same significance level $\alpha = 0.1$, first, determine the critical value of the test. When $n = 100$, $k_1 = 50$, $k_2 = 49$; therefore, by looking up the F distribution table, $F_{0.1}(50, 49) = 1.44$. Secondly, determine the critical value of K-S test: when $n = 100$, $\alpha = 0.1$, then$D_{100,0.1} = 0.0805$. Finally, respectively calculate the hypothesis test statistics of the fitted distribution function under the expanded data and make a comparative analysis. The results are shown in Table 5.

TABLE 5. Expansion data fitting distribution hypothesis test.

Distribution type	Test statistics	Critical value	Judgment hypothesis
Weibull	0.91099	1.44	accept
Exponential	0.18601	0.0805	Refuse
Normal	0.11331	0.0805	Refuse
Lognormal	0.14574	0.0805	Refuse

Combining Table 5 and Figure 7, for the extended data fitting distribution model, only Weibull passed the hypothesis test, so there are reasons to accept only the original hypothesis $H_{0,1}$ and reject the other three hypotheses. Since the expanded data is obtained through the RBF neural network, and the statistical law of the interpolation data of the RBF neural network is consistent with the original data, it can be inferred that the reliability distribution model of this series of machine tools obeys the Weibull distribution.

C. RELIABILITY EVALUATION

Through the above analysis, the optimal fault distribution model of the machine tool and the estimated value of the distribution function parameters have been determined. To further quantitatively describe the overall reliability level of the CNC machine tool, it is usually necessary to calculate some quantitative indicators. The commonly used reliability evaluation characteristics are given below. Through the above modeling analysis and calculation, the reliability distribution model of the whole system of the CNC forming gear grinding machine has been determined. As a result, its reliability evaluation functions $F(t)$, $f(t)$, $R(t)$ and $\lambda(t)$ can be expressed respectively as:

$$\begin{cases} F(t) = 1 - \exp[-(t/1011.7242)^{1.5621}] \\ f(t) = \dfrac{1.5621t^{0.5621}}{1011.7242^{1.5621}} \exp[-(t/1011.7242)^{1.5621}] \\ R(t) = 1 - F(t) = \exp[-(t/1011.7242)^{1.5621}] \\ \lambda(t) = \dfrac{f(t)}{R(t)} = \dfrac{1.5621}{1011.7242}(t/1011.7242)^{1.5621} \end{cases} \tag{31}$$

From the above formula, the characteristic curve of the reliability evaluation function of the CNC forming gear grinding machine can be fitted as shown in Figure 8.

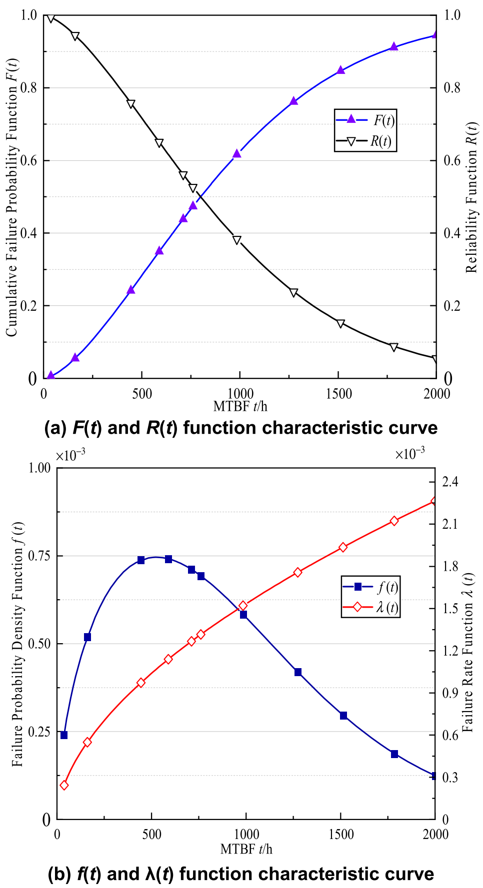


FIGURE 8. The characteristic curve of the reliability evaluation function.

