Unbalance Rotor Parameters Detection Based on Artificial Neural Network; Development of Test Rig

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Abstract

Condition monitoring techniques provide vital data for operators to avoid unpredicted and unwanted stop of machines caused by faults. One of these techniques is vibration analysis, which is used for faults diagnosis and prognosis such as shaft bending, misalignment, lousy bearing, worn gears, and unbalances of rotors, etc. Moreover, vibration signals can be employed in intelligent algorithms like Fuzzy Models, Support Vector Machine, and Neural Networks to prepare better and more accurate predictions of current and future conditions of machine. This paper discusses the application of vibration signals in prediction of rotor unbalance parameters including the unbalance location and amount. Some statistical features were applied on the inputs of the neural network had been derived from time and frequency domains of bearing acceleration signals. The experimental study shows that the developed model can estimate these parameters with acceptable accuracy.

Key words: Rotary test rig, unbalance amount, location of unbalance, eccentric mass, neural network model

1. Introduction

Rotating machinery as a broad group of machines such as turbines, pumps, compressors, etc. are used in industrial plants, and the fault prognosis of them affords more cost-saving [1]. A mutual source of vibration in turbomachinery is Rotor Unbalance. Unbalance mass of rotor generates forces to the base and supporting bearings. The stated forces may damage the machine and other tools which is connected to the machine. Balancing techniques are used for removing this effect and consequently faults. Rigid rotors are treated by plane separation, but modal balancing technique is applied for flexible shafts [2and3]. Long term and short term data collecting to faults diagnosis like an unbalance are employed for fault detection in turbomachinery [4and5]. Artificial intelligent methods such as artificial neural network (ANN) have been employed for diagnosis and prognosis of mechanical systems [6]. Ganesan et al., used ANN on diagnosis of a rotor with high speed rotating [7]. Fault prediction of rotating machine via ANN was applied by Vyas and Satish Kumar [8]. The hybridized of Wavelet transformation and ANN was used by Paya and East, and Gohari et al., [9 and 10]. Rolling bearing fault was diagnosed by employing ANN successfully via time domain vibration data [11].

Balancing of rigid rotor supported by hydrodynamic journals for calculation correction mass was tried by ANN [12]. In addition, fault diagnosis of electrical motor supported by rolling bearing was studied by ANN [7]. Other faults of shaft such as crack in rotor shaft is diagnosed via ANN [9 and 14]. Moreover, signature analysis based on ANN were presented to detect faults of induction motors [19]. The potential of ANN in fault diagnosis were compared to isolation forest in rotary systems to identify core and pons of that [20]. Other parts of rotary systems such as pully and belts were diagnosis via ANN in terms of fault classification [21]. The hybridized machine learning with frequency response analysis was introduced in shaft unbalance detection to enhanced ability of that [22]. The frequency analysis also is hybridized to other classification algorithm such as support vector machine to detect the unbalance in the shaft [23].

In a previous study [10], the simulation results of multi discs rotor were employed in the artificial neural network to study the accuracy of the ANN in the prediction of unbalance parameters such as the location of eccentric mass and value of that. The present paper makes an effort to verify the potential of the ANN model in detecting unbalance parameters by experimental acceleration recorded data.

1.1.Mathematical Modelling

A rotor system as is shown in Fig.1 is considered in this section. The rotor consists of a shaft which is assumed to be simply-supported at two ends and N_d disks which are mounted at different locations on the shaft. An unbalance mass m_i which is located at radial distance of r_i and angular position of ϕ_i-compared to a reference axis- is considered on ith disk.

