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Adaptive balancing of highly flexible rotors by using artificial neural networks

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Abstract. The present work is an alternative methodology in order to balance a nonlinear highly flexible rotor by using neural networks. This procedure was developed aiming at improving the performance of classical balancing methods, which are developed in the context of linearity between acting forces and resulting displacements and are not well adapted to these situations. In this paper a fully experimental procedure using neural networks is implemented for dealing with the adaptive balancing of nonlinear rotors. The nonlinearity results from the large displacements measured due to the high flexibility of the foundation. A neural network based meta-model was developed to represent the system. The initialization of the learning procedure of the network is performed by using the influence coefficient method and the adaptive balancing strategy is prone to converge rapidly to a satisfactory solution. The methodology is tested successfully experimentally.

Keywords: adaptive balancing; rotating machinery; neural networks; meta-modeling; nonlinear rotor.

1. Introduction

Traditionally, the problem of balancing flexible rotors has been faced by using mostly the influence coefficient method (Bishop and Gladwell 1959, Goodman 1964). This method is used very frequently in the industrial context. Other methods could also be used, such as the modal method and hybrid approaches (Kang 1997, Parkinson, *et al*. 1980, Xu and Qu 2001). It is worth mentioning that the modal method needs a representative model of the system, which is not available in a number of practical situations.

In the influence coefficient method, trial weights are used in order to determine a linear relation between radial displacements and unbalance forces for a given set of operating conditions (Rieger 1986). The standard procedure involves the application of trial weights to each balancing plane and measuring the corresponding vibrations at each measurement plane. By using this information the so-called matrix of influence coefficients can be calculated. Then, correction weights, which are able to reduce the vibration level due to unbalance, can be determined (Steffen and Lacerda 1996, Foiles, *et al*. 1998, Mahfoudh, *et al*. 1988). This means that two basic ideas give support to this method: 1- proportionality between excitation and vibration response, and 2- possibility of using the superposition property to

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obtain the final unbalance forces. This means that the dynamic behavior of the rotor can be represented by a linear model.

The previous considerations are valid in cases for which the unbalances do not lead to extremely high vibration displacements (Zhou 2001). Previous contributions have considered the possibility of using an automated balancing device (Kang, *et al*. 1996, Alauze, *et al.* 2001).

The procedure presented in this contribution was formulated due to the necessity of dealing with high radial displacements as those found in very flexible rotors or rotors submitted to very important unbalance forces. Even small nonlinearities may avoid the correct use of the influence coefficient method. This new strategy is based on multi-layer feed-forward nonlinear neural networks (Irwin, *et al*. 1995) that is used to identify the correction weights for a given rotor speed. An early contribution about this topic (Saldarriaga and Steffen 2003) presented a model based flexible rotor balancing procedure by using neural networks. However, a linear mathematical model of the rotor was taken into account for training the network. More recently, as an accurate model is quite difficult to obtain for nonlinear rotors, a neural network based meta-model was developed to represent the system (Saldarriaga, *et al*. 2007). In the present proposal a fully experimental procedure using neural networks is implemented for dealing with the adaptive balancing of nonlinear rotors. At the present stage, the adaptive procedure is restraint to the training of the network. This way, a meta-model of the rotor-bearing system is obtained. The meta-model is iteratively updated along the balancing process until a prescribed balancing quality is reached.

In the remainder of this paper the basic concepts about neural networks is presented. Then, the classical influence coefficients method is revisited in order to highlight the basic ideas behind balancing, followed by an explanation regarding the proposed balancing strategy. Finally, the results from an experimental application of this procedure on a vertical highly flexible rotor are presented.

2. Neural Networks

A Neural Network (NN) has been described (Haykin 1998) as a diagrammatic representation of a mathematical equation that receives inputs and provides outputs. Its early conception is premised on mimicking the structure of the human nervous system by using massively parallel nets composed of a large number of computational elements connected by links with adjustable weights – the perceptron. NN have the ability to adapt to and store information from training-data sets and can be tolerant to noise. Commonly neural networks are adjusted, or trained, so that a particular input leads to a specific target output. Various training algorithms are available with choices dependent on the required speed and “fineness” of convergence, as well as available processing capacity. In this work a feed-forward network was used to build a meta-model representing the flexible rotor. This architecture of network allows obtaining a desirable response by starting with a given input set. This is conducted by the interconnections between the neurons located in the multiple layers in a feed-forward way. The capability of the network to get the adequate responses depends on the training process, in which the optimal weight and bias values are calculated. The effectiveness of the training process depends on the following: the topology of the network, the way the input and output vectors are normalized, the activation functions used in each layer and also the training algorithm used in each case. In this work a resilient back-propagation algorithm was used (Riedmiller and Braun 1993). The nonlinear feed-forward network is dealt with by two “tansig” layers of eight neurons in series with four “purelin” layer neurons as illustrated in Fig. 1.

