The application of time domain and frequency domain statistical factors on rolling bearing performance degradation assessment

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Abstract

Rolling bearing performance degradation assessment is a predict and prevent technology. In order to assess the performance degradation degree of the rolling bearing, and make the time domain and frequency domain statistical factors be applied more effectively in rolling bearing performance degradation assessment, a comprehensive analysis method is proposed based on time domain and frequency domain statistical factors. Time domain and frequency domain statistical factors are calculated and analysed for the life cycle data of the rolling bearing. Outer raceway moderate fault and severe fault of the rolling bearing can be distinguished well by peak-to-peak level, the root-mean-square (RMS) value, and kurtosis value of time domain factors; normal state and mild fault can be distinguished better by frequency centroid, F_3, F_4 and F_5 of frequency domain factors than each time domain factor. The outer raceway performance degradation condition of the rolling bearing can be monitored well by using the proposed comprehensive analysis method, which uses partly frequency domain factors to analyse mild fault and partly time domain factors to analyse moderate fault and severe fault.

Keywords: rolling bearing, life cycle, statistical factor, performance degradation assessment

1 Introduction

Rolling bearing is the important rotating base element of machinery device and applied in many fields of national production, but while it is main fault source of machinery device [1-3]. Once the rolling bearing occurs faults, the machinery device may be damaged, the stability and safety of the integral production system will be influenced and enormous economic loss will be caused, even if casualty [4, 5]. So, it has become a research focus of fault diagnosis and condition assessment field to monitor and maintain the working condition of rolling bearing [6].

At present, proposed time domain and frequency domain factors usually are used for diagnosing whether the rolling bearing causes faults. For example reference [7] adopted peak-to-peak level, the root-mean-square (RMS) value, crest factor and kurtosis value to detect the fault information of the rolling bearing. The location of the fault can be detected by using spectrum analysis method and a well effect can be obtained; aiming to the rolling element damage of rolling bearing, a damage severity assessment method was proposed based on RMS by reference [8]. And compared with kurtosis value, crest factor and frequency domain amplitude of FFT transform, the validity and accuracy of proposed method is proved. In addition, based on time domain, frequency domain factors and time-frequency domain characteristic factors, some intelligent diagnosis methods for rolling bearing fault were proposed by some references [9-12].

However, there are relatively few cases to use time domain and frequency domain factors into rolling bearing performance degradation assessment. Generally speaking, when a rolling bearing is running, it passes through different stages of degradation until it is no longer functional. Because of different degradation degrees, the rolling bearing usually passes a series of different performance degradation conditions [13]. According to the integral change trend of bearing degradation degrees, the bearing degradation can be roughly divided into four conditions, that is normal condition, minor fault, moderate fault and severe fault [14]. The performance degradation of rolling bearing is a predict and prevent technology, that supported by device life cycle data and identifying the performance degradation degrees during the device performance degradation processing. By through detecting the running conditions of the device, the maintenance planning of the production device can be carried out targeted, and achieve the predict and prevent maintenance, avoid sudden fault and reach high efficiency and safety production.

The time domain and frequency domain factors are used for assessing rolling bearing performance degradation degrees in this paper. By analysing the life cycle data, the advantages and disadvantages of each statistical factor can be obtained. A comprehensive analysis method is proposed based on partly time domain and frequency domain statistical factors. Comparing the assessment curves, the validity of the proposed method is

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proved for performance degradation assessment of rolling bearing outer raceway.

2 Time domain and frequency domain statistical factors of the rolling bearing

The vibration signal of rolling bearing contains its running condition information which reflected by the time domain and frequency domain statistical factors. The calculation method of each factor is shown as follows:

1) time domain statistical factors [9]

a) peak-to-peak Level, which reflects the impact strength produced by bearing local fault point, the calculation formula is:

$$X_{P-P} = X_{\max} - X_{\min} . \quad (1)$$

b) RMS, which reflects the total energy of the signal, the calculation formula is:

$$X_{rms} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \quad (2)$$

c) Shape Factor, the calculation formula is:

$$S_f = \frac{X_{rms}}{\left|\overline{X}\right|} . \quad (3)$$

d) Impulse Factor, the calculation formula is:

$$I_f = \frac{X_{\max}}{\left|\overline{X}\right|} \quad (4)$$

e) Kurtosis Value, which reflects the statistic of vibration signal distribution characteristic, the calculation formula is:

$$K_v = \frac{\beta}{X_{rms}^4} . \quad (5)$$

f) Crest Factor, which describes the sharp peak degree, the calculation formula is:

$$C_f = \frac{X_{\max}}{X_{rms}} . \quad (6)$$

g) Clearance Factor, the calculation formula is:

$$CL_f = \frac{X_{rms}}{X_r} . \quad (7)$$

For Equations (1)-(7), $\overline{X} = \frac{1}{N}\sum_{i=1}^{N} x_i$, $X_{\max} = \max\{|x_i|\}$, $X_{\min} = \min\{|x_i|\}$, i=1,2,…,N, $X_r = [\frac{1}{N}\sum_{i=1}^{N}\sqrt{|x_i|}]$, $\beta = \frac{1}{N}\sum_{i=1}^{N} x_i^4$.

Above factors, peak-to-peak level and RMS are dimension factors and other five factors are dimensionless factors.

2) Frequency domain statistical factors

The frequency domain statistical factors of reference [9] are selected, that is F_1-F_5 (No. 1-5 in Table 1). And the frequency domain statistical factors of reference [15] are selected, that is the frequency centroid, the mean square frequency, RMS frequency and the frequency variance (No. 6-9 in Table 1).

TABLE 1 Frequency domain statistical factors

No.	calculation formulas	No.	calculation formulas	No.	calculation formulas
1	$F_1 = \frac{\sum_{k=1}^{K} s(k)}{K}$	4	$F_4 = \frac{\sum_{k=1}^{K}(s(k)-F_1)^4}{(K(F_2)^2)}$	7	$MSF = \frac{\sum_{i=1}^{N}\bar{x}(i)^2}{4\pi^2\sum_{i=1}^{N}x(i)^2}$
2	$F_2 = \frac{\sum_{k=1}^{K}(s(k)-F_1)^2}{K-1}$	5	$F_5 = \frac{\sum_{k=1}^{K} f_k^2 s(k)}{\sqrt{\sum_{k=1}^{K}s(k)\sum_{k=1}^{K}f_k^4 s(k)}}$	8	$RMSF = \sqrt{MSF}$
3	$F_3 = \frac{\sum_{k=1}^{K}(s(k)-F_1)^3}{(K(\sqrt{F_2})^3)}$	6	$FC = \frac{\sum_{i=1}^{N}\bar{x}(i)x(i)}{2\pi\sum_{i=1}^{N}x(i)^2}$	9	$VF = MSF-(FC)^2$

where, in the calculation formulas of No. 1-5, $s(k)$ is the spectrum value when k=1,2,…,K, K is the total number of spectrum lines; in the calculation formulas of No. 6-9, $\bar{x}(i) = [x(i) - x(i-1)] \times f_s$, fs is the sampling frequency.

3 The experiment and the analysis

3.1 THE LIFE CYCLE DATA OF ROLLING BEARING

The life cycle vibration signals related to the rolling bearing and the paper investigation were provided by university of Cincinnati IMS laboratory, the experimental device is shown in Figure 1.

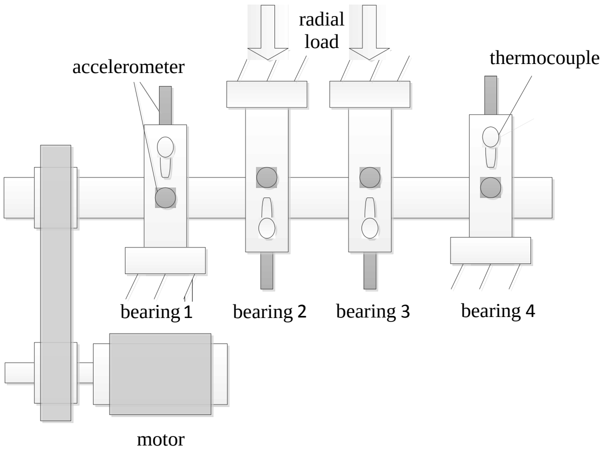


FIGURE 1 Schematic diagram of the experimental device.