The curve in Figure 8 shows an upward trend. Combined with the bathtub curve theory, it can be seen that this machine tool has entered product consumption and shelf life after a long time of use. During this period, the failure rate of machine tools has a gradual upward trend with universal characteristics. The main reason may be that with the passage of time and the influence of the working environment, there are different degrees of fatigue, wear, and aging of the components of each subsystem of the machine tool. At this stage, to ensure the reliable operation of the equipment, it is necessary to consider replacing the machine tool parts or do further failure analysis on the various subsystems of the machine tool to find out the direct cause of the failure.

Then, the reliability evaluation index of the machine tool is calculated quantitatively. Generally, MTBF is used to directly assess the reliability level of the machine tool. MTBF observations can be calculated directly as:

$$\text{MTBF} = \frac{1}{N_0}\sum_{i=1}^{n} t_i = \sum_{i=1}^{n} t_i \Big/ \sum_{i=1}^{n} r_i \tag{32}$$

The calculated MTBF is 915.74h. The calculation formula of MTBF point estimation is as follows:

$$\text{MTBF} = \int_0^\infty \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} \exp\left[-\left(\frac{t}{\eta}\right)^{\beta}\right] t dt \tag{33}$$

where $y = (t/\eta)^\beta$ and $t = \eta y^{1/\beta}$ are set, then

$$dy = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} dt \tag{34}$$

Substituting equation (33) into equation (34) has:

$$\begin{aligned} \text{MTBF} &= \int_0^\infty \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} \exp\left[-\left(\frac{t}{\eta}\right)^{\beta}\right] t dt \\ &= \eta \int_0^\infty y^{\frac{1}{\beta}} \exp(-y) dy \\ &= \eta\Gamma\left(1 + \frac{1}{\beta}\right) \end{aligned} \tag{35}$$

where $\Gamma(x)$ is the gamma function,

$$\Gamma(x) = \int_0^\infty y^{x-1} e^{-y} dy \tag{36}$$

Therefore, the estimated value of the MTBF point can be calculated by the formula (35):

$$\text{MTBF}_{est} = \eta\Gamma\left(\frac{1}{\beta} + 1\right) = 909.20\text{h}$$

The observed value of MTBF is consistent with the point estimate value in a statistical sense. In practical applications, there will be some differences between the two due to the influence of fitting error and sample size.

V. RELIABILITY ANALYSIS BASED ON FTA-AHP

A cycloid gear grinding machine is precision equipment for grinding and processing gears composed of a combination of multiple functional systems. When troubleshooting it, it often takes a lot of trouble to find the cause of the equipment failure. To avoid this situation, this section adopts FTA-AHP method for the analysis of cycloidal gear grinding machines. Fault tree analysis (FTA) is one of the important tools for failure analysis of mechanical equipment. With its systematic analysis process, it can accurately find the mechanism and cause of equipment failure. AHP can simplify the complex model of FTA analysis, decompose it into multiple levels and

TABLE 6. Event name and code.

