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Intelligent Vibration-Based Diagnostics for Rolling Mill Bearing Failures

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***Abstract*—As industry becomes more automated and intelligent, there is an increased need for real-time monitoring and diagnosis of rolling mill bearings. This paper introduces an intelligent vibration-based analysis method for detecting and diagnosing faults in rolling mill bearings. By installing sensors at critical points and applying signal processing techniques like resonance demodulation and kurtosis analysis, we can accurately identify bearing issues. The method has been proven effective in experiments, offering a scientific basis for maintenance and preventive measures in rolling mills.**

Keywords—Rolling Mill Bearing Fault Diagnosis, Vibration Analysis, Resonance Demodulation, Kurtosis Coefficient

I. Introduction

Rolling mills, essential in metal processing, are directly linked to product quality and efficiency through their stability and reliability. Core components like rolling bearings, under high loads and speeds, are critical for mill safety. Prolonged operation can lead to wear, fatigue, and damage in bearings, causing equipment failure and production stops. Thus, effective monitoring and diagnosis of these bearings are vital for continuous production and lower maintenance costs[1]. Traditional diagnosis methods, dependent on experience, lack real-time capabilities [2]. In contrast, intelligent vibration-based analysis offers precise, immediate data for early detection of bearing issues [3]. Despite the noisy and interfering environment in mills [4], this study introduces an advanced vibration signal analysis method for accurate fault diagnosis in rolling mill bearings. The aim is to enhance diagnostic accuracy and real-time response, reduce equipment failures, and prolong equipment life.

II. Method

A. Mechanism of Failure

Bearing wear faults generate impact pulse forces when the damage points roll over, leading to two types of vibrations: first, the low-frequency "passing vibration," which is caused by the repeated collision of damage points on the working surface of the bearing components with adjacent components during operation; its periodicity can be calculated based on the bearing's speed and geometric dimensions but varies depending on the location of the damage (inner race, outer race, or rolling elements) [5]. Second, the high-frequency natural vibrations are those induced by the impact, involving complex vibrations of the bearing system itself, including the radial bending vibrations of the inner and outer races, the vibrations of the rolling elements, and even the natural vibrations of the vibration sensors, which can be revealed in the bearing's vibration signals due to damage [6]. By detecting the presence or absence of these high-frequency vibrations, resonance demodulation methods can be effectively used for bearing fault diagnosis, especially those characteristic frequencies below 1 kHz, which are key information in the diagnostic process. The overall framework and raw signal diagnosis process are shown in Figure 1 and Figure 2 respectively.

The formulas for the fault frequencies of four different parts are as follows:

Cage hitting outer ring frequency:

$$f_{CPF} = \frac{f}{2}\left(1-\frac{d}{e}\cos\beta\right) \tag{1}$$

Inner race fault frequency:

$$f_{BPFI} = \frac{b\times f}{2}\left(1+\frac{d}{e}\cos\beta\right) \tag{2}$$

Outer race fault frequency:

$$f_{BPFO} = \frac{b\times f}{2}\left(1-\frac{d}{e}\cos\beta\right) \tag{3}$$

Rolling element fault frequency:

$$f_{BFF} = \frac{e\times f}{2}\left(1-\left(\frac{d}{e}\right)^2\cos^2\beta\right) \tag{4}$$

Where f represents the rotational frequency of the shaft in Hertz (Hz), b represents the number of rolling elements, d represents the diameter of the rolling elements in millimeters (mm), e presents the pitch diameter of the bearing in millimeters (mm) and β represents the contact angle of the bearing.

B. Signal Preprocessing

Due to the complexity of the on-site environment, the collected vibration signals often contain noise and other interfering signals [7]. Therefore, signal preprocessing becomes a crucial step in extracting effective features. The preprocessing process includes steps such as filtering, noise reduction, and signal conditioning. By using band-pass filters, we can remove low-frequency and high-frequency interference and retain frequency components related to bearing faults. In addition, noise reduction techniques, such as wavelet transform

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or spectral subtraction, are employed to further reduce the impact of noise.

