Unbalance Rotor Parameters Detection Based on Artificial Neural Network

Mohammad Gohari and Ahmad Kord

Faculty of Mechanical Engineering, Arak University of Technology, Iran.

Unbalance is an important fault that can damage or shut down vital rotary systems such as the gas turbine, compressors, and others, so to avoid this trouble, the balancing process is very crucial, even though it is time-consuming and costly. Thus, having a technique which can predict the unbalance location and its parameters will be valuable and practical. The current study represents a model that can identify the unbalance's mass, radius, and location of the eccentric mass based on the artificial neural network (ANN) model. The inputs of the proposed ANN, which is based on a feed forward with back propagation model, is the bearing acceleration signal in the frequency domain. It has 10 hidden layers with 10 neurons through each layer. The accuracy in prediction was acquired at 96%, 96%, and 94% for the disc number (plane), the eccentric radius, and eccentric mass values, respectively.

1. INTRODUCTION

Rotors are important components in rotary systems such as turbines, pumps, compressors, etc. Faults in this component can produce global failure in machinery. Common faults of the rotor dynamic consist of instability because of self-excited vibration, which is oscillation generated by an external load such as a mass unbalance or a bending of the shaft.[35] Normally, unbalance is known as a fault and occurs in rotational machinery.[1] Most rotational machines contain unbalance generated during the manufacturing process or installation, and consequently, they need balancing to avoid faults, which will be created after some cycles performed. Commonly given tolerances are used as the thresholds of a balancing operation. The fault of unbalance can be created by various phenomenon. In fact, rotor unbalance is a situation in which the centre of mass of a rotating component, normally the shaft and its fixed components, like disks and blades etc., is not coincident with the centre of rotation. In the operation condition, rotors can never be exactly balanced due to manufacturing errors such as generated porosity in casting, non-homogenous density of material, or the loss of material through forming.[17]

Sometimes, unbalance is created by the operation of rotary machines in long term use. For example, in a gas turbine, unbalance might happen due to blade damages, internal defects during blade manufacturing, inaccurate installation after overhaul of assembly, cavitation, or a corrosive fluid.

Nowadays, rotating machinery should be more reliable and unpredicted fault maintenance is a big challenge for companies. This issue has gotten more important due to consumers asking machinery producers to design and manufacture machines with shorter turnaround times because they would like to decrease cost.[2] Although reliability levels are increased, unbalance remains as a rotor fault, which needs unscheduled maintenance.[3]

The localization of unbalance and finding eccentric mass radius values accurately in the complex machines provides good information for technicians to access fault points and do the balancing directly. The traditional balancing techniques such as borescoping and multi-plane balancing are time consuming procedures.

Many researches were conducted on unbalance in rotational machines and this issue already remains an open area for the technical researchers. Some of them focused on the relationship between misalignment and unbalance,[4,5] and some of them report on unbalance diagnosis.[6,7] In addition, a number of investigators try to employ simulation techniques such as unbalance prediction,[8,9] and indoor experimental approaches.[10,11] The details of existing unbalance detection methods are reviewed in several publications.[12–15] Also, fault diagnosis of a rotor-bearing system for misalignment and unbalance was investigated in a steady state.[36]

In spite of some techniques available to diagnosis unbalance, localization of the unbalance and the identification of how much is the eccentric masses generating unbalances are very useful. One of the attempts that tried to employ mode shapes and modal masses instead of a test run was carried out by Krodkiewski et al.[16] They established a mathematical model for a multi-bearing rotor system. This idea has been developed for a flexible rotating machine via a single run.[17,18] Furthermore, the shaft deflection measurement was utilized to reach the position of the unbalance.[19,20] The frequency response of the system, which was simulated by the NASTRAN software, was applied in a prediction of the unbalance position.[21]

Finite element modelling has been employed to study variation of stiffness, which is generated by faults such as crack, impact, rubbing, and other. These variations can be used for finding the localization of the unbalance.[22,23]

Artificial neural network (ANN) is one of the intelligent techniques that can be used for prediction in the systems in which the mathematical model is not clear or linear. For instance, it was performed for fault detection in the bear-

ings,[24–26,37] shaft mode shapes classification for the recognition of cracks,[27] fault detection and classification in the rotary machines via Neuro-fuzzy tools,[28] failure identification and detection in the gears and bearings by Self Adaptive Growing Neural Network (SAGNN).[26] In addition, the number of the systems equipped by a hybrid of ANN and fuzzy systems have been used to detect unbalance in the rotary system,[28] to classify faults of the turbo generators,[28] and to approximate the correction masses value for the balancing rotor.[29] The integration of ANN with Wavelet, Possibility Theory, and Taguchi were tried in rotary system diagnosis.[38–40] The unbalance localization via ANN was developed for a multi-disc rotor. It could identify the plane of the unbalance.[30] An algebraic method had been operated to identify the unbalance in the system for its active controlling.[31] Active systems can cancel the unbalance effects by means of some external forces in the rotors.[32]