Event level	Event name	Event code	Event name	Event code
Level one	Cycloidal gear grinding machine failure	N1	----	----
Second floor	Electrical control subsystem failure	T1	Feed servo subsystem failure	T2
	Grinding Wheel Subsystem	T3	Machine Tool Hydraulic Subsystem	T4
Third floor	Electronic control component failure	Y1	Abnormal start and stop of the motor	Y2
	Power system failure	Y3	Work light failure	Y4
	CNC failure	Y5	Servo drive alarm fault	Y6
	Servo motor failure	Y7	Position detection unit failure	Y8
	Speed control unit failure	Y9	Ball screw pair failure	Y10
	Rotary table failure	Y11	Grinding wheel failure	Y12
	Grinding wheel motor spindle failure	Y13	Oil temperature rise	Y14
	System traffic unstable	Y15	System Vibration and Noise	Y16
	System pressure imbalance	Y17	Grinding wheel clogged	Y18
	Wheel wear	Y19	Grinding wheel burst	Y20
Fourth floor	Poor contact	Z1	Mechanical jam	Z2
	Damaged contactor	Z3	Coil open circuit	Z4
	Mechanical vibration, shock	Z5	Damaged release	Z6
	Overload	Z7	Line aging	Z8
	Air switch disconnected	Z9	Wrong program leads to crash	Z10
	Not enough storage	Z11	Parameter setting error	Z12
	ROM adjacent cell crosstalk	Z13	Motherboard corrosion	Z14
	Damaged detection element	Z15	Damaged or bad circuit board	Z16
	Component damage	Z17	Damaged switch	Z18
	Main circuit board failure	Z19	CNC software failure	Z20
	CNC control panel malfunction	Z21	Storage unit failure	Z22
	Drive control unit failure	Z23	The power phase sequence reversed	Z24
	No enable signal on the control side	Z25	Excitation circuit disconnection	Z26
	Hydraulic pump failure	Z27	Hydraulic oil leak	Z28
	Control valve failure	Z29	Too many air bubbles in the tank	Z30
	Seal aging	Z31	Drive module temperature rise	Z32
	Poor connection between motor and driver	Z33	Power supply voltage low	Z34
	Power supply voltage too high	Z35	Bearing wear	Z36
	Bearing too tight	Z37	Grating pollution serious	Z38
	The pulse encoder oily	Z39	Pulse encoder connection loose	Z40
	Inductive synchronizer damaged	Z41	The frequency of shifting too high	Z42
	Speed unit gain too high	Z43	Ball screw movement is not flexible	Z44
	Poor screw movement accuracy	Z45	Large screw reverse error	Z46
	Excessive screw torque	Z47	Ball screw pair noise	Z48
	Coupling loose	Z49	Mechanical damage	Z50
	Rotational system clearance too large	Z51	Fuel tank level too low	Z52
	The pump and the motor not on the same axis	Z53	Moving parts commutator lacks damping	Z54
	Motor vibration	Z55	Pipe Cracks	Z56
	Pipe blockage	Z57	The speed of the grinding wheel too high	Z58
	Poor quality grinding wheel	Z59	Poor quality of grinding fluid	Z60
	Wear and tear	Z61	Oxidative wear	Z62
	plastic wear	Z63	Improper storage of grinding wheels	Z64
	Improper method of operation	Z65	Cracks caused by external impact	Z66
	Ball screw pair noise	Z67	Vibration and noise	Z68
	Spindle running abnormally	Z69	Working accuracy is out of tolerance	Z70
	Rotor cage bars broken or have poor contact	Z71	Axial preload is too large	Z72
	The shaft is bent	Z73	Rotor winding open circuit	Z74

TABLE 6. ***(Continued.)*** **Event name and code.**

Slow down or unstable speed	Z75	Poor bearing accuracy	Z76
Poor accuracy of grinding wheel adaptor	Z77	The oil viscosity too high	Z78
Mechanical friction heat, poor heat dissipation	Z79	High work pressure	Z80
Improper piping design	Z81	Leakage causes volume loss to heat	Z82

their corresponding influencing factors, compare the influence degree of each level of influence factors on the previous level, and determine the weight influence value of each factor. This method combines qualitative and quantitative analysis, and finds out the key failure factors of each subsystem by establishing an analytic hierarchy process, which is convenient for maintenance masters to find the faults of the cycloid gear grinding machine equipment, and take effective measures to maintain and increase the machine tool's service life. Trouble-free working time.

A. DEFINITION FAULT EVENTS

The structure of the cycloidal gear grinding machine is relatively complex. To conduct fault analysis more rationally, this section divides the cycloidal gear grinding machine into four main functional subsystems according to the principle of FTA. The faults of the four main functional subsystems including the electrical control subsystem, feed servo subsystem, grinding wheel subsystem and hydraulic subsystem of the machine tool are only analyzed. The faults of other systems are not considered here for the time being.