The resilient back-propagation algorithm is such that only the sign of the derivatives is used to calculate the weight updates. The size of the weight change is determined by a separate update value,

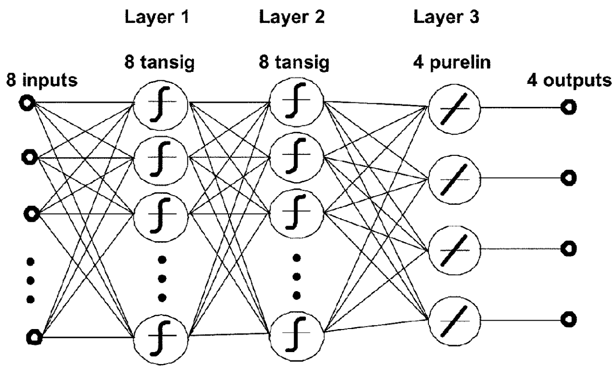

Fig. 1 Neural Network architecture

instead of the classical back-propagation algorithm in which the size of the weight change depends on the magnitude of the partial derivatives. This training procedure allows to speed up the convergence and to improve the performance of the trained networks with a minimal increment of memory requirements as compared with the classical back-propagation approach. Besides, it allows a more stable behavior in the training process than the one obtained by the Quasi-Newton and Levenberg-Marquardt algorithms.

3. Proposed methodology

The principle is based on the determination of a "Transfer Function" (a Meta-Model) that relates the response measured to the excitation due to the unknown unbalance. In this work the Meta-Model is obtained by training a neural network by using data stemming from the influence coefficients method. This is a wide known experimental balancing method for which the model of the system is not necessary. However, the dynamic behavior of the system facilitates the choice of both measuring and balancing planes. The method assumes two basic assumptions: i) the displacements are linearly proportional to the excitation forces; ii) the initial unknown unbalance can be represented by a discrete finite number of unbalance moments that are placed on chosen balancing planes:

$$A_{ini} = CT_{ini} \tag{1}$$

A_{ini} (NM*NV lines, 1 row) is the vector of the complex radial displacements of the rotor due to the initial unbalance for the NV speeds of rotation. Consequently, the elements of A_{ini} contain magnitude and phase information with respect to a previously defined reference phase in the rotor. Besides, this vector is organized according to the successive speeds of rotations used. T_{ini} (NP lines, 1 row) is the complex vector of the unknown unbalance weights. C (NM*NV lines, NP rows) is defined as the complex matrix of initial influence coefficients. Consequently, the method aims at determining balancing weights T_c to be placed at NP balancing planes so that the magnitudes of radial displacements of the rotor, which are measured at the NM measuring planes, are minimized for NV rotation speeds. The following equation holds:

$$C(T_{ini} + T_c) \Rightarrow 0 \tag{2}$$

The influence coefficients matrix is the model of the system that is determined experimentally by using trial weights B_T and measuring the resulting displacement A_R:

$$C(T_{ini} + T_T) = A_R$$

$$C = \frac{A_R - A_{ini}}{T_R} \tag{3}$$

Once the model is determined the correction weights can be calculated either by direct inversion, if the number of acting forces is equal to the number of measurements:

$$T_C = -\frac{A_{ini}}{C} \tag{4}$$

or by minimizing the residual displacements when the number of measurements is larger than the number of acting forces:

$$T_C = -\frac{\overline{C}^t A_{ini}}{[\overline{C}^t C]} \tag{5}$$

where $\overline{C}$ represents the complex conjugate of matrix C.

