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Fault Prediction of Automotive Bearings Based on Weibull Distribution

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1. Introduction

In mechanical equipment, bearings not only play the role of support and positioning, but also have many important functions such as reducing friction and wear, transferring load, realizing motion transmission, damping and buffering [1, 2]. Bearing performance not only directly affects the performance and life of the equipment, but also plays a key role in the entire production process and product quality. However, with the development of technical equipment requirements, the importance of service performance indicators of rolling bearings has exceeded the fatigue life. Accurately sensing and predicting the performance degradation trend of bearings can effectively prevent fault escalation, and is of great significance for reducing the maintenance cost of bearings [3, 4].

The degradation process of bearings is a gradual evolution process. When the operating state of bearings changes, its performance parameters will also show corresponding changes [5, 6]. Common performance parameters of rolling bearings include vibration acceleration value, friction torque, temperature and runout during bearing operation, etc. Compared with friction torque, temperature and runout, vibration acceleration not only has higher accuracy, sensitivity, real-time and response speed, but also can quickly adapt to complex working environments. A large number of state evolution data obtained from vibration monitoring also provide sufficient data sources for bearing performance evolution and fault prediction based on vibration. Gustafsson [7, 8] first proposed the method of analyzing bearing vibration signals collected by acceleration sensors in 1962, and vibration monitoring was subsequently widely used in the monitoring of operating conditions of rotary machinery. Xia X T [8] proposed that the vibration performance of rolling bearings directly affects the running condition of the working machine. This study correctly pointed out that there is a significant correlation between the vibration performance of bearings and the overall performance. However, its analysis mainly remained at the level of phenomenon description and correlation, lacking quantitative modeling and analysis.

However, in reality, the performance degradation of bearings is not a stable process; it involves multiple stages such as normal service, early deterioration, and accelerated deterioration. The vibration feature evolution patterns vary across these stages, especially the transition point from the healthy stage to the deterioration stage is difficult to be accurately captured by traditional steady-state models. Therefore, how to achieve sensitive identification of the deterioration stages, particularly the early signs, has become the key to improving prediction accuracy and practical engineering application. Shao L. D [9] proposed a series dynamic prediction model of bearing vibration performance based on self-service least square linear fitting to improve the accuracy of bearing performance analysis. Ye L, SUN F, Liu, Z. [10, 11, 12]. Realizing the limitations of existing analysis models in bearing performance analysis, the maximum entropy principle is utilized to model the uncertainty of vibration signals, enabling more sensitive capture of the probability distribution changes in the early stage of degradation. Meanwhile, machine learning methods are widely applied to mine the nonlinear degradation patterns and stage characteristics in high-dimensional vibration data. These studies aim to go beyond the steady-state assumption and construct performance evaluation models that can dynamically adapt to different degradation stages through intelligent analysis of the entire life cycle data of bearings, thus providing a new path for solving the problems of early warning and precise prediction. Xia X. T. [13] Used the vibration signals of rolling bearings to extract indicators to measure bearing degradation performance, and built data-driven reliability and life prediction models respectively. Serhat [14] uses statistical analysis and spectrum analysis techniques to detect motor vibration signals, takes the standard deviation value of vibration signals as the statistical parameter of bearing performance degradation, and establishes the standard deviation index model of motor bearing performance degradation. The basis of these methods is to assume that the degradation process is stable. However, bearing failure usually goes through different stages such as normal operation, early degradation, accelerated degradation, and critical failure, and the evolution patterns of vibration characteristics in each stage are completely different from the failure physical mechanism. The most crucial issue is that it is impossible to effectively capture the turning point from the healthy period to the degradation period, which leads to the inability to be flexibly applied in failure prediction in engineering.

Weibull distribution based on statistical principle is widely used in the study of bearing life and performance. Ma [15] proposed a bearing performance degradation evaluation method based on Weibull distribution and deep belief networks to effectively prevent catastrophic failures and reduce maintenance costs. Based on the vibration performance data of rolling bearings. Cheng [16] established the bearing performance degradation trend parameter model based on Weibull distribution. The research results show that the vibration performance degradation parameters can accurately describe the bearing degradation trend. Xu [17] proposed a particle swarm optimization method based on chaotic simulated annealing to estimate Weibull parameters, and experimental analysis shows that this method is feasible and effective. Zaretsky [18] calculated the value of shape parameter β of the two-parameter Weibull distribution model with the help of a large number of bearing fatigue life test data accumulated by SKF for a long time. Shimizu S. [19] carried out fatigue life tests on 90 samples, verified the test results by using lognormal distribution, two-parameter Weibull distribution and three-parameter Weibull distribution respectively, and gave the slope consistent with the test results. Poplawski [20] selected Weibull distribution model, Lundberg-Palmgren model, Ioannides-Harris model and Zaretsky model to analyze the fatigue life of cylindrical roller bearings, and obtained the difference information of different calculation models. However, the existing Weibull distribution research focuses on the bearing life calculation and fault diagnosis, and does not involve the quantitative analysis of bearing performance degradation.

