A Review of Methods for Condition Monitoring of Large, Slow-rotating Bearings

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ABSTRACT

Rolling element bearings (REBs) are key components in most rotating machinery. Large, slow-rotating REBs found in heavy industrial applications like offshore drilling equipment, steel- and paper mills and wind turbines are the topic of this paper. In such applications, bearings are normally non-redundant components, meaning bearing failure will cause system downtime. Execution of unplanned, on-site maintenance may be costly, time-consuming and difficult or even impossible. Implementation of condition-based maintenance strategies is a means to reduce total lifecycle costs by improving utilization of component lifetime while maintaining system availability. Condition monitoring systems capable of early, reliable detection and diagnosis of incipient faults is necessary for the planning of maintenance actions in due time. In this paper, novel and established condition monitoring methods are surveyed for this purpose. Prominent challenges are speed variations, non-stationary behavior, and low signal-to-noise ratio. Advanced signal processing methods, including order tracking and resampling from time to angular domain, higher order statistics, and cyclic spectral analysis are presented. Methods for data acquisition and maintenance decision making are also discussed. A discussion of the surveyed methods and suggestions for future research concludes the paper.

Keywords: Slow-rotating machinery, Condition Monitoring, Advanced Signal Processing, Large Roller-element Bearings, Diagnosis

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1. INTRODUCTION

Roller Element Bearing (REB)s are essential mechanical components, used in virtually all types of rotating machinery. The range of types, variants and sizes match the diversity of applications. This paper aims to provide insight into condition monitoring (CM) methods suitable for large, slow-rotating bearings, typically found in paper and steel mills, offshore drilling equipment, wind turbines and similar heavy industries. It is difficult to define strict limits with regards to size and speed. However, other similarities can be defined. Replacement and maintenance is expensive, time-consuming, and in many cases not possible on site. Combined with operational non-redundancy, this motivates CM for increased control of machine health. The ability to utilize more of the component lifetime while reducing the risk of unexpected failure potentially reduces lifecycle costs.

A survey presented at the Noble Analyst Day 2012 mapped causes of downtime on drilling rigs in the period 2011-December 2012 [1]. Looking at downtime by equipment on all rig types, top drive failure is the second largest contributor, with a total of 13 %. Further analysis shows that bearing failure is the main overall cause of downtime in top drives, despite variations between manufacturers and types. In top drives, a large tapered roller thrust bearing supports the weight of the drill string. With an outer diameter of up to 750mm and a rotational speed of 240 rpm (4 Hz), top drive main bearings qualify as both large and slow-rotating. The statistics show a potential for improved CM of large, slow-rotating bearings in the offshore industry.

2. CONDITION BASED MAINTENANCE STRATEGIES

Most systems require maintenance to a certain extent. The approach to maintenance is influenced by factors such as consequences of failure, maintenance cost, and failure rates. Development in technology has enabled more advanced maintenance strategies beyond corrective and preventive maintenance strategies. Lee et.al [2] reviewed the field of Prognostics and Health Management (PHM) for rotating machinery, presenting a generalized methodology for selection and implementation of a maintenance strategy. A maintenance transformation map is proposed as a guideline for maintenance strategy selection based on system complexity and uncertainty. Typically, condition monitoring of bearings falls in the Condition-Based Maintenance (CBM) category. However, as bearings get larger, maintenance is more complicated. External factors like long spare part lead times, complicated maintenance procedures and limited maintenance opportunities add complexity, justifying strategies like PHM. Common for both CBM and PHM is the need for reliable health assessments for the equipment. Jardine et.al [3] reviews generalized diagnostics and prognostics methods for successful implementation of Condition Based Maintenance (CBM), identifying data acquisition, data processing and maintenance decision-making as the three main steps. The influence of bearing size and speed on these steps is discussed in the next section.