As mentioned before, previous works tried to present an approach for predicting the unbalance and its localization, although most of them just could recognize the plane of the unbalance. Thus, this field of research is still an open area because the industries need robust and accurate techniques for this purpose. The current study attempts to establish a method which can localize the unbalanced mass between various discs (planes) and approximate eccentric mass and radius values via the artificial neural network. The ANN has been selected as a predictor tool due to its learning property and its application in the area of vibration.[33,34]

2. METHODOLOGY

In the balancing operation of rotary systems, identifying the plane on which an unbalanced mass is located, radius and mass values are necessary. To attain this purpose, an ANN model has been established to verify this idea. Whereas ANN requires examples set for training, a rotary system with multi-discs was simulated to generate the proper data.

2.1. Simulation and Data Analysis

Firstly, a shaft with four discs was modelled as a rotor by ADAMS Software. As illustrated in Fig. 1, the rotor is placed on the base plate by two simple ball bearings, and the base plate was constrained by 12 springs. So, the plate has six degrees of freedom (6 DOF). The rotor, discs, and base plate are rigid and solid, though the springs show flexible behaviour. The diameter of the shaft is 0.02 m, and the discs' radius and thickness are 0.13 m and 0.02 m, respectively. The system was rotated by 20 Hz angular speed value, and various eccentric masses with different distances to the rotor centre were attached on different disc numbers. In each case, the accelerations of both bearings were recorded by the software. The eccentric radiuses were 6, 8, and 11 cm, and unbalanced masses were 10, 15, 20, and 25 gr. Therefore, vibration data were obtained for the 48 samples. Out of that data, 60% has been used as a training example, 20% and 20% were considered as test and evaluation steps, respectively. Finally, the time
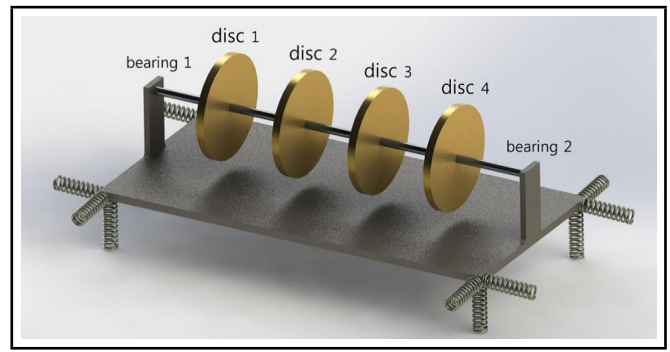

Figure 1. The simulated rotary system.

domain accelerations were converted to frequency domain by Fast Fourier Transformation (FFT).

For example, a 20 gr. unbalance mass with an 11 cm eccentric radius was situated on the disc number 1, next number 2, then 3, and lastly on disc number 4. The amplitude of the vertical accelerations in frequency domains were plotted at the bearing number 1 for all four discs and are shown in Fig. 2.

