Experimental Investigation of the Diagnosis of Angular Contact Ball Bearings Using Acoustic Emission Method and Empirical Mode Decomposition

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Early detection of angular contact bearings, one of the important subsets of rolling element bearings (REBs), is critical for applications of high accuracy and high speed performance. In this study, acoustic emission (AE) method was applied to an experimental case with defects on angular contact bearing. AE signals were collected by AE sensors in different operating conditions. Signal to noise ratio (SNR) was calculated by kurtosis to entropy ratio (KER), then acquired signals were denoised by empirical mode decomposition (EMD) method, and optimal intrinsic mode function (IMF) was selected by the proposed method. Finally, envelope spectrum was applied to the denoised signals, and frequencies of defects were obtained in different rotating speeds, loadings, and defect sizes. For the first time, a small defect with width of 0.3 mm and loading of 475 N was detected in early stage of 0.04 KHz. Moreover, a comparison between theoretical and extracted defect frequencies suggested that our method successfully detected localized defects in both inner and outer race. Our results show promise in detecting small size defects in REBs.

1. Introduction

Rolling element bearings (REBs) are widely used in rotating machines and in various industries such as steel, mining, paper, and railways [1]. Specifically, angular contact bearings (in this paper) have many applications such as vacuum pumps, machine components for semiconductor industry, high-speed rolling mills, high-precision machine tools, printing machineries [2]. Since it can be used in very accurate applications at high speeds (such as the shafts in process pumps), it is critical case and necessary for early detection of failure in the early stages. Failure of bearings is a major cause of machinery breakdown, economic losses, and even loss of human lives. Undesirable vibrations can be caused by faulty installation, poor maintenance, or surface spall that finally leads to development of REB failure [3].

There is enormous amount of research in the field of diagnosis of REBs [4]. One of the important issues is how to identify bearing fault before it reaches the final failure state. Bearing failure is reported to account for almost 40%–50% of motor failure cases in industries [5]. Several methods have been applied in diagnosis of REBs such as vibration analysis, thermographic inspection, and nondestructive testing (NDT) techniques like acoustic emission (AE). AE technology is superior to other methods in detecting defects in early stages. Another advantage of using of AE is the discovery of defects in slow-speed and extremely slow-speed bearings that cannot be detected through other methods [6, 7].

Balderston used the AE method in the diagnosis of bearings for the first time [8]. One of the methods for analyzing the signal in diagnosis of REBs is the use of AE parameters and indicators in discovering such cases as location of defects, size, and defect growth, taking into account the sensitivity of AE parameters to operating speeds and loading. Examples of these parameters and indicators
include counting parameter, peak amplitude, energy, rise
time, time, RMS, skewness, kurtosis, crest factor (CF).

Yoshioka and Fujiwara [9] did a research on fatigue of
rolling contact bearings and claimed that AE measurements
can make it possible to understand the entire failure process.
Rogers [10] inspected slowly rotating bearings for gas ex-
traction cranes using AE method and kurtosis indicator. He
used this method to detect defects in the early stages and
locate the fatigue cracks. By comparing the results of AE test
with vibration analysis, he showed that the vibration analysis
was difficult due to the low speed of the crane bearings and it
was not possible to detect defects in the early stages.

Tandon and Nakra [11] studied AE method in REBs by
making artificial defects on inner, outer, and rolling ele-
ments and concluded that the peak amplitude of frequency
of signals is higher than healthy bearing in various operating
conditions, but they could not detect faults in slow-speed
bearings. Tandon and Choudhury [12] reviewed the
methods of vibration and AE in diagnosis of REBs and stated
that the AE has typical frequency content in the range of
100 kHz to 1 MHz, so AE is not influenced or distorted by
unbalancing or misalignment which are at low-frequency
ranges. The AE technique and AE parameters have a sig-
ificant advantage over vibration measurement methods
due to their high sensitivity to the detection of the incipient
bearing faults. Choudhury and Tandon [13] investigated
defects on inner race and rolling elements by AE method,
and they chose counting and peak amplitude parameters of
AE for detection of defects. They argued that counting
parameters can detect and peak amplitude can show the size
of defects, but they did not investigate defects on outer race
of REBs.

Mba [14] studied the defects in the inner and outer race
of a radially roller bearing, considering two RMS and
counting parameters in different operating conditions by
changing rotational speed and load and considering two
types of defects, small and large. He chose an appropriate
threshold level for AE count and emphasized that selection
of an appropriate threshold depends on the experience
of investigator and type of system. His experiments showed
that upon increasing the speed, the load and also the small
and large defects of the outer race can cause an increase in
the RMS value. However, in the case of defects in the inner
race, the same trend was not observed. Mba and Rao [15]
reviewed AE applications for condition monitoring and
diagnosis of different rotating machines including bearings.