3. CHALLENGES OF LARGE, SLOW BEARINGS

Large and slow-rotating bearings pose challenges for conventional condition monitoring methods. Compared to smaller bearings operating at higher speeds, prominent challenges include low vibration energy, sensitivity to speed fluctuations and a need for accurate localization in the frequency domain to isolate fault frequencies.

It is commonly accepted that discrete faults in bearings cause impulse-like impacts when the fault interacts with another rolling surface. This impact triggers a transient response at resonance frequencies in the bearing, surrounding structure and transducer. As acceleration is the second derivative of displacement, a reduction in rotational speed leads to significant reduction in acceleration levels. For slow-rotating bearings, fundamental fault frequencies will also be relatively close in the frequency domain, increasing the risk of interference. Bechhoefer recommends a minimum of 10, preferably 30, frequency bins between fault frequencies [4]. Frequency resolution is the inverse of acquisition time, which makes the measurement more prone to capture speed fluctuations, leading to smearing of the frequency spectrum. Larger size also means increased distance between fault and transducer. All these factors contribute to a lower signal to noise ratio (SNR).

4. MODELLING BEARING FAULTS

The periodic nature of impacts can be modeled mathematically. Time between impacts is governed by a combination of shaft speed, bearing geometry and localization of the fault. For REBs, faults can be associated with the characteristic fault frequencies of the bearing components, Ball Pass Frequency Inner race (BPFI), Ball Pass Frequency Outer race (BPFO), Cage Pass Frequency (CPF) and Ball Spin Frequency (BSF) [5]. Normalizing by shaft frequency transforms frequencies to shaft order domain for easier comparison across operating speeds.

Characteristic fault frequencies assume ideal operating condition, including perfect rolling motion between rolling elements and races. In reality, rolling elements experience some random slip, causing variation in the time between impacts. Additionally, the impact response amplitude can be periodically modulated with smaller random variations. Antoni includes this randomness in a more realistic model for a bearing vibration signal, given in equation (1) [6]. The vibration signal is $x(t)$, where $h(t)$ is the response to a single impact, $q(t) = q(t + P)$ is periodic modulation caused by load distribution of period P, and T represents the time between the arrival of two consecutive impacts. The random jitter in arrival time and amplitude is handled by τ_i and A_i respectively.

$$x(t) = \sum_{i=-\infty}^{i=\infty} h(t - iT - \tau_i) q(iT) A_i + n(t) \quad (1)$$

This randomness in arrival times causes smearing in the frequency spectrum, but allows separation of the bearing signal from deterministic frequency components from gears and shafts [5].

4.1. Cyclostationarity

Processes that shows cyclic behavior is said to exhibit cyclostationarity [6]. Cyclostationary theory provides a generalized framework for describing a wide range of stationary and non-stationary processes [7]. In the context of cyclostationarity, a periodic component at a frequency α is referred to as the cyclic frequency. The period of α is termed cycle. These terms are used to avoid confusion with spectral frequency f and its period T. Figure 1 shows a time signal, highlighting the difference by indicating the cycle of α and period of f.

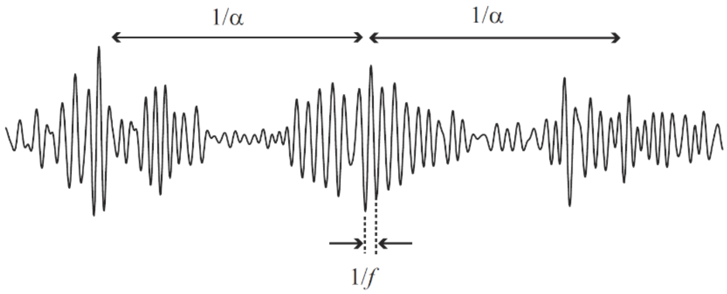

Figure 1. The difference between cyclic frequency and spectral frequency [7].