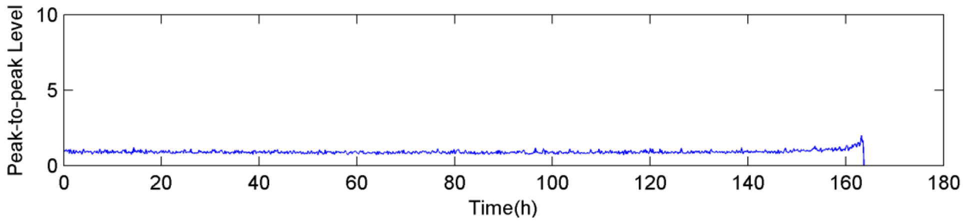
Four bearings were mounted on the same shaft, bearing rotating speed remained 2000 rpm, PCB 353B33 high sensitivity accelerometer sensor is mounted on each bearing. The vibration data of the experiment are collected once every ten minutes using NI 6062E data acquisition card, the sampling frequency is 20 kHz, the data collecting time is about 164 hours. There are 984 files and each file consists of four rows and 20480 columns data, that is four passages data and each passage data is 20480 points.

3.2 THE ASSESSMENT CURVES ANALYSIS OF TIME DOMAIN AND FREQUENCY DOMAIN STATISTICAL FACTORS FOR THE EPERIMENTAL DATA

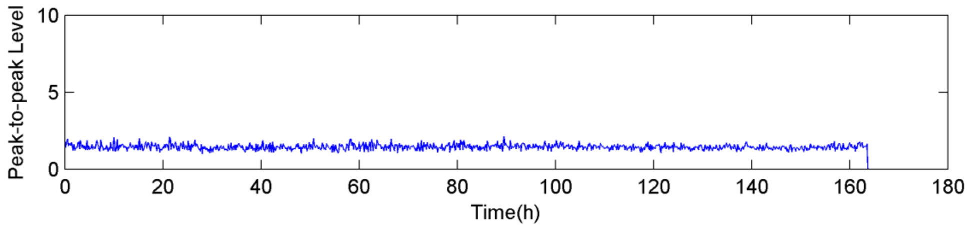
After the experiment, according to each passage data respectively, the time domain and frequency domain statistical factors of every data segment can be calculated. Then the statistical factors of all data segments, that is the life cycle data, are drawn and the life cycle assessment curve of rolling bearing could be obtained.

1) The assessment curves and analysis of the domain factors.

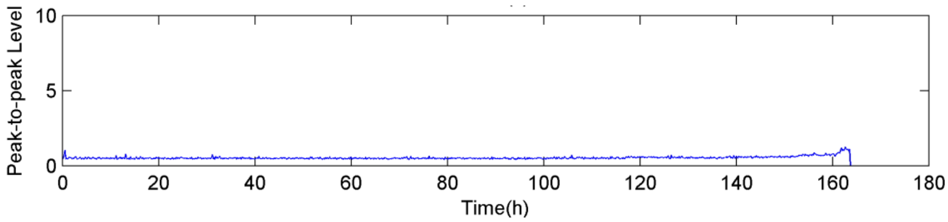
The peak-to-peak level assessment curves of rolling bearing 2, 3 and 4 are shown in Figure 2, the assessment curves of each time domain statistical factor of rolling bearing 1 are shown in Figure 3.



