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Unbalance Localization of a Multi-Disc Rotor by Hybridizing Wavelet Transformation and Neural Network

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Abstract. Rotating machinery is widely working within the industry, and fault diagnosis and prognosis of them may be a vital issue that can save money continually. Unbalance is a crucial fault in rotary systems, and it is focused by many researchers to develop methods to detect that for correcting before global failure happening within the machine. Hence, the establishment of a procedure that will estimate the unbalance location and its specifics are going to be valued and practical for correcting operations. The recent study exemplifies a model that can detect the unbalance parameters, for example, the location of unbalance mass and value of that based on the hybridizing Wavelet Transformation and artificial neural network (ANN) model. The inputs of the model are wavelet coefficients derived from the bearing acceleration signal. It includes two hidden layers constructed by six neurons within each layer. The parameters estimation accuracy was attained 95%, 97%, and 96% for the disc number, the eccentric radius, and unbalance mass values, correspondingly.

Keywords. Unbalance mass and eccentric radius, Artificial neural network (ANN), Fault detection, Wavelet Transformation. Multi-disc rotor

1. Introduction

Generally, in rotating equipment, unbalance is known as a fault and frequently happens (Bently, 2002). Commonly, some revolving machines have to unbalance created through manufacturing operations or installation, and subsequently, they necessitate balancing to prevent prevalence failures, which will be produced subsequently some cycles executed. Regularly, prearranged tolerances are used as awareness points or attentiveness thresholds of the balancing process. The 'Unbalance' may be generated by several origins. For instance, in a gas turbine, unbalance might be occurred by blade looseness, internal defects (micropore or macropore) during blade fabrication, incorrect installation, incorrect maintenances, and an incomplete repair.

Currently, rotating machinery must be more consistent, and unexpected failure repair is an enormous challenge for factories and industrial centers. This problem had been gotten more vital due to users demanded from machinery manufacturers to design machines with lower angular velocity since they'd like to diminish the costs of repair and maintenances (Jennions, 2011). While reliability levels were enhanced, rotors encounter to unbalance problem, which requires unplanned maintenance (Hassan et al., 2012).

The unbalance localization and its parameters (unbalance mass and radius of eccentric mass) precisely in the rotating machines supply appropriate points for users to detect fault location and starting balancing quickly. The conventional balancing methods, including Borescoping and multi-plane balancing, are time-taking operations.

Numerous researches focused on balancing in the turning equipment, and this matter even now keeps an open area for the engineers. Some of the experts concentrated on the correlation among the unbalance and misalignment (Ganeriwala et al., 2009; Xue et al., 2012), and few researchers studied about the diagnosis of unbalance (Han et al., 2009; Jiao et al., 2012). Furthermore, several investigators attempt to develop the simulation methods for unbalance detection (Abdul-Aziz et al., 2012-a; Abdul-Aziz et al., 2012-b) and laboratory methods were carried by tests (Edwards and Lees, 2010; Foiles and Allaire, 1998). The useful and practical points of available unbalance discovery approaches are studied in several technical papers (Randall and State, 2004; Mosaad and Saleem, 2014; Krodkiewsk et al., 1994).

Even though some methods are offered to unbalance detecting, unbalance localization, and to understand how much is eccentric masses causing unbalances very valuable. One of the earlier efforts were aimed to utilize mode shapes and modal masses rather than the run test was presented by Krodkiewski et al. (1994) and Sinha et al. (2002). They developed a model based on mathematic for a rotor system with multi bearings. The presented concept has been industrialized for a flexible shaft of the revolving machine by a single run (Saleem et al., 2012; Walker et al., 2011). Additionally, the measurement of shaft deflection was employed by Mottershead et al. (1999) to identify the position of unbalance. The frequency response of the system simulated by the NASTRAN software has been used by Feldman et al. (1999) in unbalance localization.

Finite element modeling has been exploited to investigate the difference of stiffness produced by faults like crack, rubbing, etc. These disparities will be applied for finding the location of the unbalance (Li and Chow, 1998 and 2000).

