Abstract

Two of the most common defects in rotating systems are abnormal wear of the bearing bushing and bearing misalignment. The present paper introduces a new fault diagnosis model that uses artificial neural networks (ANN) in order to identify the increase of wear depth and/or the increment of the misalignment angle. Reynolds equation is solved by FEM and provides data about bearing wear and misalignment. The proposed model uses eccentricity, altitude angle and minimum film thickness and feeds with their values an ANN that is trained in order to provide reliable identification of the variation of each defect. The accuracy of the proposed model is demonstrated - for several misalignment angles, worn depths and L/D ratios - for a worn/misaligned rotor bearing and its applicability as a real-time condition monitoring system is discussed.

Keywords: journal bearing, fault diagnosis, artificial neural networks, wears, misalignment, Reynolds equation.

1 Introduction

1.1 Wear and misalignment as defects in general

Wear is a type of surface damage that arises from the relative motion between interacting solid surfaces. It is a dynamic and complex process that incorporates surface and material properties, operating conditions, stresses, lubricants and geometry [4]. Wear plays an important role in determining life span of products or machine elements.

The available knowledge regarding material science and mechanical tools provides to the engineers the ability to predict - with reasonable accuracy - the functional behaviour of a component of a product or process with respect to strength, fatigue
etc. However, the lifetime of a component depends on wear. Wear is difficult to measure because of its dynamic and complex nature.

Detection and monitoring of wear are rather important in tribological research as well as in industrial applications. Some typical examples are: measurement of dynamics of wear processes, engineering surface inspection, coating failure detection, tool wear monitoring and so on. With wide and extensive use of wear resistant materials, wear itself diminishes so that - in some precision applications - reaches even nanometer scale. Accordingly, new techniques, methodologies, and instruments for detecting or monitoring of micro-wear are increasingly required. Due to the dynamic and complex nature of wear process, measurement of wear is usually conducted offline [1, 2, 3], i.e. during measurement, the wear process needs to be interrupted and the machine element to be periodically removed in order to measure the evolution of wear as a function of time, number of cycles, or sliding distance. Reliable online detection and monitoring of wear, in which the wear process is not interrupted and the wear environment (temperature, humidity, lubrication etc.) is not changed, remains a challenge to tribological research [5, 6].

There are many causes to may generate misalignment such as deflection of a rotor under its own weight, geometrical defect of alignment, applied torque on the journal bearing, deflection of the rotor, operating faults and malfunctions such as insufficient lubrication in one or more bearings in a rotor bearing system. Misalignment may be a cause of bearing wear and all machines, using bearings, are always subjected to misalignment conditions. This is the reason why early detection of certain defects is so important.

1.2 Journal bearing wear

Journal bearing is one of the most common components in rotating machines. The tribological bearing behavior has been studied by many researchers and, in the present work, part of their significant work is reviewed.

Dufrane et al. [7] investigated worn steam turbines and measured them during overhaul periods to determine both the extent and nature of the wear. They established two models of wear geometry for use in further analysis of the effect of wear on hydrodynamic lubrication. These worn models were not of circular type. The first of the proposed models was based on the concept of imprinting itself in the bearing, and the second one on a hypothetical abrasive wear model with the worn arc at a radius larger than the journal.

Fillon and Bouyer [8] presented a thermodynamic analysis of a worn plain journal bearing. They concluded that the worn bearings present not only disadvantages but also some advantages, such as lower temperature, since in certain cases of significant defects due to wear, the geometry approaches that of a lobe bearing.

Vaidyanathan and Keith [9] evaluated the performance characteristics of non–circular journal bearing for different bearing profiles namely circular, worn-circular, two lobe and elliptical. Hasimoto et al. [10] examined theoretically the effects of wear under normal operating conditions in both laminar and turbulence regimes and

Hashimoto et al. [12] investigated the effects of geometric change due to wear on the hydrodynamic turbulent regimes. They observed good agreement between the theoretical model for the lubrication of journal bearings and experimental results. The steady state characteristics of the bearings such as film pressure, attitude angle, and Sommerfeld number were analyzed by a semianalytical finite element method for various wear depth parameters and the theoretical results were compared with the experimental results. It was found that the geometric change due to wear has significant effects on the steady-state characteristics in both laminar and turbulent regime.

1.3 Bearing Misalignment

Bouyer et al. [13] presented a study dealing with experimental determination of the performance of a 100mm diameter journal bearing with an applied misalignment torque. It was proven that the misalignment caused more significant changes in bearing performance when the rotational speed or load was low.

