Development of Acoustic Emission (AE) based defect parameters for slow rotating roller bearings

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Abstract. Detection of bearing failures is a crucial time-based process amongst all industries. Usually the standard vibration analysis (Fourier analysis, spectrum analysis) is used. In certain cases, the usability of vibration analysis comes to an end. In particular the damage-detection sensitivity of slow rotating bearings (e.g. in the mining industry) is weak and therefore vibration analysis fails to detect failures as soon as possible. The target of this paper is to present high frequency AE based defect parameters in order to detect roller bearing damages at the outer and inner race in a very early stage. Each type of damage is simulated in a test bench and analysed individually, so that the origin of the damage is comprehensible and further damage predictions are reproducible. In a test bench both vibration and AE is measured and compared. Therefore the AE waveform will be presented to show changes in the waveform while a defect is emerging. In order to show the potential of an acoustic emission based analysis, the results of the test bench (vibration and AE) are compared related to changes in the waveform and origin of the defect as well as time to failure detection. The developed parameters are based on new technique that reduce the amount of data required, so that online monitoring of slow rotating roller bearings becomes more manageable. Due to the characteristic of the developed parameters, it is possible to use them in the maintenance of slow rotating machines, so that a failure prediction can be done even before the standard vibration analysis starts to detect a commencing damage.

1. Introduction

Slow rotating bearings are among the highly stressed components in heavy machinery, such as wind turbines, grinding mills and bucket wheel excavators. Normally, theses bearings are subject to heavy loads and hostile working conditions. Machinery rotating below 100 rpm can be considered as low rotational machinery speed, despite the fact that no formal rotational speed limit does exist. Since theses rolling bearings are one of most important components in low speed rotating machine; their condition monitoring is a crucial issue. Measurement of vibrations is the most used technique for monitoring rolling elements bearings. However, bearings rotating at a low speed present difficulties to evaluate their mechanical integrity through vibration monitoring. Some troubles are: Optimum measurement parameters, instrument limitations and sensor requirements for low frequency analysis [1]. Here, at low frequencies, the vibration velocity amplitude becomes weak. Besides, rolling bearing parts do not present significant changes in its vibration waves at low rotational speed. Next to that,
Shumin Hou [2] has been successful in the development of a new low-Frequency Resonance Sensor method, which is suitable for detecting the extremely low speed rolling bearing faults. Nevertheless, this technique is not able to detect incipient failures. The usage of acoustic emission (AE) measurement promises a better prediction of the condition of a slowly rotating system. Normally, the frequency bandwidth of AE measurement method is in the range of 25 kHz to several MHz. For the purpose of interpreting an AE signal and to correlate its waveform with the characteristics of the sources, parameters from the AE signal must be extracted. AE methods have been developed since the late 1960 regarding to application for monitoring bearings by e.g. Belerston [3]. Miettinen and Pataniitty [4] could identify faults in low speed rotating bearing using AE pulse counts and AE time signals. They concluded that the AE technique is a very sensitive method to evaluate the condition of low speed bearing. Hua Qing Wang [5] used AE signals and vibration signals to evaluate faults in low speed rolling bearings. He concluded that AE signals are more appropriate than the vibration signals in order to evaluate failures in low speed rotating bearing. Based on these findings, the development of an AE based defect parameter will be shown.

2. Test Bench
The test rig (figure 1) contains a 5cm diameter shaft, two bearing blocks (A and B) and two roller bearings (type FAG 6205). The shaft is mechanically powered by an inverter-driven motor. To reduce electromagnetic interferences from the inverter, double shielded cable as measuring lines are used. To simulate the bearing load a manually adjustable screw as placed in the middle of the rotating shaft. This allows the application of a defined radial force on the shaft. The roller bearings to be analyzed are installed in bearing block A. The Sensor (model: VS160-NS, broadband type [100-450 kHz]) is placed on the base plate next to the bearing A.

2.1. Sensors and Data Acquisition
To monitor the system and compare vibration and AE, a vibration sensor, an AE sensor and a laser-optical rotational speed sensor were installed. The first two sensors, vibration and AE, are installed beneath bearing block A in order to reduce attenuation caused by physical transitions. The used AE sensor has its highest frequency response at 150 kHz. The AE data was recorded with a National Instrument PXI System at a sampling rate of 1 MHz, using LabView and Matlab code. The vibration sensor (type: 622A01 ICP) has a frequency range of 3 Hz to 9 kHz and a resonant frequency of 20 kHz. The laser-optical sensor was placed on the right site of screw using a reflective tape to count the rates per second. The shaft rotates at a constant speed of 1 Hz.