Both responses and excitation forces are physical quantities that are expressed with a magnitude and an angular position with respect to a given reference on the rotating machine. For computational purposes, it is more practical to represent those variables by complex numbers. If we consider only a single excitation force (T) and a single measured response (A), this relation is expressed as:

$$\begin{bmatrix} C_1 & C_2 \\ C_3 & C_4 \end{bmatrix} \begin{Bmatrix} T_{real} \\ T_{imag} \end{Bmatrix} = \begin{Bmatrix} A_{real} \\ A_{imag} \end{Bmatrix} \tag{6}$$

The unbalance can then be calculated as:

$$T_{real} = \frac{C_4}{C_1 C_4 - C_2 C_3} A_1 - \frac{C_2}{C_1 C_4 - C_2 C_3} A_2$$

$$T_{imag} = \frac{C_3}{C_1 C_4 - C_2 C_3} A_1 + \frac{C_1}{C_1 C_4 - C_2 C_3} A_2 \tag{7}$$

To achieve a better balancing quality, an adaptive process is iteratively applied so that the meta-model is refined and a new balancing run can be tested. Once the desired balancing quality is reached the procedure can be stopped. It passes through three steps:

1. the learning phase that enables obtaining a so-called meta-model of the system for a given operating condition,
2. the calculation of the correction weights by using the measured responses,
3. the updating of the meta-model by using the calculated correction weights and the residual measured displacements.

The advantage of using the proposed NN architecture is due to its capacity to model nonlinear systems. The nonlinearity in this study results from the large displacements measured due to the high flexibility of the foundation. A scheme of the general balancing procedure is presented in Fig. 2.

In order to perform the balancing process, by using NM sensors and NP balancing planes, a three

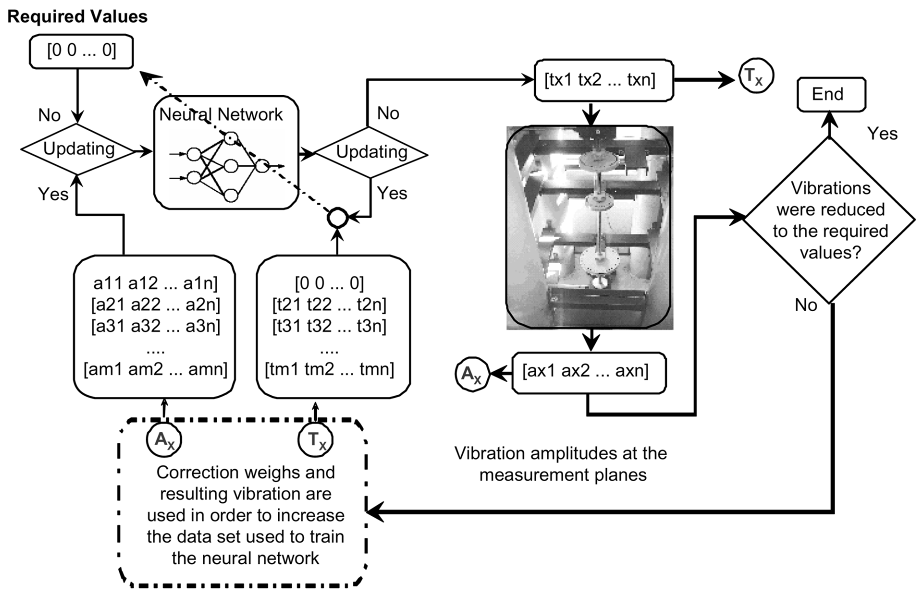

Fig. 2 Scheme of the proposed methodology

layer network is chosen containing 2xNM neurons in the input and the hidden layers and 2xNP neurons in the output layer. Two neurons are needed for each variable in such a way that magnitude and phase values can be handled. The activation function that was able to achieve the best performance was the hyperbolic tangent sigmoid for the two first layers and the linear activation function for the output layer.

The neural network is initially trained by using two data sets. The input set is composed by the response obtained from the sensors. The magnitude and the phase angle with respect to a reference are split in real and imaginary parts. The output set comprises the unbalance moments (due to the test weights) divided according to their orthogonal directions also.

The first member of the set of input parameters are the magnitude of the vibrations measured for the initial condition of the rotor without test weights ([a11 a12... a1n]), and consequently, the corresponding exit is a null vector. The set of correction weights is obtained for the case in which the network calculates the unbalance weights corresponding to a null vibration. After computing the balancing set of weights, they are installed at the corresponding balancing planes. If it is necessary, the procedure is repeated several times, by adding the additional resulting vectors to the sets of unbalance moments and vibration measurements determined in the previous stages, thus forming the adaptive procedure. This way, the adaptive training skills of the network are implemented.

In this work, input and output vectors are normalized for simplifying the calculation of the weights and improving the performance of the network.

