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Experimental Study on Condition Monitoring of Low Speed Bearings : Time Domain Analysis

Eric Y. Kim [1], Andy C. C. Tan [1], Bo-Suk Yang [2] and Vladis Kosse[1]

[1]*School of Engineering Systems, Queensland University of Technology, Australia*
[2]*School of Mechanical Engineering, Pukyong National University, South Korea*

Abstract: In condition monitoring of low speed rolling element bearings (REBs), traditional techniques involving vibration acceleration may not be able to detect a growing fault due to the low impact energy generated by the relative motion of the components. This study presents an experimental evaluation for incipient fault detection of low speed REBs by using an acoustic emission (AE) sensor and an accelerometer. A low speed fault simulation test rig was developed to simulate common machine faults with shaft speeds as low as 10rpm under loading conditions. Tests were conducted on the rig with various seeded defect bearings. This study reveals the best frequency bandwidth and suitable parameters for condition monitoring using AE signal for early detection of low speed bearing defects by means of statistical parameters in time domain.

Keywords: Acoustic Emission, Condition Monitoring, Rolling Element Bearing, Low Speed Machinery.

1. Introduction

Rolling element bearings (REBs) are critical components in rotating machines and are often expected to carry heavy loads and operate at high efficiency and reliability. An undetected failure can cause consequential damage to the machine and human casualty as well. Numerous methods have been developed to detect faults in rolling element bearings. Most of the research on bearing diagnosis can be categorized in time domain and frequency domains. The RMS, crest factor, probability density moments (skewness, kurtosis) are the most popular statistical time domain parameter for bearings [1]. In the frequency domain, the enveloping method, also known as demodulation or HFRT (High Frequency Resonance Technique), is among the most popular technique for detection of localized bearing defects [2-3]. In low speed machine condition monitoring, traditional techniques involving vibration acceleration may not be able to detect a growing fault due to the low impact energy generated by the relative moving components. As an alternative to accelerometers, Acoustic Emission (AE) has also been increasingly used, especially for the detection of incipient bearing defects.

Application of AE technology can be seen in machine tool wear monitoring, machinery and structural health monitoring, bearings condition monitoring and tribological process monitoring. Mba and Rao [4] provided a review on the state-of-the-art of AE technology in machine condition monitoring. Yoshioka [5] have shown that AE technique can detect defects before they appear in the vibration acceleration range and can also identify possible sources of AE generation during a fatigue life test of thrust ball bearing. Shiroishi et al [6] compared acceleration signal and AE technique for the detection of different sizes of localized defects using an ALE (Adaptive Line Enhancer) and HFRT (High Frequency Resonance Technique). They concluded that the acceleration was comparable to or better than the AE at detecting the different types of defect. However, the results by Shiroishi are problematic in low speed situations. Jamuludin and Mba [7] showed promising results of AE application for low speed machine. Most of their AE applications have been focused on frequency range of 100kHz to 1MHz using specialized data acquisition/analysis system. This study focuses on the frequency range up to 100kHz to enable the high frequency AE signal to be captured by general vibration DAQ systems.

Although extensive literature is now available on diagnosing REB defects using vibration analysis for medium and high speed machines, there is limited literature on the application of the AE technique for low speed machinery. This article presents experimental study for incipient fault detection of low speed bearing. An AE sensor was used to determine the effectiveness of the sensor in detecting an incipient failure at low speed. An elaborate test rig was developed to simulate common machine defects running with a shaft speeds as low as 10rpm. Tests were conducted on the rig with various seeded defect bearings. This paper reveals the best frequency bandwidth of AE signal for early detection of low speed bearing defects in terms of time domain statistical parameters.

2. Time Domain Statistical Parameters for Condition Monitoring of REBs

The time series signal can be used to perform fault and failure diagnosis by analysing the vibration or acoustic data obtained from the equipment. Statistical methods are widely used to investigate the random characteristics of a physical system. It is important to be able to summarize the data obtained and be able to draw meaningful and useful features. One of the simplest methods is to use overall root-mean-square (RMS) level and crest factor, i.e., the ratio of peak value to RMS. This method has been applied with limited success in the detection of localized defects [8-9]. Probability density has also been used for bearing defect detection [9-10].

