Proceedings of COBEM 2005
18th International Congress of Mechanical Engineering
November 6-11, 2005, Ouro Preto, MG

BALANCING METHODOLOGY OF A RIGID ROTOR USING ARTIFICIAL NEURAL NETWORK

Eduardo, A.C.
Post-Doc of the Department of Mechanical Engineering (DEMEC), Federal University of Minas Gerais (UFMG).
Av. Antônio Carlos, 6627 – Pampulha, Campus Universitário, Belo Horizonte/MG, 31270-901
email: aceduard2003@yahoo.com.br

Santos, F.L.
Former M.Sc. Student of the Department of Mechanical Engineering (DEMEC), Federal University of Minas Gerais (UFMG).
Av. Antônio Carlos, 6627 – Pampulha, Campus Universitário, Belo Horizonte/MG, 31270-901
email: ffabiolss@yahoo.com.br

Duarte, M.L.M.
Lecturer and Researcher of the Department of Mechanical Engineering (DEMEC), Federal University of Minas Gerais (UFMG).
Av. Antônio Carlos, 6627 – Pampulha, Campus Universitário, Belo Horizonte/MG, 31270-901
email: mlduarte@dedalus.lcc.ufmg.br

Abstract. *Recently, Artificial Neural Networks (ANN) have been employed as an alternative technique for fault diagnosis and detection in mechanical systems. Neural networks are noise tolerant and their ability to generalise the knowledge, as well as to adapt during use, are extremely interesting properties. A balancing methodology of a rigid rotor supported by hydrodynamic journal bearings using artificial neural network is proposed in the paper.The balancing procedure uses the responses of the unbalancing rotor bearing system and the correction masses given by the plane separation balancing technique. The ANN is based on the use of Multilayer Neural Network architecture (MLP) in order to predict the location of the correction masses, for the case when only the responses are provided to the neural network. This paper investigates the relation between the number of hidden neurons in a MLP, the generalization error and the amount of noise in the input data. Through simulation testing, the results obtaneid indicate that neural networks can be effective agents in the balancing of rigid rotors. The results show that the balancing methodology together with the artificial neural network using function approximation has reduced performance as the number of neurons increases, because the learn solution is not general.*

Keywords*: Rigid Rotor Balancing, Artificial Neural Network, Rotor Systems, Multilayer Neural Network.*

1. Introduction

Techniques of balancing rotating machinery to reduce vibration levels have seen a tremendous level of research activity. Balancing involves placing correction masses onto the rotating shaft, so that centrifugal forces due to these masses cancel out those forces caused by the inherent unbalance mass, thus canceling out vibration. Since, in most cases, it is unlikely that an additional mass can be placed directly in the same plane as the inherent unbalance, special planes, known as balance planes, are often chosen specifically for the purpose of adding balancing weights, especially in larger machines. Balancing is performed on both rigid and flexible rotors and specific methods have been developed to deal with both cases. Rigid rotors are rotors that exhibit no significant deformation, usually due to a low speed of rotation or a high diameter/length ratio (Vance, 1988). Conversely, flexible rotors are rotors, which undergo substantial deformation whilst in operation, due to their long lengths and high operating speeds (Bovik and Hogfors, 1986).

The two main types of balancing for flexible systems are the modal and influence coefficient methods. Modal balancing is the procedure, whereby the unbalance forces at each mode considered are cancelled out individually. Unbalance planes are chosen and the magnitude of unbalance components are determined, depending on the number of modes required by the system. Suitable unbalance masses are then chosen to counteract the forces produced by the unbalance components at each mode (Lee and Kim, 1987). Balancing by influence coefficients involves the selection of correction masses so that vibration is reduced to zero at various specified shaft locations for various constant shaft speeds.