Artificial neural network (ANN) is one amongst intelligent methods that may be used for forecasting within the systems which their mathematical model is not available. For example, it had been applied for detecting of the defect in the bearings (Tao and Qingkai, 2010; Qiu and Rao, 2005; Barakat et al., 2011), the classification of shaft mode shapes for the crack identifying(McCormich and Nandi, 1997), classification of fault types within the revolving machines by Neuro-fuzzy systems (Li et al., 2010), failure detection within the gears and bearings via Neural Network which is working by Self Adaptive Growing (SAGNN) (Barakat et al., 2011). Besides, some of the test rigs were implemented by a system by hybridizing of neural network and fuzzy logic systems have been performed to identify unbalance within the rotational equipment and to fault categorize of the turbo-generators (Li et al., 2010), and to estimate required mass for the rotor balancing (Santos et al., 2009). The localization of rotor unbalance by the neural network was established for a rotor, including multi discs. It can identify the unbalance plane in rotor (Walker et al., 2014). A mathematical model had been developed by Beltran-Carbajal and Silva-Navarro (2013) to detect unbalance in the system for automatic control by active techniques. The unbalance effects can be canceled via active control using external forces within the rotors (Cupial and Koziol, 2013). Moreover, the discrete wavelet transform was employed to analyze the vibration of the rotor in both the time and frequency domain to detect unbalanced rotor faults online (Rahman and Uddin, 2017). Artificial intelligent methods are focused by researchers to estimate unbalance parameters by real-time approaches (Pavlenko et al., 2019; Gohari and Kord, 2019; Gohari and Eydi, 2020).

As declared before, previous works effort to present methods for discovering the unbalance and localization of that; however, most of them can detect unbalance planes. As a result, this area of

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research requires innovative studies since the plants necessitate robust and exact approaches for this demand. The present study deals to unveil a technique that can identify the plane of the unbalance mass between various discs and estimate unbalance mass via the Wavelet coefficients. The ANN model has been designated as a predictor implement due to its inputs, which are wavelet coefficients reached by decomposing mother vibration signal of bearing.

2. Methodology

In balancing the procedure of the rotary systems, recognizing plane which unbalance mass situated on that, radius and mass values are required. To reach these values, the hybridized model has been developed to authenticate this idea. Since the ANN model needs input parameters, a rotary system with multi discs was fabricated to generate data and used as model inputs.

2.1. Mathematical Model of Unbalance Rotor

To have better sense about unbalance rotor and generated forces due to this issue, dynamical model of system is stated here. The simplified Jeffcott Model were employed for this purpose and shown in Fig.1 (a) and (b). The motion equation of rotor bearing system after linearization is mentioned as:

$$M\ddot{q} + I\omega\dot{q} + Kq = F \tag{1}$$

Where rotating velocity is ω, and F is vector of unbalance force. M, I, and K are mass, mass moment of inertia (generating gyroscopic force), and stiffness matrices. The unbalance force can be shown by:

$$F = \begin{pmatrix} f_x \\ f_y \end{pmatrix} = \begin{bmatrix} \cos \omega t & -\sin \omega t \\ \sin \omega t & \cos \omega t \end{bmatrix} \begin{pmatrix} A\cos\varphi \\ A\sin\varphi \end{pmatrix}$$
$$A = me\omega^2 \tag{2}$$

Where time is indicated by t, and e is eccentricity of unbalance mass. φ is unbalance phase, and m is unbalance mass.

2.2. Experimental Test Rig and Data Analysis

Initially, a shaft with four discs was fabricated as a rotor, which revolving via an electrical motor with 0.5 hp and 1500 rpm. As exemplified in Fig. 1(c), the rotor is situated on the base plate by two ball bearings. The rotor, discs, and base plate are made as rigid solid, and numerous eccentric masses with various distances to the rotor center were mounted on different disc numbers. In each case of experiments, the accelerations of mutual bearings were logged by the accelerometers (ADXL 335), which attached to the rotor base. The ADVANTECH 4711A DAQ was utilized for the gathering of data. The eccentric radiuses were 6, 8, and 11 cm, and unbalanced masses were 10, 15, 20, and 25 gr. In this effort, an unbalanced mass is located in disc one and two by various radius values and various mass values. Thus, vibration data were attained for the 24 samples.

