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FAULT DETECTION IN SLOWLY ROTATING LARGE SIZED BEARINGS

Matej Žvokelj*, Samo Zupan, Robert Kunc and Ivan Prebil

Faculty of Mechanical Engineering, University of Ljubljana
Aškerčeva c. 6, SI-1000 Ljubljana, Slovenia
matej.zvokelj@fs.uni-lj.si

Abstract

Bearings can be classified among the most frequently used machine elements in machine engineering. Owing to their multiple usage, the requirements which a bearing should meet are highly diverse. Bearing usage ranges from applications in which a bearing collapse does not constitute a major problem, to the applications in which a collapse of a bearing could lead to enormous economic damage and potential disastrous consequences for the people. Large-sized bearings used in rolling rotational connections are an example of such applications.

The aim of monitoring bearings in these applications is to detect faults at an early stage, diagnose the fault and stop operation of the system before the consequences of the fault have grown to disastrous proportions. Faults in bearings are best detected by accelerometer-based monitoring of vibrations. Special attention needs to be paid to high frequency vibration components which are generated in the bearing and indicate the occurrence of a fault. One of the key problems in monitoring large sized bearings with low rotational speed is a weak level of high frequency components and, at the same time, a high level of low frequency components in measured signals [1]. In order to be able to detect and monitor high frequency components in the signals generated by slowly rotating bearings, we need to have high quality measuring equipment.

With a view to avoiding the mentioned disadvantages, we have attempted to use an alternative technique of monitoring the operation of bearings. To this aim, we have used strain gauges placed on the bearing housing, non-contact displacement sensors which measure micro-displacements below the bearing raceway and purpose built rotational resistance sensor. The signals obtained have been processed with the use of a number of signal processing techniques, namely the PCA method, wavelet transform and the Fourier analysis.

INTRODUCTION

A rolling rotational connection is a composition of machine elements which enables relative rotation and cyclic movement of two structural parts. The basic element of a rotational connection is a large sized rolling bearing with holes in bearing rings for fitting, and with a gearing on one of the rings for propulsion. Such rotational connections are frequently used in mechanical engineering. They are particularly popular in the construction of transport devices (elevators, cranes - *Figure 1a*, transporters, turning tables, etc.). [6], [12]

A purpose-built laboratory test stand (*Figure 1b*) has been manufactured for experimental verification of the carrying capacity and service life of large sized rolling rotational connections. One of the objectives of test stand construction is to research and develop methods for condition monitoring of large sized bearings, which involves finding suitable measuring methods and studying appropriate techniques for processing and evaluation of signals that would enable more reliable monitoring and diagnostics of rolling rotational connections in practice. The test stand has been designed as an independent unit able to perform simulations of actual loads on rolling rotational connections which are used in a variety of applications.