A signal can exhibit cyclostationarity at different orders. As an example, a periodic signal masked with additive white noise will have a periodic mean value and thus exhibit first-order cyclostationarity. Consider a signal of amplitude-modulated white noise only. As the mean value is constant, no periodic first-order components exist. Squaring the signal, a second-order transformation, reveals periodic components and consequently second-order cyclostationarity in the signal. A second order transformation is normally enough to reveal bearing diagnostics information. Interested readers can consult the works of Randall [5], [8], [9] and Antoni [6], [7], [10] in particular for further information on the topic and its applications. Cyclic spectral analysis, based on cyclostationary theory, is introduced in section 5.5.

5. CONDITION MONITORING METHODS

This section is divided in three, discussing methods for data acquisition, data processing and maintenance decision-making; identified by Jardine et.al [11] as the three main steps in CBM. Here, signal enhancement is included as data processing.

5.1. Data Acquisition

Choosing a measurement technique capable of observing the symptoms of failure is critical. Tandon and Choudhury [12] identifies four main categories for bearing fault detection methods; vibration measurements, acoustic measurements, lubrication analysis and temperature measurements.

5.1.1. Vibration Measurements

Vibration monitoring using accelerometers is widely used in the industry, and has been researched actively since the 1980s [12]. Traditional vibration analysis faces some challenges when applied to large, slow bearings, as discussed in section 451. Displacement measurements can also be used for monitoring vibration. Measuring displacement directly instead of acceleration makes it suitable for slow applications with low acceleration levels. Shakya et.al [13] investigated the use of proximity probe as a standalone method for bearing fault detection and in combination with an accelerometer, and showed improved detectability for inner race defects.

5.1.2. Acoustic Measurements

Acoustic measurements refer to vibrations from 20 kHz and upwards, including both ultrasonic and Acoustic Emission (AE) measurements. An increase in AE activity could be an early indication of oil degradation. AE activity in bearings can be related to metal-to-metal contact, indicating a broken oil film. Yoshioka and Fujiwara [14], [15] showed in early research that AE could detect faults before vibration methods. Further research successfully used AE for detection of subsurface cracks [16], which Tan [17] concluded could be useful for detection of pitting. Chacon et. al [18] presented a method for incipient fault detection in REBs using AE measurements for envelope analysis. Jamaludin and Mba review monitoring of extremely slow REBs [19], [20], using AE measurements to detect faults at very low speeds.

5.1.3. Lubrication Analysis

Many bearing failure modes can be related to insufficient lubrication; fatigue, wear, corrosion, deformation, and fracture. Examples of condition indicators from lubrication analysis are accumulated particle mass, water content, viscosity, conductivity and debris analysis. Dempsey [21] compared oil debris analysis and vibration based CIs for detection of pitting. All CIs increased when pitting occurred. However the article highlighted the need for improved threshold setting and combination of CIs for improved reliability. Bechhoefer et.al [22] compared lubricant, vibration and temperature data from wind turbine bearings. Lubrication analysis indicated a fault in one damaged bearing but also gave one false alarm. In combination with vibration analysis better accuracy was achieved.

5.1.4. Temperature Measurements

The use of temperature as a CI alone is not likely sufficient, especially in offshore equipment where ambient temperature will vary. Load variations will also affect bearing temperature, and lower rotational speed will generate less heat than in high-speed bearings. This combination makes temperature measurements less suitable for condition monitoring. In a comparative study of vibration, lubricant analysis and temperature for condition monitoring [22], temperature failed to indicate failure on a large, slow-rotating wind turbine bearing.

5.2. Signal Enhancement

In cases where information carried in the signal is severely masked, pre-processing techniques can be applied to separate, enhance or in other ways improve the signal of interest. The methods do not provide any diagnostics information on their own, but facilitate the use of other CM methods.