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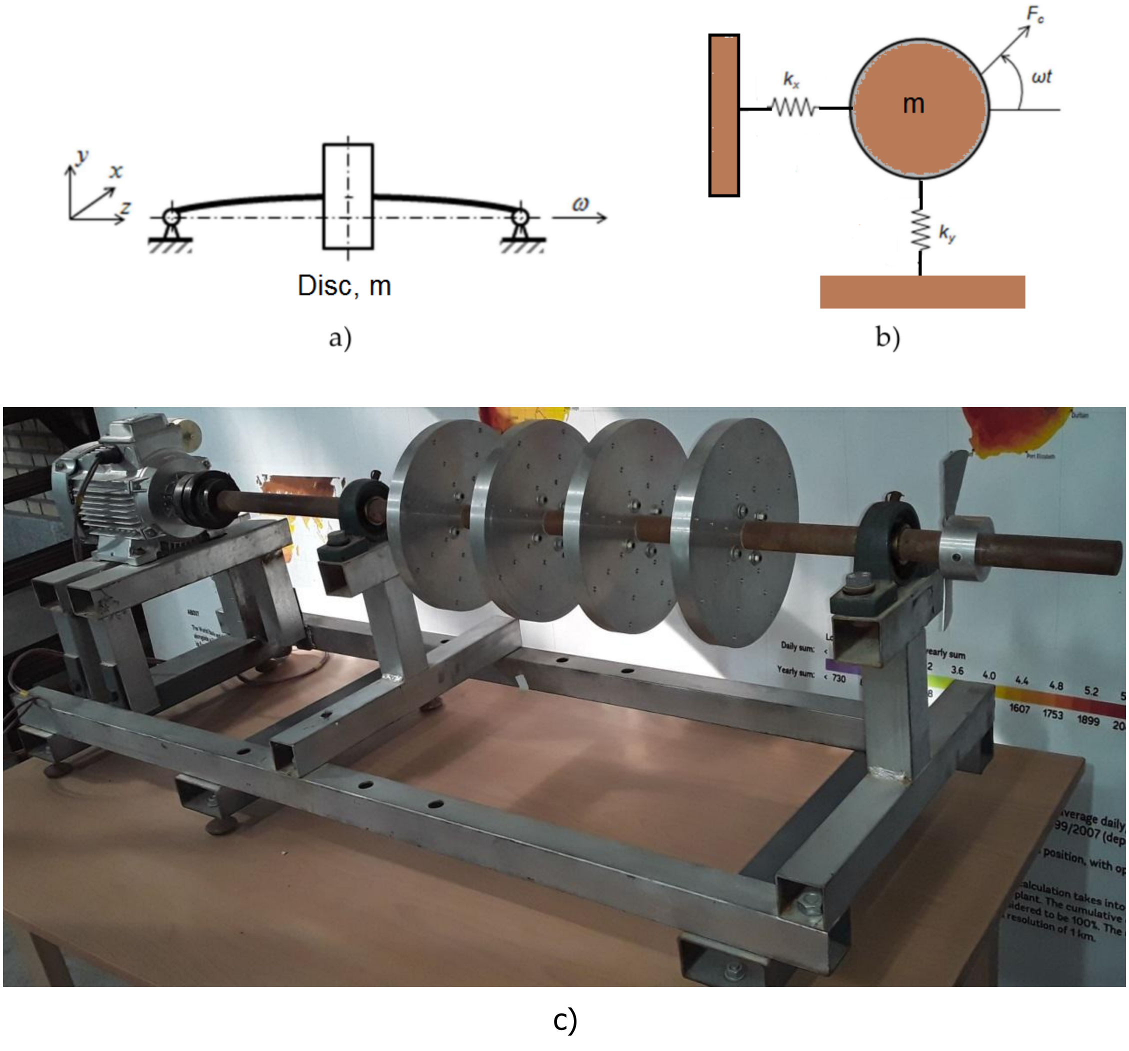

Figure 1. (a) rotor model (Jeffcott Model), (b) simplified model, (c) The fabricated rotary system

For example, 15gr unbalance mass with an 11cm eccentric radius were mounted on disc number 1, and finally on disc number 2.