The aim of this study lies in determining the best frequency band and the best parameter for early detection of low speed REB. This study examines popular 9 parameters: root mean square (RMS), Crest Factor (CF), Peak Value (PK), skewness (SK), kurtosis (KT), entropy (ENT), histogram upper bound (UB), histogram lower bound (LB) and RMS frequency (RMSF). They are defined as following equations for time series vector $\{X_i, i = 1,..., N\}$.

$$RMS = \sqrt{\frac{\sum_{i=1}^{N} X_i}{N}}, \quad PK = \max(|\ X\ |), \quad CF = \frac{PK}{RMS} \tag{1}$$

$$SK = \frac{\frac{1}{N}\sum_{i=1}^{N} X_i^3}{\sigma^3}, \quad where\ ,\ \sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_i - mean\ (\mathrm{X}))^2} \tag{2}$$

$$KT = \frac{\frac{1}{N}\sum_{i=1}^{N} X_i^4}{\sigma^4}, \quad RMSF = \sqrt{MSF}, \quad where\ , MSF = \frac{\sum_{i=1}^{N} \dot{X}_i^2}{4\pi^2 \sum_{i=1}^{N} X_i^2} \tag{3}$$

$$UB = \max(\mathrm{X}) + \frac{1}{2}\frac{\max(\mathrm{X}) - \min(\mathrm{X})}{N-1}, \quad LB = \min(\mathrm{X}) - \frac{1}{2}\frac{\max(\mathrm{X}) - \min(\mathrm{X})}{N-1} \tag{4}$$

Entropy is usually known as a measure of uncertainty of a process. For a set of events with probability density function (PDF) of $\{X_i, i = 1,..., N\}$ the Shannon entropy is defined as [11]

$$H(P) = -\sum_{i=1}^{N} p_i \log\ p_i \tag{5}$$

where, p_i are the probabilities computed from distribution *X*.

3. Low Speed Test Rig and Seeded Defective Bearings

The Low Speed Test Rig was developed to simulate common machine faults on low speed machinery [12]. It is a unique test rig that enables modelling of bearing and gearbox faults under different loading conditions and verification of condition monitoring techniques at very low speed as low as 10 rpm. An AE sensor and an accelerometer were located on the top of the bearing housing as shown in the Fig. 1 (a). The AE sensor was held in position by using a magnetic holder.

A low frequency resonance type AE sensor, ‘R3a’ from Physical Acoustics Corporations (PAC), which has an operating frequency range of 25-530 kHz was used. PAC’s AE data acquisition and analysis system (PCI-2) was used to record continuous AE signal and acceleration wave forms as shown in the Fig. 1 (b). A laptop computer was fitted with a PCI board to form a Micro-DiSP system capable of 18-bit, 10 MHz A/D conversion, on-board processing. 15 to 20 time wave forms were captured for each condition. The feature extraction and analysis were performed on MATLAB 7.0.

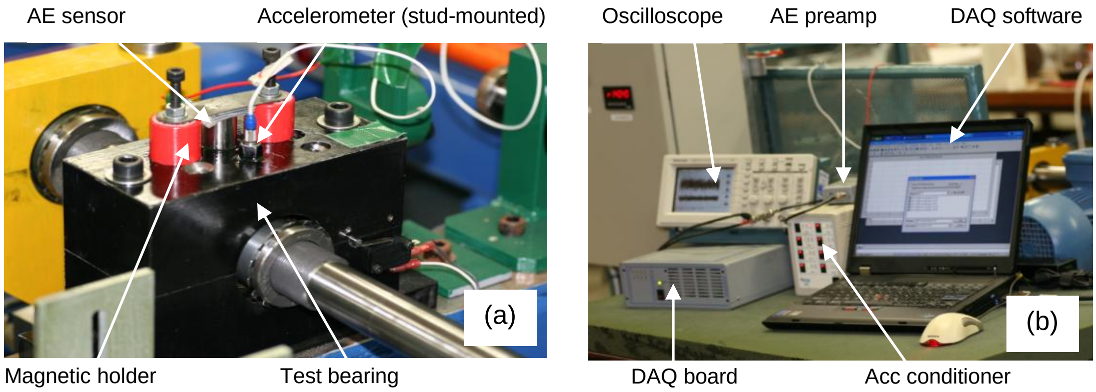

Fig. 1 Location of AE sensor and accelerometer (a) and instrumentation (b)

The bearing used in this study is cylindrical roller bearings, SKF NF307 and N307 which have a separable inner ring and outer ring. The test bearing enable an easy access to the raceway for seeded defects and to observe the surface condition. Two types of seeded defects were made on the raceway perpendicular to the direction of roller motion as shown in the Fig. 2. Figs 2 (a) and (c) simulate a hair-line scratch generated by using a diamond bit. These defects are to simulate crack type defects. The rest of figures in the Fig. 2 show spall-type defects which were made by grinding the surface using a high speed air-grinding tool. The type and size of seeded defects are listed in the Table 1. OF and BF represent a spall type defect on inner-race, outer-race and roller, respectively. IFC and OFC denote crack type defect on inner-race and outer-race, respectively. The last number in the name represents the size of defects, namely 1 for a small defect, 2 for a medium size defect.