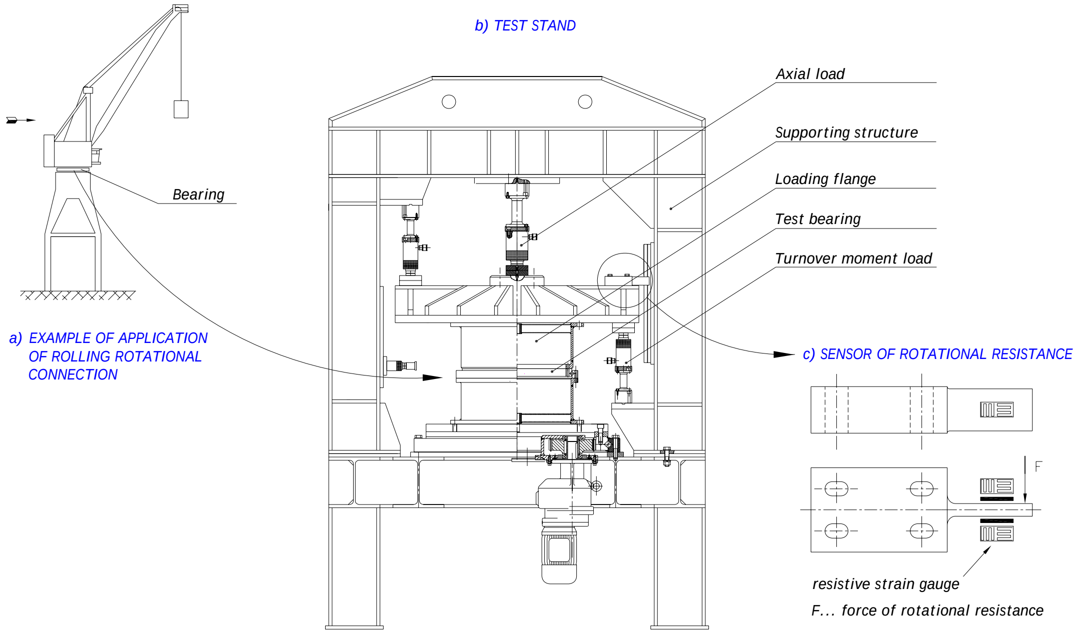


Figure 1 – Test stand and sensor of rotational resistance

MEASUREMENT SYSTEM

The integrated measuring system in the test stand enables monitoring and provides for the possibility of modifying certain parameters such as simulated external load, speed and direction of rotation. The response of the system to input loads is measured by three independent measurement systems which monitor:

1. Micro-deformations or micro-displacements of the raceway

   Six REBAM sensors (Bently-Nevada), operating on the principle of eddy current, monitor micro-deformations of the bearing raceway which can be used as a basis for an indirect assessment of local loads in rolling elements.

2. Deformations of the loading flange

   Nine measurement points equipped with resistive strain gauges distributed along the edge of the loading flange detect the deformations and normal stresses which appear in these points as a result of simulated loads.
3. Bearing rotational resistance

   A purpose-built bending sensor (*Figure 1c*) measures the force in the static outer ring, created as a result of friction in rotation of the inner ring.

Owing to symmetric geometry and the nature of external load, resistive strain gauges are only placed along a half of the loading flange, whereas the REBAM sensors are placed around the largest artificially-created deformation of the bearing ring (*Figure 2*). This artificially-created deformation was achieved through large simulated unflatness of the mounting surface of the bearing with intention to simulate unfavourable running conditions.

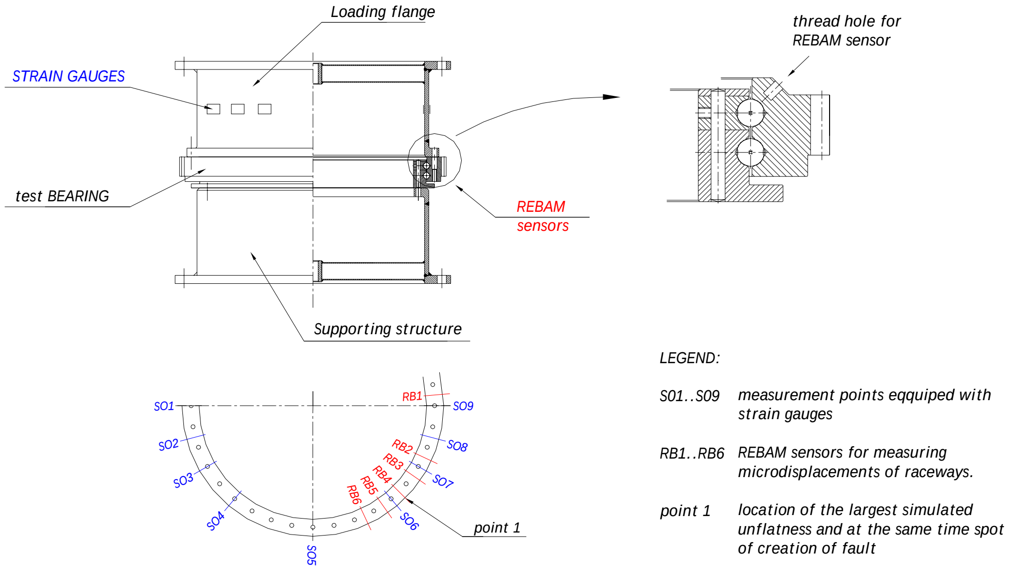


Figure 2 – Placement of resistive strain gauges and REBAM sensors

METHODS FOR THE PROCESSING OF MEASUREMENT SIGNALS

The number of methods available for signal processing is, to say the least, high. Nevertheless, none of the methods can be claimed to be a lot better than the others as the efficiency of a method depends largely on the characteristics of data. Each of these methods comes with its advantages and disadvantages and is as such suitable for a specific work area. Hence, our aim was to research the widest possible scope of methods and select the methods which are suitable for the specific problem of controlling the bearings used in rolling rotational connections.

In consideration of the properties of the existing signal processing techniques and the characteristics of measured signals, we decided to study in more detail the Principal Component Analysis [3], [4], [5], the Wavelet Transform [7], [8], [11] and the Fourier Analysis [8].

