Four-Stage Degradation Physics of Rolling Element Bearings

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ABSTRACT

Rolling element bearings are a critical component of rotating machinery. Timely prediction of bearing faults become of great importance to minimizing unscheduled machine downtime. Most of the bearings experience gradual condition degradation due to repeated mechanical loads. Vibration signals are often used for bearing diagnosis and prognosis with a predefined threshold. However, false (positive/negative) alarms are often observed, thus leading to unnecessary downtime and expensive corrective maintenance. This is mainly because the thresholds are defined without accounting for bearing physics and a great deal of uncertainty in manufacturing and operation condition. To resolve this difficulty, this study aims at investigating the degradation physics of rolling element bearings using a vibration signal, while accounting for bearing physics and a substantial amount of uncertainty in manufacturing and operation condition. First, bearing feature engineering is thoroughly studied through time domain and frequency domain analyses. This study proposes the features that are most sensitive to the change in bearing physics. Second, bearing degradation physics is investigated so that the bearing degradation process can be modeled into four degradation stages. To the end, the proposed idea is demonstrated with vibration data measured from rolling element bearings, which experience accelerated life tested to simulate naturally induced degradation. This study will benefit to enhance physical understanding for bearing faults in various engineering applications.

1. INTRODUCTION

Rolling element bearings (REBs) are the most critical component of industrial applications. Therefore condition monitoring techniques have been widely applied to measure the REBs' defects using vibration and acoustic measurements, temperature measurements and wear debris analysis. Among these, vibration measurements are the most widely used (Tandon & Choudhury, 1999).

By the advantages of vibration analysis, various feature extracting techniques have been developed for several decades. There is no unique way to categorize feature extraction methods used for bearing diagnostics and prognostics, but Yan, Qiu, and Iyer (2008) proposed a taxonomy of vibration-based feature extraction method. A number of admirable review articles are possible that have addressed the state-of-the-art of the related techniques, among which some representative ones are given in (Lee, Wu, Zhao, Ghaffari, Liao, & Siegel, 2014, Jardine, Lin, & Banjevic 2006).

On the other hand, the studies carried out by many researchers pertaining to the physics of bearing degradation in the field of tribology and dynamics. Although the failure modes and mechanisms of bearings vary widely due to their various operating conditions, it has been proposed that in cases where the rolling element bearing is properly operated, the main mode of failure is material fatigue due to Hertzian contact (Sadeghi, Jalalahmadi, Slack, Raje, & Arakere 2009). Once an incipient fault is generated by material fatigue, rolling contact wear is the most frequently seen phenomenon.

In practice, signals generated by transient vibrations in rolling bearings due to structural defects are non-stationary in nature. To solve this problem, many research studies have considered the vibration responses (Patel, Tandon, & Pandey, 2010, Ahmadi, Petersen, & Howard, 2015) and modeled the wear process of bearing (Hanson & Keer, 1992, El-Thalji & Jantunen, 2014). However, each prior study is a bit apart from an actual situation of REBs' degradation.

This study present a descriptive four degradation stages model that includes not only the effective vibration analysis also the understanding of bearing degradation physics.

Based on the work performed herein, a good correlation between physics and measured data can be seen.

2. SPECTRAL ENERGY FEATURE EXTRACTION FROM BEARING CHARACTERISTIC FREQUENCIES

Generally, we can easy to trace condition of bearing by time domain features. One of the most traditional time-domain feature extraction methods is to calculate descriptive statistics of vibration signals. These are root mean square (RMS), peak, kurtosis and so on. RMS and peak are good for measuring level of degradation with time. In case of rolling element bearing, amplitude of RMS/Peak rises rapidly when it closed to failure. In case of kurtosis, for a normal state, value of kurtosis is 3. It goes up when crack evolves on the inner/outer race or contamination.

One of the most famous frequency domain analysis is FFT analysis. However, in the bearing fault cases, we do not see a big spike or peak occurring at the frequency that each ball passes over crack because of amplitude-modulating effect. So envelop analysis used for diagnostics and prognostics where faults have an amplitude-modulating effect on the characteristic frequencies of the machinery. When the ball strikes the defect, a shock is produced, exciting high frequency resonances of the structure. The presence of such a defect causes a significant increase in the vibration level. The frequency of the shocks can be calculated by bearing characteristic frequencies (BCFs).