Pierre et al. [14] presented in detail a three-dimensional thermodynamic approach to consider thermal effects and also to take into account the lubricant film rapture and reformation phenomena caused by conservation of mass flow rate. An experimental validation was also carried out by comparison with measurements extracted by their experimental apparatus for various operating conditions and misalignment torques.

Boedo et al. [15] investigated the transient and steady-state behavior of grooveless (angularly) misaligned bearings using finite element formulations of the completed two-dimensional Reynolds equation. Sun et al. [16] developed a special test bench for the study of lubrication performance of cylindrical journal bearings. The effects of journal misalignment as a result of shaft bending under load were also studied.

Nikolakopoulos et al. [17] presented an analysis of a misaligned journal bearing operating in nonlinear regions. FEM was used to find the solution of the Reynolds equation. After the solution was obtained, they calculated the linear and nonlinear dynamic properties for the misaligned bearing depending on the developed forces and moments as a function of the displacements and misalignment angles. Finally, Goenka [18] described a finite element formulation with low computational cost for transient analysis of journal bearings.

1.4 Online monitoring using Artificial Neural Networks (ANN)

Wear is a type of surface damage that arises from the relative motion between interacting solid surfaces. Misalignment could be a cause of wear. Condition monitoring of rotating machinery involves one or more maintenance philosophies
applied for the purpose of reducing operating and maintenance costs while, at the same time, assuring maximum operating time and achieving the highest possible production rate. An online wear and misalignment monitoring process that would be based on artificial network theory could be proposed that would offer higher accuracy without presupposing either the interruption of the wear process or the change of the wearing or misalignment environment.

Artificial Neural Networks (ANNs) are composed of simple elements that imitate the biological nervous systems. In the last few decades, significant research has been reported in the field of ANNs and the proposed ANN architectures have proven their efficiency in various applications in the field of engineering. Artificial neural networks are classified as a non-symbolic artificial intelligence technique, which simulates the human brain and its underlying processes on a basis of graphs and algorithms for addressing real-world applications. Artificial neural networks have also been combined with other non-symbolic artificial intelligence techniques, which simulate biological processes (e.g. genetic algorithms), and symbolic techniques that rely on rules and inference logic (e.g. fuzzy logic). From a computational point of view, the systematic development of neural network learning algorithms has resulted in efficient solutions to demanding engineering problems, even in cases where there was adequate knowledge for the problem under consideration. In several applications, ANNs outperform conventional methods and have proven to be effective in solving problems of approximation, prediction, pattern recognition, etc.

The performance of an ANN is determined by the connections among its building elements, which are called neurons [22, 23]. The neurons operate in parallel and they are capable of accomplishing different functions depending on the adjustment of the connection weights. In general, the ANNs are submitted to an adjustment of connection-weights called training with the anticipation that specific inputs should lead to specific target values. The network’s training is based on the comparison of the output and the target values and is deployed until a convergence is achieved (within a specific calculated error). The training of the ANN by using pairs of input and output vectors is called supervised learning [22, 23].

A simple neuron model with a vector of inputs \( p \) is used here. The inputs \( p_1, p_2, \ldots, p_p \) are multiplied by the weight matrix \( W \) with its weights \( w_{1,1}, w_{1,2}, \ldots, w_{1,R} \) for the \( S \) neurons and the weighted values are summed. The sum is denoted as \( W_p \) and is the dot product of matrix \( W \) and vector \( p \). Each neuron has a bias \( b \) that is summed to the weighted inputs in order to form the net input \( n \) that is utilized as an argument for a transfer function \( f \).

\[
 n = w_{1,1}p_1 + w_{1,2}p_2 + \ldots + w_{1,R}p_R + b
\]  

(1)

The transfer function can be selected from a wide set of functions, e.g. hard-limit, linear, log-sigmoid, tan-sigmoid, etc. A network may have multiple layers, with each layer having a weight matrix \( W \), a bias vector \( b \) and an output vector \( a \). The outputs of each intermediate layer are used as inputs for the next layer. The layer that produces the network output is called the output layer, while the intermediate layers are called hidden layers.
Research activity on using Artificial Networks on damage detection methods has already been reported in the literature. Ünlü et al. [19] determined the friction coefficient for CuSn10 Bronze radial bearings, using experimental data in combination with artificial neural networks. In these experiments, the bearings performance has been examined at dry and lubricated conditions and at different loads and velocities. Kalkat et al. [20] presented a direct-coupled rotor system to analyze the dynamic behavior of rotating systems in regard to vibration parameters. The vibration parameters used were amplitude, velocity, and acceleration in the vertical direction. The vibration parameters were found, saved and then employed as necessary parameters for the network. A neural network was designed for analyzing the vibration parameters of the system. The results showed that the network could be used as an analyzer of such systems in experimental applications.