Based on the results represented in Fig. 2, whenever the unbalanced mass has a longer distance from the first bearing, the peak of the produced vibration has a lower value. In fact, this concept can be applied by the ANN to identify the disc number that is generating vibration due to the unbalance.
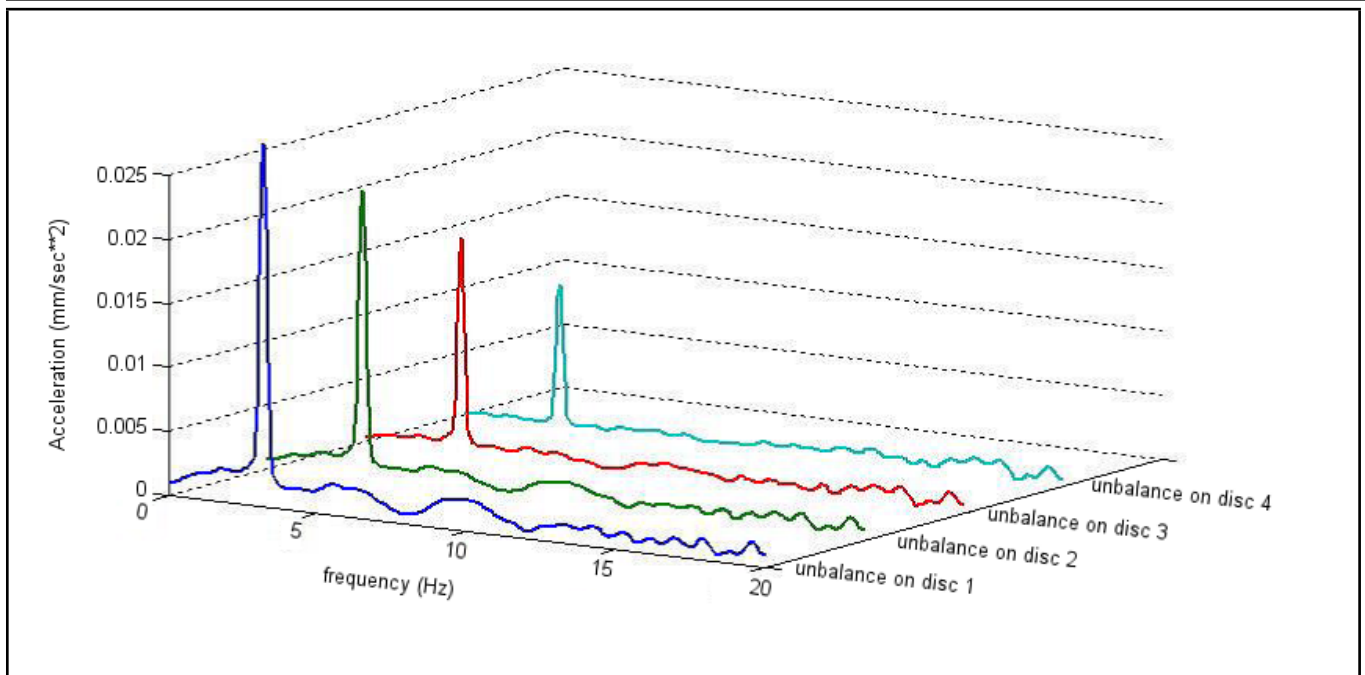
2.2. Architecture of ANN

Artificial neural networks stimulated from human brain are generally presented as unit of intersected "neurons" which can compute values from inputs, and are able of machine learning due to their adaptive nature. A single neuron processes multiple inputs and generates an output resulting in the utilizing of an activation function to a linear combination of the inputs:

$$y_i = \varphi_i\Big(\sum_{j=1}^{N} \omega_{ij}x_j + b_i\Big); \tag{1}$$

where $\{x_j\}$ is the set of inputs, ω_{ij} is the synaptic weight connecting the jth input to the ith neuron, b_i is a bias, $\varphi_i(\ )$ is the activation function, and y_i is the output of the ith neuron considered. In Fig. 3, the schematic topology of ANN is exemplified.

In this application of the ANN, the aim is that acceleration of the bearing is considered as an input signal. The unbalance mass, disc number (plane) which has an unbalanced mass and eccentric radius is the outputs of the ANN. The feed-forward ANN structure was employed, and it was constructed in MATLAB Software. Various topologies of the ANN include of different hidden layers and different numbers of neurons that were assessed in terms of performance. The input signal consists of the first bearing's acceleration in three directions. Fig. 4 illustrates the proposed ANN model for the determination of the unbalance parameters.

The architecture and achieved accuracy of the ANN model will be stated in next part. Three parameters are checked: finding the disc number which has eccentric mass, prediction of

Figure 2. Frequency responses of first bearing through different location of unbalanced mass (20 gr).
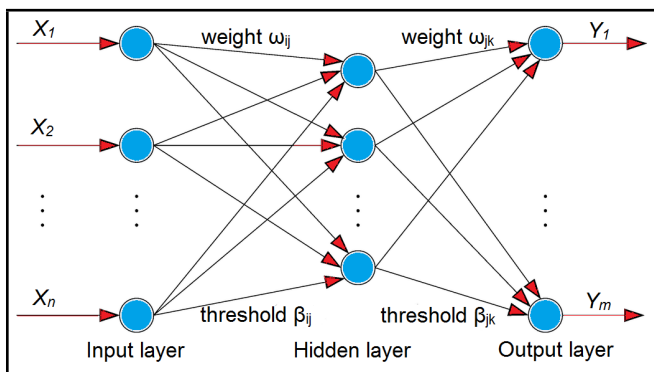
Figure 3. Schematic architecture of ANN.

eccentric mass, and the radius values.