a) bearing 2

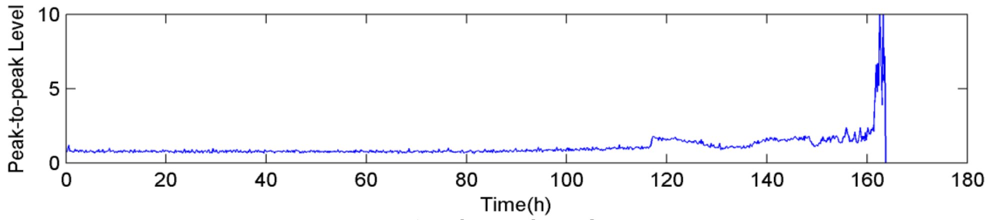


b) bearing 3

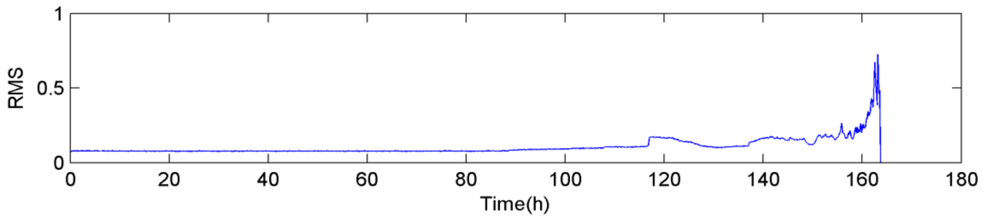


c) bearing 4

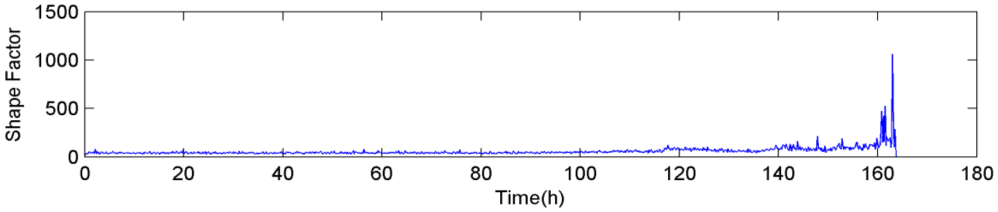
FIGURE 2 Peak-to-peak Level assessment curves of bearing 2, 3 and 4