Saridakis et al. [21] investigated three parameters, the location, the depth and the angle of rotation of two cracks in a cracked beam problem. In their approach the analytical model was approximated through an artificial neural network, which was used in order to solve the inverse problem of crack identification. A genetic algorithm produced values for the cracks’ attributes (position, depth and angle) as input arguments to the neural network, and searched for a solution comparing the outputs with experimentally measured values of responses. For this optimization, five alternative objective functions were used, with two of them based on fuzzy logic mathematics.

In the present work a method for predicting online wear is presented. The basic bearing characteristics, namely the eccentricity, the attitude angle the minimum film thickness are calculated as a function of several wear depths, and misalignment angles using a finite element method. An artificial neural network is submitted to a training process, which eventually provides an ANN-structure capable of identifying
the progress of each defect. The calculation of the above parameters is performed with high accuracy and speed, so as to be considered as an efficient online monitoring tool for the specific parameters.

Figure 2: Geometry of a) journal bearing and b) worn journal bearing

2 Analysis

2.1 Bearing model formulation

In this paper, the bearing is considered to be rigid rather than elastic and focus is given to misalignment and wear. The journal bearing is assumed to operate in the steady-state situation. The flow is chosen to be laminar and an isothermal regime is also assumed. The geometry of worn bearing follows the model introduced by Dufranne et al. [7] and is shown in Fig. 1, where, \( O_b \) is the bearing centre, \( O_j \) is the journal centre, \( R_b \) is the bearing radius, \( R_j \) is the journal radius, \( e \) is the bearing eccentricity, and \( L \) is the bearing length. The eccentricity ratio is defined as \( \varepsilon = e/c \), where \( c \) is the radial clearance. The external vertical load is considered to be constant.
2.2 FEM Numerical model

As it was shown previously by Goenka [18] in the FEM formulation, the true pressure distribution \( P \) in an incompressible lubricant film minimises the discretized power functional \( I(P) \),

\[
\frac{\partial I(P)}{\partial P} = \left\{ \int \left[ \frac{h^3}{24\mu} \nabla P - hU \right] \cdot \nabla P \right\} dA + \int_{S_q} QP ds = 0
\]  

(2)

where \( h \) is the film thickness, \( \mu \) the viscosity of the fluid, \( U \) the velocity of the journal surface parallel to the film, \( A \) the integration surface, \( S_q \) is the boundary segment, and \( s \) is the fluid film boundary.

This differentiation leads to the following equation in matrix form,

\[
\begin{bmatrix} K_p \end{bmatrix} \{ P \} = \{ q \} - \begin{bmatrix} K_U \end{bmatrix} \{ U \} - \begin{bmatrix} K_V \end{bmatrix} \{ V \}
\]  

(3)

where \( q \) is the volume flow, \( V \) is the squeeze velocity, and \([K_p],[K_U]\) and \([K_V]\) are the element fluidity matrices such that:

\[
K_{p_i} = -\int_A \frac{h}{12\mu} \left( \frac{\partial N_i}{\partial x} \frac{\partial N_j}{\partial x} + \frac{\partial N_i}{\partial z} \frac{\partial N_j}{\partial z} \right) dA
\]

\[
K_{U_i} = \int_A h \frac{\partial N_i}{\partial x} N_j dA, \quad K_{V_i} = \int_A h \frac{\partial N_i}{\partial z} N_j dA
\]  

(4)

\[
\{ q \} = \int_{S_q} Q N_i ds
\]

\[
Q = h \left( U - \frac{h^2}{12\mu} \nabla P \right) \cdot \hat{m}
\]  

(5)

where \( Q \) is the flow vector, \( \hat{m} \) is the outward normal vector along the boundary and \( N_i \) are shape functions given by,

\[
N_i(\theta,z) = \frac{(a_i + b_i \theta + c_i z)}{2A'}
\]  