3. RESULTS AND DISCUSSION

Various ANN topologies were assessed in performance by testing different numbers of neurons and different hidden layers. Also, other types of ANN such as perceptron, Hopfield, Recurrent etc. were tested, but feed-forward back-propagation showed better performance. The input and output sets were exerted into the network. After training and adapting of the ANN was done by a Levenberg-Marquardt (LM) algorithm, the best architecture has been obtained by 10 hidden layers with 10 neurons in each layer. From that, 60% of the data was used in the training step, and 20% and 20% of the data have been utilized in the test and evaluation process, respectively. The ANN was reached after 50 epochs. The weights of the neurons were reached during training of the ANN algorithm in the software. In fact, a closed loop was run to minimize the difference between the target and the ANN output. Weights are adjusted to reach minimum difference.

Subsequently, the accuracy of the ANN in the prediction

Table 1. The accuracy of the ANN model in predictions.

Prediction of the disc number which has unbalanced mass	Prediction of the eccentric radius	Prediction of the eccentric mass
96%	96%	94%

purpose was verified. For this goal, all of the 48 examples were entered as the inputs, and the outputs of the ANN were compared to the actual values. The Fig. 5 (a), (b), and (c) exemplifies this comparison between the actual value to that of the predicted value by the ANN model for the disc number, the eccentric radius, and the mass values, respectively. Table 1 represents the accuracy of the ANN in predictions. As can be seen in Fig. 5 and Table 1, the best accuracy of prediction has been reached in eccentric radius, and the lowest was acquired for the unbalance localization.

As can be seen, the ANN model accuracy in prediction of the eccentric mass is low, but in the disc number and the eccentric radius are around 96% accurate. Thus, by this ANN architecture, the accuracy of all outputs including the mass value, the disc number, and the eccentric radius are higher than 90%. The correctness of the proposed ANN model compared to the earliest presented model in Walker et al. is a little lower, though the current ANN model has the ability to predict the radius and the mass value of the unbalance with acceptable accuracy.[30] As stated in a literature survey, in active rotor balancing, identifying the location of the unbalanced mass with good accuracy and online output is very useful.[31,32] This achieved ANN model can be applied in this aim. Most of the former established ANN models generally were created for fault classification,[24–29] but some of them were employed to identify unbalance parameters.[30,33]
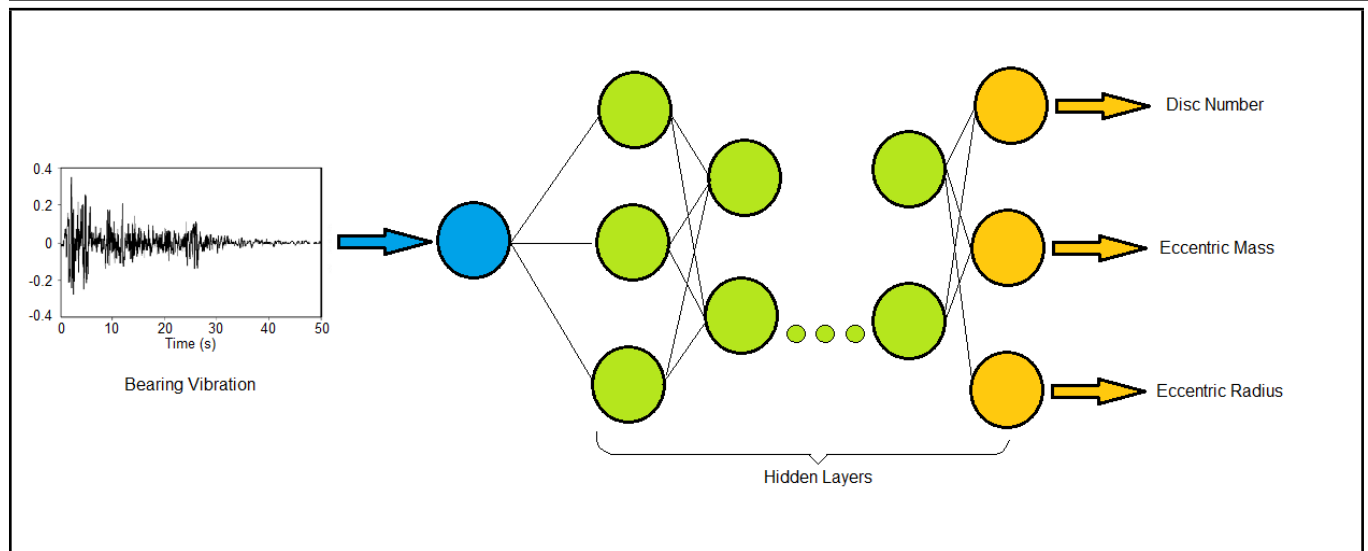
Figure 4. Proposed ANN model for unbalance parameters identification.