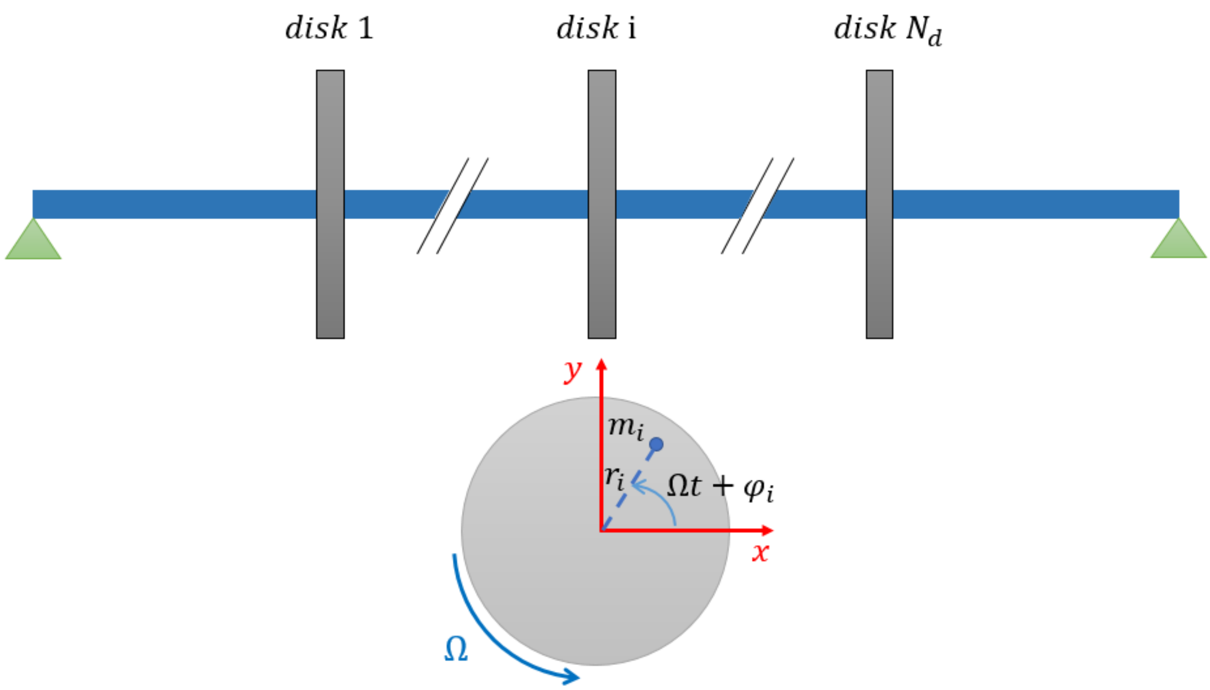


Fig.1 a rotor system containing an unbalanced disk

The equations governing the dynamic response of the rotor system shown in figure (1) can be expressed by employing FE modeling approach as,

$$[M]\{\ddot{d}\} + \Omega[G]\{\dot{d}\} + [K]\{d\} = \{F(t)\} \tag{1}$$

Where $[M]$ is the positive definite symmetric mass matrix which is derived from the kinetic energy of lateral vibration of the rotor, $\Omega[G]$ is the skew-symmetric gyroscopic matrix obtained from rotational kinetic energy and the symmetric elastic stiffness matrix $[K]$ is derived from strain energy of the shaft Displacement vector $\{d\}$ consist of lateral and rotational displacements of each point of the shaft, i.e. $\{x_i, y_i, \theta_{xi}, \theta_{yi}\}$. $\{F(t)\}$ is the vector of unbalance forces which for the case shown in figure (1) can be expressed as:

$$\{F(t)\} = m_i r_i \Omega^2 [0,0, \cdots, \cos \Omega t + \varphi_i \,, \sin \Omega t + \varphi_i \,, \cdots ,0,0]^T \tag{2}$$

Solving equation (1) results in the dynamic response of different points of the shaft. The lateral vibration of j^{th} node of the shaft in x and y directions is functions of rotational speed Ω, the location of unbalance mass along the shaft, unbalance mass properties and time and one may express them as:

$$x_j(t) = f_j(i, m_i, r_i, \phi_i, \Omega, t), \qquad j = 1,2, \dots , n \tag{3}$$

$$y_j(t) = g_j(i, m_i, r_i, \phi_i, \Omega, t), \qquad j = 1,2, \dots , n \tag{4}$$

The matrices Me, □Ge, and Ke are the typical elemental mass/inertia, gyroscopic, and stiffness matrices. The mass/inertia matrix Me, derived from the kinetic energy, is a positive definite symmetric matrix; the conservative gyroscopic matrix □Ge, derived from the rotational kinetic energy, is a real skew-symmetric matrix; the stiffness matrix Ke can be a general real matrix, which contains a symmetric elastic matrix derived from the strain energy of the shaft element and the non-symmetric and non-conservative stiffness from the axial torque and gravity for vertical rotors along the spinning axis. The force vector Qe is the generalized force vector, which contains all the excitations acting at the shaft element. The details of these matrices and generalized force vector are documented in [16,17, and18] and not repeated here.