(6)

where, \( a_i = \theta_2 z_3 - \theta_3 z_2, \quad b_i = z_2 - z_3, \quad c_i = \theta_3 - \theta_2, \quad \alpha_2 = \theta_3 z_1 - \theta_1 z_3, \quad b_3 = z_3 - z_1, \quad c_2 = \theta_1 - \theta_3, \quad \alpha_3 = \theta_2 z_2 - \theta_2 z_1, \quad b_2 = z_1 - z_2, \quad c_3 = \theta_2 - \theta_1 \) are the interpolation coefficients and \( A' \) is the determinant:

\[
A' = \left| \begin{array}{ccc}
1 & \theta_1 & z_1 \\
1 & \theta_2 & z_2 \\
1 & \theta_3 & z_3 \\
\end{array} \right| = \iint d\theta dz = \frac{1}{R_b} A
\]  

(7)
with $A$ being the area of the triangular element. The coordinate $\theta$ is defined from the negative X-axis, and the Reynolds equations is developed in the coordinate system $(x=R\theta,z)$ as shown in Fig. 2.

In the FEM analysis, the global fluidity matrices and flow vector can be assembled numerically from element matrices and vectors in the usual manner. In its discretized form, the problem is solved by minimizing the system functional (2) with respect to the unknown (generally interior) nodal pressures subject to the non-negativity constraint. A finite element grid of size 50 x 9 is used in order to obtain the solution, including the geometry of the worn and misaligned bearing. Fifty elements are used for the circumferential dimension and nine elements in the longitudinal direction.

2.3 Equilibrium position

The hydrodynamic forces and moments developed in the bearing can be evaluated by integrating the fluid pressure over the entire bearing area.

$$F_x = \int_{-L/2}^{L/2} \int_{\theta_1}^{\theta_2} P(\theta, z) R \cos \theta \, d\theta \, dz$$

$$F_y = \int_{-L/2}^{L/2} \int_{\theta_1}^{\theta_2} P(\theta, z) R \sin \theta \, d\theta \, dz$$

For a given external loading condition $F_{ext}$, the static equilibrium position of the journal centre can be found by equating the hydrodynamic forces with the externally applied load. A two-dimensional Newton-Raphson search technique is applied for the calculation of the equilibrium position of the journal centre when the sum of the hydrodynamic forces and the external loads is equal to zero. In the equilibrium position, the eccentricity $e_0$ and the attitude angle $\phi_0$ are the variables in the Newton-Raphson method and are determined for a given wear amount. In this algorithm, the horizontal and the vertical hydrodynamic forces at the equilibrium are compared at each step with a tolerance factor which is 0.001 or less. The angles $\theta_1$ and $\theta_2$ mark the extent of the pressure field, which depends on boundary conditions applied.

$$\sum (F_{\text{hydr}} + F_{\text{ext}}) = 0$$

The basic operational and geometrical parameters which are used in the analyses and the evaluation are the Sommerfeld Number $S$, the journal revolution $N$, the oil viscosity $\mu$, the $L/D$ ratio where $L$ is the bearing length, and $D$ as the journal diameter. The Sommerfeld number is given by:

$$S = \frac{\mu N D L (R/c)^2}{F_{\text{hydr}}^2}$$

where $F_{\text{hydr}} = \sqrt{F_x^2 + F_y^2}$
2.4 Geometry of worn bearing

The geometry of the worn bearing surface used in the present analysis is the well known model presented by Dufranne et al. [7]. The film thickness is given by superposition of film thicknesses as is mentioned by Nikolakopoulos et al. [17] and Dufranne et al. [7] for the abrasive bearing wear model as it is depicted in Fig. 1c,

\[ h(\theta, z) = c + e_0 \cos \theta + z \left[ \psi_\theta \cos(\theta + \phi_0) + \psi_z \sin(\theta + \phi_0) \right] + \delta h \]  

where,

\[ \delta h = c(d_0 - 1 - \cos \theta) \]

Eq. (12) describes the change in the film thickness due to the bearing wear, and is applicable between the angles relevant to the worn region, otherwise \( \delta h = 0 \). The worn zone is assumed to be centred on the vertical load direction, where \( d_0 = \delta_0 / c \) is the dimensionless wear depth (which corresponds to the percentage of the wear depth in relation to the radial clearance), and \( \delta_0 \) is the maximum wear depth. The worn zone is supposed to be centred to the vertical load direction and is estimated by the equation [7, 8],

\[ \cos \theta_w = d_0 - 1 \]

where \( \theta_w \) is the angle of the worn area.