Weibull distribution based on statistical principle is widely used in the study of bearing life and performance. Zaretsky [18] calculated the value of shape parameter β of the two-parameter Weibull distribution model with the help of a large number of bearing fatigue life test data accumulated by SKF for a long time. In pursuit of higher fitting accuracy, scholars have been constantly optimizing distribution models and algorithms. Shimizu S. [19] carried out fatigue life tests on 90 samples, verified the test results by using lognormal distribution, two-parameter Weibull distribution and three-parameter Weibull distribution respectively, and gave the slope consistent with the test results. Poplawski [20] selected Weibull distribution model, Lundberg-Palmgren model, Ioannides-Harris model and Zaretsky model to analyze the fatigue life of cylindrical roller bearings, and obtained the difference information of different calculation models. Xu [17] proposed a particle swarm optimization method based on chaotic simulated annealing to estimate Weibull parameters, and experimental analysis shows that this method is feasible and effective. These works jointly solidified the statistical foundation of the Weibull distribution in bearing reliability engineering, but their conclusions are essentially group-oriented and difficult to reveal the specific degradation process of individual bearings in actual operation.

To achieve the micro-dynamic of performance degradation during the service process of individual bearings. Cheng [16] established the bearing performance degradation trend parameter model based on Weibull distribution. The research results show that the vibration performance degradation parameters can accurately describe the bearing degradation trend. Ma [15] proposed a bearing performance degradation evaluation method based on Weibull distribution and deep belief networks to effectively prevent catastrophic failures and reduce maintenance costs. Based on the vibration performance data of rolling bearings. However, these studies have significant limitations in achieving the depth of "quantitative analysis". They usually take a global characteristic of the vibration signal or a parameter from the model output as the degradation indicator, ignoring the nonlinear evolution stage of the bearing performance degradation or the transformation of the failure mechanism, and thus lack practical application value.

In order to achieve the quantitative analysis of bearing performance degradation and predict bearing failure, the best method of Weibull parameter estimation is first selected, and then the parameter variation law corresponding to different bearing operating states is analyzed as a whole. Finally, the vibration time series is divided into vibration time sub-series with the same sample size, and the parameters of each sub-series are calculated. The results show that the bearing vibration time series accords with Weibull distribution, and the degradation degree of bearing performance can be quantitatively analyzed by the change of parameters, and then the bearing fault can be predicted. The research results provide a new idea for bearing performance analysis.

2. Test

With the performance evolution of rolling bearing as the research purpose, the vibration performance parameters of rolling bearing are taken as the monitoring object, and the whole cycle life endurance test is carried out. This process can not only observe the bearing performance evolution from normal operation to failure process, but also obtain sufficient performance data to provide a basis for subsequent analysis.

2.1. Test equipment

The equipment used in this test is SYJ-LG-NJ wheel bearing durability testing machine, which is mainly composed of test bench, load device, speed control device, data acquisition system, control system and other parts. The test bench is a structural frame that supports and holds bearings and applies loads. The load device and speed control device are used to apply load and speed to the bearing to simulate the actual working condition. The data acquisition system is used to record and monitor various parameters and data in the test process, such as load, speed, temperature, etc. The control system is used to control and monitor the various parameters and devices in the test process to ensure the stability and accuracy of the test.

The axial cylinder and the radial cylinder simultaneously apply a suitable load to the bearing, while the motor drives the bearing to rotate through the spindle. The schematic diagram of the equipment is shown in Fig. 1, the

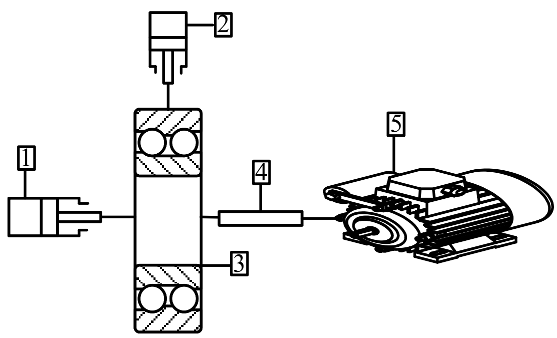

Fig. 1 Schematic diagram of the equipment: *1* – axial cylinder, *2* – radial cylinder, *3* – test bearing, *4* – main axis, *5* – motor