The time-domain data were preprocessed to reach Wavelet coefficients as ANN inputs feature. In fact, by discrete wavelet transformation (DWT) time-domain acceleration signal was divided into some sub-bands, and wavelet coefficients were extracted. Then, the acquired wavelet coefficients were fed to the ANN as the inputs, and this model is known as DWANN. The steps of the model establishment are shown in Fig. 2.

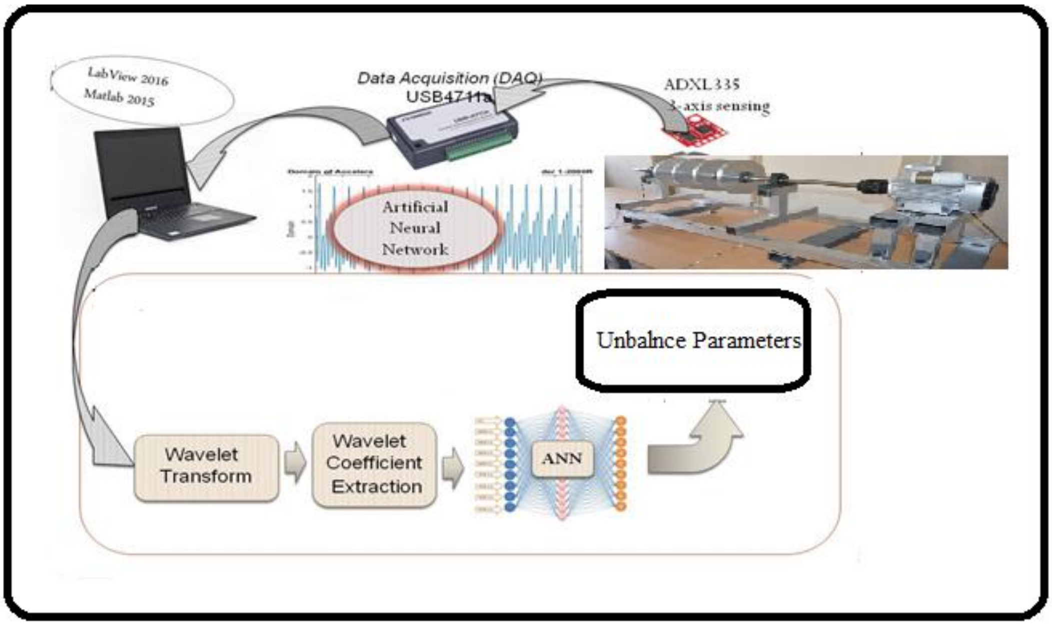

Figure 2. Structure of DWANN Model in unbalancing multi-disc rotor parameter detection

2.3. Selecting Proper Feature Vector

The accuracy of wavelet-based models is influenced by selecting the mother wavelet. The appropriate mother Wavelet must have the most similarity to the signal, which is decomposed. The continuous wavelet transform decomposes a signal f (t) into shifted and scaled versions of the mother wavelet ψ.

In a few words, simultaneous analysis of the vibration signal by way of continuous wavelet transform is based on energy function. In a mathematical statement, it is the convolution of the input data function and mother wavelet:

$$CW(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} f(t) \cdot \psi^{*}\left(\frac{t-b}{a}\right) dt \tag{3}$$

Like as other mathematical transformation, wavelet has inverse transform definitude to:

$$f(t) = \frac{1}{C_{\psi}} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} CW(a,b) \cdot \frac{1}{a^{2}} \cdot \psi\left(\frac{t-b}{a}\right) dadb \tag{4}$$

Correspondingly, the definition of C_{ψ} is:

$$C_{\psi} = \int_{0}^{\infty} \frac{|\psi(\omega)|^{2}}{\omega} d\omega \langle \infty \tag{5}$$

The coefficients, $W_x(a,b)$, are function of a and b, demonstrating high-frequency components for narrow wavelets. In opposite, wide wavelet coefficients belong to low-frequency. Desecrate Wavelet Transform is given by:

$$DW(j,k) = \sqrt{2^{j}} \int_{-\infty}^{+\infty} f(t) \cdot \psi^{*}\left(2^{j} t - k\right) dt \tag{6}$$

Where DW(j,k), j, and k are the matrix of the coefficients, the scale of the frequency domain, and the time shift of the mother wavelet, respectively.