Many of these methods were developed in different fields, such as in control theory, signal processing and artificial intelligence (AI). Artificial neural networks can be included in the last mentioned field. Its use has dramatically increased in recent years in applied mechanics in order to model complex system behavior. Its potential has been recognized in monitoring and control of structures (He *et al*., 2001; Skoundrianos and Tzafestas, 2002). In spite of the researches published about monitoring and fault detection using artificial intelligence techniques, there are few studies in which such techniques, mainly ANN techniques, are used to predict the balancing corrections in mechanical systems. This paper intends to work in that direction, showing some specific points about its implementation.

The contribution of the paper is to show a balancing methodology for rotating mechanical systems using Artificial Neural Network (ANN) to predict the location of the correction masses in respective balancing plane. Some specific points about its implementation are focused. The objective of the paper is to investigate the relation between the number of hidden neurons in a MLP, the generalization error and the amount of noise in the data. Training and validation sets are generated using the system unbalancing response and the correction masses provided by the plane separation balancing technique. These sets are normalized in order to improve the neural network performance. The results show that the balancing methodology together with the artificial neural network using function approximation has a reduced performance as the number of neurons increases, because the ANN was not able to generalize the learn solution.

This paper is organized as follows: in section 2, the rotor-bearing system is modeled. Section 3 presents the balancing equations. Section 4 shows the proposed methodology with the results and discussions given in section 5. Finally, section 6 highlights the conclusions of the present study.

2. Rotor-Bearing System Modelling

In the present study, the rotor bearing system modeling is done by using the Stodola-Green shaft model, in which the main effects present in rotating systems are modeled such as gyroscopic effect, rotating inertia, besides a linearized bearings model represented by damping and cross-coupling stiffness coefficients.

The equation of motion of the rotor bearing system can be written as:

$$[\vec{M}]\{\ddot{q}\}+[C]\{\dot{q}\}+[K]\{q\}=\{Q\} \tag{1}$$

where $\vec{M}$, K, and C are the mass, damping and stiffness matrices of the system, respectively; Q represents the unbalance forces vector and $\ddot{q}, \dot{q}, q$ are the acceleration, velocity and displacement vectors.

The displacements are represented as:

$$q^T = \{X \quad Y \quad b \quad a\} \tag{2}$$

where coordinates X, Y are the displacements translations and coordinates a e b are the displacement rotations of the system.

Such a system is illustrated in Fig. 1 along the (XY) reference frame employed to describe the rigid rotor.

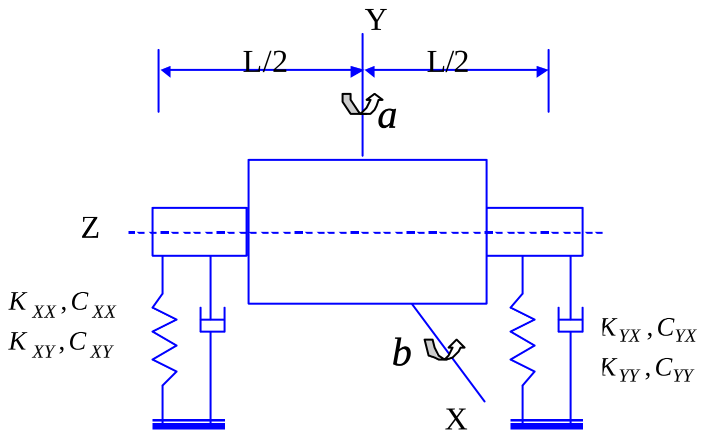

Figure 1. Rigid Rotor

The diagonal mass matrix $\vec{M}$ *is*,

$$\vec{M} = diag\{M \quad M \quad I_t \quad I_t\} \tag{3}$$

where M is rotor mass and I_t is transversal moment of inertia.