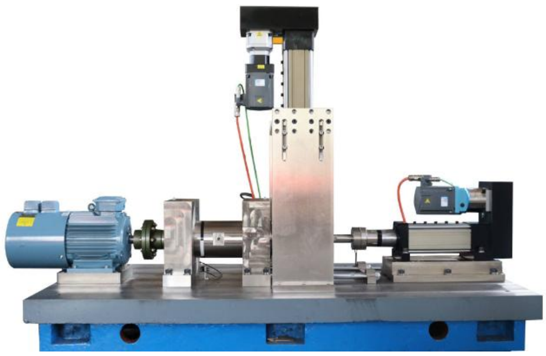

Fig. 2 Picture of the physical equipment

Table 1

Parameters of testing machine

Project	Parameter
Maximum axial load, kN	±30
Axial load accuracy	±1% of the set value
Axial load loading or unloading speed, kN/0.8s	15
Axial displacement sensor range, mm	100
Maximum radial load, kN	±30
Radial load accuracy	±1% of the set value
Radial load loading or unloading speed, kN/0.8s	15
Radial displacement sensor range, mm	100
Range of speed, rpm	50-2200 positive and negative rotation
Speed accuracy accelerate and decelerate, rpm	±1% of the set value 400

physical diagram of the equipment is shown in Fig. 2, and the parameters of the testing machine are shown in Table 1.

2.2. Test subject

The durability test subject is an automobile wheel hub bearing, bearing parameters are shown in Table 2.

2.3. Test condition

In order to simulate the actual application condition of the bearing, the design test is a constant speed and constant load accelerated life test. Radial load, axial load and speed are 7.8 kN, 4.4 kN and 350 rpm respectively.

After the end of the test, different degrees of damage occurred on the raceway of the bearing inner ring, as shown in Fig. 3.

Table 2

Bearing parameters

Projects	Parameters
Inside diameter	34 mm
Outside diameter	83 mm
Material	GCr15
Rolling diameter	12.7 mm
Pitch diameter	57 mm
Contact angle	35°

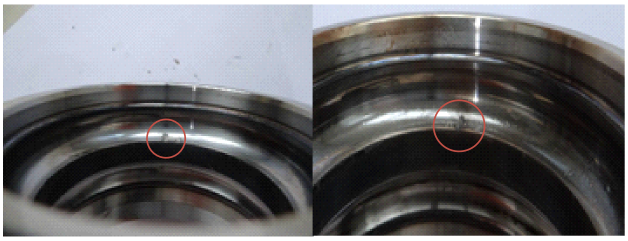

Fig. 3 Bearing damage condition

2.4. Test data

The vibration time series of bearings throughout their life cycle is shown in Fig. 4. The test lasted 184 hours and 42 minutes. During the test, one sample (vibration acceleration data) was extracted every five seconds, and a total of 132,998 samples were extracted. The initial sample is 0.049 mm/s^2, and the 129130th sample suddenly increases to 0.076 mm/s^2, which is larger than the measured value at any time before. This point is called the acceleration mutation point, and it is considered that the bearing begins to fail at this time. Since then, the vibration acceleration has increased rapidly, there is obvious noise during the test, the bearing failure degree is deepened, and the time experienced before the bearing failure is 179 hours and 20 minutes.

3. Weibull Parameter Estimation

The probability density function $f(v)$ of the three-parameter Weibull distribution and the cumulative density function $F(v)$ can be expressed as:

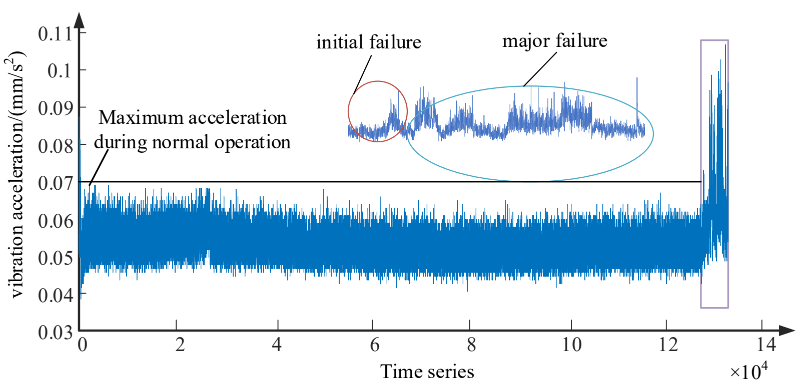

Fig. 4 Vibration time series of bearing throughout its life cycle

$$f(v)=\frac{k}{c}\left(\frac{v-\gamma}{c}\right)^{k-1} exp\left[-\left(\frac{v-\gamma}{c}\right)^{k}\right], \quad (1)$$