C. *Kurtosis Coefficient Analysis*

The kurtosis coefficient is a dimensionless parameter that is particularly sensitive to impact signals and is suitable for the diagnosis of surface damage-type faults. Kurtosis coefficient analysis can help us determine whether a fault exists, especially in the early stages of the fault [8]. By calculating the kurtosis value of the vibration signal and comparing it with the kurtosis value of a normal bearing, abnormal changes in kurtosis can be identified, indicating potential faults.

$$\text{Kurtosis} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^4}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^2\right)^2} \tag{5}$$

Where x_i represents the sample values of the vibration signal time series, $\bar{x}$ is the mean value of the vibration signal, n is the number of samples.

D. *Resonance Demodulation*

Resonance demodulation technology can effectively diagnose local faults in rolling bearings. Direct envelope demodulation analysis of vibration signals is often affected by noise, making it difficult to extract fault characteristic frequencies. Therefore, noise reduction preprocessing of the signal is required before demodulation analysis. Typically, only the signal frequency band of interest is analyzed [9]. Since the frequency band of impact pulse force is wide, it inevitably covers the natural frequency of the monitored components [10], thereby exciting the system's high-frequency natural vibrations. Depending on the actual situation, a certain high-frequency natural vibration can be chosen as the object of study.

- Use band-pass filters to separate signals that match the natural frequency of the bearing.

Band-pass filters: $$s(t) = x(t) * h(t) \tag{6}$$

where $s(t)$ is the filtered signal, $x(t)$ is the original signal, and $h(t)$ is the impulse response of the band-pass filter.

- Apply the Hilbert transform to perform envelope demodulation of the signal to extract the low-frequency envelope signal containing fault characteristics.

Hilbert transform: $$Hx(t) = \frac{1}{\pi}\int_{-\infty}^{\infty}\frac{x(\tau)}{t-\tau}d\tau \tag{7}$$

Signal becomes: $$\tilde{x}(t) = x(t) + jHx(t) \tag{8}$$

- Perform spectral analysis on the envelope signal to identify fault characteristic frequencies, i.e., the amplitudes of various fault characteristic frequencies.

Envelope signal: $$E(t) = \sqrt{x(t)^2 + (Hx(t))^2} \tag{9}$$

Perform spectral analysis on the envelope signal using the Fourier Transform:

$$x(f) = \int_{-\infty}^{\infty} E(t)e^{-j2\pi ft}dt \tag{10}$$

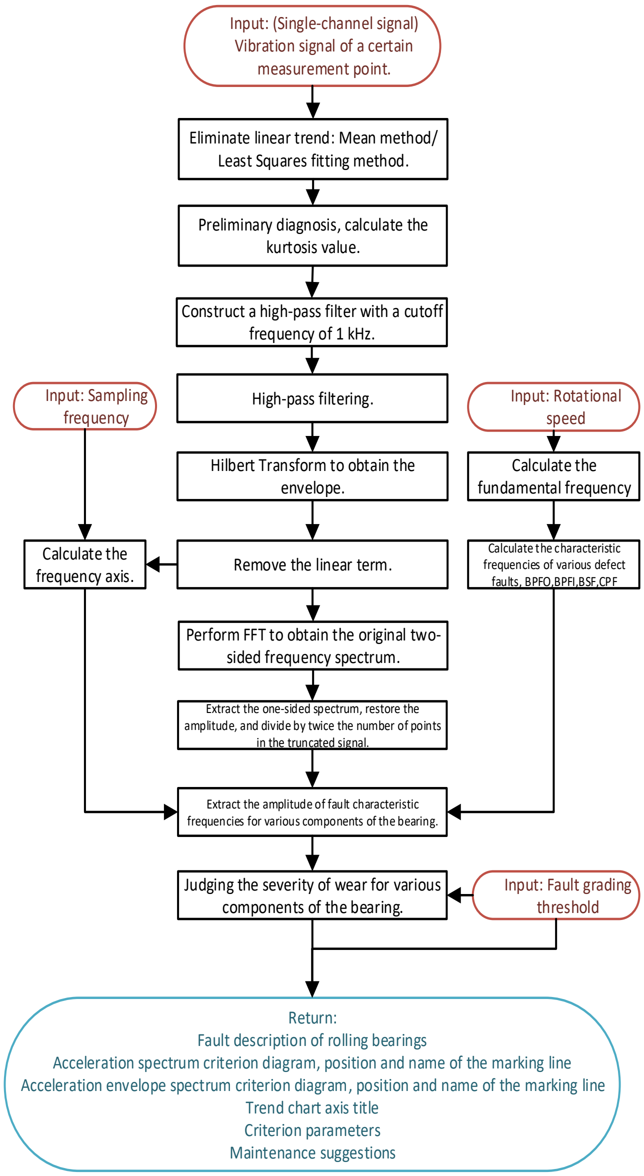

Fig. 1. overall framework (High-frequency Envelope Diagnosis)

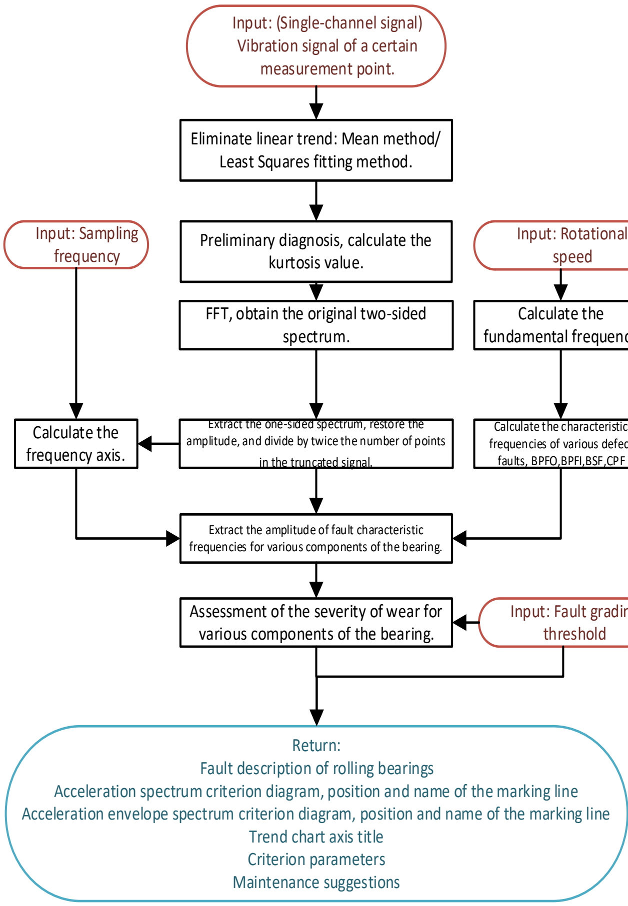

Fig. 2. Raw Signal Diagnosis

E. *Visualization Results*

Fault diagnosis mainly focuses on the characteristic frequency components of bearing faults marked with gray lines in the figure. The larger the characteristic frequency components, the greater the possibility of faults.

Figure 3 shows an example of acceleration envelope spectrum and acceleration spectrum diagram, with frequency/Hz on the horizontal axis and amplitude mm/s2 on the vertical axis.

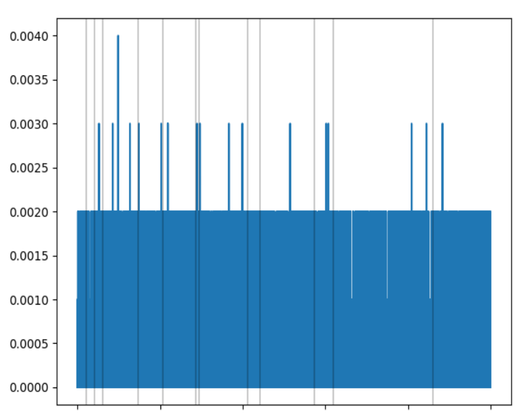

Fig. 3. Raw Signal Diagnosis

with frequency/Hz on the horizontal axis and amplitude mm/s^2 on the vertical axis.