5.2.1. Correcting for Speed Variation

Variations in shaft rate during sampling will distribute frequency content across more bins in the spectra. As discussed, characteristic fault frequencies are close for large, slow-rotating bearings, which makes low-speed applications sensitive to variations in shaft speed. Order tracking corrects for shaft speed variations by using shaft angle as a reference instead of time. In addition to the original measurement, shaft angle is recorded simultaneously. Measured data is then resampled to angular domain, which effectively manipulates the sampling frequency. Bechhoefer et. al [4] recorded speed variations in the range of 2% on a wind turbine, which caused smearing of frequency content. Order tracking effectively removed these variations, resulting in a sharper spectrum. Resampling vibration data using improved the detection and diagnosis [23]–[25].

5.2.2. Isolating the Bearing Signal

Shafts and gears can interfere heavily with the bearing signature, particularly in slow-rotating applications where the SNR of fault signatures is low. Linear prediction, adaptive and self-adaptive noise cancellation, Discrete/random separation and Time Synchronous Averaging (TSA) for use in bearing diagnostics are presented by Randall and Antoni in [5]. Borghesani et.al [26] demonstrated a cepstrum based pre-whitening method for extraction of the bearing signature. Common for all methods is that the bearing signature can be isolated from discrete frequency components by exploiting the randomness of bearing vibration as opposed to deterministic gear and shaft signatures.

5.3. Established CM Methods

In the context of bearing condition monitoring, analysis of time waveform data from vibration, acoustic and ultrasonic is the established industry standard, with notable work by Tandon, Nakra and Choudhury [12], [27], Kim et.al [28], Ho [29] and Randall [8], [30]. Fourier Analysis is fundamental CM, particularly using the Discrete Fourier Transform (DFT). However, diagnostics information often lies in the periodic modulation of a given carrier frequency. Thus, Fourier analysis of the raw signal alone might not be able to detect or diagnose faults. Envelope analysis is perhaps the best example, widely regarded as a benchmark for bearing fault detection [5]. Here, Fourier analysis is preceded by bandpass filtering around an assumed carrier frequency before the signal envelope is calculated. A challenge is to choose the correct bandpass filter. In digital signal processing, envelope extraction of a signal is often done by taking the absolute value of its Hilbert transform [5]. Then, Fourier analysis is performed on the envelope to reveal frequency component corresponding to the fault frequencies from section 4. Envelope analysis and applications have been thoroughly examined in [8], [12], [27], [29]–[31].

Other methods can be applied directly in time domain, such as Root-Mean-Square (RMS) and Crest Factor (CF). Kim et. Al [28] compared vibration and ultrasonic measurements for bearing fault detection across a range of low speeds. RMS was shown to decrease almost linearly with shaft speed. However, healthy bearings have shown big variance in RMS values, indicating RMS change is a better CI than predefined threshold values. CF, the ratio of peak amplitude to RMS value, will increase immediately when a fault first appears. Williams et.al [32] recorded the CF in bearing run-to-failure experiments, and reported an increase followed by a decrease as the fault developed. This indicates fault detection capabilities, but limitations as a trendable parameter for diagnostics purposes.

5.4. Advanced CM Methods

Traditional CM methods are often insufficient for reliable fault detection in large, slow-rotating bearings. This section presents a selection of advanced and novel CM methods available to overcome the challenges.

5.4.1. Higher Statistical Moments

For nominal bearings, the acceleration Probability Density Function (PDF) can be assumed to have a Gaussian distribution. Thus, any changes in the shape of the PDF can indicate failure [12]. Statistical moments of first and second order, mean (μ) and standard deviation (σ) respectively, are well known. For CM purposes, moments of a higher order *k*, calculated as in equation (2). Mainly skewness (*k*=*3*) and kurtosis (*k*=*4*), are used as CIs.

$$\frac{1}{N}\sum_{n=1}^{N}\left(\frac{x[n]-\mu}{\sigma}\right)^{k} \tag{2}$$

Skewness describes the asymmetry of a distribution, i.e. the relative energy above and below the mean. Nguyen et.al [33] identified skewness as one of three optimal features for reliable fault detection in low-speed bearings, but skewness is not consistently reported as a reliable CI. Kurtosis is as a measure of tailedness, i.e. the presence of tail extremities in a dataset [34]. A Gaussian distribution always has a kurtosis of 3. High amplitude accelerations from impacts yield a heavy-tailed distribution and high kurtosis. This makes kurtosis suitable as a standalone CI, requiring no prior knowledge to quantify the condition.

