Wear and multiple fault diagnosis on rolling bearings using vibration signal analysis

D. Koulocheris, A. Stathis, Th. Costopoulos, A. Atsas

School of Mechanical Engineering National Technical University of Athens Iroon Polytexneiou 9, Athens 15780, Greece

ABSTRACT: Vibration analysis has been an effective tool for condition monitoring and the identification of potential faults on rolling element bearings. Many times bearings are operated and maintained under harsh environmental conditions and they suffer from excessive wear due to debris contaminants in the lubricant. In these cases bearings exhibit multiple faults and the identification of an occurring fault becomes difficult due to the excessive noise in the signal. In this work we investigate the ability of vibration analysis methods to detect wear damage and identify multiple faults using various vibration analysis techniques. A test rig is utilized in order to evaluate the performance of such a system using a rolling element bearing filled with pre-contaminated grease aiming in acceleration of the wear phenomena. The results of the experimentation are satisfactory as occurring faults can be clearly identified with the use of vibration analysis techniques regardless of the excessive noise in the measured signal and the randomness of the occurring faults. At the end of the tests, optical inspections using a stereoscope verify the vibration analyses results indicating that industrial implementation of the method can be useful.

KEYWORDS: Wear, bearings, vibration analysis, maintenance, condition monitoring

I. INTRODUCTION AND THEORY OVERVIEW

Rolling element bearings produce mechanical vibrations and noise as they rotate. When faults are present, these vibrations are increased as the motion of the rolling elements is more disturbed. These faults can be minor cracks or even spalls due to fatigue, denting, scuffing, scoring, wear, or any other kind of deformation of the contact surfaces. The spectra of the vibrations can contain [1]:

a. Bearing rotation defect frequencies (1-1000Hz).

b. Natural frequencies of bearing components (0.1-20kHz).

c. Random ultrasonic frequencies (20-50kHz).

d. Frequencies due to material microstructure, stress and Rayleigh waves (above 50kHz - acoustic emission).

These vibrations can be measured close to their source, but often they can be detected on other elements which are in contact, but in this case increased noise is affecting the signal [2-4].

Displacement, velocity and acceleration transducers can be used to extract these vibration signals. The most common arrangement is the use of an accelerometer which is permanently attached on the bearing housing. The accelerometer can measure the excitation in one direction or even in three if it is a tri-axial one. The signal is processed in order to retrieve the desired characteristics and to reduce the noise. This can be achieved with the use of appropriate frequency filters (low - high pass filters, Wiener filter) and the compensation of the systemic noise [5-8]. After this initial signal processing, data can be further processed in the time or in the frequency domain.

In time domain, data are processed with statistical and arithmetic methods. The most common values that are measured or calculated are [9-10]:

a. The minimum and the maximum amplitude (min-max).

b. The peak count.

c. Mean μ and standard deviation σ :

$$\mu = \frac{1}{n} \sum_{i=0}^{n} \mathbf{x}_i \tag{1}$$

$$\sigma = \sqrt{\frac{1}{n} \sum_{i=0}^{n} (x_i - \mu)^2}$$

(2)

d. Root Mean Square (RMS):

$$x_{rms} = \sqrt{\frac{1}{n} \sum_{i=0}^{n} (x_i)^2}$$
(3)

e. The crest factor (peak to rms).

f. Statistical moments of higher order such as skewness S and kurtosis K:

$$S = \frac{\frac{1}{n} \sum_{i=0}^{n} (x_{i} - \mu)^{a}}{\sigma^{a}}$$
(4)

$$K = \frac{\frac{1}{n} \sum_{i=0}^{n} (x_{i} - \mu)^{4}}{\sigma^{4}}$$
(5)