4. CONCLUSIONS

As mentioned before, in rotary systems, elimination of harmful vibrations produced by an unbalanced mass is essential, and to remove these vibrations requires some parameters about unbalance, such as the unbalance mass value and the location of it. In this study, a novel technique was utilized to detect and predict the unbalance rotor parameters. To acquire this objective, an ANN model has been unveiled which can predict the location and value of the eccentric mass. The reason the ANN was selected as the intelligent tool is having the ability to model by nonlinear characteristics. The trained ANN by a LM algorithm with 10 hidden layers and 10 neurons in each layer presented the best performance in this application. The potential accuracy of the ANN in the prediction of finding the disc which has an unbalanced mass and the location of it was between 94 to 96%. It seems that the accuracy of the proposed model demonstrates good accuracy, and can be developed for industrial purposes. In future study, a test rig will be constructed to apply this concept.

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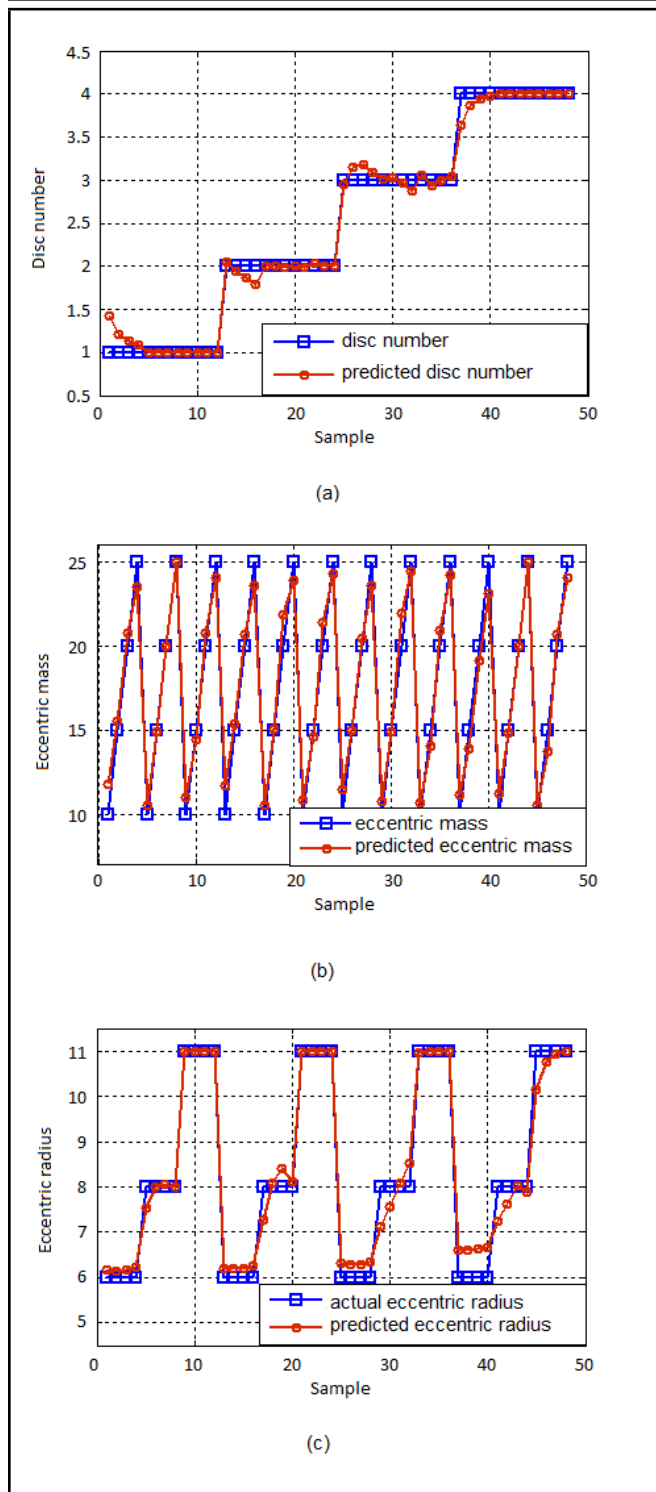
Figure 5. The comparison between actual and predicted by ANN model values: (a) prediction of the disc number which has unbalance mass, (b) the eccentric radius value, (c) the eccentric mass value.

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