2. Research Methodology

After reaching acceptable and relatively accurate results from the ANN model by simulating a multi discs rotor [10], a test rig was developed to establish the ANN model based on experimental data. The research steps are described in the following parts.

2.1. Data Collection and Analysis

The test rig is fabricated of a shaft and four discs supported by two rolling bearings. The Shaft is connected to an electrical motor via a universal coupling. Power of electrical motor is 0.5 hp and made by Pars Electric Co. Each disc includes 24 holes which are shown in Fig.2. Unbalances mass called Eccentric mass can be mounted to the discs by bolt and nut in several positions. The distances of holes from center line of shaft are 4, 6.5, and 9 cm. Two accelerometers were attached on the shaft supporters near to the bearings [11]. ADXL 335 which is commercial accelerometer using micro Piezo-cantilever bar by analogue voltage output is proper for this measurement (Fig.3.a). The analogue outputs are available in three directions; X, Y, and Z (Fig.3 b). Furthermore, rotation speed and phase angle are collected by an Opto-coupler (Infrared transmitter and photoelectric receiver) generating electrical pulse which is countered by data logger.

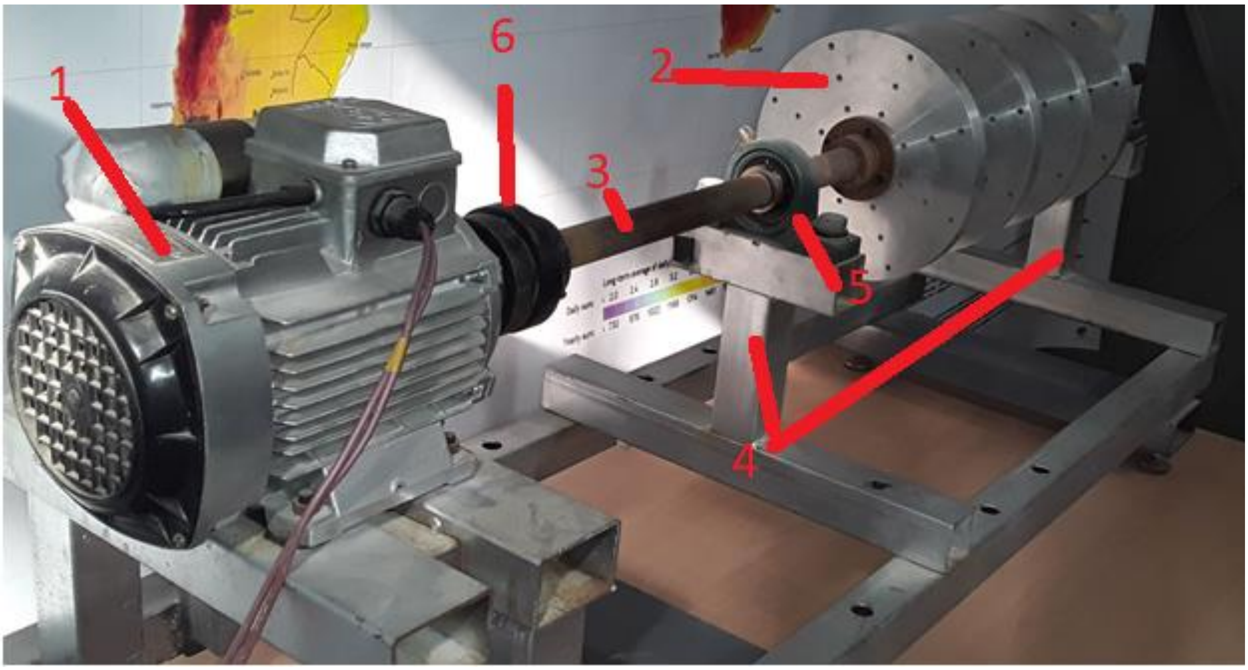
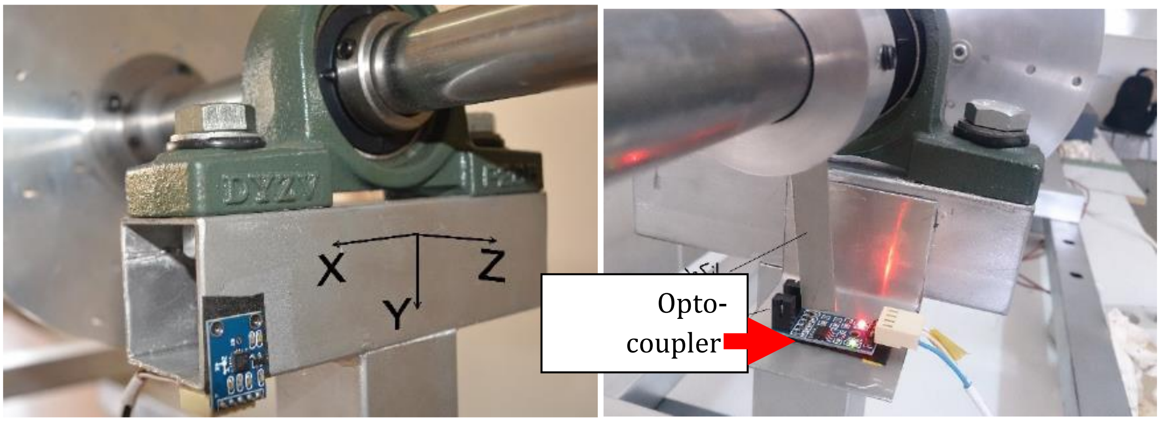


