Application of artificial neural networks to fault diagnostics of rotor-bearing systems

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Abstract. The article is dedicated to the pattern recognition of unbalanced rotor vibration trajectories. The diagnostics of rotary machines with fluid-film bearings is studied. The feedforward neural networks were used to analyze the measurement data of rotor vibrations and other parameters of the rotor-bearing system. The states of the system were studied at various values of the rotor unbalance. It was shown that the number of training samples and the number of neurons in the input layer have the greatest impact on recognition accuracy. As a result of training the neural network to recognize 3 classes of defects, an accuracy of more than 97% was achieved.

1. Introduction

The most common type of movement in technics is rotation. The rotation allows to reach a high-speed and high-power motion in limited space. Rotating parts are present in the most engines and machines. The bearings allow the rotating rotor to be held stationary on a fixed base and determine reliability and energy efficiency of the machine. Therefore, the diagnosis of a bearing is a very important engineering task. In this paper the fluid-film bearings are studied [1].

Two approaches, the deterministic and the stochastic are applied in fault diagnosis. Deterministic methods are connected with spectral analysis, Fourier transform, wavelet analysis, etc. and require an extensive engineering experience to apply them [1, 2, 8]. Most of the stochastic methods are connected with machine learning and artificial neural networks (ANNs). Usually, researchers combine the deterministic methods to prepare a data using filters and transforms and the shallow machine learning methods to solve a fault diagnosis problem [6, 10, 12, 17]. A promising research area is the development of compact controllers for automatic diagnostics in a real time [4]. The modern trend is an application of deep learning and feature extraction which help to decrease a human factor and an engineering experience to solve a problem of fault diagnosis [9, 11, 14]. Deep learning is indispensable when analyzed information is represented as images [14]. Otherwise, shallow learning is competitive approach. Both, shallow learning and deep learning methods represents good accuracy above 90%.

This work deals with the shallow machine learning methods to solve a fault diagnosis problem using data from multiple sensors. Similar measurement system and ANN architecture were used in [17] for the thermal wedge detection and in [13] for the bubbles detection in the lubrication systems of the fluid-film bearings. The goal of this work is design of the software for rotor-bearing systems fault diagnosis.
2. The basics of classification problems solution using artificial neural networks

A fault diagnosis problem in engineering is a classification problem in machine learning [14]. Classification is permissible both with the labeled data set (a supervised learning), and without (an unsupervised learning). To solve the problems of classifying various dynamic processes, it is more productive to use classifier programs trained on a labeled data [15, 18].

Classification problems usually consider binary functions \( Y = \{0; 1\} \) of continuous or discrete factors. The task is to approximate these functions, usually with the help of a logistic function.

First, we consider the function of one factor. Before approximation, the factor values were converted into a form \( z = f(u) \) so that one class corresponds to negative values of the modified factor, and the other to positive. It is convenient to choose the logistic function [18] for approximation:

\[
H_\theta(u) = (1 + \exp(-z(u)))^{-1}
\]  

(1)

The class boundary is determined by the relation \( H_\theta(u) = 0.5 \), which corresponds to the zero value of the function \( z(u) = 0 \). In the general, the boundary between classes can be nonlinear. It can be described by polynomials. For example, the boundary \( z(U) = 0 \) for the function of two factors can be represented in the form of the third degree polynomial:

\[
z(U) = \theta_0 + \theta_1 u_1 + \theta_2 u_2 + \theta_3 u_1^2 + \theta_4 u_2^2 + \theta_5 u_1^3 + \theta_6 u_2^3.
\]  

(2)

Equation (2) can be converted into a linear form by means of a replacement:

\[
z(U) = \theta_j u_j, \ j = 0, N, \ u_0 = 1,
\]  

(3)

where \( u_3 = u_1^2 \), \( u_4 = u_2^2 \), etc.

For the problem considered in this paper, the number of classes exceeds two. Therefore, a neural network was used for classification, the architecture of which is shown in Figure 1. The input layer contains \( N_{\text{inp}} \) neurons. The number of input neurons is equal to the number of input factors. The number of output neurons \( N_{\text{out}} \) is equal to the number of classes. The number of neurons in the hidden layer \( N_{\text{hid}} \) is arbitrary.