Principal Component Analysis

Principal Component Analysis (hereinafter referred to as PCA) is a linear statistical method for analysing covariance of multivariate data [9]. It is a feature extraction method which reduces the dimensionality of data with minimal loss of information. PCA provides a linear transformation of the input data matrix X onto a new set of orthogonal data called principal component scores, T [5]. The scores represent the inner product of the measured variables X and the linear transformation matrix, P, also called the principal component matrix. The set of input variables can be satisfactory described with only a small number of principal components which helps reduce the dimensionality of data. By way of derivation [4], the input data matrix, X, can be expressed as a sum of the reduced space and the residual.

$$X = T_a P_K^{\,T} + E_X \tag{1}$$

In this equation, K expresses the first k columns of the P matrix, called principal components of the score space, whereas E_x is the matrix of residuals also called noise space. The noise space, however, represents all the determined linear relations between the columns of the input matrix X [4].

Condition Monitoring Based on the PCA Method

Process monitoring based on the PCA method can be divided into two main steps (*Figure 3*). The first step is designed to check whether the system operates within the acceptable range, that is within the range of reference data. Monitoring is based on the application of Hotelling's T^2 statistic [3], [4], which controls the reduced space. The matrix of residuals E_x, which covers rest of the variance of input data not included in the principal component space, is monitored and controlled with the Q statistic [3], [4]. Provided the system fails to operate within the acceptable range, the reason for the change in system operation needs to be investigated and determined in the second step of the process. Contribution plots can be used to define the cause of change in the operation of the monitored system [2], [10].

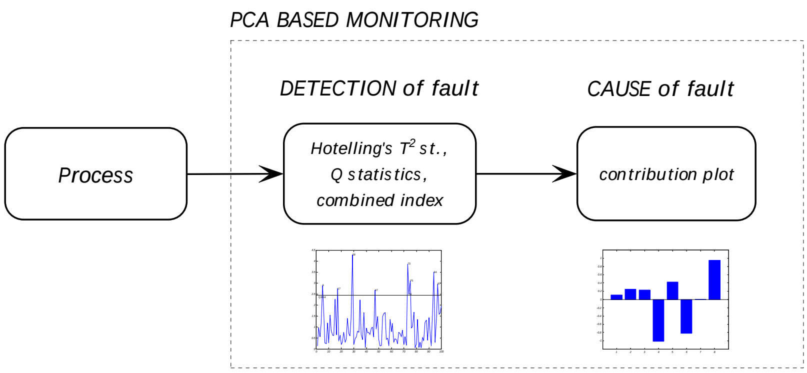


Figure 3 – Principle of system monitoring
based on Hotteling's T^2 and Q statistics and contribution plots

Wavelet Transform and Fourier Analysis

Often, though, the time-amplitude presentation of a signal and statistical analyses fail to provide sufficient data. In many cases, the majority of information is hidden in the frequency contents of a signal. In practice, the Fourier transform is one of the most frequently used and popular transforms which can provide the desired type of information. The Fourier transform reveals the frequency contents of a processed signal but provides no information on the time when a certain frequency component appeared in the signal. As far as stationary signals are concerned, this information is sufficient. However, when dealing with non-stationary signals, we also wish to know at what point in time a certain frequency component appeared. This presentation is provided by the Wavelet Transform, Short Time Fourier Transform (STFT), Priestley Transform and Gabor Transform[1], which can all be classified as linear time-frequency transforms. Another possibility is non-linear transforms such as the Wigner-Ville distribution, the Cohen-Posch and the Choi-Williams transform.

Normally, the application of an appropriate algorithm for signal processing is of critical importance for the efficiency of analysis. With regard to the characteristics of measured signals and the properties of the signal processing techniques described, the Continuous Wavelet Transform [7], [11] and the Short Time Fourier Transform [8] seemed the most suitable types of analyses for the processing of specific signals included in this research.

MEASUREMENT RESULTS

Selected signal processing analyses were used to study the effects of raceway damage on system response. Based on observations, we attempted to extract a feature which would help control the operation of a bearing and could serve as a basis for fault detection.

Principal Component Analysis

Signals were analysed at nine measurement points where strain gauges had been placed to measure the stress on the loading flange (*Figure 2*). From these signals, an input data matrix was composed and, using the PCA method (the first four principal components were used which account for 95% of the total variance of input data - *Figure 4*), transformed into the reduced space and the noise space.

By applying Hotelling's T^2 statistic (*Figure 5a*), statistical data on the operation history of the tested rolling connection were obtained from the calculated reduced space. The figure shows that Hotelling's T^2 values increased gradually in line with time, which indicates that the statistical values of the measured signals changed in relation to time. As statistical values changed, the majority of information was no longer oriented along the main axes, which resulted in an increase in Hotelling's T^2 values. The only possible explanation of why these statistical changes of the signal

[1] **Gabor transform:** STFT in which a Gaussian window is used (1946)

occurred is a change in system operation, that is damage of the bearing. Bearing damage increased with an increasing number of revolutions, and it affected statistical values of measured signals.