Rahman et al. [16] investigated the application of AE to
monitor rolling contact fatigue on a bearing. They did tests
using a test rig consisting of just a ball instead of an entire
rolling bearing running; the tests were carried out under
constant load and speed for detecting the incipient damage
and damage location. They concluded that AE counting
parameter is an important parameter for the detection of
incipient damage, but their system was simpler and the fault
detection complexity was reduced.

In real industrial environment due to high temperatures,
rotating speeds, and pressures, desired signals for diagnosis
by AE method are always masked by high levels of noise [17].
Hence, to enhance signal to noise ratio (SNR) of AE signals,
utilization of adaptive signal processing techniques is im-
portant. Therefore, there are numerous denoising tech-
niques for noise reduction in the AE signal including
Hilbert–Huang transform, spectral kurtosis, morphological
filters, and wavelet transform (WT) [18–21]. One of the most
important and widely used tools for denoising and pro-
cessing of signals in the time-frequency domain is the
wavelet transform, which has been used successfully in many
studies, alone or in combination with other signal processing
techniques.

Antoni and Randall [22] suggested the use of spectral
kurtosis (SK) for detecting and characterizing transient
signals buried in additive noise. Discrete wavelet transform
(DWT) is widely used in signal denoising of REBs due to its
high resolution in time and frequency domains [23]. However, Amiri and Asadi [24] argued that, due to the fact
that only the approximated component at each level is
decomposed by using the dyadic filter bank, the results of
frequency resolution in higher-level DWT decomposition
are less accurate. Therefore, the wavelet packet transform
(WPT), which is a generalization of wavelet transform (WT)
and DWT, offers better denoising ability in nonstationary
signals such as defected bearings.

Hao et al. [25] did reduce noises and process the AE
signals obtained from a roller bearing with various types of
defects, by means of continuous wavelet transform (CWT).
They applied this CWT to denoised signals and obtaining the
time-frequency spectrum (scalogram) and obtained domi-
nant frequencies that indicate the fault in the bearing.

Parizi et al. [26] studied the statistical parameters such as
kurtosis, crest factor (CF), energy, and counting, before and
after denoising of the signals with the help of WPT to detect
defects of bearings. They reported that the calculation of the
statistical parameters after the removal of low frequency
noise by means of a WPT showed that the values of the
parameters for the defective bearing are more than normal,
and the kurtosis is the most appropriate parameter com-
pared to others for detection of defects in REBs. Selection of
the mother wavelet plays an important role in reducing the
noise of AE signals by means of WT; there are variety of
methods for this purpose such as correlation coefficient,
variance, and energy to entropy ratio. Rodrigues and
DaAZMello [27] used these methods to select optimal
mother wavelet for nonstationary signals like bearings.

Recently, there are new methods based on optimization
denoising tool such as combination of WPT and kurtosis
to entropy ratio (KER) by Hemati et al. [28], WPT and SNR
of the output spectrum by Chacon et al. [29], empirical mode
decomposition (EMD) and fast kurtogram by Fu et al. [30],
and optimized kurtogram method by Lio et al. [31] which
combines kurtogram, Shannon entropy, and autocorrelation
function to identify defects in AE signals.

Besides the application of EMD in rotating machines,
many investigations emphasized the effectiveness of the
EMD method for denoising and obtaining desired features
from other signals. For example, EMD has an application in
biomedical signal processing. Bajaj and Pachori [32] used
intrinsic mode function (IMF) for extracting electroen-
cephalography (EEG) features and then classified seizure
and nonseizure EEG signals by applying least squares support vector machine (LS-SVM). Pryia et al. [33] used EMD for the classification of alcoholic and normal EEG signals. Jain et al. [34] used Riemann–Liouville fractional integral and EMD for electrocardiograph (ECG) denoising.

In this paper, an experiment is conducted to fault diagnosis on angular contact bearings using acoustic emission technology. An artificial line defect is considered in two different sizes (small and large). At first, signals of the bearing are extracted by AE sensors at different conditions, and then denoising of the AE signals is investigated. In the proposed method, after preprocessing, AE signal is decomposed by empirical mode decomposition (EMD), and to obtain better results, the best intrinsic mode function (IMF) based on kurtosis to entropy ratio is selected. After obtaining the desired signal, by using envelope spectrum, frequency of faults is detected. The proposed method shows good accuracy in the fault detection, and the results prove its capability for practical applications.

