FAULT IDENTIFICATION IN ROTOR SYSTEM USING MODEL BASED METHODS, EXPERIMENTAL DATA AND ARTIFICIAL NEURAL NETWORK

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Abstract. *This paper presents some results about diagnostic and identification of faults in a rotor system using Artificial Neural Network (ANN) and Model based methods. ANN is a mathematical tool inspired by the functioning of the human brain. There are many applications of ANN, like: pattern recognition, control, signal analysis, fault detection, modeling, etc. In rotor dynamics, ANN are used to diagnose some kinds of faults, but normally it is not able to evaluate the localization along the rotor and the severity of the fault. Model based methods are able to locate and to evaluate the severity of the fault, but require also specific tools to diagnose the fault type, like the evaluation of the residuals for different types of faults with similar symptoms. In regards to the ANN, we used a Multilayer Perceptrons trained with Backpropagation algorithm. There are three basics stages in this ANN: Training; Verification and Diagnostic. The model of the rotor system was obtained by finite element method using beam elements and the simulation program, which used also specific models for faults, was completely written in Matlab®. Each node of the model has four degrees of freedom (d.o.f). The experimental case is relative to the test owned by the Politecnico di Milano. It is made of a rotor composed by two rigidly coupled shafts, supported by means of four lemon shaped oil film bearings on a flexible frame. The training of the ANN was made by means of the simulated data of the model, which was already tuned and can be considered as reliable. Then, the experimental data of actual faults (unbalance) have been inserted in the ANN, obtaining the identification of faults with similar symptoms (all considered faults are one times revolution) and also its localization.*

Keywords*: artificial neural network, fault identification, rotor system.*

1. Introduction

Nowadays, there exist a great interest to understand some of physical phenomena that manage the environment where we live. This natural interest focuses in finding answers to these critical questions and in the possibility of controlling and predicting certain situations. In engineering field the system modeling and the development of diagnosis and monitoring techniques enable researches to reach these requirements. Several techniques have been applied in fault detection of machines and structures, as the neural network, which has a significant impact on the academic community due to its versatility and wide application field. Lopes Jr. *et al.* (2000) and Doebling *et al.* (1996) showed some of these applications. However, many others examples can be found in literature.

The identification procedure can be performed as usual by means of causality correlations of measurable symptoms to the faults. As regards the rotor dynamics field and limiting to the most recent contribution, two main approaches can be used (Bachschmid, Pennacchi and Vania, 2002).

In the first approach, the symptoms can be defined using qualitative information, based on human operators' experience, which creates a knowledge base. A recent contribution is given in reference (White and Jecmenica, 1999): an expert system can be built up in which different diagnostic reasoning strategies can be applied. Fault-symptom matrices, fault-symptom trees, if – then rules or fuzzy logic classifications can be used to indicate in a probabilistic approach the type, and sometimes also the size and the location of the most probable fault. Also artificial neural networks (ANN) can be used for creating the symptom-fault correlation. This qualitative diagnostic approach is widely used both in industrial environments and in advanced research work.

The second approach is quantitative and is called the model-based fault detection method. In this case, a reliable model of the system or the process is used for creating the symptom-fault correlation, or the input – output relation. However, this method has many different ways of application. Among recent contributions available in literature, Mayes and Penny (1999) introduce a fuzzy clustering method, which considers vibration data as a high-dimension feature vector. The vibration caused by a particular fault on a specific machine can be considered a point in this high-dimension space.

Fault detection in rotor machine like mass unbalance, rotor rub, shaft misalignment, gear failures and bearing defects is possible by comparing the vibration signals of a machine operating with and without fault conditions. These signals can also be used to detect the incipient failures of the machine components, through on-line monitoring system, reducing the possibility of catastrophic damage (Samanta and Al-Balushi, 2003).

Neural networks are widely used, as they can effectively realize nonlinear mapping between the input and the output samples of faults. Most faults occurring in rotating machinery are unstable state faults corresponding to the shock signals. Fault diagnosis is a type of pattern recognition, and ANN classifiers appear to be reasonable alternatives to traditional classifiers. Because ANNs can learn and adapt from input data to actual fault, they can represent the complex relations of fault and symptoms that are difficult to model with traditional physical engineering relations or knowledge-based expert systems (Chen and Mo. 2004).