![Figure 1. Neural network scheme.](image)

The sigmoid function of type (1) is used as an activation function on the hidden layer and the “softmax” function is used in the output layer [19]. The “softmax” function is used for the multiclass classification as a generalization of the logistic function (1).
The proposed ANN was implemented in the developed program. The ANN was trained according to the results of a physical experiment. The experimental results were obtained on the test rig which is described below.

3. Experiment and results

The test rig is a rotor-bearing system with a short fluid-film bearing of 20 mm length and 20 mm radius (see Figure 2). The mean gap of the bearing is 75 μm. an electromotor, a lubrication circuit and an information-measuring system. The hydraulic lubrication circuit includes a tank for storing water lubrication, a pump, filters, a servo valve and pipelines in which pressure and flow rate sensors are mounted. The “ELTE_TMPE3_12/2” spindle with frequency converter was used for controlled rotor drive.

![Figure 2. The test rig.](image)

The sensory and control system (SCS) of the test rig was developed in the same engineering programming environment as the ANN [20]. The scheme of the SCS is shown in Figure 3.

![Figure 3. Sensory and control system of test rig.](image)
During the experiment, the effect of rotor imbalance influence on the oscillations trajectory was investigated. Three levels of imbalance were investigated. At the entrance to the neural network were fed from 2 to 7 measured values. It was necessary to determine the type of imbalance. The fragments of measured rotor trajectories are shown in Figure 3. The third order Savitzky-Golay filter was used to smooth the measured signals.

To analyze the accuracy of fault detection, a series of computational experiments was carried out. The plan and results of the numerical experiment are presented in Table 1. The data for the computational experiment was randomly taken from the data of a physical experiment for measuring rotor vibrations and pressure in the bearing. According to the plan of the computational experiment, the number of training samples, as well as their size, and the number of neurons in the hidden layer were varied. The training samples were divided into 3 parts for training, validation and testing of ANNs, respectively. The following parameters were used as input parameters for training the neural network: the pressure, the contact resistance ratio in the lubrication film, the flow rate, the rotor displacements in horizontal and vertical directions, the torque and the temperature of the electromotor.

![Figure 4. The fragments of the measured rotor trajectories.](image)

| Variable parameters of ANN | Values of variable parameters | Minimal accuracy, % |
|---------------------------|-------------------------------|-------------------|
| The number of training samples, $Q$ | 9 | 30.3 |
|  | 60 | 76.3 |
|  | 120 | 80.3 |
|  | 360 | 97.3 |
|  | 10 | 70.3 |
|  | 20 | 76.3 |
|  | 50 | 72.4 |
|  | 60 | 79.6 |
| The number of hidden neurons, $N_{hid}$ | 70 | 75.8 |
|  | 100 | 97.2 |
|  | 150 | 93.1 |
|  | 500 | (overfitting) |
|  | 600 | (overfitting) |
|  | 700 | (overfitting) |
| The number of input neurons | 7 | 97.2 |
|  | 5 | 53.5 |
|  | 2 | 60.5 |
It can be seen from the results of a computational experiment that the greatest influence on the accuracy was exerted by the number of training samples. This is well-known fact that the bigger the dataset the better the accuracy. The smallest influence on the accuracy was extended by the number of neurons in the hidden layer. Thus, as a result of a series of computational experiments, an accuracy of 97.2% was achieved in solving the problem of classifying and diagnosing the condition of the rotor-bearing system.

4. Conclusions
A number of rotor systems have a distinctive feature such as a change in the process of operation of mass and size characteristics. Such features complicate the study of the dynamic characteristics of rotary machines. However, in the process of design and operation it is necessary to study the dynamic properties of the system as a whole. As part of the fault diagnosis in the above dynamic systems it is necessary to use modern methods of monitoring and recognition of the state by a set of measured parameters.

The rotor imbalance has a significant effect on the state of the mechanical system. It was possible to establish this effect with an accuracy of more than 97.3% using an artificial neural network after processing the measurement data. The accuracy is depended mostly on the number of sensors and the volume of the dataset. Thus, artificial neural networks are an effective and affordable means of diagnosing the state of rotor systems with fluid-film bearings.

The further research will be connected with multiclass classification and with develop of the diagnostics hardware.

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