The fault events are defined and numbered. To facilitate the analysis, the faults of the four subsystems are defined as the top events of their respective system failures, the failures of the main functional components of each system are defined as the intermediate events, and finally, the factors that directly cause the failures are defined as the bottom events. Finally, according to the fault information of the cycloid gear grinding machine collected on-site, the fault event code table at all levels is made after sorting, as shown in Table 6.

B. FTA-AHP ANALYSIS

According to the system structure and fault event definition of the cycloidal gear grinding machine combined with the FTA method, the fault tree of the cycloidal gear grinding machine is established. Let the fault event of the cycloidal gear grinding machine be N1, and its system faults are defined as T1-T4, and finally establish the fault tree of each subsystem as shown in Figure 9.

C. FTA ANALYSIS

The machining accuracy and quality of the cycloid gear grinding machine depend on the grinding wheel system. To improve its reliability, it is necessary to find out the cause of its failure. According to the figure, there are a total of 10 failure modes that cause the failure of the grinding wheel system, which are the failure of the rotary table, the failure of the grinding wheel, the failure of the ball screw pair, the failure of the electric spindle of the grinding wheel, the blockage of the grinding wheel, the wear of the grinding wheel, the burst of the grinding wheel, and the failure of the grinding wheel. Vibration and noise, abnormal operation of the electric spindle, and poor working accuracy, of them, will cause the occurrence of top events. However, the corresponding intermediate events and fault sources can be found according to these intermediate events, so that all fault sources causing the top event can be found.

1) ESTABLISH A HIERARCHICAL STRUCTURE MODEL

There are many levels of fault tree construction, and there may be similar fault factors in different fault modes. The hierarchical structure is complex and not suitable for AHP. On this basis, the FTA analysis method and the AHP method are combined, and the Hi The minimum split set corresponds to the corresponding failure factor. Using Fussell's descending method, the minimum cut set can be obtained as:

The minimum cut set of H1 is: {Z38}, {Z49}, {Z50}, {Z51}.

The minimum cut set of H2 is: {Z58}, {Z59}, {Z60}, {Z61}, {Z62}, {Z63}, {Z64}, {Z65}, {Z66}.

The minimum cut set of H3 is: {Z44}, {Z47}, Z48}.

The minimum cut set of H4 is: {Z71}, {Z72}, {Z73}, {Z74}, {Z75}, {Z76}, {Z77}.

According to the above, the fault hierarchical model of the grinding wheel system is constructed, as shown in Figure 10:

2) OBTAINING THE PROBABILITY WEIGHT OF THE FAILURE CAUSE

After a long-term investigation of machine tool companies, sorting and analyzing machine tool maintenance records, summarizing the failure mode and causes of the grinding wheel system, and combining with the comprehensive diagnosis data of the enterprise technicians, a probability weight judgment matrix for the failure mode of the grinding wheel system is constructed. Use MATLAB to write a program to calculate the influence weights of H1-H4 factors on the topmost T, as shown in Table 7.

TABLE 7. **Judgment matrix B of layer B for layer A.**

B	H_1	H_2	H_3	H_4	ω_i
H_1	1	3	7	1/3	0.2704
H_2	1/3	1	5	1/5	0.1286
H_3	1/7	1/5	1	1/8	0.0419
H_4	3	5	8	1	0.5591
λmax=4.2011					