2. Method

In defective rolling element bearings that are in operation, contact of rolling element with defect in inner or outer race produces AE signals (AE hits) [35]. Other reasons which lead to producing AE signals in REBs are friction and wear between components, shortage or lack of lubricant in the bearings, and also contamination of lubricant [36–38]. In this research, artificial faults caused on inner and outer race of the bearing produce AE signals. The schematic of the intended method in this paper is depicted in Figure 1.

3. Experimental Setup

A test rig for diagnosis of angular contact bearings is used as shown in Figure 2. The schematic of test rig is also shown in Figure 3. In this experiment, seven bearings have been tested, and experiments on intact and faulty bearings have been done. The conditions depend on speed, load, defect size, and type of sensor. Rotating speed is 600, 900, 1200, or 1500 rpm.

The type of bearing is 7202 BEP (SKF), which is angular contact with single row, and it can carry combined loads (radial and axial loads).

Artificial defects caused in two different sizes on inner and outer race of bearings are shown in Figure 4; all defects were caused by electrical discharge machining (EDM) method. The specifications of defects are shown in Table 1; four different load sizes were imposed on REBs, with load types including constant axial and radial (Table 2). At each load, four different rotating speeds were surveyed and data collected. The bearings are mounted inside rigid housings that can be preloaded using screws embedded in outer surface of housing.

Data were acquired with two dual-channel cards (4 channels in total), and data rate of each channel is 2 million dots per second. The card type is PAC: PCI-2 with 18 bit A/D resolution, made by PAC company. Preamplifiers type is PAC: 2/4/6 dB, and the data acquisition software, made by AEwin company, has a complete and reliable connection to the equipment. The setup with sensors and preamplifiers is shown in Figure 5. The sensor, which is used for signal acquisition, is wideband sensor, and it is shown in Figure 6. Furthermore, preloading is done by tightening the left side locking plate screws and torque wrench applying desirable loads to the locking plate screws as shown in Figure 6.

4. SNR of Raw AE Signals

The raw AE signals for different sizes of defects on outer race of the bearing in different conditions have been extracted, and some examples of them are plotted in Figure 7.
As you can see, by increasing the load and speed, the AE signal created by the defect is not visually detectable as the signal to noise ratio (SNR) increased. To investigate the SNR, a proper indicator called kurtosis to entropy ratio (KER) is proposed. In the signals obtained from the defective bearing, the lower the entropy of a signal, the higher and more periodical the concentration of energy, and the higher the SNR. The kurtosis also examines peaks of signal. It gives a measurement of the degree of impulsiveness and peakiness of the signal [10, 28]. Therefore, the use of these two indicators can be a good measure to examine the SNR in received signals as follows:

\[
\text{KER} = \frac{\text{Kurtosis}}{\text{Entropy}}.
\]  

(1)

Kurtosis is described as follows [39]:

\[
K = \frac{N \sum_{i=1}^{N} (x_i - \bar{x})^4}{\left( \sum_{i=1}^{N} (x_i - \bar{x})^2 \right)^2},
\]  

(2)

where \(x_i\) is \(i\)th sample of signal, \(\bar{x}\) is the mean of samples, and \(N\) represents the number of samples.

In addition, entropy is Shannon entropy [40]:

\[
\text{entropy} = - \sum_{i=1}^{N} P_i \times \log P_i,
\]  

(3)

\[\sum_{i=1}^{N} P_i = 1,\]

where \(P_i\) is the distribution of the energy probability:

\[
P_i = \frac{(x_i)^2}{\sum_{i=1}^{N} (x_i)^2}.
\]  

(4)

The results of KER for outer race defect at different conditions are shown in Table 3.

![Figure 4: Defects caused in outer race of the bearing.](image1)

![Figure 5: The setup with sensors and preamplifiers.](image2)

![Figure 6: The applied sensor and loading system and screws.](image3)

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**Table 1: Specifications of defects.**

| Type of defects | Size of defect | Width of defect (mm) |
|-----------------|----------------|---------------------|
| Line defect     | Small defect (SD) | 0.3                |
| Line defect     | Large defect (LD)  | 0.6                |