Fig.2 the parts of the test rig frame and rotors: (1) electrical motor, (2) disks, (3) shaft, (4) supporting bases, (5) bearing, (6) coupling



(a) (b)

Fig.3 (a) the installed accelerometers and measuring directions, (b) Opto-coupler measuring phase angle of rotor

An ADVANTECH 4711A with 150 kS/s sampling rate were utilized for data collecting. Whereas rotation speed of shaft is 25 Hz (1550 rpm), it can record acceleration signal points appropriately consequently without data losing. Unwanted noises were rejected by low pass filter in in Labview Software.

60 tests were conducted by mounting various masses (10, 15, 20, 25, and 30gr). Actually, each unbalance mess value was installed in three radiuses (4, 6.5, 9cm) at four discs. Totally, 60 trails were executed while accelerations and phase angles were recorded. Next, Hanning Window was employed on time data, subsequently Fourier Transformation were applied to convert acceleration signal to frequency domain. a converted acceleration signal by Fourier Transformation with and without Hanning Window is shown in Fig.4.

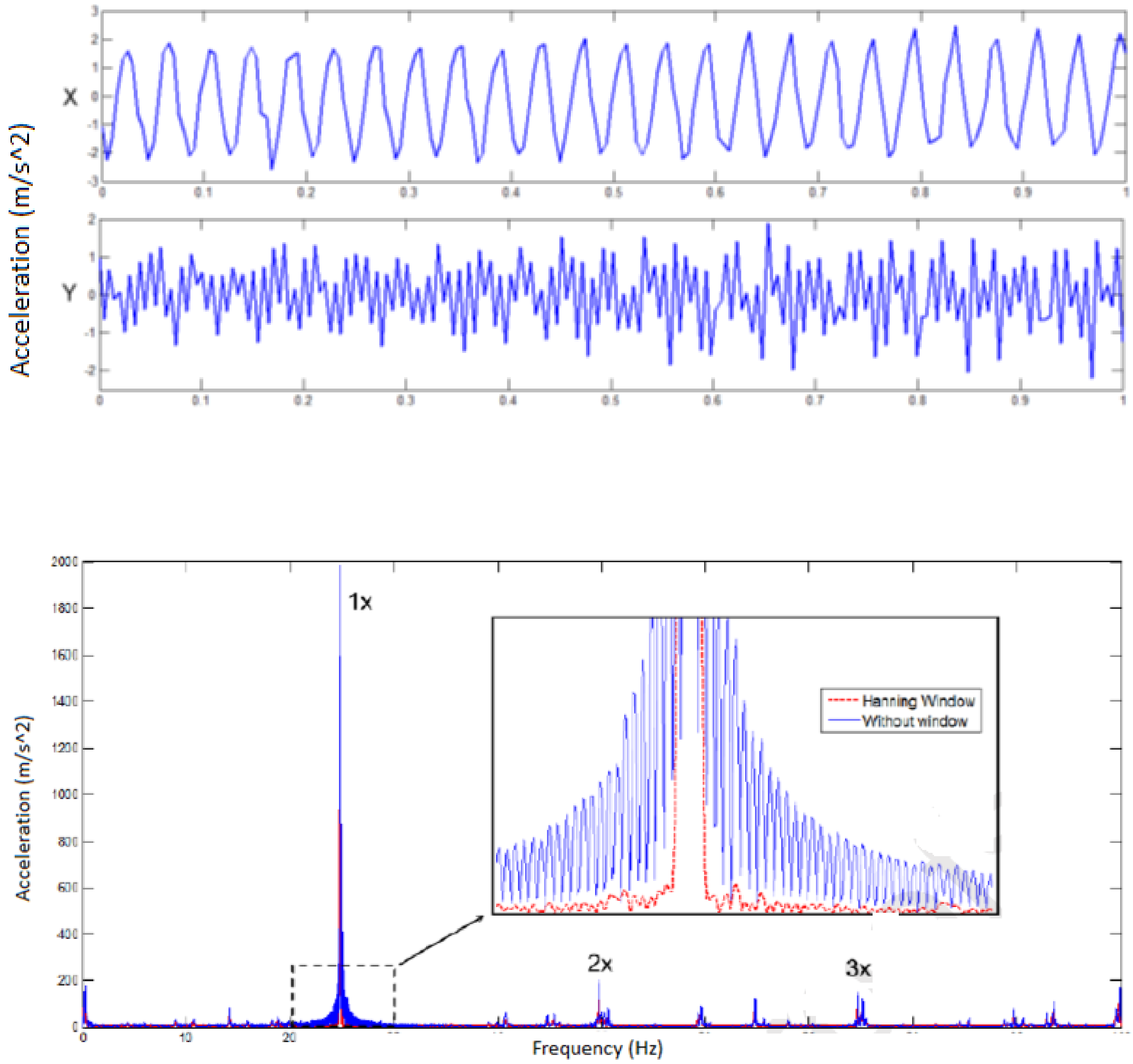


Fig.4 (up) X and Y acceleration signals when a 25gr mass is attached on 9cm radius of disc number one

(down) Acceleration signal in frequency domain (with and without Hanning Window)

As can be realized in Fig.4, windowing of data signifies enhanced unbalance fault (1X RPM). The vibration as a result of mass unbalance will peak at a frequency equal to one times (1X) the revolving velocity of the rotor. Usually, other faults reveal in 2X and 3X. Similarly, by increasing eccentric mass value, for example in first disc, the unbalance amount increases and