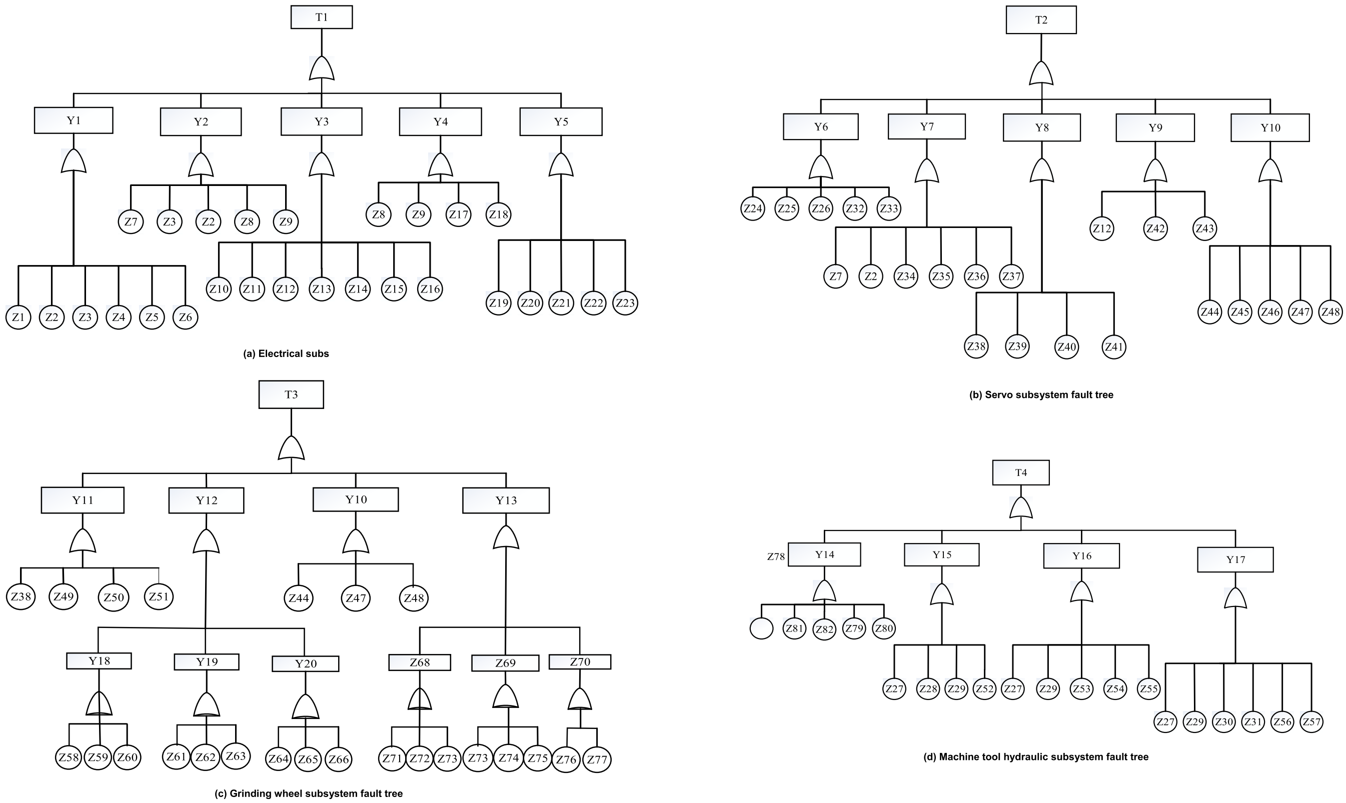


FIGURE 9. Fault tree of each subsystem of cycloid gear grinding machine.

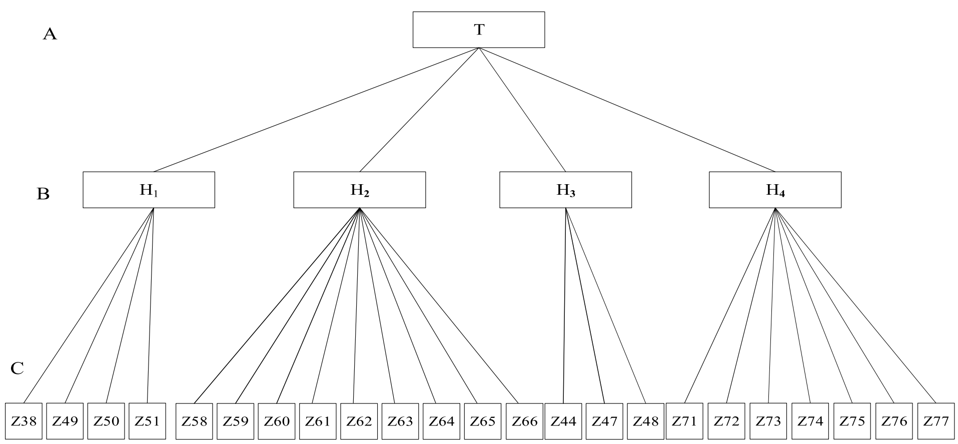


FIGURE 10. Failure hierarchy model of grinding wheel system.