**Table 2: Different loads imposed on the bearing.**

| Type of loads | Small (SL) | Medium-low (MLL) | Medium-high (MHL) | High (HL) |
|---------------|------------|------------------|--------------------|-----------|
| Imposed momentum (N.M) | 0.7       | 1.7              | 2.7                | 3.7       |
| Axial load imposed on bearing (N) | 400       | 971              | 1543               | 2114      |
| Radial load imposed on bearing (N) | 475       | 1153             | 1832               | 2510      |
Figure 7: (a) Small defect, small load, and 600 rpm. (b) Small defect, medium-low load, and 900 rpm. (c) Small defect, medium-high load, and 1500 rpm. (d) Large defect, small load, and 600 rpm. (e) Large defect, medium-high load, and 600 rpm. (f) Large defect, high load, and 1200 rpm.
From both Figure 7 and Table 3, we can conclude that, by increasing the load and speed, the KER as a measuring tool of SNR is increased and defects can be detected easily, but in low SNR signals it is difficult to detect defects in both the time signal and the frequency spectrum. Hence, the denoising of AE signals is necessary.

| KER     | Speed (rpm) | Small defect | Large defect |
|---------|-------------|--------------|--------------|
|         | 600         | 0.0126       | 0.0217       |
| Small load | 900         | 0.0114       | 0.0219       |
|         | 1200        | 0.0247       | 0.0661       |
|         | 1500        | 0.0825       | 0.2507       |
| Medium-low load | 600         | 0.0203       | 0.0273       |
|         | 900         | 0.0457       | 0.0636       |
|         | 1200        | 0.0947       | 0.2398       |
|         | 1500        | 0.1412       | 0.2474       |
| Medium-high load | 600       | 0.0506       | 0.0499       |
|         | 900         | 0.0441       | 0.2244       |
|         | 1200        | 0.0926       | 0.2426       |
|         | 1500        | 0.1190       | 0.2204       |
| High load | 600         | 0.0664       | 0.0804       |
|         | 900         | 0.0546       | 0.2495       |
|         | 1200        | 0.1006       | 0.2207       |
|         | 1500        | 0.1130       | 0.2337       |

5. Signal Denoising

5.1. Denoising by Empirical Mode Decomposition (EMD). EMD is designed to analyze nonlinear and nonstationary time series by decomposing them into intrinsic mode functions (IMFs) and residual [41]:

![Figure 8: Decomposition of the signal into different IMFs.](image)

From both Figure 7 and Table 3, we can conclude that, by increasing the load and speed, the KER as a measuring tool of SNR is increased and defects can be detected easily, but in low SNR signals it is difficult to detect defects in both the time signal and the frequency spectrum. Hence, the denoising of AE signals is necessary.
\[
\varphi(t) = \sum_{j=1}^{n} c_j(t) + r_n(t),
\]

where \(c_j(t)\) and \(r_n(t)\) are the \(i\)th IMF and the trend term (residue) obtained by decomposition of the original signal \(\varphi(t)\). For example, for a small defect with condition of small load and speed of 600 rpm, the EMD results are shown in Figure 8.

As you can see, the signal is decomposed into several IMFs, but in this level the proper IMF should be chosen; however, selecting the proper IMF, which shows the faulty state, is not easy and some criteria should be investigated to choose the proper IMF.

5.2. The Proposed Method. One of the most effective ways in diagnosis and fault detection of bearings is to monitor the value of the kurtosis of the acquired signal [42]. Entropy is also commonly used in signal processing and condition monitoring [43, 44]. Adding a little noise to a signal will cause a significant change in the value of entropy. Thus, KER can be appropriate for identifying the signal components with the highest fault characteristics.

For selecting the denoised signal, in this paper, at first in the preprocessing stage, smoothing based on moving average method has been carried out on the raw signal for better results in signal decomposition especially for low SNR signals. After that, the obtained signals were decomposed by EMD, then KER values of all IMFs were calculated, and the highest value was selected as a desired signal. For the test with small defect with condition of small load and speed of 600 rpm, the KER values of all IMFs are shown in Figure 9.

As you can see, the IMF 7 has the highest KER, and it has little noise and is good for the fault detection. Accordingly, the denoised signal is depicted in Figure 10.

This process has also been done for other signals, and the results are shown in Figure 11.
Figure 11: The denoised signals for other conditions. (a) Small defect, medium-low load, and 900 rpm. (b) Small defect, medium-high load, and 1500 rpm. (c) Large defect, small load, and 600 rpm. (d) Large defect, medium-high load, and 600 rpm. (e) Large defect, high load, and 1200 rpm.
As you can see, by the proposed method, signals are improved, and noise is reduced.