first peak of acceleration signals rise while there are not any notable changes in other peaks. It means that the unbalance amount is good feature in ANN training. Hence, acceleration signal is suitable data to detect unbalance parameters. The unbalance amount is mentioned as product of mass to distance from unbalance mass to rotor centerline [14].

2.2. Applying ANN in detecting unbalance location

The main purpose of using ANN in current research is predicting unbalance amount value and location of that on the rotor (disc number). As cited previously, unbalance parameters are unbalance amount, location of that (disc number), and angle of eccentric mass on disc. By detecting three parameters, eliminating unbalance by mounting correction mass is possible.

From the time domain data as raw data, some statistical features were extracted to feed in ANN [13]. The exploited statistical features are listed in following:

$$pv = max(a) \qquad \text{(peak value)}$$

$$A = \frac{1}{N}\sum_{n=0}^{N} a(n) \qquad \text{(Average)}$$

$$\bar{A} = \frac{1}{N}\sum_{n=0}^{N} |a(n)| \qquad \text{(absolute Average)}$$

$$RMS = \sqrt{\frac{1}{N}\sum_{n=0}^{N} a^2(n)} \qquad \text{(Root Mean Square)}$$

$$PAR = \frac{max\{|a|\}}{\bar{A}} \qquad \text{(Peak to Average Ratio)}$$

$$CF = \frac{Peak\ value}{RMS} \qquad \text{(Crest Factor)}$$

$$IF = \frac{Peak\ value}{|\bar{A}|} \qquad \text{(Impulse Factor)}$$

$$SF = \frac{RMS}{|\bar{A}|} \qquad \text{(Shape Factor)}$$

$$CLF = \frac{Peak\ value}{\left\{\frac{1}{N}\sum_{n=0}^{N}\sqrt{|a(n)|}\right\}^2} \qquad \text{(Clearance Factor)}$$

$$KV = \frac{\frac{1}{N}\sum_{n=0}^{N}(a(n)-A)^4}{RMS^4} \qquad \text{(Kurtosis Factor)}$$