$$F(v)=1-exp\left[-\left(\frac{v-\gamma}{c}\right)^{k}\right], \quad (2)$$

where, k is the shape parameter, c is the scale parameter, γ is a positional parameter. The shape parameter determines the basic shape of the function curve, the scale parameter determines the horizontal coordinate range of the function curve, and the position parameter determines the starting position in the function coordinate system. It can be seen that the position parameters have nothing to do with the trend of bearing performance degradation, so only the shape parameters and scale parameters of the Weibull distribution of the data are analyzed. When the analysis sample changes, the height and width of the Weibull distribution function curve will change, and then the shape parameters and scale parameters will change. Taking vibration time series as an example, with the deepening of bearing performance degradation, vibration acceleration gradually increases, at this time the curve width will increase, the height will increase, and the shape parameters and scale parameters will change accordingly. Weibull distribution is sensitive to data changes and can be used for bearing fault prediction.

3.1. Parameter calculation methods

For the two-parameter Weibull distribution [11], the commonly used parameter estimation methods under the classical probability statistical theory include maximum likelihood method (MMLM), linear regression method (LR), moment method (MM), etc.

3.1.1. Linear regression method

Because the calculation process is simple, linear regression method is always the best method to solve Weibull parameters of small samples, and it can also be used to judge whether the test samples conform to Weibull distribution.

Take the logarithm of both sides of the cumulative probability density function twice, then the Eq. (2) becomes:

$$lg\, lg\frac{1}{1-F(v)}=k\, lg\, v-k\, lg\, c\,. \quad (3)$$

Let $x = lgv$, $y = lglg1/(1-F(v))$, then the Eq. (3) becomes:

$$y=kx-k\, lg\, c\,. \quad (4)$$

Based on the principle of linear regression method, the fitting of vibration time series is shown in Fig. 6. The green points are the transverse and vertical coordinates corresponding to the conversion of the vibration acceleration during the normal operation of the bearing. The green line segment is obtained by fitting the actual vibration acceleration with linear regression method. The blue points are the transverse and vertical coordinates corresponding to the conversion of vibration acceleration in case of bearing failure. The blue line segment is obtained by fitting the actual vibration acceleration with linear regression method.

If the determination coefficient is greater than 0.80, the fitting effect is good [17]. The determination coefficients of each stage are shown in Table 2. Since the determination coefficients are all above 0.8, the time series of vibration acceleration conforms to Weibull distribution.

Table 3

Determination coefficient of each stage

Project	A1	A2
R^2	0.9343	0.8315

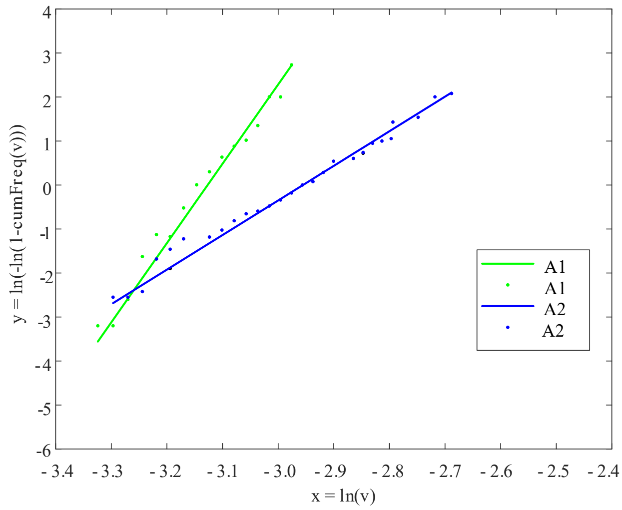

Fig. 5 Vibration time series fitting

3.1.2. Maximum likelihood method

The maximum likelihood estimation method holds that the occurrence of sample data is related to the parameters of the population distribution. When our estimates of the parameters change, the corresponding sample data also changes. Therefore, we determine the most reasonable parameter estimation results by maximizing the probability that the sample data will occur. In other words, we find the value of the parameter that makes the observed sample data appear with the greatest probability as an estimate of the population parameter.