As mentioned in previous section, BCFs are critical features to diagnose and predict REBs' failure. The energy contribution of characteristic spectral components to the envelop spectrum of vibrations can be a good indicator of wear evolution that localized fault grows to the distributed fault (Dolenc, Boškoski, & Juričić, 2016). The filter output is used to calculate the power contribution of a particular frequency component in a signal as in Eq. (1).

$$E_f = \frac{1}{T}\int \left|e_f(t)\right|^2 dt \tag{1}$$

where $e_f(t)$ is envelope signal filtered around frequency *f*, and *T* is the time duration of the measurement (Dolenc et al., 2016).

In case of inner race defect, we used spectral energy features that were obtained from the ball pass frequency inner race (BPFI), E_{BPFI} , harmonic signals of the BPFI($E_{BPFI_{nX}}$, $E_{BPFI_{nFTFI}}$), and residual signals of the BPFI ($E_{Residual}$) (Eq. (2)-(5)).

$$E_{BPFI} = \{ f \mid f = m \times BPFI \} \tag{2}$$

$$E_{BPFI_{nX}} = \{ f \mid f = m \times BPFI \pm nf_r \} \tag{3}$$

$$E_{BPFI_{nFTFI}} = \{ f \mid f = m \times BPFI \pm nFTFI \} \tag{4}$$

$$E_{Residual} = \{ f \mid f \notin (BPFI \cup BPFI_{nX} \cup BPFI_{nFTFI}) \} \tag{5}$$

$$m, n \in \mathbb{N},\ \ m, n \neq 0$$

where f_r is shaft frequency and FTFI is fundamental train frequency inner race.

3. INVESTIGATION OF BEARING DEGRADATION PHYSICS

3.1. Degradation Process along to Wear Evolution

Rolling contact wear is quite complex phenomenon that might involve different wear mechanismsand different stress concentration mechanisms (El-Thalji & Jantunen, 2014). However, it has been proposed that in cases where the rolling element bearing is properly loaded, lubricated, installed, and kept free of foreign contaminants, the main mode of failure is material fatigue. Once an incipient fault is generated by material fatigue, rolling contact wear is the most frequently seen phenomenon (Sadeghi et al., 2009).

Therefore, the modelling of wear evolution in REBs is simply described with help of the following equation of motion:.

$$M\ddot{X} + C\dot{X} + KX = F \tag{6}$$

where *M*, *C*, and *K* are respectively matrices of system mass, damping coefficient and stiffness. *F* is the excitation force matrix. The change of surface topology due to wear evolution affects stiffness and excitation force over the lifetime.

3.2. Brief Descriptive Four-stage Degradation Model for Rolling Element Bearings

The surface topographical changes during the wear evolution process generate dynamic responses. Thus we can regard features from vibration measurement as a dynamic response which is bearing health-related index.

Recently, El-Thalji and Jantunen (2014) presented a descriptive model of wear evolution which is composed of