2.5 Minimum film thickness

Another useful parameter which indicates the bearing lubrication regime is the minimum film thickness \( h_{\text{min}} \), which occurs at one of the two ends of the bearing. The minimum film thickness for misaligned journal bearings is defined by the expressions (14) and (15) [17].

\[ h_{\text{min}}_{x=L/2} = c - \sqrt{(e_0 \sin(\phi_0) - \psi_z L/2)^2 + (e_0 \cos(\phi_0) + \psi_z L/2)^2} \]  
\[ h_{\text{min}}_{x=-L/2} = c - \sqrt{(e_0 \sin(\phi_0) - \psi_z L/2)^2 + (e_0 \cos(\phi_0) - \psi_z L/2)^2} \]

2.6 Wear and misalignment detection using ANN

Wear may take place at every phase in the life of parts or machine elements, including the manufacturing process. It plays an important role in determining life span of machine elements. Timely detection of wear, therefore, is highly demanded in many applications in order to predict remaining life of elements, avoid further
bigger damage to a whole system, safeguard product reliability and reduce potential cost.

This section presents a general framework that models the wear identification problem through a neural network that approximates the analytical theoretic model. The basic bearing characteristics, like the eccentricity, the attitude angle the minimum film thickness are calculated as a function of several wear depths, and misalignment angles using the finite element method. Several records of values for these input and output parameters of the problem are generated by using an analytical model. The goal is to use these records in order to solve the inverse problem in real-time fault diagnosis conditions, in which the operating characteristics can be monitored by specific measuring systems. A conventional method is to use a retrieval scheme to find the most similar sets of input values \((\psi, e, h_{\text{min}} \text{ at } z=-L/2 \text{ and } h_{\text{min}} \text{ at } z=L/2)\) in the records so as to extract wear depths and misalignment angle \((\psi_x, \psi_y, d_0)\). However, this process may lead to several inconsistencies. First, the input values may not match exactly with any of the input values in the records sets and therefore the values extracted for the wear depths and misalignment angle will not be accurate. Moreover, during operating conditions, it is rare, yet possible, for some values to lie slightly out of the limits produced by the analytical model. In order to overcome these two problems, an alternative approach based on ANN approximation is proposed. An artificial neural network is submitted to a training process, which eventually provides an ANN-structure capable of identifying the progress of each defect by solving an inverse instance of the initial analytical model. The ANN is submitted to supervised training, in which the learning rule is provided with a set of examples of desired network behaviour: \(\{p_1, t_1\}, \{p_2, t_2\}, \ldots, \{p_Q, t_Q\}\) with \(p_q\) to be the input to the network and \(t_q\) to be the corresponding target input. As each input is applied to the network, the network output is compared to the target (Fig.3). The error is calculated as the difference between the target output and the network output. The algorithm tends to the average of the sum of these errors by adjusting the weights and the biases of the neural network. The mean square error function can be expressed through the following relation:

\[
\text{mse} = \frac{1}{Q} \sum_{k=1}^{Q} e(k)^2 = \frac{1}{Q} \sum_{k=1}^{Q} (t(k) - a(k))^2
\]

With \(Q\) the number of records, \(t(k)\) the initial output values that are used for training, \(a(k)\) the values that are extracted as outputs from the ANN.

In the present research work, the order with which the input vectors are considered for ANN’s training is not taken into account. Thus the ANN is static and propagates the values to the successive layers in a feed-forward way. The training of the neural network is performed through a back-propagation algorithm. In general, the back-propagation algorithm is a gradient-descent algorithm in which the network weights are moved along the negative of the gradient of the performance function. Finally, the trained ANN can extract sets of values for the output parameters \((\psi_x, \psi_y, d_0)\) by inputting values that are measured on-line by monitoring systems (Fig.4).
ANN is capable to interpolate among values of the records that have been initially used for the training and/or extrapolate if the monitored values are positioned close but out of bounds of the records sets. Moreover, the time needed for one calculation cycle is $2.41 \times 10^{-4}$ secs, which is adequate for a real-time on-line fault diagnosis system.