Wavelet packet transform (WPT) denotes decomposes approximations with detail. In the first step,

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two packets are created by decomposing of the signal: A and D. First term is belonging to the component in low-frequency, and the second term is related to the higher frequency element of the signal. In the second step of decomposition, sub-packets are generated as AA, AD, DA, and DD. This process of decomposition continues to form the WPT tree. The mathematical expression of the WPT is:

$$W_{j,k}^{n}(t) = 2^{j/2} W(2^{j} t - k), \quad j,k \in Z \tag{7}$$

Where j and k are belonging to the scale and time shift, respectively.

In the present paper, 1 dB is evaluated as a mother wavelet, and its coefficients applied as the DWANN inputs. Fig. 3(a) shows a flowchart of signal decomposing to sub-bands. Proposed mother wavelets used to break up signals are exposed in Fig. 3 (b).

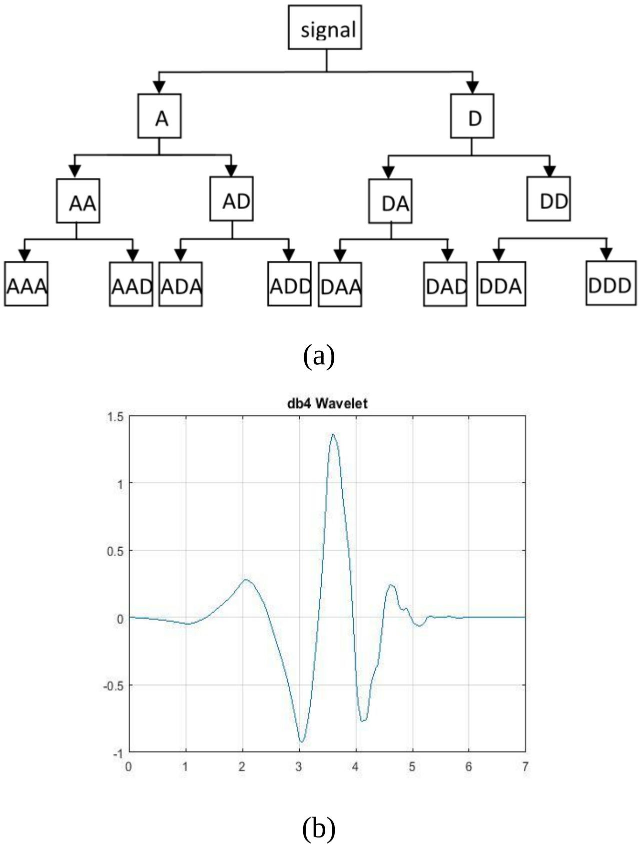

Figure 3. Mother wavelet employed to obtain coefficients

2.4. Topology of the WANN Model

The ANN model fed to the wavelet coefficients includes 100 inputs nodes (wavelet coefficients) and two hidden layers with six neurons in each layer. The schematic architecture of DWANN is exhibited in Fig. 4. Sixty-five percentages of data were entered into the DWANN model through the training step, and 15% of data was employed in the validation step. The Levenberg–Marquardt Algorithm showed superior performance, as can be seen in Fig. 5. The correlation ratio was overtaken 0.9856.