4. Experimental test

Before presenting the adaptive balancing procedure, the influence coefficients method is applied to highlight the nonlinearity of the rotor. Table 1 shows the results for two different balancing configurations. It can be seen that the influence coefficients are not the same for both cases. This means that the behavior of the rotor is nonlinear. The technique could be hardly applied since that a prohibitive number of runs

Table 1 Identified model characteristics

		Test 1		Test 2	
		Modulus	Phase (degree)	Modulus	Phase (degree)
Trial weight (gr.mm)		670.2	-90	730.6	-130
Influence coefficients	plane 1	70.7	-83.0	77.1	27.2
	plane 2	0.55	-145.4	1.03	-58.6
	plane 3	42.8	-58.2	36.6	37.6
	plane 4	3.8	-179.6	4.6	-103.9

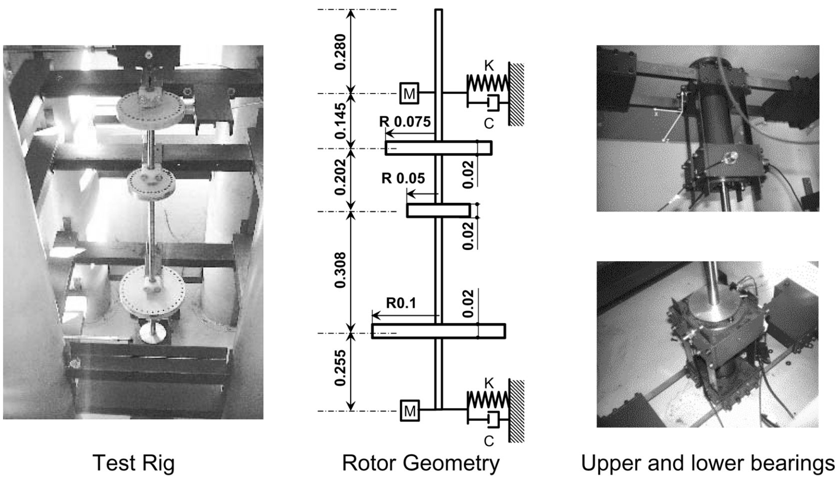

Fig. 3 Flexible Rotor Test Rig

would be necessary.

Now, it will be shown that the adaptive neural network approach is able to handle the nonlinear characteristics of the rotor and lead to fast convergence in finding the balancing weights and their corresponding angular positions.

With the aim of testing the proposed procedure, a flexible rotor test rig dedicated to the study of the dynamic behavior of drilling machines in the petroleum industry was used. The particularity of this test rig is the high flexibility of the links relating the whole rotor-bearing system to the foundation.

The test rig (Fig. 3) is composed of a vertical rotor supported at the ends by bearings, which are elastically connected to the foundation. The diameter of the rotor cross section is 0.017 m and the length is 1.28 m. Three discs (radii 0.075 m, 0.06 m and 0.01 m) are attached to the shaft. Fig. 3c depicts the geometry of the system. The rotor is driven by a 1.5 kW electric motor and the rotation speed can be controlled from zero to 7,200 rpm.

The system responses considered were displacements and accelerations. The displacement responses were measured by using a pair of eddy current type proximity probes located at the upper disc. Two accelerometers placed in a plane (x and z directions) at each bearing provide the acceleration responses. In this study, only system responses issued from accelerometers were considered for the training procedures and for the calculation of unbalance. In order to identify the phase angles of the unbalance vibrations and the unbalance moments, a reference system was adopted to measure the relative angular positions of the discs. In this case, they were measured by using an optic encoder.

The motor speed was monitored by means of an HP 35658A tachometer in combination with an optical encoder installed in the lower part of the shaft. The measurements are collected by a data acquisition system that is coupled to a Pentium III 900 MHz PC.

The data acquisition system consists of an HP 35658A tachometer, an HP35655A eight channel input module, and an HP35654B interface/signal processor. A National Instruments PCI-GPIB card provides communication between the PC and the data acquisition system. The acquisition process is conducted by using an HP3566A/67A data acquisition/analyzer software.

The system can be balanced by using holes placed in the border of the discs; each disc has 36 holes that are circumferentially located along the border of the discs. The calculated unbalance is decomposed along several axes corresponding to the position of the holes. Nevertheless, due to the precision of the available applied masses, errors as large as 2.8% for the angle values and 3.3% for the weight values are expected as compared with the calculated correction weights.