Certain faults and malfunctions exhibit signal peaks in characteristic frequencies. Faults in rolling element bearings produce signals in frequencies which depend on the geometrical characteristics of the bearing and the rotation frequency. In the case of a single row rolling element bearing with a rotating inner ring and a stationery outer ring (Fig.1), these frequencies are approximately given from the following equations:

$$f_{c} = \frac{f}{2} \left(1 - \frac{D}{d} \cos a \right) \tag{6}$$

$$f_{bpor} = Zf_{c}$$

$$f_{bpor} = Z\frac{f}{2}\left(1 - \frac{D}{d}\cos a\right)$$
(7)

$$f_{bpir} = Z(f - f_c)$$

$$f_{bpir} = Z \frac{f}{2} \left(1 + \frac{D}{d} \cos a \right)$$
(8)

$$f_r = \frac{f}{2} \frac{d}{D} \left[1 - \left(\frac{D}{d} \cos a\right)^2 \right] \tag{9}$$

where: f = shaft rotation frequency $f_c =$ cage rotation frequency D = rolling element diameter d = pitch diameter [\approx (di+do)/2] $d_i =$ inner raceway diameter $d_o =$ outer raceway diameter a = contact angle $f_{bpor} =$ ball pass outer raceway frequency Z = number of rolling elements $f_{bpir} =$ ball pass inner raceway frequency $f_r =$ ball rotation frequency

Data which have been recorded in time domain can easily be represented in the frequency domain with the use of a Fourier transformation. The most common Fourier transform method is the Discrete Time Fourier Transform (DTFT) which is calculated efficiently with the use of a Fast Fourier Transform (FFT) algorithm. In frequency domain various types of analyses can be performed such as spectral analysis, cepstrum analysis or bispectral analysis [11].

Many researchers have shown satisfactory results in diagnosing and predicting the evolution of bearing faults using various vibration analysis techniques [12-16]. Most of the times, the diagnosis of a fault is based on observations regarding changes in the measured characteristics (peak counts, increase in magnitude, extreme variation). Artificial intelligence (AI) and artificial neural networks (ANN) are new areas of research [17-20]. ANNs are trained to observe signals that correspond to an abnormal operation. With the use of decision trees [21-22] and fuzzy logic [23], various parameters are evaluated in order to decide whether a failure has occurred.





Most studies regard experimental setups with minimum distortion and low noise to affect the measured signals. Laboratory conditions and specific setups, where the bearing under testing differs from the rest, help in measuring the vibration signals produced by faults in preliminary or advanced stages with low noise. Usually an artificial fault is made on the contact surface and investigations on fault detection techniques are conducted. In most real life situations things are more complicated. Vibrations and noise are introduced into the signal due to angular and axial misalignment, shaft imbalance, improper support and fixings, electrical noise, transducer position, load variation. These parameters are limiting the use of time domain analysis as the magnitude of the measured signal is dominated mostly by noise rather than the measured characteristic. In these situations frequency domain analysis seems to present more useful results [24].

In this paper we experimentally evaluate vibration signal analysis methods for bearings under various lubricant contamination conditions which cause accelerated wear. The vibration analysis is performed in the time and in the frequency domain in order to evaluate the accuracy of each indicator under these operating conditions and lubrication. At the end of the experiments the vibration analyses findings are verified with optical inspections of the bearings.

II. EXPERIMENTS

2.1 Experimental setup

The schematic of the bearing test rig on which the experiments are carried out is shown in Fig. 2. Three different types of bearings are used, having the same bore diameter. This selection has been made in order to use in each housing bearings with different characteristic frequencies and as a result to have a clearer indication about the source of the measured vibration signal. All bearings have conical internal rings with a bore diameter of 35mm and they are mounted on the shaft with the use of proper adapter sleeves.



Figure 2: Photo and Test Rig 3D model.

Two Kistler type 8792A25T three-axial accelerometers are mounted with magnets on the top of the two plumper type housings. Visualization and processing of the signals is made through HBM CATMAN software installed on a Laptop PC. The naming of the axes is following the naming of the accelerometer's axes which is: x for the axis of the shaft, z for the axis of the load direction and y for the axis vertical to the plane xz. Also, a K-type thermometer was used in order to measure the shaft, bearings and housings temperatures and the ambient temperature

2.2 Pre-contaminated grease

Pre-contaminated samples of grease were made by mixing solid contaminant particles with clean grease. The grease used was SKF LGMT3 mineral oil based, lithium soap thickened grease with base oil viscosity of $120-130 \text{mm}^2/\text{s}$ at 40° C and 12 mm 2/s at 100° C. The solid particles which were used as contaminants were corundum particles with a hardness of about 2000HV and particle sizes varied from $60 \mu \text{m}$ to $175 \mu \text{m}$ (US mesh sizes 220 to 80). In each test a quantity of $0,75 \text{cm}^3$ of particles was mixed with 50grams of clean grease and then filled in the bearing and its housing. Most of the quantity used remains in the housing and only a small amount of grease is recirculating. The actual amount of particles which enter the contact zone is only a fraction of the used quantity.