Fluid film bearings, commonly used in heavy rotating machines, play a significant role in the dynamic behavior of the rotor. The stiffness and damping properties of the oil film significantly alter the dynamics of the rotor. When a hydrodynamic bearing is modeled, the fluid force that supports the shaft is provided by the pressure developed between the eccentric annulus, which occurs when the shaft is displaced in the circular bearing. It is common to represent the effects of these pressures by bearing stiffness and damping matrices, which can couple the motion in orthogonal planes. For the present study these matrices have the following internal structure (Vance, 1988):

$$C = \begin{bmatrix} 2C_{XX} & 2C_{XY} & 0 & 0 \\ 2C_{YX} & 2C_{YY} & 0 & 0 \\ 0 & 0 & C_{YY} & \left(C_{YX} + \dfrac{I_P w}{L^2}\right) \\ 0 & 0 & \left(C_{YX} - \dfrac{I_P w}{L^2}\right) & C_{XX} \end{bmatrix} \tag{4}$$

$$K = \begin{bmatrix} 2K_{XX} & 2K_{XY} & 0 & 0 \\ 2C_{YX} & 2K_{YY} & 0 & 0 \\ 0 & 0 & K_{YY} & K_{YX} \\ 0 & 0 & K_{YX} & K_{XX} \end{bmatrix} \tag{5}$$

The K_{XX}, K_{XY}, K_{YY}, K_{YX} are the stiffness coefficients; C_{XX}, C_{XY}, C_{YY}, C_{YX} are the damping coefficients; I_P is the polar moment of inertia; w is rotor angular velocity and L is the rotor length.

The unbalance forces vector is given by:

$$Q(t) = \begin{Bmatrix} \sum_{i=1}^{m} m_i w^2 u_i \cos(wt + y_i) \\ \sum_{i=1}^{m} m_i w^2 u_i \,\mathrm{sen}(wt + y_i) \\ \sum_{i=1}^{m} \left(m_i w^2 u_i \cos(wt + y_i)\right) l_i \\ \sum_{i=1}^{m} \left(m_i w^2 u_i \,\mathrm{sen}(wt + y_i)\right) l_i \end{Bmatrix} \tag{6}$$

where m_i is the mass of rotor section; l_i is the length of rotor section and u_i is the eccentricity of the unbalancing mass.

The fourth order *Runge-Kutta* integration method can be used to obtain the time responses of the rotor bearing system, in terms of coordinates X, Y, a e b. From that, a Fast Fourier Transform (*FFT*) is used to give the responses of the system in the frequency domain. For the present study, the responses of the system are obtained for the center of the rotor and for the two journal bearings of the system.

Table 1 shows the descriptions and values used for the rotor in the simulations.

Table 1. Rotor parameters

Rotor Parameters	
Length (m)	0,6
Diameter (m)	0,05
Specific mass (kg/m^3)	7800

The rotor is supported by hydrodynamic journal bearings. The damping and stiffness dynamic coefficients of the bearings employed in the system simulation are presented in Table 2.

Table 2. Journal Bearings Dynamic Coefficients

Journal Bearings Dynamic Coefficients			
Stiffness Coefficients (N/m)			
K_{XX}	K_{XY}	K_{YY}	K_{YX}
0,2310E+06	0,2449E+05	0,2020E+06	-0,2182E+05
Damping Coefficients (N.s/m)			
C_{XX}	C_{XY}	C_{YY}	C_{YX}
1,718E+03	1,672E+03	1,713E+03	1,672E+03

3. Balancing Equations

A rigid rotor can be balanced by adding correction masses in any two balancing planes. One technique used for that is the plane separation technique. It is important to emphasize that, for rigid balancing, the process needs to be performed considering speeds below its first critical, typically between 100 and 600 rpm (Rieger, 1988).

Figure 2 represents the unbalancing distributions along the shaft in which two balancing planes are defined.