2.2. Pre-damaging the bearing elements
To simulate an emerging defect the bearings were slightly pre-damaged. The defects at the inner and outer race were seeded by using an electric engraver. To make sure that the damage is growing fast.
enough; the installed shaft has an unbalance. This ensures that the bearing gets an unnatural stress in pre-damaged area and the defect is growing.

3. Data Reduction

One of the major problems in handling AE Data is the high average data transfer rate, which reduces the online usability of AE based condition monitoring systems. For example: an hour of recording raw data (sampling freq. 1 MHz, resolution 16 bit) uses more than 6.7 GB disk space. To reduce the amount of data, an automated AE burst-detection was implemented.

3.1. Examples

Figure 2 shows a typical curve of a rectified AE signal. In order to show some AE bursts the damage of the bearing is in an advanced stage. The associated file (a data optimized National Instrument file) is about 250 MB in size.

![Figure 2. Rectified AE Signal.](image)

Due to the file size, it is necessary to reduce the amount of data without losing information about the type of damage. In fact, the only important events are the AE bursts. These bursts need to be separated from the background noise. To detect these significant AE bursts, it is important to set a firm or dynamic reference line. Consider the example AE signal from figure 2: If the reference line set to 10 mV (c.f. figure 2), four significant AE bursts (cf. figure 3) are detected. The associated file is about 470 KB in size which is a substantial reduction of the required space on the hard disk while the information about the burst is still available.

![Figure 3. Four exemplary AE bursts.](image)

As shown in figure 4 the information about the burst is still available. Hence, the typical AE parameters such as rise time, fall time in relation to a certain threshold level and amplitude can be analyzed [6][7]. From figure 2 and figure 4 can be deduced that it is important to make a separation
between an AE burst reference line and the AE threshold, which describes the mentioned AE parameters. The former is responsible for the detection and the latter determines the range for the description of the parameters.

Figure 4. Zoomed Rectified AE Signal.

4. Results and Data Analysis
Over a period of several weeks slightly pre-damaged bearings were tested in the above mentioned test bench. To get the amount of data in the handle, only the relevant AE signals were monitored. By means of the vibration sensor the progress of the damage was monitored.

4.1. Vibration
It is well known that each bearing has its typical damage frequencies. These frequencies (bearing type: 6205 FAG) are shown in table 1.

Table 1. Kinematic Frequencies of the Damage for the used Bearings.

| Damage Location     | Kinematic frequency (Hz) |
|---------------------|--------------------------|
| Inner race          | 5.4                      |
| Outer race          | 3.5                      |
| Rolling element     | 2.3                      |
| Bearing cage (fixed outer race) | 0.4                  |

To describe the damage-progress with a standard vibration sensor, the common known signal processing method spectral analysis (Fast-Fourier-Transformation, FFT) was used. Changes in the FFT are displayed in figures below. Figure 5 shows the development of a damage at the inner race. The top picture shows a very flat spectrum. The high peak at 1 Hz is due to the previously mentioned unbalance of the shaft. The harmonics (2, 3, 4 Hz etc.) are also apparent. No further kinematic frequencies are shown. As damage evolves (middle picture) the unbalance frequency and its harmonics are still observable. Hence, at this period no roll-over frequencies were visible.
In order to make the kinematic frequencies visible at all, the rotational frequency of the shaft was increased to 8.4 Hz (lower image of figure 5). Then, the first kinematic frequency of the inner race is clearly visible at 45.4 Hz. The damage of the bearing can now be detected by the vibration sensor, remembering that the inner race damage is in an advanced stage. In case of the outer race figure 6 represents the development of the spectral analysis of the bearing. Again the top picture of figure 6 shows a very flat spectrum, where only the frequencies of the shaft are detectable. In the middle part is still no kinematic roll-over frequency activity observable. In the lower image of figure 6, the rotational frequency of the shaft was adjusted to 8.4 Hz. The first kinematic frequency of the outer race (29.4 Hz) is hardly recognizable. At this advanced stage of the damage including an increase in the rotational speed the vibration sensor is able to detect the bearing defect.
4.2. Acoustic Emission

Parallel to the vibration analysis AE Signals were recorded. In order to reduce the amount of data, the data reduction method presented in Section 3 was used. By using this method it is possible to line up all significant AE bursts in one time-based diagram. Figure 7 shows these lined up AE bursts in relation to the outer race and Figure 8 in relation to the inner race.
From the beginning of the test AE bursts were measured. Both inner and outer race show significant AE activity over the entire period. With progressing damage, the frequency of AE signals rise too. In order to distinguish between the origins of damage two methods are discussed below.