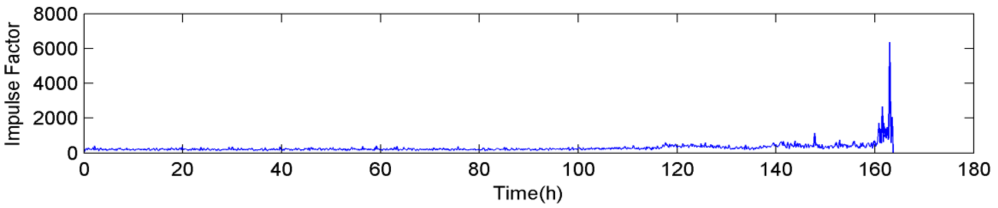
a) Peak-to-peak Level



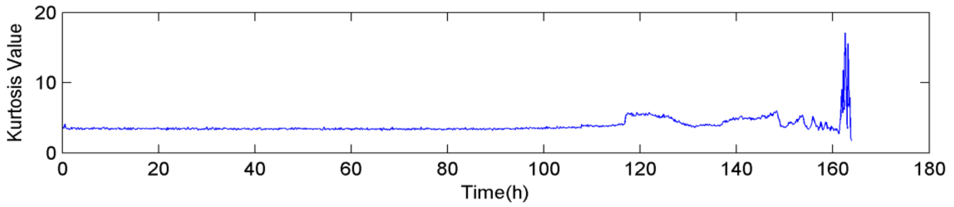
b) RMS



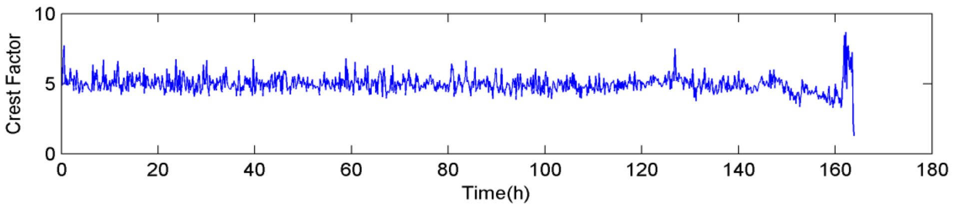
c) Shape Factor



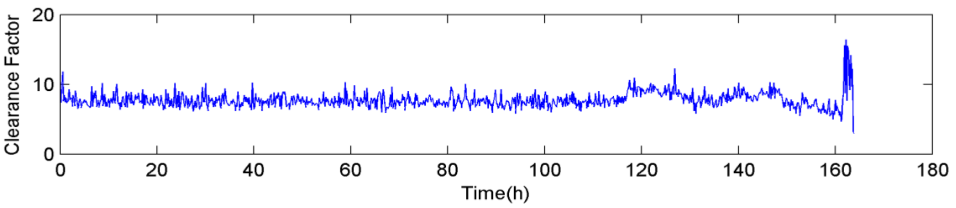
d) Impulse Factor



e) Kurtosis Value



f) Crest Factor



g) Clearance Factor

FIGURE 3 The assessment curves of time domain statistical factors of bearing 1

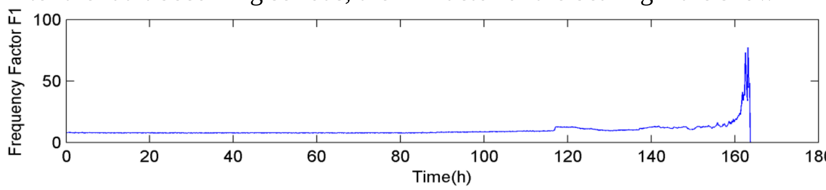
From the assessment curves of time domain statistical factors in Figure 2 and Figure 3, the change trends of peak-to-peak level factor of bearing 2, 3 and 4 are relatively consistent and keep stably. The similar curves can be obtained for other time domain statistical factors. So, it can be preliminarily judged that bearing 2, 3 and 4 are normal condition and no severe fault; but comparing with other bearing curves, the latter stage of each factor assessment curve of bearing 1 fluctuates violently, so the bearing 1 occurs fault. And with the increase of fault degree, the performance of the bearing degrades faster and faster that is consistent with the actual condition. The assessment curve amplitudes of bearing 2, 3 and 4 increase slightly about at 160h around, in fact, it is influenced by the fault of the bearing 1. When the end of the experiment, the outer of the bearing 1 occurs fault and finally the bearing becomes failure because of serious fault.

Next, the bearing 1 with the fault is analysed detailed. From Figure 3 (a) and Figure 3 (b), it can be seen that peak-to-peak level and RMS of the bearing 1 all remain consistent and stable condition at the beginning of a long period of time, which shows that the rolling bearing runs well; at 88.5h around, the amplitudes of peak-to-peak level and RMS increase slightly, the rolling bearing occurs minor fault and can work stably at this stage; until 116.7h around, the amplitudes of peak-to-peak level and RMS increase obviously, which represents the bearing degradation degree becomes serious and comes into the moderate fault stage. After the fault becoming serious, the degradation speed of the bearing accelerates and the amplitudes fluctuate stronger; at 158.3h around, it can be seen that the fluctuation becomes further stronger from the two factors' change, and the amplitudes rise obviously, the bearing comes into the severe fault stage; until 163.5h around, the factors rise rapidly, the bearing could not run and finally it is no longer functional, the experiment finishes. From Figure 3 (c), (d) and (e), it can be seen that the shape factor, impulse factor and kurtosis value all show sensitively reflection to the moderate fault and the severe fault. Among these three factors, the amplitudes of kurtosis value change more seriously and have better validity for identifying the moderate fault. From Figure 3 (f), the entire change trend of crest factor assessment curve fluctuates bigger and only reflects to the severe fault. From Figure 3 (g), clearance factor reflects to the moderate fault and severe fault, but cannot distinguish them easily.

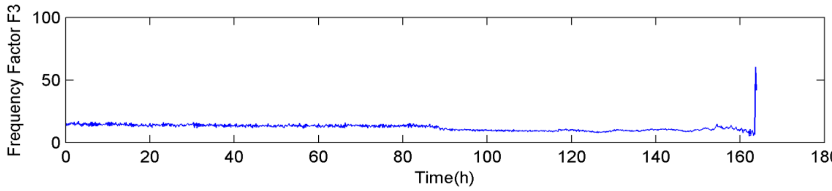
Summary, peak-to-peak level and RMS factors reflect relatively weakly for outer raceway minor fault of rolling bearing and the sensitivity is low; other time domain statistical factors do not reflect to outer raceway minor fault of rolling bearing. Except for crest factor and clearance factor, other time domain statistical factors are sensitive to the moderate fault, the severe fault and the failure condition.

(2) The assessment curves and analysis of the frequency factors

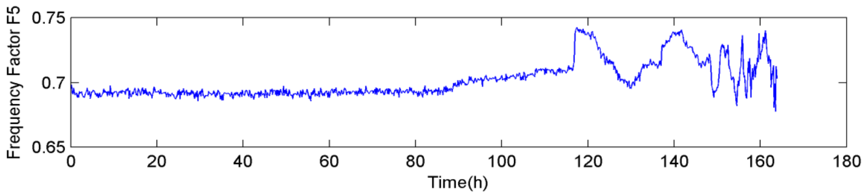
The assessment curves of each frequency statistical factor of the bearing 1 are shown in Figure 4.