Let the distribution density function of the population be $f(v, k, c)$, where k, c are the parameters to be estimated, V1, V2... Vn is the sample, the probability of v_1, v_2... v_n is:

$$\prod_{i=1}^{n} f(v,k,c)dt_v\,. \quad (5)$$

Determine the parameter value to make it maximum, then the likelihood function of the parameter is:

$$L(k,c)=\prod_{i=1}^{n} f(v,k,c)\,. \quad (6)$$

Replace the probability density function with the likelihood function, in order to calculate the logarithm of both sides of the equation:

$$ln\,L(k,c) = n\,ln(k/c) + \sum_{i=1}^{n} ln(v/c)^{(k-1)} -$$

$$-\sum_{i=1}^{n}(v/c)^k. \quad (7)$$

Differentiate the two parameters separately:

$$\partial\, ln\,L/\partial k = n/k + \sum_{i=1}^{n} ln(v/c) -$$

$$-\sum_{i=1}^{n}(v/c)^k\, ln(v/c)\ , \quad (8)$$

$$\partial\, ln\,L/\partial c = -n/c - n(k-1)/c + k/c\sum_{i=1}^{n}(v/c)^k. \quad (9)$$

Let Eqs. (11) and (12) be equal to 0 to solve the shape parameters and scale parameters:

$$1/k = \sum_{i=1}^{n} v^k\, ln\,v / \sum_{i=1}^{n} v^k - 1/n\sum_{i=1}^{n} ln\,v\ , \quad (10)$$

$$c = \left(\sum_{i=1}^{n} v^k / n\right)^{1/k}. \quad (11)$$

3.1.3. Method of moments

The most basic idea of the method of moments is to use the moments of a sample to estimate the moments of a population. Let the distribution density function of the population V be $f(v, k, c)$, where k, c are the parameters to be estimated, V1, V2... Vn is the subsample, then the first n moments of the population V are expressed as:

$$u_k = ET^k. \quad (12)$$

The j-order moment of the subsample is:

$$A_j = 1/n\sum_{i=1}^{n} T_i^{\,j}. \quad (13)$$

Let:

$$u_k = ET^k = A_j = 1/n\sum_{i=1}^{n} T_i^{\,j}. \quad (14)$$

That is, n equations with n unknown parameters are established, and the estimation results of parameters can be obtained based on these equations.

For a two-parameter Weibull distribution, the first two moments are expressed as:

$$EX = c\Gamma(1+1/k) = 1/n\sum_{i=1}^{n} X_i\ , \quad (15)$$

$$EX^2 = c^2\Gamma(1+2/k) = 1/n\sum_{i=1}^{n} X_i^2\ , \quad (16)$$

$$\Gamma(a) = \int_0^{\infty} x^{a-1}\, exp(-x)dx. \quad (17)$$

The shape parameters and scale parameters can be obtained by Eqs. (15), (16), and (17).

3.2. Accuracy test method

The root mean square error, Chi-square test and determination coefficient are used to evaluate the Weibull parameter estimation method.

3.2.1. Root mean square error

The RMSE represents the deviation between the predicted value and the experimental value. The deviation between the predicted and experimental values is inversely proportional to the RMSE values.

$$RMSE = \left[1/n\sum_{i=1}^{n}(y_i - x_i)^2\right]^{1/2}. \quad (18)$$

3.2.2. Chi-square test (χ^2)

Chi-square test is the degree of deviation between the actual observed value and the theoretical inferred value of the statistical sample. The degree of deviation between the actual observed value and the theoretical inferred value determines the size of the chi-square value. The larger the chi-square value is, the greater the degree of deviation between the two. On the contrary, the deviation between the two is smaller; If the theoretical value is exactly equal to the observed value, the chi-square value is 0.

$$\chi^2 = \sum_{i=1}^{n}(y_i - x_i)^2 / x_i. \quad (19)$$

3.2.3. Determination coefficient (R^2)

The coefficient of determination determines the linear relationship between the calculated value and the measured data. A higher R^2 represents a better fit using a theoretical or empirical function, and the maximum it can get is 1.

$$R^2 = \sum_{i=1}^{n}\left(y_i - \overline{y_i}\right)^2 - \sum_{i=1}^{n}\left(y_i - \overline{x_i}\right)^2 / \sum_{i=1}^{n}\left(y_i - \overline{y_i}\right)^2\ , \quad (20)$$

where, y_i is the actual data (measured data, observed data), x_i is the data predicted by Weibull distribution, $\overline{y_i}$ is the average y_i, n is the number of samples.

3.3. Parameter calculation method analysis results

According to the vibration acceleration of bearing during normal operation and failure, the vibration frequency histogram is drawn, and the probability density function of different parameter calculation methods is obtained, as shown in Fig. 6 and Fig. 7. The accuracy of different parameter calculation methods is shown in Table 5 and Table 6.