Table 8 shows the probability judgment matrix that C_2 is the C layer. The weight judgment matrix of the remaining C layers can be obtained as above.

Table 9 shows the weights of the influencing factors of the C_2 layer.

3) CONSISTENCY TEST OF HIERARCHICAL SINGLE ORDERING

The order of the importance of a factor in the previous level by many factors at the same level is a single level order. Generally, establishing a judgment matrix of factors, preventing the interference of other factors, and objectively reflecting the difference of the influence of a pair of factors, when comparing multiple factors, usually shows inconsistent results, so it is necessary to carry out a consistency test.

$$\lambda_{\max} = \sum_{i=1}^{n} \frac{(A\omega)_i}{nw_i} \tag{37}$$

$$C.R. = \frac{C.I.}{R.I.} \tag{38}$$

$$C.I. = \frac{\lambda_{\max} - n}{n-1} \tag{39}$$

TABLE 8. Judgment matrix C_2 of layer C relative to layer B.

C_2	Z58	Z59	Z60	Z61	Z62	Z63	Z64	Z65	Z66
Z58	1	1/4	5	1/3	6	5	1/7	2	5
Z59	4	1	4	5	7	6	3	4	8
Z60	1/5	1/4	1	1/3	2	3	1/5	1/2	3
Z61	3	1/5	3	1	2	3	1/3	2	3
Z62	1/6	1/7	1/2	1/2	1	2	1/4	1/3	1/2
Z63	1/5	1/6	1/3	1/3	1/2	1	1/5	1/3	2
Z64	7	1/3	5	3	4	5	1	5	8
Z65	1/2	1/4	2	1/2	3	3	1/5	1	3
Z66	1/5	1/8	1/3	1/3	2	1/2	1/8	1/3	1

TABLE 9. The weight value of each influencing factor of C2 layer.

Weights	Weight value	Weights	Weight value	Weights	Weight value
ω_8	0.1125	ω_{11}	0.1107	ω_{14}	0.2538
ω_9	0.3144	ω_{12}	0.0333	ω_{15}	0.0673
ω_{10}	0.0506	ω_{13}	0.0300	ω_{16}	0.0275

where A represents the constructed judgment matrix, n represents the order of the matrix, $\lambda_{\max}$ is the maximum eigenvalue of the matrix, R.I. represents the test index of the average random consistency, and Table 10 is the R.I. value table.

TABLE 10. R.I. value of average consistency index.

Order	R.I.	Order	R.I.	Order	R.I.
1	0	5	1.12	9	1.46
2	0	6	1.26	10	1.49
3	0.52	7	1.36	11	1.52
4	0.89	8	1.41	12	1.54

According to the requirements of the consistency check, when $C.R. < 0.1$ or $\lambda_{\max} = n$, $C.I. = 0$, it means that the matrix meets the requirements, if not, the matrix should be trimmed until it meets the requirements of the consistency index. Table 11 shows the results of the matrix consistency test.

TABLE 11. Maximum eigenvalue and consistency test results.

Matrix	λ max	C.I.	R.I.	C.R.
B	4.2011	0.0670	0.89	0.0745<0.1
C1	4.0776	0.0259	0.89	0.0288<0.1
C2	10.127	0.1409	1.45	0.0972<0.1
C3	3.0183	0.0091	0.52	0.0158<0.1
C4	7.7787	0.1298	1.41	0.0983<0.1

All judgment matrix $C.R.$ values in the test results are less than 0.1, indicating that the factor comparison value is effective.