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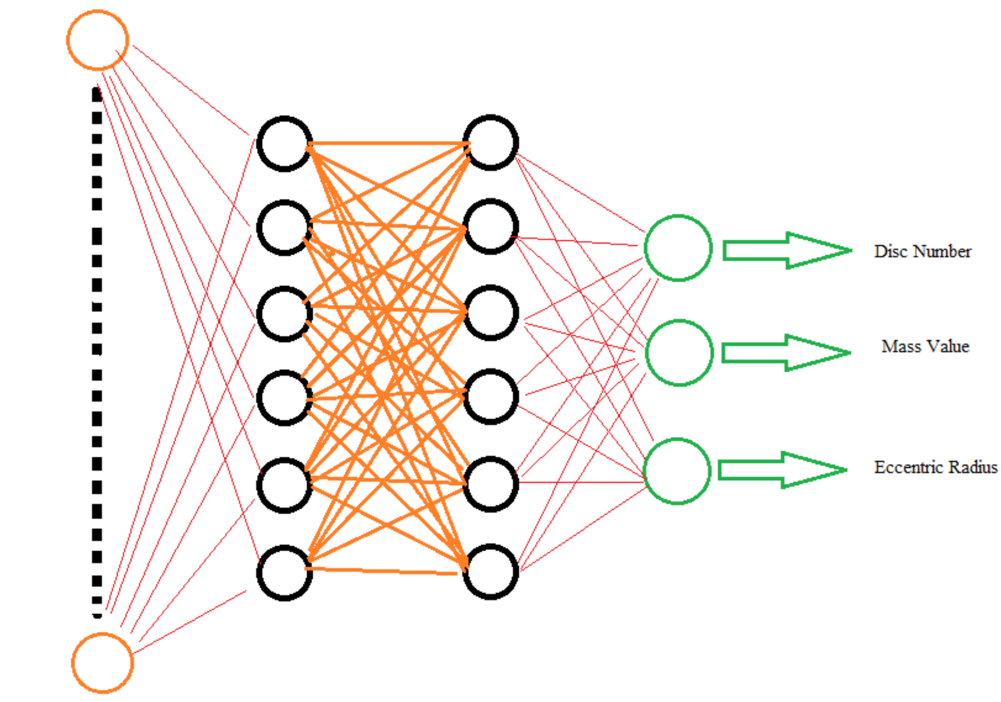

Figure 4. Representation architecture of DWANN model

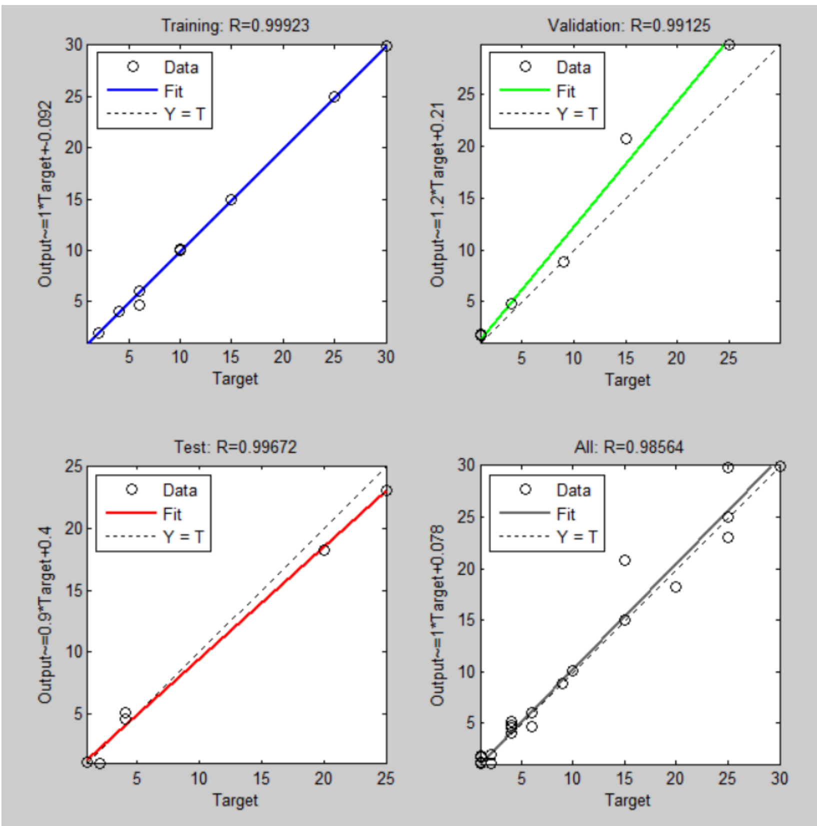

Figure 5. Correlation ratio of ANN model during training step, validation, and test steps