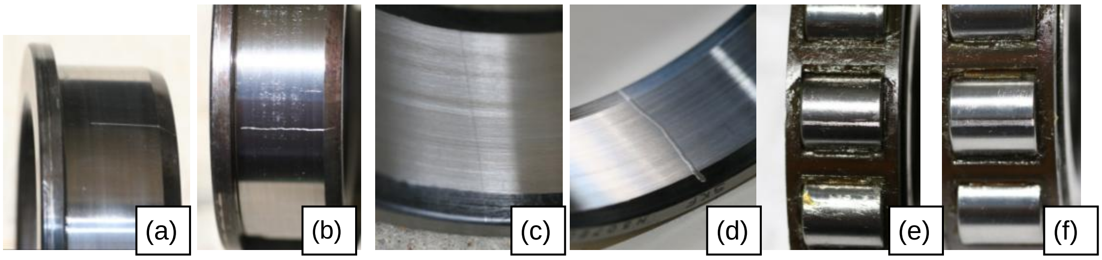

Fig. 2 Seeded defects on the bearing. (a) IFC1, (b) IF1, (c) OFC1, (d) OF1, (e) BF1, (f) BF2

Table 1 Seeded defective bearings

Type of defective bearing		Width (mm)
Crack type hair line on outer-race (OFC1)	(c)	0.1
Spall type small line on outer-race (OF1)	(d)	0.7
Crack type hair line on inner-race (IFC1)	(a)	0.1
Spall type small line on inner-race (IF1)	(b)	0.6
Spall type small line on roller (BF1)	(e)	1.0
Spall type medium line on roller (BF2)	(f)	1.6

AE technique has been successfully applied in the bearing fault detection in the high frequency range over 100kHz [6-7]. However, high frequency AE measurement requires a high sampling rate, normally 1~5MHz and is one of the shortcomings of AE application. Hence, a highly specialized data acquisition system is required. The situation is even worse in low speed applications. Longer data recording time is required in low speed condition monitoring in order to observe mechanical defect frequencies. This has limitation in hardware in terms of memory and data storage. AE data are normally analysed in the hit-based or continuous time-based, not in the frequency spectrum due to high sampling frequency. This also restricts the application of many advanced signal processing techniques in AE signal processing. Therefore, this study focuses on the frequency range up to 100kHz where the data can be captured by general vibration data acquisition systems and enabled further signal processing techniques, such as noise cancellation or wavelet analysis. In this study AE signals were captured with a sampling frequency of 500 kHz for 10 sec.

4 Results and Discussion

Fig. 3 shows a sample plots of all parameters extracted from the AE signals of a normal bearing and a spall type outer-race defective bearing (OF1) at 140 rpm. Each column represents different band-pass filter ranges used (BPF1:5-15kHz, BPF2:15-25kHz, BPF3:25-35kHz, BPF4:35-55kHz, BPF5:55-75kHz, BPF6:75-100kHz). RMS and Entropy value are the best parameters which clearly show the distinction between normal and defective bearing with a small deviation regardless of band-pass filter range. Peak value also shows a consistent increase over the filter ranges. RMS frequency (RMSF) is sensitive to BPF range and good with BPF 3, 5 and 6. Other parameters (Crest Factor, Skewness, Kurtosis and Upper Bound) show large fluctuation. Comparing the difference in average value of two conditions is not an appropriate method to examine the sensitivity of the parameter to the defect. This is because their units are not the same and some parameters have large deviation. For this reason, in this study it is assumed that better parameter is those which has bigger difference in mean values and smaller standard deviations. This idea leads a new index, *seperation index* (SI, equation (6)) which is defined as the difference of the mean values of the two conditions over the sum of the standard deviations. SI expresses the graphical difference of two data groups of data and is non-dimensional.

$$SI = \frac{Mean\ (P_{defective}) - Mean\ (P_{healthy})}{Std\ (P_{defective}) + Std\ (P_{healthy})} \tag{6}$$

where, $P_{defective}$ and $P_{healthy}$ represent parameter value of the defective and the healthy bearing, respectively, *Mean* and *Std* denote the mean value and the standard deviation of the parameter, respectively.