4) OVERALL RANKING OF FAULT FACTORS

In a complex system, to better determine the weight of the fault factor on the top event, that is, it is necessary to sort the fault factors of the hierarchical model, and calculate the total importance of the bottom fault factor to the top event. order, and then the reliability analysis can be carried out.

The formula for calculating the total ranking weight is as follows.

$$x_i = \sum_{j=1}^{4} x_{ij} w_{ij} \tag{40}$$

Table 12 is the calculation result of each factor's weight.

TABLE 12. Factor probability weight ranking.

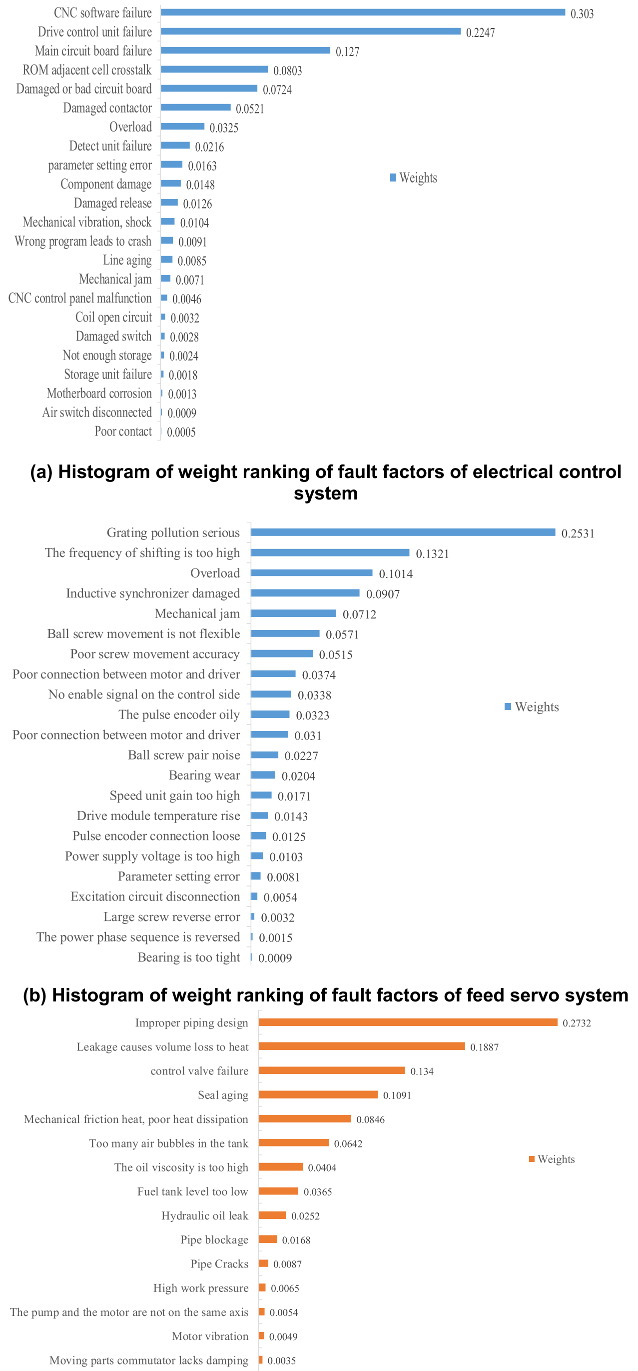
Failure factor	Total weight A1 0.2704	A2 0.1286	A3 0.0419	A4 0.5591	Comprehensive weight	Weight sorting
Z75				0.3634	0.2032	1
Z51	0.5738				0.1552	2
Z74				0.2218	0.1240	3
Z73				0.1628	0.0910	4
Z71				0.1335	0.0746	5
Z38	0.2388				0.0646	6
Z59		0.3144			0.0404	7
Z72				0.0720	0.0403	8
Z50	0.1310				0.0354	9
Z65		0.2538			0.0326	10
Z44			0.5584		0.0234	11
Z47				0.0418	0.0233	12
Z49	0.0563				0.0152	13
Z58		0.1125			0.0145	14
Z61		0.1107			0.0142	15
Z77				0.0247	0.0138	16
Z44			0.3196		0.0134	17
Z64		0.0673			0.0087	18
Z60		0.0506			0.0065	19
Z48			0.1220		0.0051	20
Z62		0.0333			0.0043	21
Z63		0.0300			0.0039	22
Z64		0.0275			0.0035	23