4.2.1. Statistical Characteristics. At first glance it seems possible to separate the signals just by comparing the amplitude. The maximum AE amplitude is 34 mV at the inner race and 250 mV at the outer race. The root mean square (RMS) is three times higher at the outer race (6 mV) than at the inner race (2 mV). In retrospect it is possible to separate the origin of the defect by comparing the amplitudes and RMS of the two signals. But an a priori distinction between the sources of AE bursts based on RMS values is only possible if structural changes on both, inner and outer race occur simultaneously.

4.2.2. Development of an AE based defect parameter. While the defect is emerging and because of the possible simultaneous occurrence of inner and outer race damages, it is necessary to take a closer examination of the results. With the intention of separating an inner race damage from an outer race damage, bursts with equal or rather similar amplitude were analyzed. An example of such an area is given in the figure below. Both, inner and outer race, are displayed in figure 9.

The detailed waveform of the outer and inner race shows that the maximum amplitude of the outer race is located further to the right. Hence, if both bursts have similar amplitudes the outer race damage
can be separated from the inner race by comparing the rise time. In order to show the difference in the rise time, it is possible to count the time from the threshold level to the maximum amplitude. Since the rise time of a burst strongly depends on the amplitude of the observed burst, it was required to develop an AE defect parameter which allows us to separate an inner from an outer race damage, which is independent of the amplitude. To achieve this, several steps are necessary. First it is important to set a certain threshold to recognize the start of the burst. It should be noted here that a burst is only counted if the threshold is exceeded over a certain period. Mathematically, this can be implemented via a hysteresis. The threshold level depends on the background noise. In order to determine the threshold, the noise of an undamaged bearing was measured. The results have shown that the three-time RMS (Root Mean Square) value is a good indicator for the identification of the threshold.

\[
Threshold = 3 \cdot \sqrt{\frac{1}{t_{End} - t_{Start}} \int_{t_{Start}}^{t_{End}} AE(t)^2 dt}
\]  

(1)

If the threshold is exceeded the next step is to normalize the considered area. The generated regression curve is therefore based on the normalized AE burst. The upper part of figure 10 shows the normalized regression curve of an outer race damage, while lower part shows the inner race damage. As shown in equation (2) the slope of the normalized regression curve describes the origin of the defect.

Based on the slope of linear regression function [8]:

\[
reg(y) = \frac{\sum x_i y_i - \frac{1}{2} \sum x_i \sum y_i}{\sum x_i^2 - \frac{1}{n} (\sum x_i)^2}
\]

(2)

The damage parameter can be calculated according to:

\[
D_0 = \frac{reg(|y|)}{|y_{max}|} \frac{dy}{dt}
\]

(3)
Figure 10. Normalized AE burst with regression.

The tests have shown that the parameter $D_0$ varies in a narrow range. According to the tests, it was possible to differentiate between the types of damages because no overlap of the range was present.

Table 2. AE damage parameter.

| Damage Type | Damage Parameter $D_0$ |
|-------------|------------------------|
| Inner Race  | $1,2 \cdot 10^{-3} - 4,9 \cdot 10^{-3}$ |
| Outer Race  | $2,9 \cdot 10^{-4} - 6,9 \cdot 10^{-4}$ |

4.3. Further findings

While reviewing the results some special AE bursts were detected. The figure below shows an AE burst which doesn’t fit in the before mentioned examples. This very broad signal is atypical for an AE burst and was observed in the late stage of the damage. In order to detect the cause of this waveform, we simulated the unnatural behaviour of moderately damaged bearing and found out that these signal types could involve rolling friction as manually induced friction shows a similar course. A validation of this waveform needs a closer inspection.
5. Conclusion
Developing an AE based defect parameter is crucial for the condition monitoring of slow rotating machines in order to detect damages as soon as possible. Standard vibration analysis fails to detect damages in an early state. Furthermore, the tests have shown that without increasing the rotational frequency of the shaft it wasn’t possible to detect the inner e.g. outer race damage. In concern of the AE signal, it could be shown that it is possible to separate an inner race damage from an outer race damage by using two essential characteristics – Amplitude and rise time. The developed parameter is based on the slope of the normalized regression curve of a separated AE burst. Considering the threshold, future work should implement a dynamic threshold which is based on the RMS value of the actual signal. Due to the characteristic of the developed parameters, it is possible to use them in the maintenance of slow rotating machines, so that a failure prediction can be done even before the standard vibration analysis starts to detect the beginning of a damage.

6. References
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