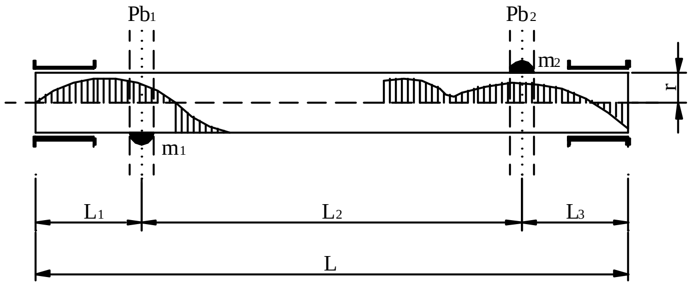

Figure 2. Balancing Planes

Equations (7) represent the force and moment equations, considering the balancing planes shown in Figure 2 obtained from the plane separation technique:

$$\begin{aligned} &\hat{R}_1 e^{-if_1} + \hat{R}_2 e^{-if_2} + m_1 r w^2 e^{if_{b1}} + m_2 r w^2 e^{if_{b2}} = 0 \\ &L \hat{R}_2 e^{-if_2} + (L_1 + L_2) m_2 r w^2 e^{if_{b2}} + L_1 m_1 r w^2 e^{if_{b1}} = 0 \end{aligned} \qquad (7)$$

Such equations when solved will reduce the unbalancing synchronous response of the rotor bearing system. The solution provides the correction masses (m_1 and m_2) and their respectively angular positions (f_{b1} and f_{b2}), as represent by the equations (8),

$$\begin{aligned} &S_1 = m_1 e^{if_{b1}} \\ &S_2 = m_2 e^{if_{b2}} \end{aligned} \qquad (8)$$

From a random unbalancing distribution along the shaft, the response of the system were obtained using the parameters given in Table 1 and the dynamic coefficients given in Table 2, considering a balancing speed of 400 rpm. The unbalancing responses were obtained at the rotor center and at the bearings. The same procedure was performed for the bearings position and similar results are obtained.

4. Proposed Method

A network of artificial neurons (usually called a neural network) is a data processing system consisting of a large number of simple, highly interconnected processing elements in an architecture inspired by the cerebral cortex portion of the brain structure. Neural Networks may be designed to classify input patterns in predefined classes or to create categories that group patterns according to their similarity. Perhaps the most important characteristic of neural networks is their ability to model processes and systems from actual data. The neural network is supplied with data and then “trained” to mimic the input-output relationship of the processes or system (Haykin, 1999).

Here, it is proposed a methodology for a rigid rotor balancing using artificial neural network using Multi Layers Perceptron (MLP) to map the correction masses in both balancing planes 1 and 2. Multi-layer perceptrons (MLP) are neural nets usually referred to as function approximators. A MLP is a generalization of Rosenblatt’s perceptron (Haykin, 1999). The fundamental importance of a neural network is not only the way a neuron is implemented but also how their interconnections (more commonly called topology) are made.

One of the easiest forms of this topology used in recent years is made of three layers:

- One input layer (the inputs of the network);
- *N* hidden layers;
- One output layer (the inputs of the network).

Polar input data, related to the unbalancing responses of the rotor bearing system, are calculated in Cartesian Coordinates according equation (9). The same procedure is performed for the output data, related to the balancing correction masses, as represented by the equation (10).

$$x_{e_i} = \cos(f_i)\hat{R}_i$$
$$y_{e_i} = \mathrm{sen}(f_i)\hat{R}_i \qquad (9)$$

where: x_{ei} and y_{ei} = input Cartesian coordinates;
f_i = phase angle i;
$\hat{R}_i$ = System response at i position.

$$x_{s_i} = \cos(f_{bi})m_i$$
$$y_{si} = \mathrm{sen}(f_{bi})m_i \qquad (10)$$

where: x_{si} and y_{si} = output Cartesian coordinates;
f_{bi} = correction angle obtained for the balancing plane i;
m_i = correction mass obtained for the balancing plane i.

In order to improve the Artificial Neural Network generalization capability, the input and output data need to be normalized. So, Eqs. (11) are employed in the input and output data normalization that will be used on Artificial Neural Network training and validation steps (Saldarriaga and Steffen, 2003).

$$N(y) = 2\frac{(R(y) - y_{\min})}{(y_{\max} - y_{\min})} - 1$$
$$N(x) = 2\frac{(R(x) - x_{\min})}{(x_{\max} - x_{\min})} - 1 \qquad (11)$$

where: $N(x)$ and $N(y)$ = x and y normalized coordinates;
$R(x)$ and $R(y)$ = x and y coordinates to be normalized;
$y_{\min}$ and $y_{\max}$ = maximum and minimum displacement of the coordinate y;
$x_{\min}$ and $x_{\max}$ = maximum and minimum displacement of the coordinate x.