5) CONSISTENCY TEST

Although the single-level ordering meets the requirements of consistency, inconsistency among the levels may accumulate during the consistency test of the overall ordering of the hierarchy, which may cause the final consistency test result of the analysis to fail to meet the requirements. Therefore, it is necessary to test the overall ordering of the hierarchy. The consistency of the test formula is as follows:

$$C.R. = \frac{\sum_{j=1}^{4} \omega_j C.I._j}{\sum_{j=1}^{4} \omega_j R.I._j} \tag{41}$$

The C_j consistency index in the formula is denoted by $C.I._j$, the average random consistency index of C_j is denoted



(a) Histogram of weight ranking of fault factors of electrical control system

(b) Histogram of weight ranking of fault factors of feed servo system

(c) Histogram of weight ranking of fault factors of hydraulic system

FIGURE 11. Histogram of weight of fault factors for subsystems.

by $R.I._{j}$, calculated according to the formula: $C.R. = 0.079 < 0.1$.

Calculated by the formula, the total ranking of each weight level conforms to the consistency test. From the total ranking results, it can be found which fault factors have a great influence on the grinding wheel system. Reasonable solutions are proposed for the main fault factors to improve the reliability of the grinding wheel system.

The remaining three subsystems of the cycloid gear grinding machine: electrical control system, feed servo system, and machine tool hydraulic system are analyzed with the above-mentioned FTA-AHP analysis of the grinding wheel system, and the weight ranking diagram of the failure factors affecting their respective systems is obtained as shown in Figure 11, it is convenient for maintenance personnel to troubleshoot the machine tool and take reasonable maintenance decisions, thereby reducing the downtime of the machine tool.

From Figure 11, the main factors affecting the electrical control system, feed servo system, and machine tool hydraulic system can be obtained. For example, the main factors for motor control system failure are CNC software failure, drive control unit failure, main circuit board failure, and feed servo. The main factors of system failure are serious grating pollution, high-speed change frequency, overload load, etc. The main factors of machine tool hydraulic system failure are unreasonable pipeline design, volume loss and heat caused by leakage, control valve failure, etc. Maintenance personnel can According to the obtained fault spectrum, the maintenance plan is formulated, and there is no need to spend a lot of time in the fault tree to check the cause of the fault as before, which improves the efficiency of fault diagnosis and greatly shortens the time for fault diagnosis.

VI. CONCLUSION

Aiming at the uncertainty of the fault distribution model of the cycloid gear grinding machine in the case of lack of data, an RBF neural network fault data expansion algorithm model is established. The data expanded by this algorithm will not change the statistical distribution of the original data, so it is also reliable for lack of data. Modeling provides an effective solution. Secondly, parameter estimation and hypothesis testing are carried out on the fault data expanded by the algorithm, which can uniquely determine that the fault distribution type of this type of cycloidal gear grinding machine conforms to the Weibull distribution. The model parameter estimation results are also more accurate. Then, based on this research work, the reliability evaluation feature quantities and key index estimates of the machine tool are given, the reliability evaluation of the whole machine system is completed, and the cycloid is obtained. The MTBF of the wheel grinder is 909.2h. Finally, the FTA-AHP analysis of the cycloid gear grinder are performed to establish the fault tree of each subsystem of the machine tool. Find out the fault of the cycloidal pinwheel grinding machine equipment and take effective measures to repair it to increase the trouble-free working time of the machine tool.

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