### 6. Fault Detection

There are different methods for detecting the location of fault in the components of the REBs by extracting the characteristic defect frequency. The envelope spectra are a common tool for this purpose. The characteristic defect frequencies $F_{BPFO}$ and $F_{BPFI}$ are those of the outer race and inner race, respectively. They can be theoretically calculated as follows [45]:

$$F_{BPFO} = \frac{n_b}{2} \cdot f_s \left( 1 - \frac{d_b \cos \alpha}{d_p} \right),$$

$$F_{BPFI} = \frac{n_b}{2} \cdot f_s \left( 1 + \frac{d_b \cos \alpha}{d_p} \right).$$

### Table 4: Frequencies of the bearing in different speeds.

| Shaft speed (rpm) | 600  | 900  | 1200 | 1500 |
|-------------------|------|------|------|------|
| $F_{BPFO}$ (Hz)   | 40.272 | 60.408 | 80.543 | 100.679 |
| $F_{BPFI}$ (Hz)   | 59.728 | 89.592 | 119.457 | 149.321 |

![Envelopespectrumofsignalsbeforedenoising.(a)Smalldefect,smallload,and600rpm.(b)Smalldefect,medium-lowload,and900rpm.(c)Smalldefect,medium-highload,and1500rpm.(d)Largedefect,smallload,and600rpm.(e)Largedefect,medium-highload,and600rpm.(f)Largedefect,highload,and1200rpm.](image-url)
where $f_s$ is the frequency of the shaft, $n_b$ is the number of rolling elements, $d_b$ is the ball diameter, $d_p$ is the pitch diameter, and $\alpha$ is the contact angle. Table 4 shows the calculated characteristic frequencies of the bearing in different speeds.

In order to extract the characteristic defect frequency via AE signals, the envelope spectrum of the signals before applying the proposed method for denoising is depicted in Figure 12, and then the denoised signals by the proposed method are presented in Figure 13 for outer race at different operational conditions.

As can be seen from the above figures and compared with theoretically characteristic defect frequency (Table 4), this method detects faults successfully. Even in conditions with low SNR (Figures 7(a) and 7(d)) as shown in Figure 13, it can detect faults on both inner and outer race with good accuracy.

6.1. Faults on Inner Race. The process of detecting defects on inner race, in a similar way to outer race, is done. For example, for small defect with medium-low load and speed of 900 rpm, the process is depicted in Figure 14.

Envelope spectrum for other datasets, where faults are in inner race, at different operating conditions before and after applying the proposed method is depicted in Figures 15 and 16, respectively.

As can be seen from above figures and compared with theoretically characteristic defect frequency (Table 4), this method detects faults successfully.
Figure 14: Fault detection on inner race. (a) Raw signal. (b) Denoised signal. (c) Envelope spectrum and fault detection.

Figure 15: Continued.
**Figure 15:** Envelope spectrum of signals before denoising. (a) Small defect, medium-high load, and 1500 rpm. (b) Small defect, high load, and 600 rpm. (c) Large defect, small load, and 1500 rpm. (d) Large defect, medium-low load, and 1200 rpm. (e) Large defect, high load, and 600 rpm.

**Figure 16:** Envelope spectrum of signals after denoising. (a) Small defect, medium-high load, and 1500 rpm. (b) Small defect, high load, and 600 rpm. (c) Large defect, small load, and 1500 rpm. (d) Large defect, medium-low load, and 1200 rpm. (e) Large defect, high load, and 600 rpm.
7. Conclusion

This paper is intended to present an efficient and accurate method, AE method, for fault detection of REBs. For this purpose, an angular contact bearing was selected and an experimental study was carried out.

In this work, AE signals were gathered and then denoised by EMD, and appropriate IMF based on KER was selected. KER indicator was able to successfully choose optimized IMF with the highest SNR. Then, defect frequencies were extracted by envelope spectrum of desired signal, and defects were detected. The experiment was performed under different conditions such as defect size, loading, and rotational speed.

The results demonstrate the effectiveness and robustness of the proposed method in detecting defects on both inner and outer race even in the cases of small defects and low SNR AE signals. The proposed method has been implemented successfully for a defect size of 0.3 mm (small defect) on the outer race with a small load and speed of 600 rpm, and it showed a fault frequency of 0.04 kHz. Furthermore, the proposed method precisely detected the small defect on the inner race with medium-low load and speed of 900 rpm.

Detection of small defects with a small load and small speed could be one of the advantages of the proposed method. However, the method still needs to be implemented on different conditions and cases and for higher loads with higher speeds. Moreover, there are some efforts to improve the performance of diagnosing; for example, if the speed of the machine is not constant, the current approach shall be modified. In the future, the proposed method can be investigated in terms of the diagnosis of other rotating components such as gears.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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