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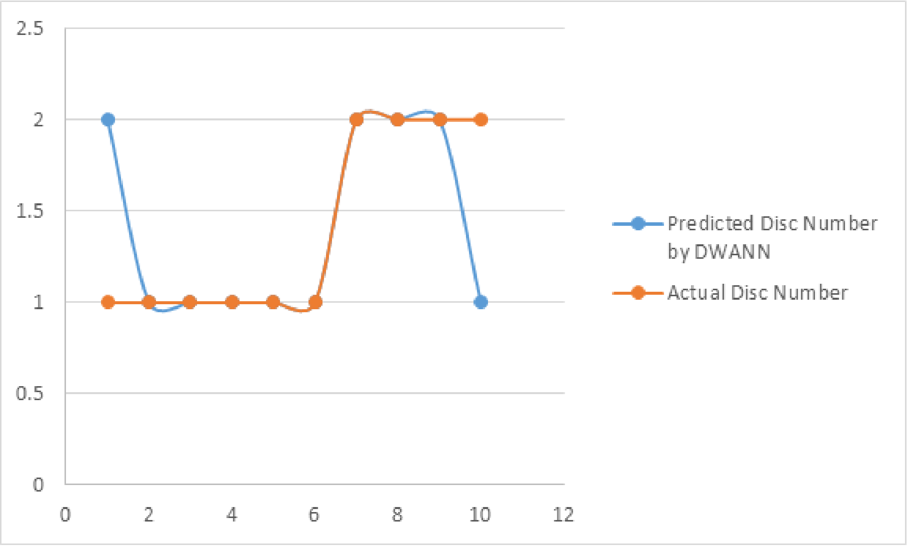
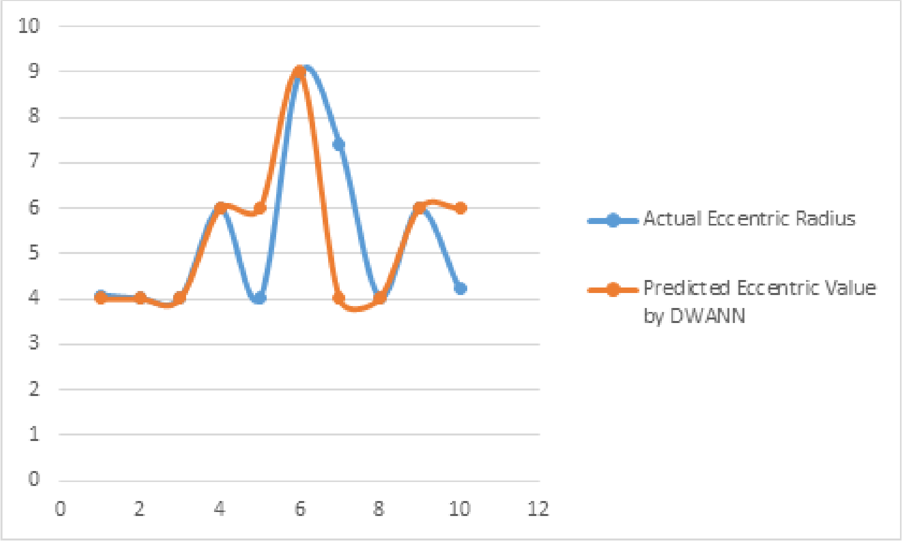
3. Results and Discussion

After training and adapting of the ANN was done, the best architecture has been obtained, the accuracy of the DWANN in prediction purpose was verified. For this aim, all of the 24 examples were considered the inputs, and the outputs of the DWANN were compared to actual values. Fig. 6a, b, and c demonstrate this comparison between actual value to the predicted by DWANN model for the disc number, the eccentric radius, and the unbalance mass values, respectively. Table 1 exemplifies the accuracy of the DWANN in predictions of unbalance parameters. As can be seen in Fig. 6 and Table 1, the best accuracy of prediction has been reached in the eccentric radius, and the lowest was acquired for the unbalance localization.