Bachschmid, Pennacchi and Vania (2002) show an identification of multiple faults in rotor systems. A model-based identification method for multiple faults is presented. In this work they modeled elements like rotor, bearings and foundation. The models of the faults were represented by harmonic components of equivalent force or moments systems. In the present work we describe fault identification in rotor machinery with ANN using the same model of the test-rig and the equivalent force used by the referred authors. The training of the ANN was made by means of the simulated data of the model, which was already tuned and can be considered as reliable. Then, the experimental data of actual faults (unbalance) have been inserted in the ANN, obtaining the identification of faults.

2. Fault modeling

Before introducing the fault models, it is necessary to introduce the reference systems used in two-dimensional (2D) finite element (f.e.) model of the rotor. Each node of the model has four degrees of freedom (d.o.f.). If one considers the two subsequent nodes, the jth and the j+1th, they define the element jth, Fig. 1 (Bachschmid, Pennacchi and Vania, 2002).

Defining the vector $\mathbf{x}^{(j)}$ of generalized displacements of the jth node as

$$\mathbf{x}^{(j)} = [x_j \ \upsilon_{x_j} \ y_j \ \upsilon_{y_j}]^{\mathrm{T}} \tag{1}$$

the vector $\mathbf{x}$ of generalized displacements of all nodes of the rotor is composed of every ordered vectors $\mathbf{x}^{(j)}$:

$$\mathbf{x} = [\cdots x_j \ \upsilon_{x_j} \ y_j \ \upsilon_{y_j} \ x_{j+1} \ \upsilon_{x_{j+1}} \ y_{j+1} \ \upsilon_{y_{j+1}} \ \cdots]^{\mathrm{T}} \tag{2}$$

Moreover, a rotating force $\mathbf{F}^{(k)}$ of amplitude $F^{(k)}$ and phase $\varphi^{(k)}$, and a rotating moment $\mathbf{M}^{(k)}$ of amplitude $M^{(k)}$ and phase $\varphi^{(k)}$, with a frequency of $n\Omega$ acting on the jth node have the following representation:

$$\mathbf{F}^{(k)} = [0 \ \vdots \ \underbrace{1 \ 0 \ i \ 0 \ \vdots \ 0}_{jthnode}]^T . F^{(k)} \mathrm{e}^{i\varphi(k)} \mathrm{e}^{in\Omega t} \tag{3}$$

$$\mathbf{M}^{(k)} = [0 \ \vdots \ \underbrace{0 \ 1 \ 0 \ i \ \vdots \ 0}_{jthnode}]^T . M^{(k)} \mathrm{e}^{i\varphi(k)} \mathrm{e}^{in\Omega t} \tag{4}$$

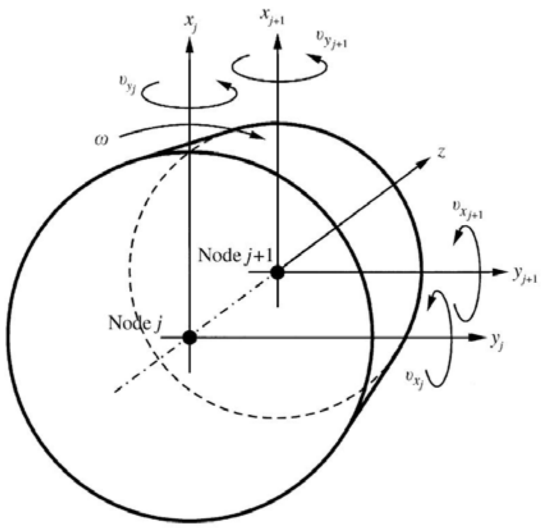

Figure 1. Reference system on a general rotor element j.