5.4.2. Spectral Kurtosis and the Kurtogram

Spectral Kurtosis (SK) identifies non-Gaussian components in signals along with their location in the frequency spectrum. The method was proposed in 1983 by Dwyer [35]. Wang, Y et. al [36] and Wang, P. et. Al [37] published a review on the use of SK for fault detection, diagnostics, and prognostics for bearings. SK has also been shown to aid optimal selection of frequency band for envelope analysis [38].

The kurtogram was proposed by Antoni in [39], mapping SK as a function of center frequency and filter bandwidth. Wang, P. et. al [37] similarly utilized SK for frequency band selection, but proposed an enhanced kurtogram based on kurtosis of the power spectrum.

5.4.3. Wavelets

A wavelet is a waveform with a limited duration that integrates to zero and can be scaled and shifted in time. The Wavelet Transform (WT) provides a time-scale representation of the signal, where scale is qualitatively comparable to frequency. An important advantage is the good time resolution at high frequencies and high frequency resolution at low frequencies. Klepka presented a wavelet-based demodulation technique [40], which combined the use of the continuous and discrete-time WT for filtering, envelope estimation and fault detection on synthetic bearing data. Gelman et. al [41] proposed an improved method, using SK for optimal selection of frequency band while maintaining the advantages of wavelet demodulation compared to Fourier analysis.

5.4.4. Empirical Mode Decomposition

Empirical Mode Decomposition (EMD), also known as the Hilbert-Huang Transform, obtains instantaneous frequency information of an oscillatory signal by separating it into several Intrinsic Mode Functions (IMFs) which can be amplitude- and frequency-modulated non-linearly. EMD is the data-driven and adaptive, as IMFs are based on the sampled signal only. Lei et.al [42] reviews the application of EMD to fault diagnosis of rotating machinery. Žvokelj et. al [43] demonstrated fault detection on large, slow rotating bearings using EMD and Principal Component Analysis (PCA).

5.4.5. Cepstrum Analysis

The (real) cepstrum, defined in equation (3), identifies repeating “echoes” of a signal, which can be used for detection of periodic signatures. Bechhoefer et.al [4] tested cepstrum analysis for fault detection on wind turbine main bearings, and observed indications of an outer race fault. Cepstrum RMS and kurtosis were tested as possible CIs, but were not able to give actionable results alone. Further study was recommended.

$$cepstrum = IFT\left\{\ln\left|FT\{x\}\right|\right\} \tag{3}$$

5.5. Cyclic Spectral Analysis

Cyclic spectral analysis relies on the concept of cyclostationarity from section 4.1. Here, two approaches for detecting cyclostationarity in signals will be introduced. The first extracts periodic components of the instantaneous power, while the second is based on the autocorrelation function. An operator $\mathrm{P}\{\bullet\}$ is presented in [7]. The operator is implemented as an estimator, shown in equation (4), where n is the sample number and T_s is the sample period. The estimator extracts Fourier coefficients at cyclic frequencies α in set A, from a given discrete data sequence $\{\bullet\}$.

$$\hat{\mathrm{P}}\{\bullet\} = \sum_{\alpha \in A} DFT_{\alpha}\{\bullet\} e^{j2\pi\alpha n T_s} \tag{4}$$

5.5.1. Power Decomposition and Instantaneous Autocorrelation

Cyclostationary behavior can be detected by decomposition of signal power to periodic components. Consider a signal x[n] with power P_x. Estimation of mean instantaneous power $P_x[n]$ is done by applying $\hat{\mathrm{P}}\{\bullet\}$ to the signal power $|x[n]|^2$. A Fourier series expansion of $P_x[n]$ then gives the cyclic powers P_x^{α}. The quantities mean instantaneous power spectrum and cyclic modulation spectrum are obtained by a time frequency decomposition and Fourier series expansion respectively, further elaborated in [7].