As shown in Table. 4 and Table. 5, the Weibull distribution goodness of fit of vibration time series is high when bearings are running normally, while the calculated value of vibration acceleration is significantly different from the actual value when bearings are faulty. This means

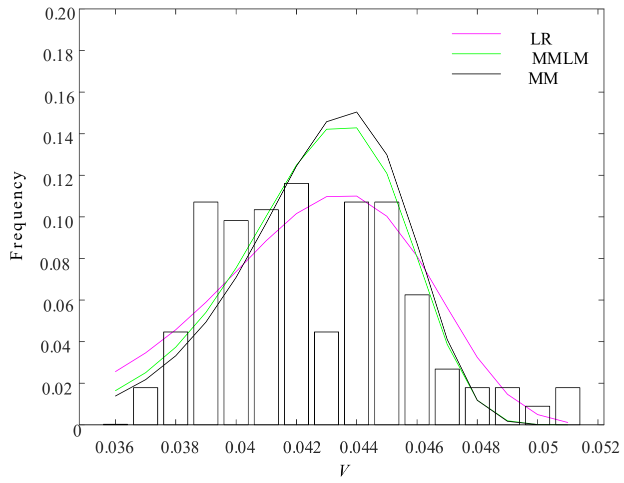

Fig. 6 Bearing vibration frequency histogram and probability density function graph of different calculation methods during normal operation

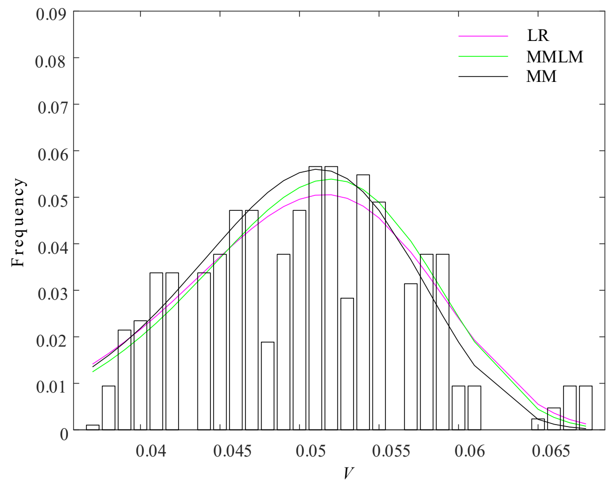

Fig. 7 Bearing failure vibration frequency histogram and probability density function graph of different calculation methods

Table 4

Comparison of calculation accuracy of bearing parameters during normal operation

	MM	LR	MMLM
k	17.2082	18.0231	15.1811
c	0.0437	0.0439	0.0438
RMSE	0.0170	0.0193	0.0145
χ^2	0.0219	0.0394	0.0203
R^2	0.9401	0.9343	0.9420

Table 5

Comparison of calculation accuracy of bearing parameters during fails

	MM	LR	MMLM
k	7.6832	7.1746	7.0215
c	0.0529	0.0527	0.0526
RMSE	0.0420	0.0443	0.0305
χ^2	0.0458	0.0367	0.0246
R^2	0.8201	0.8315	0.9110

that the vibration time series is more consistent with the Weibull distribution when the bearing is running normally. The root mean square error, Chi-square test and determination coefficient are used to evaluate the vibration time series of bearings under normal operation and failure. The results show that the parameters calculated by the maximum likelihood method are closer to the real situation.

4. Weibull Parameter Analysis

132,998 data were divided into 20 groups. The first 19 groups each contain 6650 vibration data samples, and the 20th group contains the remaining 6648 data. The shape parameters and scale parameters of the 20 groups of data were calculated respectively. The results are shown in Table 6: The shape parameters and scale parameters of the first 19 sub-sequences fluctuated within a certain range without significant regularity, indicating that the bearing state in the first 19 sub-sequences did not change significantly. The bearing state in the 20th subsequence has changed significantly.