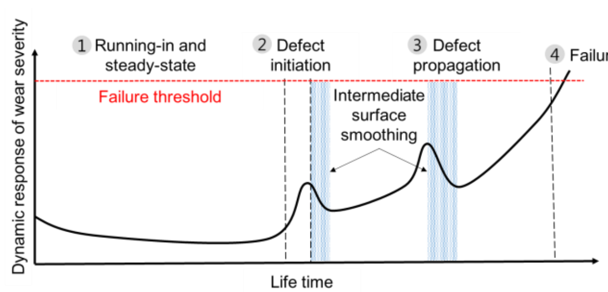

Figure 1. A descriptive four-stage degradation model for REBs

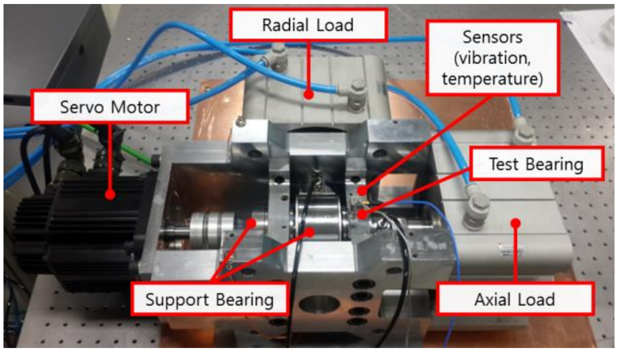

Figure 2. The accelerated degradation life test-bed

five stages. However, in the perspective of vibration analysis, running-in and steady-state stage hard to distinguish each other. When the defect is initiated, defect propagate until failure therefore vibration response has growing up. During defect propagation, we can inspect the signal decreases such as shaded regions in Fig.1 due to the asperity smoothing on the surface.

Consequently, we can make a scenario of whole life of REBs as shown in Fig.1. In this work, we recomposed a previous model to four-stage degradation model which made up of 1) Running- and steady-state, 2) Defect initiation, 3) Defect propagation with an intermediate surface smoothing, and 4) Failure. When a proposed model was constructed, we considered that this model and condition monitored results might lead to be well matched each other.

4. A CASE STUDY

4.1. Experimental Setup

As shown in Fig 2, an angular contact ball bearing (NSK 7202A) is used for test with supported by two angular contact ball bearings (NSK 7205A) and two roller bearings (NSK NF207). The vibration of bearing is measured on bearing housing using a tri-axial accelerometer (PCB, Model 356A15). The temperature of test bearing is sensed by the thermocouple equipped on the bearing outer race. The measured vibration signals were sampled at 10 kHz with 10 seconds interval. At the end of the experiment, fault occurred in the inner-race of test bearing.

4.2. Demonstration with Vibration Data Measured from Test-bed

Experimental results in Fig. 3 indicate the dynamic response of bearing degradation process. First half of lifetime appears the steady-state response and we can ignore the running-in effects. After that a sudden arising comes out due to defect initiation. During fault propagation, we can observe fault smoothing effects in Fig. 3. When the asperity of defects smoothed, following the crack newly evolves with that responses of bearing getting reascend. This phenomenon appears repeatedly along to bearing degradation. After all, dynamic response reaches to the failure threshold and test-bed stopped.

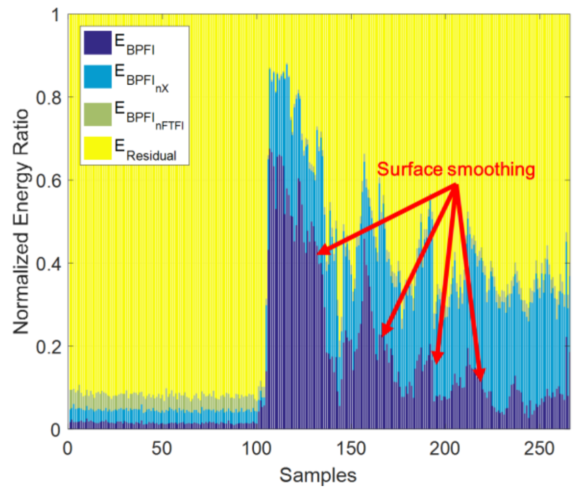

Figure 3. Normalized energy-based features ratio of vibration acceleration in laboratory test

5. CONCLUSION

Rolling element bearings are a critical component of rotating machinery. Timely prediction of bearing faults become of great importance to minimizing unscheduled machine downtime. For successive prognostic of REBs, it is necessary to achieve deeper understanding of physics and to find more effective features from measured data. We extract the features that are most sensitive to the change in bearing physics. In addition, this study present a descriptive four degradation stages model that includes not only the effective vibration analysis also the understanding of bearing degradation physics. Based on the work performed herein, a good correlation between physics and measured data can be seen.

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BIOGRAPHIES

Keunsu Kim received his B.S. degree from Seoul National University, Seoul, Republic of Korea, in 2013. He is a Ph.D. student at the Department of Mechanical and Aerospace Engineering in Seoul National University. His research area includes prognostics and health management for machine tools. He received an award including the IEEE PHM Data Challenge Competition Winner (2014) and the PHM Society Data Challenge Competition Winner (2015).

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