The presence of periodicity in a signal creates a correlation of spectral components at the cyclic frequency. Antoni describes in [6], [7] how the instantaneous autocorrelation function can be utilized to detect cyclostationary behavior. Given a signal $x(t)$, the instantaneous autocorrelation $R_x(t,\tau)$ is defined as applying $\mathrm{P}\{\bullet\}$ to the symmetric autocorrelation function, shown in equation (5).

$$R_x(t,\tau) = \mathrm{P}\{x(t+\tau/2)x(t-\tau/2)\} \tag{5}$$

The Fourier series expansion of the instantaneous autocorrelation function expressed is called the cyclic autocorrelation function $R_x^{\alpha}(\tau)$. Applying a Fourier transform to $R_x^{\alpha}(\tau)$ yields the spectral correlation density $SC_x^{\alpha}(f)$, a frequency-frequency representation of $x(t)$. Note that cyclic frequency α is the frequency counterpart of time, and spectral frequency f is the dual of shift τ. The spectral correlation (SC) is non-zero if a frequency component f is periodic with cyclic frequency α. These connections and the relationship to the Wigner-Ville spectrum, classical autocorrelation function, and the PSD are examined in [7].

5.6. Maintenance Decision-making

A condition monitoring system should be able to make or aid in maintenance decisions. However, a single CIs may be insufficient to provide reliable decisions. Fusion of data of different types, both on sensor and feature level can be utilized for improved diagnostics and prognostics of bearings [2]. Dempsey and Loutas [21], [44] investigates a combination of on-line oil analysis, AE and vibration as a way of improving CI performance. Bechhoefer et. al [45] presents a method for optimal threshold setting, by fusing several CIs in a Health Index (HI), which quantifies bearing damage without the need for user interpretation. The HI is constructed from the norm of n Gaussian CIs, and can be shown to form a Nakagami-distributed PDF. This method allows for setting a desired Probability of False Alarm (PFA) and normalizing the HI to be 1 when this probability is reached. The method is successfully demonstrated on data from three large, slow wind turbine bearings [4], where the faulty bearing was shown to have a HI well above one.

6. CONCLUSION

This paper presents an overview of relevant CM methods for large, slow-rotating bearings. The combined requirement of cost reduction and uptime facilitates the emergence of more advanced condition monitoring systems. Main challenges of condition monitoring of large, slow-rotating bearings can be summarized by a low energy impacts, large distance from fault to transducer, comprehensive background noise and speed variations, resulting in a low SNR. Detection capabilities of traditional CM methods, especially envelope analysis, can be improved by longer acquisition times, order tracking and separation of random and discrete components. SK aided bandpass filtering before envelope extraction further improves performance. Other data acquisition methods can also be used. AE signals carries similar diagnostics information as vibration, but in a frequency band less subjected to noise.

Another development in bearing condition monitoring is the transition from a stationarity assumption implicated by the Fourier transform to a more realistic, non-stationary or cyclostationary approach. Time-frequency and cyclostationary analysis tools takes this into account. In cases where cyclic behavior is heavily masked in non-stationary signals, CS analysis appears to be a powerful tool.

It seems unlikely to find a single CI, data acquisition or signal processing method that solves all challenges for CM of large, slow-rotating REBs. Hence, combining CM data from different sources seems more reasonable. The concept of a PFA-controlled HI is attractive from an operator point of view, and can preferably be utilized in systems for automated fault detection and diagnostics. Finding good CIs and methods for fusing them should be a priority in future work.

ACKNOWLEDGEMENT

The research presented in this paper has received funding from the Norwegian Research Council, SFI Offshore Mechatronics, project number 237896.

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