Table 6

Shape parameter and scale parameter of different subsequences

Serial number	k	c	Serial number	k	c
1	21.115 0	0.048 5	11	23.792 2	0.048 2
2	22.156 8	0.050 2	12	25.167 0	0.047 9
3	26.646 8	0.048 3	13	27.571 1	0.048 2
4	23.958 9	0.048 6	14	28.326 5	0.048 0
5	25.211 0	0.049 3	15	28.304 1	0.048 1
6	25.260 0	0.049 2	16	27.126 2	0.048 6
7	25.452 7	0.049 0	17	29.410 9	0.047 7
8	25.428 9	0.048 6	18	26.068 4	0.048 6
9	25.779 8	0.048 6	19	25.021 8	0.048 8
10	26.537 9	0.048 9	20	7.2887 0	0.057 3

According to Eqs. (1), (2) and (4), the probability density function image, cumulative distribution function image and linear equation image of each sub-sequence are plotted respectively. The results are shown in Fig. 4: The distribution of the probability density function and cumulative distribution function corresponding to the first 19 sub-sequences is relatively concentrated, and there is no significant change. The horizontal span of the corresponding function of the 20th subsequence increases significantly, and the peak value shifts to the right, indicating that the bearing vibration acceleration in the 20th subsequence increases, which is consistent with the vibration time series in the test. The slope and intercept of the first 19 subsequences did not change significantly, but the slope of the 20th subsequence significantly decreased and the intercept significantly increased.

The results (Fig. 8) show that the shape parameters and scale parameters of Weibull distribution can describe the bearing state evolution process, and the statistical rules of different interval data can characterize the inherent properties of bearing state evolution.

5. Fault Prediction Analysis

The above research uses the complete life cycle

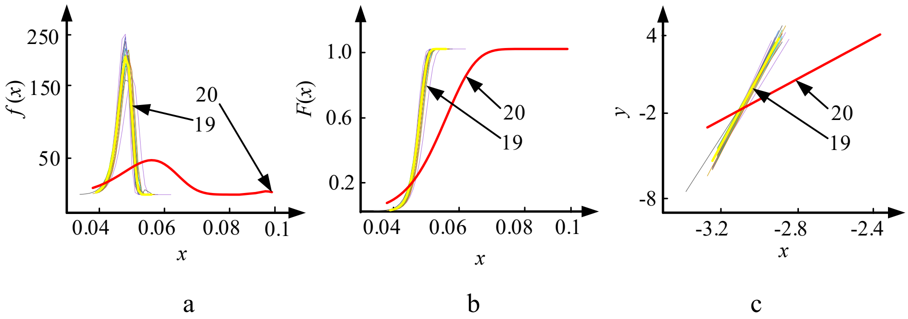

Fig. 8 Weibull distribution functions of different subsequences: a – probability, b – cumulative distribution, c – linear equation

data of the whole fatigue life test, including the final fault data. In actual engineering applications, bearing faults need to be predicted in advance. In order to enhance the engineering application value of this research, data within a period before the failure is selected for further analysis.

5.1. Data grouping

Assuming that the total amount of recorded data (bearing vibration value) is N, the time series V of bearing vibration can be expressed as:

$$V=\left(v(1),\ \ldots,\ v(s),\ \ldots,\ v(N)\right);\ s=1,\ 2,\ \ldots,\ N\,. \qquad (21)$$

In Eq. (21), v is the vibration value recorded in the test, s is the data serial number, and the total amount of data is N.

Each subsequence contains 1000 vibration data. According to the time sequence relationship of the overall sample, the vibration time series is divided into I groups, and the serial number of each sub-sequence is Vi. The sub-sequence is expressed as:

$$V_i=\left(v(i),\ \ldots,\ v(i+999)\right);\ i=1,\ \ldots,\ N-999\,. \qquad (22)$$

5.2. Analysis results

The whole life cycle of bearing contains 132,998 vibration acceleration values, and the 129,130 acceleration is abrupt, so only Weibull parameters of the pre-128130 subsequence are analyzed. The shape parameters and scale parameters are drawn into line charts respectively, as shown in the figure and figure.

As can be seen from the line chart, with the passage of time, the change trend of shape parameters and scale parameters is the same, and the two parameters continue to fluctuate within a certain range during normal operation of the bearing, until a short period of time before the fault begins to change dramatically. The time experienced before the bearing failure was 179 hours and 20 minutes, the shape parameter of the 127595 subsequences began to plummet, and the scale parameter began to increase sharply. The total time before the parameter change was 178 hours and 36 minutes, and the bearing failure was predicted 44 minutes in advance.