2.3 Procedure of experimentation

A load of 2800N was applied to the flanged housing resulting in a load of 3500N at the front bearing and a load of 700N at the rear bearing. The motor and shaft rotation speed was set to 2400rpm (40Hz). The signal from six channels was recorded, corresponding to the three axes of each of the two accelerometers. The sampling rate was set to 2400 samples per second (sampling frequency) for each channel.

The duration of the experiments was 14 hours for each test, representing about 2 millions of revolutions. After the completion of each test, the front housing was opened and cleaned from the remaining grease. The bearing was dismantled and its parts were cleaned from the grease. After cleaning, the parts of each bearing were subjected to optical inspection with a LEICA stereoscope.

During the tests, the vibration signals from the accelerometers were monitored in real time and recorded All data were recorded and saved in .BIN type file format which can be further processed with Matlab software.

2.4 Data and calculations

The characteristic bearing potential frequencies of each bearing can be calculated with the use of equations (6) - (9). The dimensions of the bearings are required but instead, the manufacturer provides these values according to the operation speed. For the rotational speed of 2,400rpm (40Hz) and for a contact angle of 00 the characteristic frequencies are given in Table 1.

Table 1. Frequencies of potential damage in the tested ball bearings.			
	SKF 1207 EKTN9 'front'	SKF 2207 EKTN9 'rear'	SKF YSA 207 - 2FK'load'
f	40.0 Hz	40.0 Hz	40.0 Hz
f_c	16.8 Hz	15.8 Hz	15.8 Hz
f_{bpfo}	251.0 Hz	190.0 Hz	143.0 Hz
f_{bpfi}	349.0 Hz	290.0 Hz	217.0 Hz
f_r	119.0 Hz	89.1 Hz	92.1 Hz
$2 x f_r$	238.0 Hz	178.0 Hz	184.0 Hz

III. EXPERIMENTAL RESULTS

During the tests the vibration signals were monitored in real time. The duration of each test was 14 hours (2 million revolutions). The measured signals are processed in time domain and in frequency domain. The axes of greater importance are the x axis, which is the axis of the shaft and represents the axial loads of the bearing, and the z axis which is the axis of the applied radial load. The y axis, which is the axis vertical to the applied load, shows similar trends to the others but with much lower signal amplitudes.



Figure 3: Acceleration peaks and rms values of three experiment cases.

Due to the numerous sources of vibrations as various particles enter the loading zone and the randomness of their nature, the statistical variables of higher order such as skewness and kurtosis do not give any useful results. The importance of these variables is grater when a fault appears on a bearing running under normal conditions. In these situations, the aforementioned variables, which normally show small fluctuation, will change significantly. Such behavior has been successfully reported by other researchers [9-10] when they created an artificial single point defect.

The amplitudes of both acceleration peaks and rms values are increasing during the tests it is very interesting that in the test where the smallest particles are used, the peak and rms values initially are lower compared to the rest of the tests, but they are rising with a higher rate and finally they are exceeding them. Near the end of this test, the rms value on the x axis is more than 4g and on the z axis is about 1g, clearly showing that the particular bearing is performing abnormally.

The vibration analysis in the time domain can show a malfunction of the bearing only when it is affecting the vibration levels. The exact source of this malfunction is unknown and only assumptions can be made. In our case, the source of the increased vibrations could not be identified only from the vibration analysis results. Vibrations could be generated by particles entering randomly the contact zone, or by permanent deformations on the raceways.

Processing the acquired data in the frequency domain, results in the identification of the true source of the vibrations and in the detection of possible faults. Frequency spectrum plots of the obtained data are created by implementing a fast Fourier transform in Matlab software environment. In order to reduce the spectral leakage and make the dominant frequencies easier to be identified, the power spectrum is used, where the outputs of the FFT are raised to the square. Also, in order to filter out some non-harmonic noise we plot the frequencies which are greater than 1Hz as lower frequencies indicate small periodicity.