(a)



(b)

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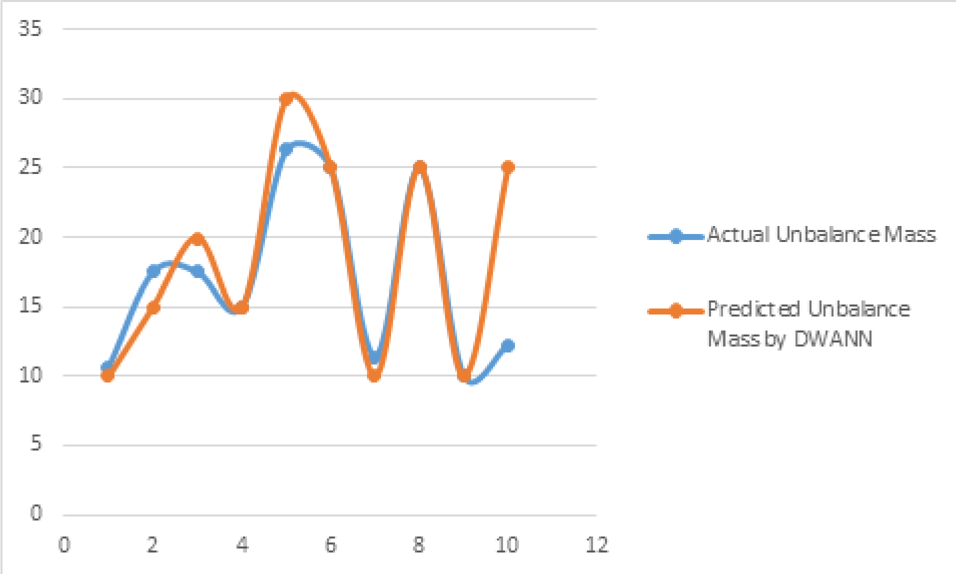

(c)

Figure 6. The comparison between actual and predicted by ANN model values a) prediction of the disc number which has unbalanced mass b) the eccentric radius value c) the unbalanced mass value.

Table1. The DWANN model accuracy in predictions

Prediction of the disc number which has unbalanced mass	Prediction of the eccentric radius	Prediction of the unbalanced mass
95%	97.26%	96.28%

As can be seen, the DWANN model accuracy in prediction of the localization of unbalanced mass is lower, but in the eccentric radius and unbalance value is around 96%. Consequently, by this DWANN architecture, the accuracy of all outputs, including the mass value, the disc number, and the eccentric radius, is higher than 95%. The correctness of the proposed DWANN model compared to the earliest model presented Walker et al. (2014) is a little higher thought current DWANN model can predict the radius and the mass value of the unbalance with adequate accuracy. As specified in the literature survey, in the active rotor balancing [30, 31] detecting the location of the unbalance mass with proper accuracy and online output is very advantageous (Beltran-Carbajal and Silva-Navarro,2013; Cupial and Koziol, 2013). This accomplished DWANN model can be employed in this aim. Most of former established ANN models generally were created for fault classification (Tao and Qingkai, 2010; Qiu and Rao, 2005; Barakat et al., 2011; McCormich and Nandi, 1997; Li et al., 2010; Barakat et al., 2011), but some of them were employed to unbalance parameter identification (Walker et al., 2014; Rahman and Uddin, 2017). Moreover, current DWANN performance in prediction of unbalance parameters is better than the KNN Algorithm (Gohari and Eydi, 2020), Decision Tree Algorithm (Gohari and Eydi, 2020), and ANN (Gohari and Kord, 2019) which was fed by statistical features derived from time-domain vibration signal of bearings.

4. Conclusion

In rotary machines, removal of damaging vibration created by unbalanced mass is crucial, and to eliminate these vibrations necessitate some factors about unbalance such as unbalanced mass value and location of that. In the current effort, a novel approach was operated to identify and estimate unbalance rotor parameters. To accomplish this target, a hybridizing of Wavelet Transformation and the neural network has been revealed, which can identify the location and value of the unbalance mass. The reason for the ANN applying as intelligent tools is the potential of modeling by nonlinear features. The accuracy of the suggested model exhibits good accuracy and can be advanced for industrial applications.

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