![Figure 3: ANN supervised training](image)

![Figure 4: Approximation of analytical model with ANNs for on-line monitoring of rotor bearings’ wear](image)

### 3 Results

A journal bearing with slenderness ratio $L/D=1$, radial clearance $c=65\mu m$, journal radius $R_j=0.0254mm$ rotating at 400rad/sec and lubricated with an oil with viscosity $\mu=0.012$Pasec, is used as an application example. Two cases are examined; in the first the bearing is externally loaded by a force of 1000N and for the second this force increases to 3000N. The wear of the bearing also variates from $d_0=0$ to $d_0=0.5$ and the dimensionless misalignment angles from 0 to 0.5.
In order to select an efficient architecture for the neural networks, several tests were conducted to evaluate the accuracy and the required training time. When designing the architecture of a neural network it is difficult to speculate in advance its performance. For the current application, several different architectures were tested following a trial-and-error process. The proposed settings (architecture and training method) proved to be efficient for the specific problem but probably it may not be the optimal ones, considering all aspects (convergence speed, accuracy, simplicity, computational cost). The same practice was followed for the selection of the training method and several training methods were tested for validation. The analytic model was approximated by a neural network of five (5) hidden layers. These three layers contain 5, 20, 5, 5 and 3 neurons, respectively and use the transfer functions 'purelin', 'logsig', 'purelin', 'logsig', 'purelin' [24]. The training of the neural network was performed by the Levenberg-Marquardt back-propagation algorithm [24] using 1331 recorded sets of input–output values for 9000 cycles of training (epochs). The training resulted in a mean square error (MSE) for the training examples equal to 1.9123x10^-5 for 1000N load and 2.3978x10^-5 for the 3000N. Each training session (training for each load) lasted 55 minutes using an Intel® Pentium® M 1.6 GHz processor. The obtained accuracy is considered to be adequate for the scope of the current application but better results could be obtained if more training cycles have been deployed. Furthermore, a specific ANN architecture has been selected experimentally, thus a better architecture and/or training algorithm could be found resulting in lower MSE in less training time. However, there is no guideline to define in advance the optimal architecture or training algorithm for the specific problem. Assuming that there is the following record set that includes values from the theoretic model and from the trained ANN:

<table>
<thead>
<tr>
<th>Output parameters (theoretic model)</th>
<th>Output parameters (approximated by ANN)</th>
<th>Deviation (theoretic-approximated)/interval</th>
<th>Average deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\psi_x$, $\psi_y$, $d_0$</td>
<td>$\psi_x$, $\psi_y$, $d_0$</td>
<td>$\psi_x$, $\psi_y$, $d_0$</td>
<td></td>
</tr>
<tr>
<td>0, 0, 0</td>
<td>0.002770, 0.000340, 0.000197</td>
<td>0.554%, 0.068%, 0.039%</td>
<td>0.220%</td>
</tr>
</tbody>
</table>

Then, based on the values of the six first columns, it is possible to calculate the deviation for each of the three output parameters using the following formula:

$$\text{Deviation}_{\psi_x} = \frac{|\psi_x_{\text{theoretic}} - \psi_x_{\text{ANN}}|}{\psi_x_{\text{interval}}} = \frac{0.002770}{0.5} = 0.554\%$$

The interval is equal to 0.5 for all three parameters and this value is used in the calculations. In the same way the Deviation$_{\psi_y}$ and the Deviation$_{d_0}$ are calculated for each record. Finally, the average deviation is calculated for the three parameters for each record set:

$$\text{Average deviation} = \frac{(\text{Deviation}_{\psi_x} + \text{Deviation}_{\psi_y} + \text{Deviation}_{d_0})}{3} = \frac{(0.554\% + 0.068\% + 0.039\%)}{3} = 0.220\%$$

Figure 5 depicts the average deviations for all record sets and for the two external loads that has been used in the present example case (1000N & 3000N). This figure
visualizes the accuracy achieved by the trained network, which can be further improved if more training epochs are used or a better ANN architecture is found for the specific application. In any case the results achieved in this example can be characterized as efficient to validate the proposed method as a powerful online fault diagnosis tool for cracks characteristics.

![Graph](image)

(a) Average Deviation for 1331 record sets with 1000N load

(b) Average Deviation for 1331 record sets with 3000N load

Figure 5: Deviation percentages between theoretic and approximated values for loads 1000N (a) and 3000N (b)

4 Conclusions

The proposed method contributes to the identification of defects on the rotor bearing systems, such as misalignment and wear. The utilization of artificial neural networks provides a very effective tool for on-line monitoring of wear and misalignment due to fast and accurate calculation. Moreover, when compared to conventional retrieval or heuristic methods, it provides the capability for interpolation among values of existing records or even extrapolation out of the limits that are defined by the elapsed records. Future work will be undertake to train a dynamic – instead of a static – artificial neural network with values extracted by real systems with actual measurements aiming at investigating the sequence according to which values are varied in the proposed theoretic model.
References