Fig. 4 shows the SI of all parameters from OF1 bearing at 140rpm and 50rpm. It is noted that SI of RMS and Entropy value result in high SIs. This means these values show good distinctions between normal and defective bearing and can be used effectively as an indicator for condition monitoring. At 140 rpm, BPF5 is the best frequency band for all parameters whereas at 50rpm RMS and Entropy in BPF6 have the best results. In BPF5 and BPF6 RMS frequency is a good indicator for the defect detection especially at low speed. This result can be explained by the fact that higher frequency of AE signal is generated by the defect. Fig. 5 shows SIs from the OF2 bearing at 140rpm and 50rpm. The results show very similar results with those from the OF1 bearing with the exception of RMSF.

Fig. 6 shows the results of SIs from the IF1 bearing. At 140 rpm, RMS and Entropy have high SI in BPF2. RMS frequency shows the best SI in BPF6, however the results are inconsistent in overall. At 50 rpm, RMS and Entropy give high SIs in BPF1 and BPF2. BPF6 is the best for RMS, Entropy and RMS frequency.

5 Conclusions

This study presented experimental evaluation for incipient fault detection of rolling element bearings under low speed situations. AE signals were to evaluate the effectiveness through statistical parameters. Six band-pass filter ranges up to 100kHz were used to find the best frequency band. Separation Index (SI) was introduced to evaluate the effectiveness of the parameters for detecting an incipient defect by examining distinctive increase of parameters between the normal and defective bearing. The following conclusions were obtained.

- RMS and entropy value were the best parameters which clearly show distinction between normal and defective bearing regardless of speed and type of the defect.
- For outer-race defect, BPF2 and BPF5 were good for high speed at 140 rpm, whereas BPF1 and BPF6 were good for low speed at 50 rpm. RMS frequency in BPF5 and BPF6 was a good indicator especially at the low speeds.
- For inner-race defect, RMS and entropy in BPF2 were the best at 140rpm, while BPF6 is the best region for 50 rpm.

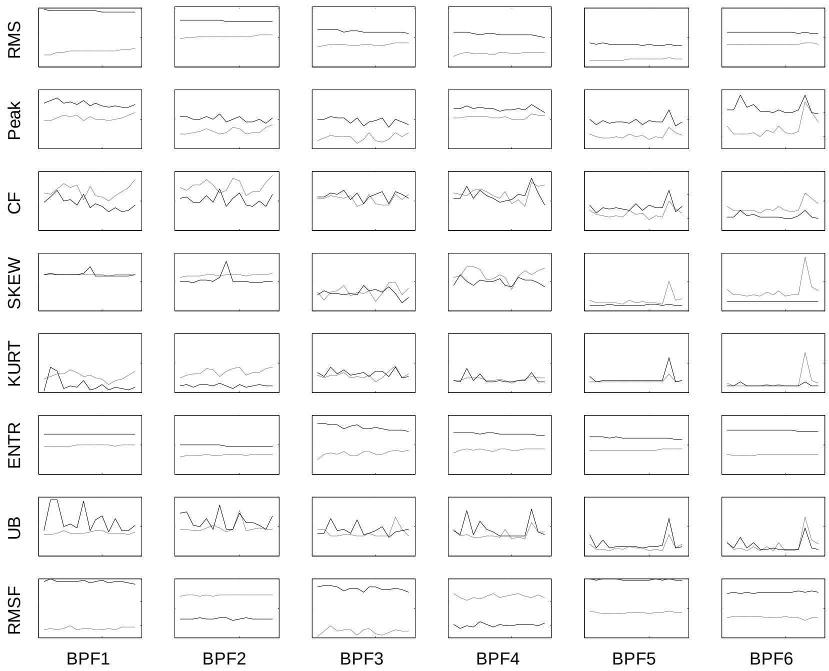

Fig. 3 Parameters with different BPFs at 140 rpm (dotted line: normal bearing, solid line: defective bearing(OF1), BPF1:5-15kHz, BPF2:15-25kHz, BPF3:25-35kHz, BPF4:35-55kHz, BPF5:55-75kHz, BPF6:75-100kHz).