All neurons from one layer are connected to all neurons in the next layer. One-way to show this is by representing the mapping of the correction mass (balancing planes 1 and 2), as illustrated in the Fig. 3.

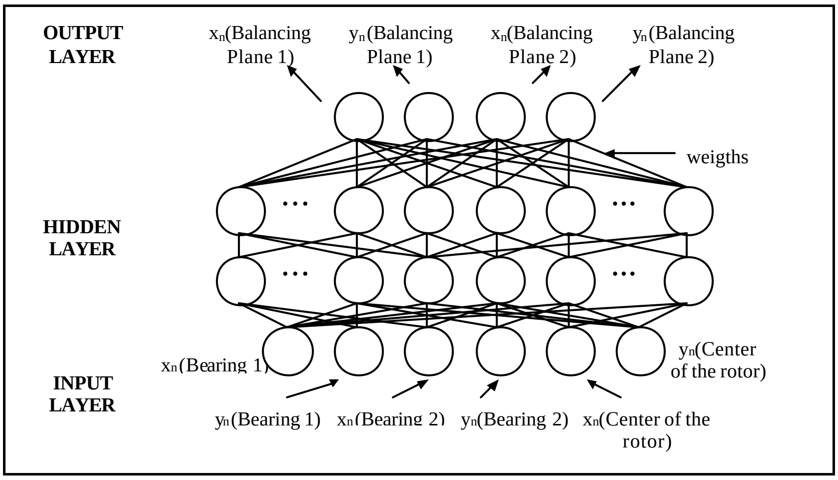

Figure 3. Neural structure for a rigid rotor balancing

Structurally speaking, this net is composed by six neurons in the input layer (corresponding to the estimated responses in the bearings 1 and 2 and the center of rotor, *NxN* neurons in layer hidden and four neurons in output layer (corresponding to the balancing responses in planes 1 and 2.

In the present study backpropagation is used as algorithm for training (Haykin, 1999). The algorithm uses the delta rule to compute the weights between connected processing elements so that the difference between the actual output and the desired output is minimized in a least-squares sense, according equation (12):

$$w_{ji}^{(l)}(n+1) = w_{ji}^{(l)}(n) + z\,[w_{ji}^{(l)}(n-1)] + gd_j^{(l)}(n)y_i^{(l-1)}(n) \qquad (12)$$

where : $d_j^{(l)}$ = represents a local gradient for a neuron j in a layer l; z = momentum constant; g = learning rate.

For the learning procedure of the Error Backpropagation algorithm (Haykin, 1999) was employed. The artificial neural network learning parameters used in this stage are described in Table 3.

Table 3 – Artificial Neural Network Parameters

Neural Network Parameters	**Error Backpropagation**
Transfer function	tansing
Rate of learning	0,05
Increase factor of learning	0.9
Performance goal	0,003
Momentum	0,03
Interactions	1000

5. Results and Discussions

In order to process data using neural networks, the input data must be scaled to the operating range of the Error Backpropagation algorithm. For this project, the database is generated using the unbalancing responses of the system and the correction masses given by the balancing process. In this study, the rotor bearing system was simulated using theoretical data.

The database is generated using the unbalancing responses of the system and the correction masses given by the balancing process. The data was normalized before presentation to the network to account for differences in recording amplitude. From the database, the tests and validation sets are obtained.