In the parameter estimation approach, the identification of changes in the system parameters due to faults seems to be more difficult task than to identify equivalent external forces. The system parameters influence the complete mass, stiffness and damping matrices of the system. In other words, with reference to the standard matrix equation of the system

$$\mathbf{M}\ddot{\mathbf{x}}_t + \mathbf{D}\dot{\mathbf{x}}_t + \mathbf{K}\mathbf{x}_t = \mathbf{F}(t) \tag{5}$$

it seems difficult to identify the changes in matrices **M**, **D**, and **K** from measurement of vibration $\mathbf{x}_t$, in only a few measuring points along the shaft, such as those that occur in real machines. Indicating by d**M**, d**D** and d**K** the changes in mass, damping and stiffness matrices due to system parameter changes caused by the fault, Eq. (5) yields.

$$(\mathbf{M} + \mathrm{d}\mathbf{M})\ddot{\mathbf{x}}_t + (\mathbf{D} + \mathrm{d}\mathbf{D})\dot{\mathbf{x}}_t + (\mathbf{K} + \mathrm{d}\mathbf{K})\mathbf{x}_t = \mathbf{W} + (\mathbf{U} + \mathbf{M}_u)\mathrm{e}^{\mathrm{i}\Omega t} \tag{6}$$

in which the right side external forces $\mathbf{F}(t)$ are generally unknown. The force vector is composed of weight (which is known) and of original unbalance and bow (which are unknown). If the system is considered to be linear, then the total vibration $\mathbf{x}_t$ can be considered to be split into two terms, which can be simply superposed:

$$\mathbf{x}_t = \mathbf{x}_1 + \mathbf{x} \tag{7}$$

The first term of the right side ($\mathbf{x}_1$) is due to weight **W** as well as the unknown unbalance force $\mathbf{U}\mathrm{e}^{\mathrm{i}\Omega t}$ and unbalance moment $\mathbf{M}_u\mathrm{e}^{\mathrm{i}\Omega t}$, and the second term ($\mathbf{x}$) is due to the fault. The component **x** may be obtained by calculating the vector differences of the actual vibrations (due to weight, original unbalance and fault) minus the original vibrations measured, in the same operating conditions (rotation speed, flow rate, power, temperature, etc.) before the fault occurrence. Recalling the definition of $\mathbf{x}_1$, the pre-fault vibration, following equation holds:

$$\mathbf{M}\ddot{\mathbf{x}}_1 + \mathbf{D}\dot{\mathbf{x}}_1 + \mathbf{K}\mathbf{x}_1 = \mathbf{W} + (\mathbf{U} + \mathbf{M}_u)\mathrm{e}^{\mathrm{i}\Omega t} \tag{8}$$

which when substituted into Eq. (6) gives

$$\mathbf{M}\ddot{\mathbf{x}} + \mathbf{D}\dot{\mathbf{x}} + \mathbf{K}\mathbf{x} = -\mathrm{d}\mathbf{M}\ddot{\mathbf{x}}_t - \mathrm{d}\mathbf{D}\dot{\mathbf{x}}_t - \mathrm{d}\mathbf{K}\mathbf{x}_t \tag{9}$$

The right side of Eq. (9) can be considered as a system of equivalent external forces, which force the fault-free system to have the change in vibrations defined by **x** that is due to the developing fault only:

$$\mathbf{M}\ddot{\mathbf{x}} + \mathbf{D}\dot{\mathbf{x}} + \mathbf{K}\mathbf{x} = \mathbf{F}_f(t) \tag{10}$$

Using this last approach, the problem of fault identification is then reduced to a force identification procedure with known system parameters, keeping in mind that a particular force system corresponds to each type of fault considered. If one considers a steady state situation, assuming linearity of the system and applying the harmonic balance criteria from Eq. (10), one gets, for each harmonic component, the equations

$$\left[-(n\Omega)^2\mathbf{M} + \mathrm{i}n\Omega\mathbf{D} + \mathbf{K}\right]\mathbf{X}_n = \mathbf{F}_{f_n}(\Omega) \tag{11}$$

where the force vector $\mathbf{F}_{fn}$ has to be identified. This force vector could be a function of Ω or not, depending on the type of the fault.

2.1. Unbalance fault model

The unbalance has only a one time revolution (1*x*) component. The complex vector of the general *k*th fault force system $\mathbf{F}_{f_1}^{(k)}$ becomes in this case:

$$\mathbf{F}_{f_1}^{(k)} = [0 \vdots 1 \;\; 0 \;\; i \;\; 0 \vdots 0]^{\mathrm{T}}.(mr)^{(k)}\Omega^2 \mathrm{e}^{i\varphi(k)} \tag{12}$$

where the only elements different from zero are the ones relative to the horizontal and vertical d.o.f. of the node *j*, where the unbalance is supposed to be applied. Note that in this case the fault force system is function of the rotating speed Ω.