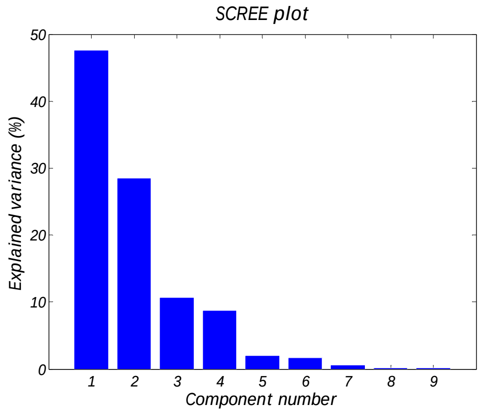
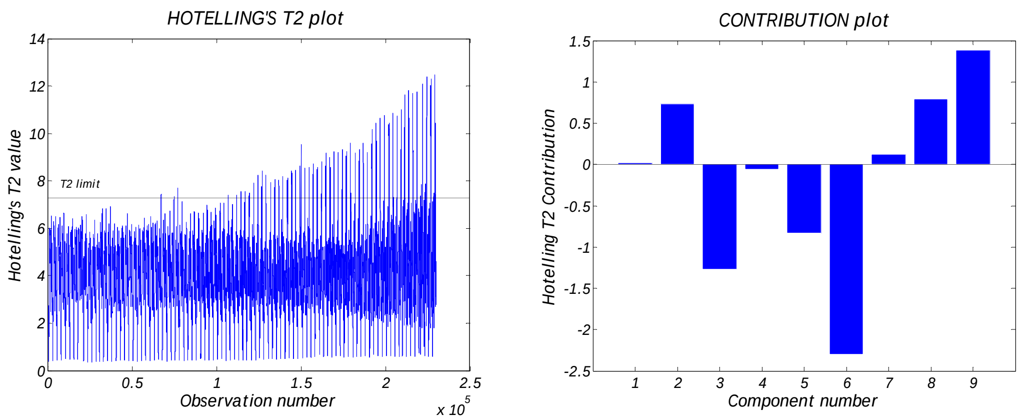


Figure 4 – Percentage of explained variance of individual principal components

In as far as the observed Hotelling's T^2 values remain within the limit T^2_{lim} [2], the operation of the system is satisfactory. However, once these values exceed the limit, this indicates a change in the operation of the system. A contribution plot can be used to determine which component or measurement point made the most important contribution to the fact that a certain value has exceeded the limit (*Figure 5b*). By determining the measuring point which has caused the excess of limit value, it can further be concluded that this measurement point is closest to the location of the damage. Therefore, the diagram shows that Component 6, representing the measurement point *S06*, makes the highest contribution to the total Hotelling's T^2 value. The figure (*Figure 2*), however, shows that the measurement point *S06* is the closest to the point of raceway damage as has been expected on the basis of results obtained.



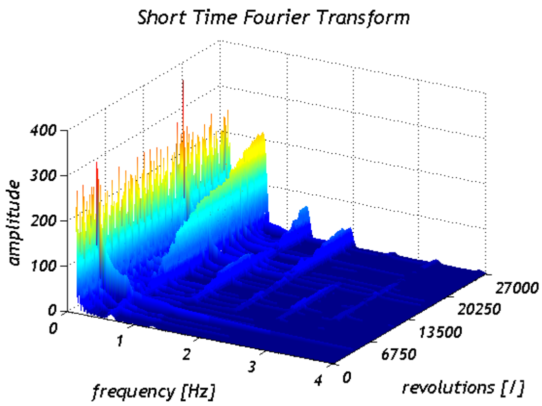
a) *b)*

Figure 5 – Hotelling's T^2 plot and contribution plot for the measurement point 67224

Good results, although of slightly lower quality than provided by Hotelling's T^2 statistic, were also obtained with the Q statistic.

Short Time Fourier Transform

In determining the time of damage creation and its growth, the value measured at the measurement point *S06* (*Figure 2)* was of particular importance as it, being located in the immediate vicinity of the damage, recorded the highest values of normal stress in the loading flange. *Figure 6* presents the time-frequency contents of the signal *S06*, which was obtained by applying a Short Time Fourier Transform. The picture shows gradual occurrence of higher harmonic frequencies as multiplied values of the fundamental frequency of rolling bearings passing over damage. In addition to the presence and increase in higher harmonics, a rise in the number of revolutions causes a rise in the amplitude of the fundamental frequency of the rolling element passing over damage. Hence, changes in the amplitude of the fundamental frequency and occurrence of higher harmonics are two symptoms which indicate the presence of damage on the bearing raceway.