As the service time of the bearings accumulates, their performance shows a clear degradation trend, which can be quantitatively characterized by the evolution of the statistical characteristics of the vibration acceleration signals. By establishing a time-varying Weibull distribution

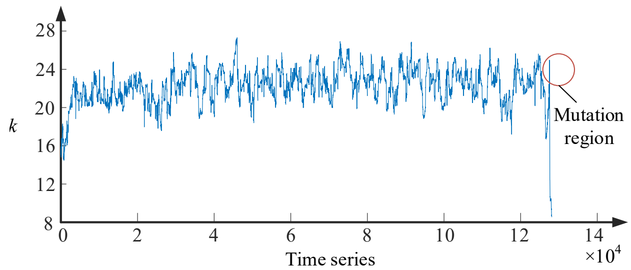

Fig. 9 Shape parameter line chart

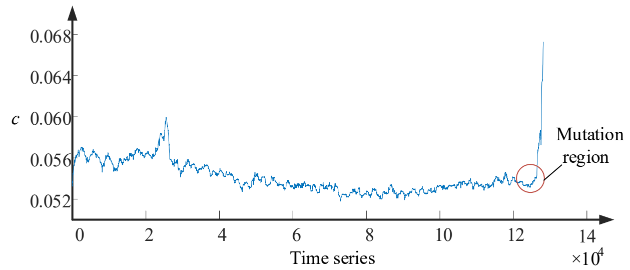

Fig. 10 Scale parameter line chart

model based on the vibration data throughout the entire life cycle, it was found that the shape parameter increases monotonically with the operating time, while the scale parameter decreases accordingly. This statistical evolution process is highly consistent with the observable physical degradation mechanism inside the bearings. From a macroscopic perspective, the most obvious phenomenon is the significant increase in the noise pressure level of operation and the roughening of sound quality. The fundamental microscopic physical mechanism lies in the emergence and expansion of fatigue damage on the contact surface of the raceways. Specifically, under the action of cyclic contact stress, microscopic cracks are generated sub-surface of the material and gradually extend to the surface to form pitting; as the operation continues, the size of individual pitting pits and their distribution area on the raceway will systematically expand. The state of the bearing raceways after the experiment is shown in Fig. 3. Indeed, large areas of concentrated peeling zones have appeared on the raceway surface, verifying the correctness of the inference.

6. Conclusion and Prospect

1. When the vibration time series is used as the analysis sample, the accuracy of Weibull parameters obtained by maximum likelihood method is the highest and the theoretical values are closer to the measured values.

2. Weibull parameters can be used as characteristic values to effectively characterize the evolution of bearing performance.

3. Weibull parameter analysis based on vibration time series can predict bearing failure 44 minutes in advance, but this situation will only occur when the number of subsequences containing samples is 1000. When the number of subsequences containing samples changes, the fault prediction time will also change.

4. Firstly, the method proposed in this study is centered on capturing the universal laws of how the statistical distribution characteristics of vibration signals evolve with physical degradation. The Weibull distribution, as a powerful statistical tool for describing material fatigue and failure times, and vibration signals as direct reflections of the dynamic state of bearings, when combined, are theoretically applicable to various rolling bearings (such as ball bearings, cylindrical roller bearings, and conical roller bearings). The differences among different bearing types mainly lie in their characteristic frequencies and dynamic responses, but this can be addressed by adjusting the focus frequency band of spectral analysis and establishing a type-specific mapping relationship between it and the Weibull parameters. This study verified the feasibility of the method using deep groove ball bearings as an example. Additionally, according to changes in the research objectives, the collected signals can include torque signals, temperature signals, acoustic emission signals, etc.

5. Regarding the extension to different operating environments (such as variable loads, variable speeds, and different lubrication conditions), we acknowledge that this is a key challenge in engineering applications and the necessary path for this method to become practical. This study verified the effectiveness of the proposed method under constant operating conditions, but the operating conditions in actual applications are variable. The core advantage of this method lies in its focus on the temporal evolution laws of the statistical distribution characteristics of signals, rather than absolute characteristic values under specific operating conditions. Therefore, by introducing mature preprocessing techniques, this method can naturally be extended to variable operating scenarios.

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FAULT PREDICTION OF AUTOMOTIVE BEARINGS BASED ON WEIBULL DISTRIBUTION

S u m m a r y

The existing prediction of automotive bearing faults has problems such as short prediction time and large errors. This paper takes Weibull distribution as the theoretical basis. Firstly, Weibull parameters of under different operating states are calculated, and the optimal parameter estimation method is determined by goodness of fit analysis. Secondly, each sub-series are calculated to determine the feasibility of Weibull parameters to characterize the evolution of performance. Finally, the vibration time sub-series in the stable interval of the test is analyzed, and the bearing fault prediction is realized by parameter change. The results show that the maximum likelihood method has the highest accuracy. There is a high goodness of fit between Weibull probability density function and the actual vibration time series when the bearing is running normally. Bearing performance evolution is consistent with Weibull parameter change, and bearing performance evolution can be analyzed by Weibull parameter change. In this way, bearing faults can be detected 44 minutes in advance.

Keywords: vibration time series, Weibull distribution, two-parameter Weibull, failure prediction.

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