Different natural frequency values are observed, in the frequency band between 2 and 25 Hz, along the orthogonal directions due to system asymmetry. Experimentally, it was shown that the first two natural frequencies in each direction are related with the rigid body modes. The other natural frequencies correspond to the shaft bending modes. A rotation of 996 rpm was selected as balancing speed. This speed is close to the third critical speed (first bending mode) resulting high initial vibrations.

5. Experimental results

In the learning procedure eight runs were necessary. Then, the first balancing results lead to a reduction as large as 33.3% in the combined overall vibration (considering the speed chosen to perform the balancing). In the second run, the reduction achieved with respect to the initial overall vibration was as large as 69.9%. Then, in a third and final run, the overall vibration level was reduced 80.4%. The correction weights determined by using the above balancing method are shown in Table 2.

In Fig. 4 the unbalance responses measured in the position of the upper disc by using two proximity probes located in the X and Z directions are shown for the selected balancing speed (996 rpm). Moreover, the vibration level was also reduced for lower rotation speeds.

These results demonstrate the good performance of the methodology developed for balancing highly

Table 2 Balancing weights and residual vibration levels

	Run 1		Run 2		Run 3	
	Modulus	angle [degree]	Modulus	angle [degree]	Modulus	angle [degree]
Correction weight [gr.mm]						
Plane 1	1223	-100	631	-60	539	-40
Plane 2	1076	-10	1012	-90	905	-70
Measurements [m/s^2]						
Plane 1	8	272	2.5	155	1.7	222
Plane 2	0.1	120	0.1	360	0.02	46.8
Plane 3	3.4	275	2.1	237.1	1.13	245.9
Plane 4	0.83	149.3	0.84	114.2	0.78	114.1
Vibration Reduction	33.3%		69.9%		80.4%	

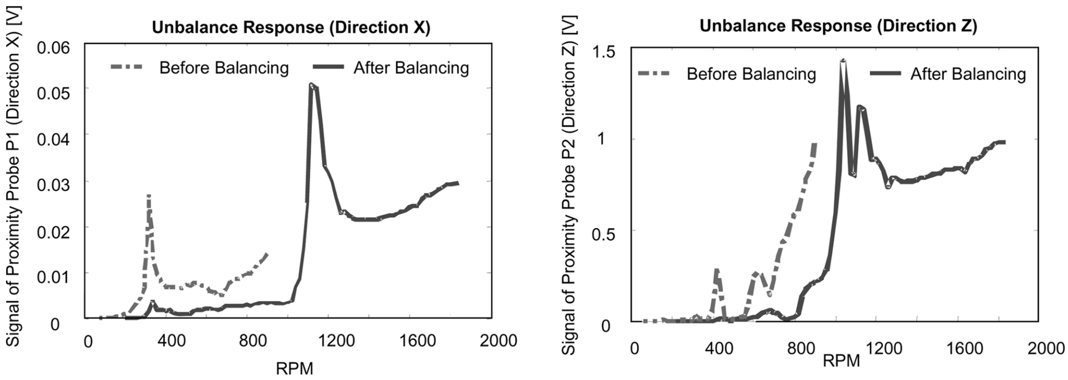

Fig. 4 Unbalance responses before and after balancing

flexible rotating machinery under severe unbalance conditions. It is worth mentioning that before balancing, it was not possible to cross the third critical speed due to the high displacement of the rotor. This behavior is due to the fact that the rotor would touch the proximity sensors and could damage them.

6. Conclusion

The present contribution is an effective approach for balancing rotating machinery in the case of nonlinear highly flexible rotors and submitted to severe unbalance loads. It was shown that the classical influence coefficients method do not perform satisfactorily when high radial displacements occur due to the flexibility of the foundation. This behavior characterizes a nonlinear relationship between the unbalance and the vibration response. Neural Networks showed to be effective in order to overcome the difficulties observed since in this case a meta-model was built to represent the system. Consequently, input and output relations can be easily established allowing the proper balancing of the nonlinear rotor. Evidently, a number of test runs were necessary for training the network in the adaptive phase. However, the authors consider that the methodology developed is very encouraging in the sense that satisfactory experimental results were obtained under very challenging balancing conditions. The present experimental methodology is efficient and could be easily implemented for systems with adaptive balancing capabilities such as automatic active balancing, even for various rotating speeds. Future research work is devoted to the concept of smart rotors in which the parameters of the system and the rotor model can be identified and updated in real time on an adaptive way. In this case the relationship between acting forces and vibration responses is established automatically. Consequently, the smart rotor would lead to effective active control and balancing procedures.

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