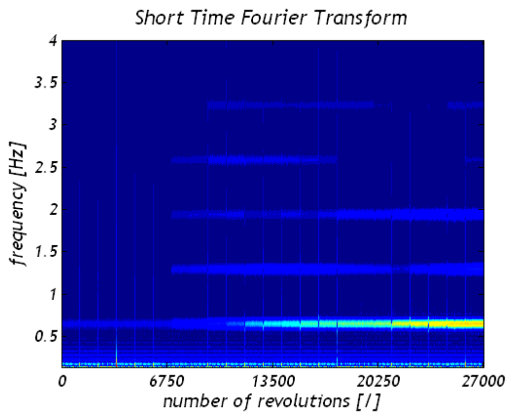


Figure 6 – Time-frequency presentation of the signal S06 in relation to the number of revolutions of the test bearing

Wavelet Transform

Unfortunately, application of the Wavelet Transform failed to give the desired results. Considering that the Wavelet Transform is relatively time-consuming, the Short Time Fourier Transform proved to be sufficiently precise to monitor the time-frequency contents of signals.

In future research, it would be interesting to study feature extraction based on the Discrete Wavelet Transform. The application of this transform would allow for monitoring of certain characteristics of sensor-provided signals at the test stand and thus enable control of bearing operation and detection of potential faults.

SUMMARY

The methods which are used for small sized bearings mounted on relatively rigid structures and working at high speeds are frequently not very suitable for monitoring the operation of the described rotational connections.

To this purpose we have attempted to obtain useful information on bearing operation and damage growth by using different measuring methods and applying a variety of methods for signal processing in a laboratory test stand. Certain methods have proved to be highly effective in continuous monitoring of system operation. Particularly promising were the results obtained through procedures based on the PCA method, which was used to monitor the statistical data on operation history of the tested rolling rotational connection. Bearing damage was determined on the basis of changes in statistical properties of measured signals. Contribution plots were used to determine an approximate location where the damage had formed.

In applying Short Time Fourier Transform and in Wavelet Transform, damage formation was assessed on the basis of a comparison of stress amplitude time history data and the frequency range of stresses in the flange and micro displacements of the raceway at the critical point. The Fourier analysis gave expected results. Continuous Wavelet Transform, however, failed to produce satisfactory results.

REFERENCES

[1] Barkov A., Barkova N., Azovtsev A., "Peculiarities Of Slow Rotating Rolling Element Bearings Condition Diagnostics" (online), Vibrotek - Vibration Technologies, Available from: http://www.vibrotek.com/article.php?article=articles/slowbear/index.htm [Accessed: 20.1.2006]

[2] Frey G.M., *Multiresolutional Partial Least Squares and Principal Component Analysis of Fluidized Bed Drying.* (University of Saskatchewan, Saskatchewan, 2005).

[3] Jackson E.J., *A User's Guide To Principal Components.* (John Wiley&Sons, New York, 1991).

[4] Klančar G., Škrjanc I., "A Principal Component Analysis in Fault Detection and Isolation: Hydraulic and Fermentation Process Example", Electrotech. Review, **69**(5), 311-316 (2002).

[5] Klančar G., *Vloga hibridnega modeliranja in metode glavnih komponent pri odkrivanju napak v industrijskih procesih*. (Ljubljana, 1999).

[6] Kunc R., *Maloциклična nosilnost tečine ležaja z utrjeno kotalno površino*. (Ljubljana, 2002).

[7] Mallat S.G., *A wavelet tour of signal processing.* (Academic Press, San Diego, 1998).

[8] Newland D.E., *Random Vibrations, Spectral & Wavelet Analysis*. (Longman, Singapore, 1997).

[9] Potočnik P., *Uporaba nevronskih mrež in genetskih algoritmov pri modeliranju in prediktivnem vodenju procesov*. (Ljubljana, 1999).

[10] Westerhuis J.A., Gurden S.P., Smilde A.K., "Generalized contribution plots in multivariate statistical process monitoring", Chemometrics and Intell. Lab. Syst., **51**, 95-114 (2000).

[11] Xue Z. W., *Data mining and knowledge discovery for process monitoring and control.* (Springer-Verlag, London, 1999).

[12] Zupan S., *Model nosilnosti vrtljive kotalne zveze v realnih obratovalnih pogojih.* (Ljubljana, 2004).