3. Artificial neural network

Artificial Neural Network (ANN) is a computing technique that represent a mathematical model. This technique is inspired at neuronal structure of intelligent organism and it can acquire knowledge through experience. ANN can be used for resolution of a large range of problems found in several applied areas as: classification problem; identification system; fault diagnosis; analysis of signals and images; and optimal control. It also can approximate and classify problems associated with nonlinearities. If the pattern of input data represent the fault appropriately, this formulation can be used with advantages, since, it can avoid the complexity introduced by model – based methods. If the model can represent appropriately the real machine, the ANN can be trained by mathematical model and be used to found problems in real machines and structures.

The basic processing element is called neuron that consists of activity level, a set of input and output connection. The output of the neuron is determined as shown in Eq. (13).

$$y = f\left(\sum_{i=1}^{n} w_i x_i + b\right) \tag{13}$$

where $\boldsymbol{x_i}$ are the input signals, $\boldsymbol{w_i}$ are the connection weighting, $\boldsymbol{b}$ is the bias value, and $\boldsymbol{f}$ is an activation function that may be a step, tanh, sigmoid function, etc. The estimation of parameters in nonlinear models is generally based on nonlinear optimization techniques, and the learning process consists of the adjustment of the weighting and bias value for a training data.

In this paper the Backpropagation´s training is used to train a feedforward neural network, where the topology can takes the form of multilayer feedforward structure. The neurons are not connected when they belong to the same layer, but they are connected with neurons of previous and successive layers. Figure 2 shows an example of this neural network topology.

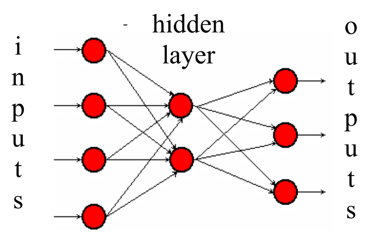

Figure 2. Example of feedforward neural network.

4. Results

For identification of unbalance, we used a finite element model of the test-rig built at Politecnico di Milano during the EC Funded research program MODIAROT (Brite Contract BRPR-CT95-0022 Model based DIAgnostics in ROTating machines). This test-rig can be used for study and analyzes of different malfunctions on the dynamic behavior of rotors. The test-rig, shown in Fig. 3 and Fig. 4, is composed of two rigidly coupled rotors driven by a variable speed electric motor and supported on four elliptical-shaped oil film bearings. Both rotors are made of steel and the rotor train is long about 2 m and has a mass about 90kg. The rotor have three critical speeds within the operating speed range 0-6000 r.p.m.. The model of the rotor has been turned and the stiffness and damping coefficients of the bearings are determined with great accuracy as described in Bachschmid *et al.* (2000).

The rotor system is mounted on a flexible steel foundation, with several natural frequencies in the operating speed range. In this case, the foundation has been modeled by means of a modal representation and further details are reported in Provasi, Zanetta and Vania, (2000). Two proximity probes in each bearing measure the relative shaft displacements, or the journal orbits; two accelerometers on each bearing housing measure its vibrations, and two force sensors on each bearing housing measure the forces which are transmitted to the foundation. The absolute vibration of the shaft is calculated by adding the relative displacement measured by the proximitors to the absolute bearing housing displacement, which is obtained integrating twice the acceleration measured by the accelerometers.

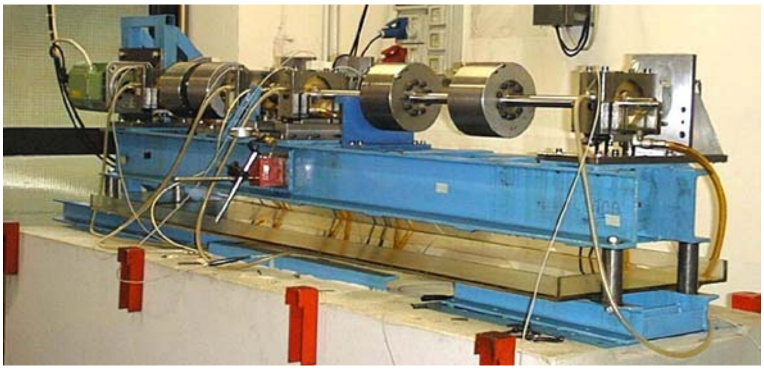

Figure 3. MODIAROT test-rig of Politecnico di Milano.