The first phase was to determine if the network could be trained to distinguish between balancing responses and unbalancing responses. A 3-layer feed-forward network with six-input nodes and four-output nodes were used. The training set was composed by 200 elements in which the unbalancing responses of the rotor bearing system are the input data and the correction masses and angles are the output data. For generalization, the neural network is training with random noise, normally distributed, with a zero mean value, variance one and standard deviation one. The convergence of the learning procedure was terminated at 0.1 % error threshold.

In the second phase the validation dataset was used. This dataset was divided into a validation set (twenty unknown elements) and validation subset (ten unknown elements). The results presented in Table 4 are for the validation subset. Noise was added to the validation subset, in varying amounts (ranging from 0.05 to 0.3) according to Table 4.

Then a neural network was trained using a varying number of hidden neurons (between 5 to 40). The transfer function for the hidden layer and the outputlayer is *tansig*. The network is trained using the Error Backpropagation algorithm. Table 4 indicates the training algorithm results investigating the relation between the number of hidden neurons in a MLP, the generalization error and the amount of noise in the input data.

Table 4 – Number of hidden neurons, Generalization Error, Noise in input data.

Noise	**Hidden neurons**	**sse**	**Noise**	**Hidden neurons**	**sse**	**Noise**	**Hidden neurons**	**sse**
0.05	5	8.21	0.1	5	8.52	0.15	1	8.12
0.05	10	0.28	0.1	10	0.43	0.15	2	0.78
0.05	15	0.08	0.1	15	0.26	0.15	3	0.62
0.05	**20**	**0.04**	**0.1**	**20**	**0.22**	**0.15**	**4**	**0.50**
0.05	25	0.05	0.1	25	0.26	0.15	5	0.58
0.05	30	0.06	0.1	30	0.28	0.15	6	0.56
0.05	35	0.08	0.1	35	0.51	0.15	7	0.74
0.05	40	0.09	0.1	40	0.32	0.15	8	0.61
0.2	5	6.86	0.25	5	8.40	0.30	5	8.00
0.2	10	0.33	0.25	10	0.65	0.30	10	0.25
0.2	15	0.25	0.25	15	0.61	0.30	15	0.51
0.2	**20**	**0.21**	**0.25**	**20**	**0.79**	**0.30**	**20**	**0.43**
0.2	25	0.25	0.25	25	1.63	0.30	25	1.44
0.2	30	0.44	0.25	30	1.11	0.30	30	1.18
0.2	35	0.43	0.25	35	0.99	0.30	35	0.92
0.2	40	0.40	0.25	40	1.24	0.30	40	1.29

It can be seen from the results presented in Table 4 that the optimal number of hidden neurons for this MLP was more or less 20. Using 20 neurons, the approximation is quite good.

Figures 4 and 5 represent the neural network response for the validation set considering 20 x 20 hidden neurons architecture which was the one that presented the lesser number of generalization error for the amount of noises added.