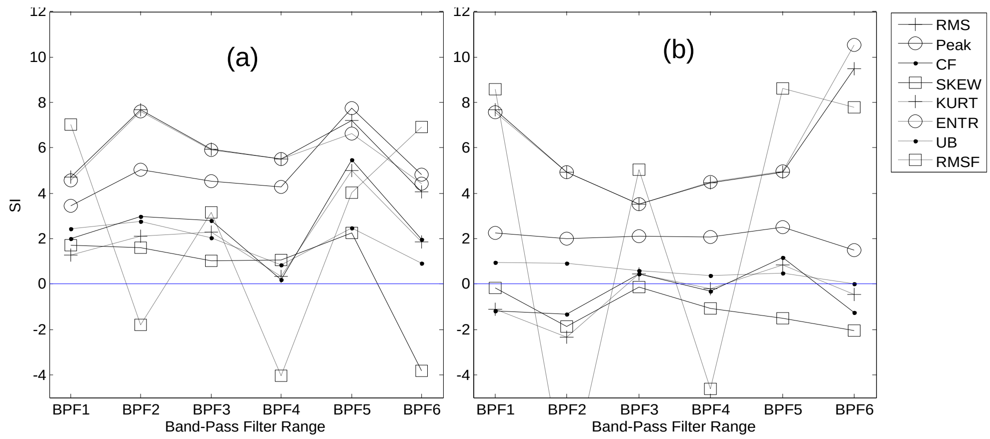

Fig. 4 SI of parameters from OF1 bearing at 140rpm (a) and 50rpm (b).

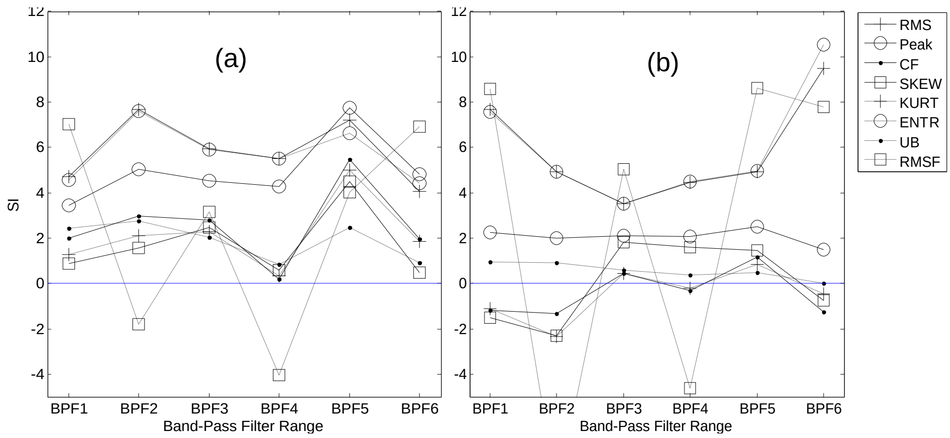

Fig. 5 SI of parameters from OF2 bearing at 140rpm (a) and 50rpm (b).

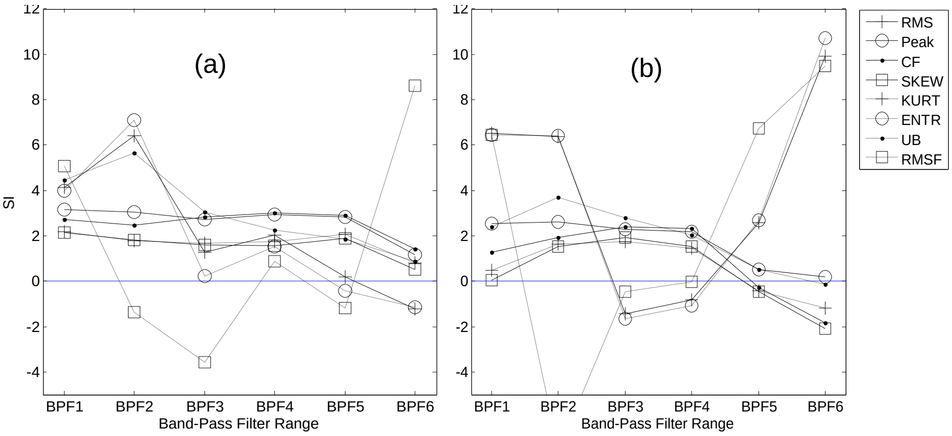

Fig. 6 SI of parameters from IF1 bearing at 140rpm (a) and 50rpm (b).

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