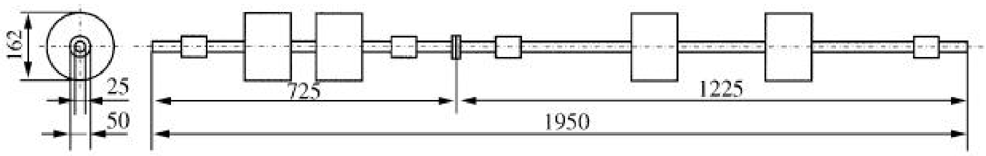

Figure 4. Sketch of MODIAROT test-rig shaft. Dimensions are in millimeters.

The finite element model used for training the ANN (Bachschmid, Pennacchi and Vania, 2002) has 47 nodes, each node of the model has four degrees of freedom. The bearings are in nodes 4, 17, 25 and 44 and the programme give the displacement in vertical and horizontal direction in these nodes.

The fault was simulate in programme by the unbalance model fault*,* describe in section 2.1, in one determined node. The programme shows the horizontal e vertical displacement in the bearings, due this unbalance. The modulus of this unbalance is unity and the phase was changed each 45º. Figure 5 shows the finite element model used.

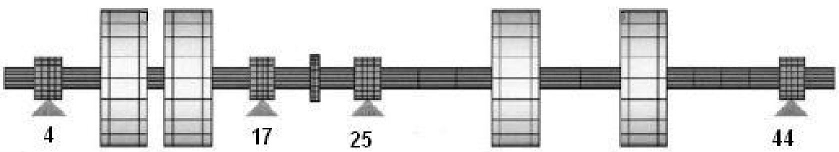

Figure 5. Finite element model of the test-rig.

To identify the position of the unbalance is necessary the identification of the node of the unbalance input. For this purpose, an ANN was trained with the modulus from these displacements due unbalances. To identify the phase of the fault, another ANN was trained with the phases of these displacements. After found the position of the fault, a specific ANN is applied to identify the phase of the unbalance. These data are obtained from simulation to 2404 r.p.m..

Both ANN´s were trained by backpropagation algorithm and they have two layers, the first one has eight neurons with sigmoidal function and the second one has one neuron with linear function.

Table 1 shows the real position of unbalances and the results obtained by ANN. During the operational condition, usually, there is variation in the rotation speed. The unbalance position were determined using more two speeds around the 2404 r.p.m.. Thus, the Tab. 1 shows the results for these three different speeds.

Table 1. Position of unbalance located by ANN trained by finite element model.

Real Position (node)	ANN Position for 2402 r.p.m. (node)	ANN Position for 2404 r.p.m. (node)	ANN Position for 2406 r.p.m. (node)
1	1,1	1,0	1,0
2	2,1	2,1	2,1
3	2,8	2,8	2,8
4	3,9	4,0	4,0
5	5,1	5,2	5,2
6	5,7	5,9	6,0
7	7,2	7,2	7,3
8	7,6	7,7	7,7
9	9,3	9,3	9,3
10	9,9	9,9	9,8
11	11,2	11,1	11,1
12	11,8	11,7	11,7
13	13,5	13,3	13,2
14	14,0	13,8	13,7
15	15,1	15,0	15,0
16	16,0	16,0	16,0
17	17,0	17,0	17,0
18	18,0	18,0	18,0
19	19,1	19,0	18,9
20	20,1	20,0	20,0
21	21,1	21,0	21,0
22	22,0	21,9	21,9
23	23,1	23,1	23,1
24	23,9	23,9	23,9
25	24,9	24,9	24,9
26	26,2	26,2	26,2
27	27,0	26,9	26,9
28	28,0	28,0	28,0
29	29,1	29,0	29,0
30	30,1	30,1	30,1
31	30,8	30,8	30,8
32	32,2	32,3	32,3
33	32,8	32,8	32,8
34	34,0	34,0	34,0
35	35,2	35,2	35,2
36	35,7	35,7	35,7
37	37,4	37,4	37,3
38	37,8	37,7	37,6
39	39,1	38,9	38,9
40	40,4	40,2	40,2
41	40,9	40,8	40,7
42	42,3	42,1	42,0
43	43,2	43,0	42,9
44	44,1	44,0	43,9
45	45,1	45,0	44,9
46	46,1	46,0	46,0
47	46,9	47,0	47,1