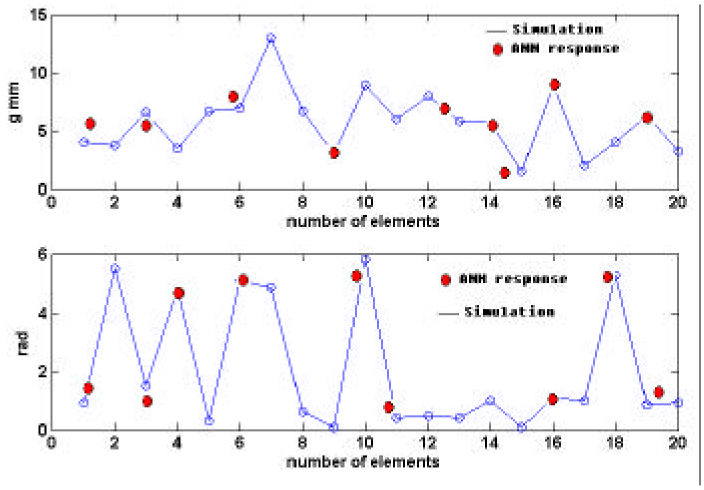

Figure 4 – Correction mass – balancing plane 1

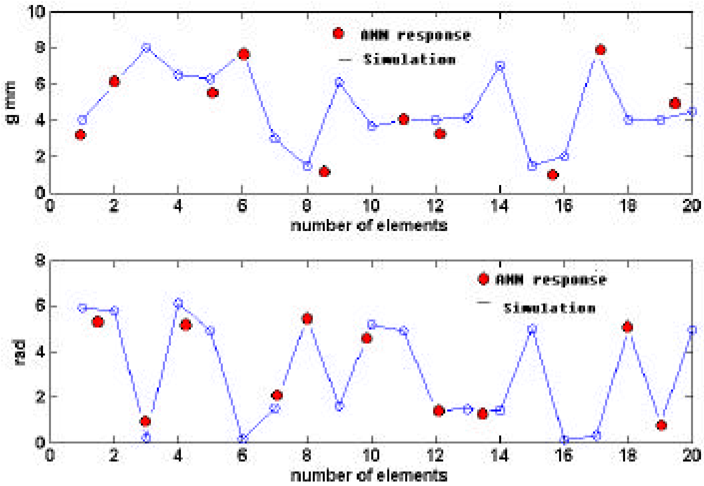

Figure 5 – Correction mass – balancing plane 2

The results show that the balancing methodology together with the artificial neural network using function approximation have reduced performance as the numb er of neurons increase, because the learn solution is not general.

6. Conclusions

Rotating machinery is widely used in industry. The developing of techniques for rotating machinery balancing is an important engineering problem to be solved for both industry and academia. In this paper, a balancing methodology of rigid rotor was conducted. The methodology applies artificial neural networks (ANN) to predict the correction masses when only the unbalancing responses of the system are provided to neural network. The network is trained using the Error Backpropagation algorithm. The database was generated using the unbalancing responses of the system and the correction masses given by the balancing process. This paper investigated the relation between the number of hidden neurons in a MLP, the generalization error and the amount of noise in the input data. From the results obtained, it can be concluded that the function approximation has reduced performance as the number of neurons increases, because the generalization learning gets compromised when the Error Backpropagation algorithm is used. Also, as the noise level increases, it was shown that the predictions from the ANN get worse.

7. References

Bovik, P., and Hogfors, C., 1986, Autobalancing of Rotors," Journal of Sound and Vibration, Vol. 111, 429-440.

Haykin, S., 1999, “Neural Networks: A comprehensive foundation”, Prentice Hall, New Jersey, USA, 2nd edition.

He, J. Z., Zhou, Z. H., Chen, S. F., 2001, “A general design technique for fault diagnostic systems”, Proceedings of INNS-IEEE International Joint Conference on Neural Networks II, Tokyo, Japan, pp. 1307 - 1311.

Lee, C.W., and Kim, Y.D., 1987, "Modal Balancing of Flexible Rotors During Operation - Design and Manual Operation of Balancing Head," Proceedings of the Institution of Mechanical Engineers Part C - Mechanical Engineering Science, Vol. 201(5), pp. 349-355.

Rieger, N. F., 1988, “Principles of Balancing and of Balancing Machines – Rotordynamics 2, Problems in Turbomachinery”, In: Internacional Centre for Mechanical Sciences, Courses and Lectures, N. 297. Edited by N. F. Rieger. Springer-Verlag-Wien, New York, pp. 67 - 93.

Saldarriaga, M. V., Steffen, V., 2003, “Balancing of flexible rotors without trial weights by using optimization techniques”, Proceedings of COBEM – 17*th* International Congress of Mechanical Engineering. São Paulo, SP.

Skoundrianos, E. N., Tzafestas, S. G., 2002, “Fault diagnosis via local neural networks,” Mathematics and Computer in Simulation, Vol. 60, pp. 169 - 180.

Vance, J.M., 1988, “Rotordynamics of Turbomachinery”, John Wiley & Sons, Inc, New York.

8. Responsibility notice

The author(s) is (are) the only responsible for the printed material included in this paper.