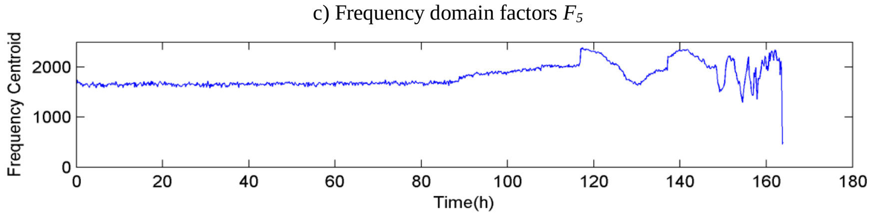
a) Frequency domain factors F_1



b) Frequency domain factors F_3



c) Frequency domain factors F_5



d) Frequency centroid

FIGURE 4 The assessment curves of frequency domain statistical factors of bearing 1

From Figure 4 (a), it can be seen that the frequency factor F_1 fluctuates slightly at 88.5h around and increases obviously at 116.7h around, the growth rate increases at 158.3h around and continues to rise until the bearing failure at 163.5h around. So, the frequency factor F_1 is very sensitive to rolling bearing outer raceway moderate fault, severe fault and the failure condition, and slightly sensitive to the minor fault. The similar result can be obtained for the frequency factor F_2 and the Figure is omitted. From Figure 4 (b), the frequency factor F_3 obviously decreases at 88.5h around which represents the rolling bearing comes into the minor fault stage, then the amplitude fluctuates slightly until 158.3h around becomes stronger and the bearing final failure at 163.5h around. So, the frequency factor F_3 is very sensitive to rolling bearing outer raceway minor fault, generally sensitive to the severe fault and relatively lack to distinguish moderate fault. The similar result can be obtained for the frequency factor F_4 and the Figure is omitted. From Figure 4 (c) and (d), the frequency factor F_5 and frequency centroid are relatively stable before 88.5h and increase obviously at 88.5h which represents the bearing comes into minor fault stage, then the amplitude increases slowly until 116.7h around further increases obviously which represents the bearing comes into moderate fault stage, next the curve amplitude strongly waves. So the frequency factor F_5 and frequency centroid are very sensitive to the minor fault and moderate fault, and nearly can't distinguish severe fault. The curve trends of the mean square frequency, RMS frequency and the frequency variance factors are similar to factor F_5 besides the amplitude, the curves are omitted.

It is visible that frequency centroid, F_3, F_4 and F_5 factors are more sensitive to outer raceway minor fault of the bearing than time domain statistical factors, but obviously lack to severe fault and the failure condition.

Based on above time domain and frequency domain factors analysis for rolling bearing life cycle data, time domain factors and frequency domain factors respectively have different assessment ability aiming to different degree faults. So, in practical application, the advantages of each factor can be used for comprehensive assessment.

4 Conclusions

By analysing time domain and frequency domain factors curves of experimental data, the change trend of the curve is basically consistent with the practical outer raceway fault condition of rolling bearing. But the assessment ability of each factor is different for outer raceway different fault degrees.

Comparing with other time domain factors, peak-to-peak level, RMS and kurtosis value can well distinguish outer raceway moderate fault and severe fault of rolling bearing. Comparing with each time domain factor, F_3, F_4, F_5 and frequency centroid of the frequency domain factors are more sensitive to outer raceway initial fault of rolling bearing and the stability is well.

By using the proposed comprehensive analysis method, partly frequency domain statistical factors (F_3, F_4, F_5 and frequency centroid) are used for analysing outer raceway minor fault of the rolling bearing, and partly time domain statistical factors (peak-to-peak level, RMS and kurtosis value) are used for analysing moderate fault and severe fault, the outer raceway performance degradation condition of the rolling bearing can be monitored well.

Although the experiment shows that the proposed comprehensive analysis method can monitor the outer raceway performance degradation condition of the rolling bearing, it is inconvenient for user to use multiple statistical factors. So, the further research focus is to study a unified and effective assessment factor for rolling bearing performance degradation.

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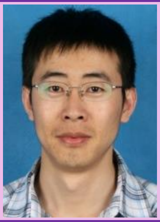

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