As showed in the Tab. 1, the real position is given by integer number but the position found by ANN is given by fractional number. This is how the ANN gives the response. In the modeling, there is no fractional node, so, the results have to be interpreted by around the next integer number.

Figure 6 shows the real position of unbalance and the position found by ANN for three different speeds (2402, 2404 and 2406 r.p.m.).

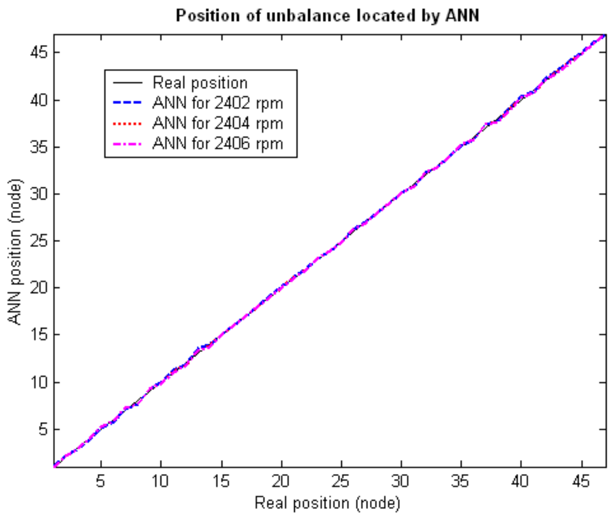

Figure 6. Position of unbalance found by ANN.

The second ANN was used to locate the phase of the unbalance. For this study, we simulated the unbalance in node 35 and we changed the phase in each 45º. Table 2 shows the real phase of the unbalance and phase found by ANN.

Table 2. Phase of unbalance in node 35 found by ANN trained by finite element model.

Real Phase (º)	**Phase found by ANN (º)**
45	45,2
90	90,0
135	135,0
180	180,0
225	225,0
270	270,0
315	315,0
360	360,0

Bachschmid, Pennacchi and Vania (2002) show that the comparison between the theoretical response of the model and the experimental data can be considered quite good using the model adopted in this paper. To verify the proposal methodology, i.e., to train the ANN with numerical data and to apply it for practical situation ,we took an experimental data with unity unbalance in node 35 and phase -90º. This fault was identified using the same ANN trained in the numerical simulation. This data was taken in speed around 2404 r.p.m.. Table 3 shows the position and the phase found by ANN from experimental data.

Table 3. Position and phase of unbalance found by ANN from experimental data.

	Node	**Phase (º)**
Real position	35	-90
ANN position	35,7	-41

The ANN presented a good result to identify the position of the unbalance fault, but it did not occur for the position of the phase. This problem happens, probable, because we used a small number of phase points (eight) for training the ANN, and the noise in the experimental data can cause some difficulties as well.

5. Conclusion

One of the major problems in the neural network-based damage identification method is that it requires the training data containing all the essential features of damaged mechanism, which is not always possible for practical situations. Hence, the main idea in this paper is to use a model-based method to train the neural network. In a second phase, experimental data sets were used to characterize the damage. So, this technique can be applied to complex structures, where prior model is available. Since, theoretical modeling is investigated in order to provide training data for the networks, the identification of simultaneous faults is a forward task. An example based on experimental measurements in the test-rig built at Politecnico di Milano (program MODIAROT) showed the good results achieved with the proposed methodology.

6. Acknowledgements

The authors would like to thanks the European Program ALPHA II "VICONDIA" for the support in this research, during the technical visit in the Politecnico di Milano, as well as CNPq and Fapesp.

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