In the first two tests there is clearly seen that the amplitude at 251.2Hz, corresponding to the frequency of a potential fault on the outer raceway is dominant and it is increasing in time. The increase is gradual, indicating that the fault is evolving and it is not occurring suddenly.



Figure 4:Frequency spectra plots of the three experiment cases.

Finally, in the fourth test, two characteristic frequencies are dominant. The first frequency at 348.2Hz corresponds to a potential fault on the inner raceway and its amplitude remains at the same levels during the test. The second frequency at 388.1Hz cannot be easily correlated with a fault. The characteristic frequencies of the bearing, at various angles of contact, do not match with this finding. Their harmonics also do not match. This vibration at 388.1Hz is near only to the characteristic frequency of a fault on the inner raceway but it is quite higher. One possible explanation is that as a fault on the inner raceway has been clearly identified, a higher frequency vibration could be produced if balls pass from this fault sooner. That could happen if the balls are slipping rather than rolling as they contact the inner raceway. This reduces rotational speed of the cage causing the balls to pass from the fault sooner.

IV. DISCUSSION

The optical inspections of the tested bearings are in conformity with the vibration analyses findings. The faults on the bearings in all three cases are critical and the performance of the bearings is poor, indicating that the bearing should be replaced soon.

The main cause of damage is abrasive wear. As the hard corundum particles come in contact with the bearing steel they cause smearing at the contact area, shaping it with the ball curvature. Serious faults are obvious on the outer raceways at the point where the balls are entering and exiting the load zone.



Figures 5a & 5b: Deformations on the bearing outer raceways of the 1st case (left) and the 2nd case (right) caused by the rolling balls as they entered and exited the load zone.



Figures 6a & 6b: Deformations on the inner raceway on the bearing raceways of the 3rd case.

At these areas, a step has been formed, as shown in Figures 5a and 5b. In addition various deformations on the raceways are present as waviness with random distribution. This kind of deformation has occurred probably due to local differences in the hardness of the bearing material. On the inner raceways the marks are less severe but small pits and indentations have occurred. In the third case a double deformation has occurred on one of the raceways of the inner ring (Fig. 6a & 6b). All the aforementioned permanent faults are the main reason for the peaks in the spectral plots. The severity of the vibrations depends on the number of these faults and their size. Despite the excessive noise due to the numerous particles that circulate within the grease, vibration analysis in the frequency domain gives a clear picture about the occurring damage. Also the existence of multiple faults on both raceways produce vibrations of the same frequency but with different phases.





When a fast Fourier transform (FFT) algorithm is applied these vibrations are added together like vectors as shown in Fig 7:

$$A\sin(\omega t + \varphi_1) + B\sin(\omega t + \varphi_2) = C\sin(\omega t + \varphi)$$

where:

$$C = \sqrt{A^2 + B^2 + 2A \cdot B \cos(\varphi_2 - \varphi_2)}$$

 $\tan \phi = \frac{A \sin \phi_1 + B \sin \phi_2}{A \cos \phi_1 + B \cos \phi_2}$

V. CONCLUSIONS

Vibration analysis is playing an increasingly important role as a tool for assisting predictive and preventive maintenance. When monitoring rolling element bearings, both vibration analyses in the time domain and in the frequency domain can give useful results. The vibration analysis in time domain can indicate if there is an abnormal operation of a bearing and show the trend of the amplitude increase. In the frequency domain, vibration analysis can indicate whether the increased vibrations are caused from a certain bearing defect or from external sources. The increase of the vibration energy on the characteristic frequencies of the bearing can also indicate the progress of that specific fault.

In the case of grease contaminated with solid particles, vibration analysis can indicate the severity of wear and monitor its progress. From the conducted tests it is concluded that multiple faults on a part of a bearing can be clearly identified using vibration analysis in the frequency domain. The random noise due to particle contaminants can be filtered out easily and industrial application of similar techniques will definitely give useful information to the maintenance personnel.

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