III. Experiment

This study has developed a comprehensive fault monitoring system for rolling mill bearings, integrating multiple vibration and current sensors to gather real-time operational data, and the rolling bearing fault-related measurement points are shown in Table 1. Deployed across 10 rolling mills, the system includes PCB Piezotronics 356A23 vibration sensors, sensitive at 10 mV/g within a frequency range of 0.5 Hz to 10 kHz, and LEM LV 25-P current sensors with a 0-600 A measurement range, ±0.5% precision, and a response time of less than 5 ms. These sensors are strategically placed in both vertical (Y) and horizontal (X) orientations on motor-driven and non-driven end bearing seats, and within high-voltage distribution cabinets to track motor current fluctuations. After a year of operation, the system has amassed 12.6144 billion data points, including 120,000 anomalies, which are poised for in-depth signal processing and diagnostic analysis to enhance bearing fault detection and prevention measures.

TABLE I. Rolling Bearing Fault-Related Measurement Points.

Serial Number	**Measurement Location**	**Measurement Direction**
1	Motor Drive End Bearing Seat	Vertical Direction Y
2	Motor Drive End Bearing Seat	Horizontal Direction X (perpendicular to Y at a 90-degree angle)
3	Motor Non-Drive End Bearing Seat	Vertical Direction Y
4	Motor Non-Drive End Bearing Seat	Horizontal Direction X (perpendicular to Y at a 90-degree angle)

The bearing fault prediction model developed in this study has demonstrated high accuracy and recall rates in actual industrial applications shown in Table 2. The model's warning accuracy increases as the warning time window is shortened, indicating that the model can predict potential failures in the near future more accurately As the warning time window narrows, the model's warning capability significantly improves, which is of great importance for reducing unexpected downtime and maintenance costs [11].

TABLE II. Experiment Result.

Warning Time Window	**Accuracy (%)**	**Recall (%)**	**Remarks**
One month in advance	84.8	79.3	The accuracy rate decreases as the warning time extends.
One week in advance	91.2	85.7	Both accuracy and recall rates improve.
One day in advance	99.4	90.1	The accuracy rate and recall rate reach the highest.

To provide a comprehensive evaluation of the proposed intelligent vibration-based diagnostics method for rolling mill bearing failures, this study compares it with existing methods, specifically time-frequency analysis of vibration signals and machine learning-based methods, including Support Vector

Machines (SVM) and Random Forests (RF). The experiment was structured around warning time windows, focusing on the critical one-day-in-advance mark. Our findings, as detailed in Table 3, indicate that the intelligent vibration-based analysis method outperformed the other two methods in terms of accuracy and recall rates within this time frame.

TABLE III. COMPARISON OF EXISTING METHODS.

One day in advance	Accuracy (%)	Recall (%)	Remarks
Intelligent Vibration Analysis Method	99.4	90.1	The accuracy rate and recall rate reach the highest.
Time-Frequency Analysis Method	96.7	89.2	Close to the Intelligent Vibration Analysis Method but slightly lower.
Machine Learning-Based Method	98.3	91.4	Performance is close to the Intelligent Vibration Analysis Method under optimal conditions.

The time-frequency analysis excels at detecting transient bearing faults but faces challenges in real-time monitoring and computational demand, while machine learning methods, despite their high accuracy, are heavily dependent on data quality and feature engineering. The proposed intelligent vibration-based method offers straightforward real-time monitoring, yet stands to benefit from the integration of advanced technologies, such as machine learning, to boost diagnostic accuracy.

IV. CONCLUSION

This study confirms the effectiveness of an intelligent vibration-based analysis method for monitoring and diagnosing rolling mill bearing faults. The results show that analyzing the acceleration envelope spectrum and kurtosis of vibration signals accurately detects bearing faults. This research enhances rolling mill reliability and reduces maintenance costs, with future work poised to further advance these technologies for industrial applications.

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