$$SK = \frac{\frac{1}{N}\sum_{n=0}^{N}(a(n)-A)^3}{RMS^3} \qquad \text{(Skewness)}$$

$$STD = \sqrt{\frac{1}{N}\sum_{n=0}^{N}(a(n)-A)^2} \qquad \text{(Standard Deviation)}$$

$$UB = \max(a) + 0.5 * \left\{\frac{\max(a)-\min(a)}{N-1}\right\} \qquad \text{(histogram upper bound)}$$

$$LB = \max(a) - 0.5 * \left\{\frac{\max(a)-\min(a)}{N-1}\right\} \qquad \text{(histogram lower bound)}$$

$$E = \sum_{n=0}^{K-1}|s[n]|^2 \qquad \text{(Energy)}$$

$$FP = \max(S) \qquad \text{(Peak in Frequency Domain)}$$

Where “α” is acceleration matrix in time domain, and “N” is number of data. Moreover, “s” is acceleration matrix in frequency domain, and “K” is number of data. The last two features are computed in frequency domain, and the rest others are calculated in time domain.

The inputs of ANN are considered stated features, and the output is unbalance amount. The 60 example sets were fed into ANN for training process. Various topologies (in terms of number of hidden layers and neuron numbers) were assessed to obtain best architecture. The selected architecture includes one hidden layer with ten neurons. The trend of validation diagram is similar to test diagram, thus overtraining is not done for this model.

Also, the correlation ratios in training, validation, test steps and over all are exemplified in Fig.5.

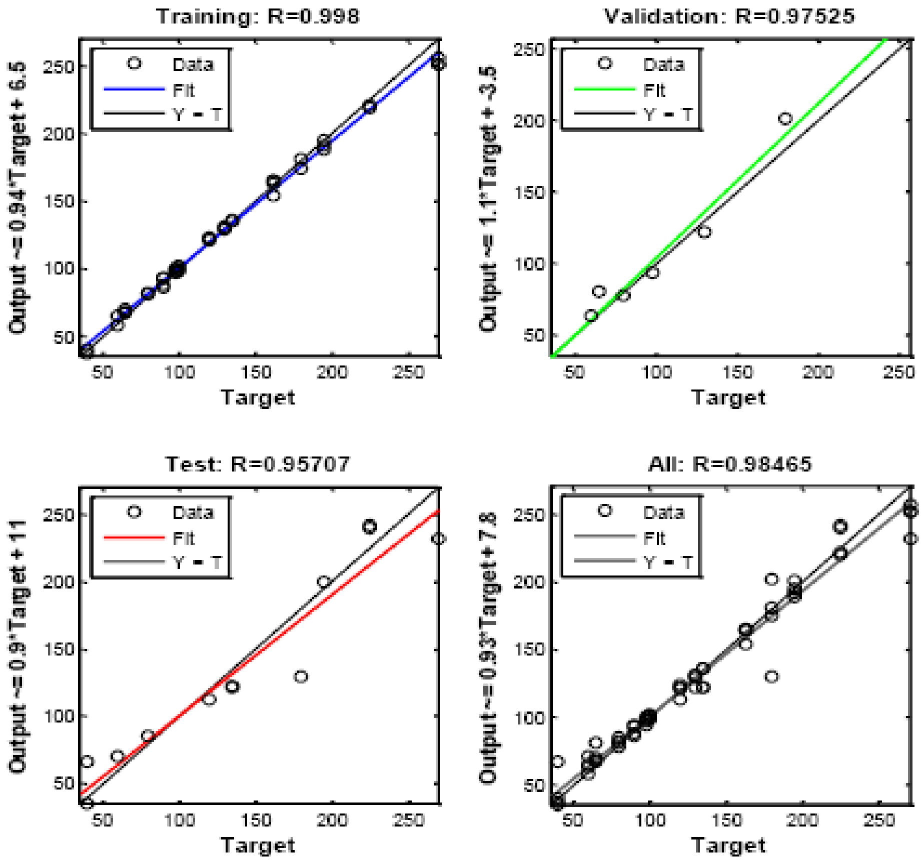


Fig.5 The correlation ratios between output and target (output of ANN toolbox of MATLAB software; (a) in training steps, (b) in validation step, (c) in test step and (d) in overall. T is target values; Y is predicted output by model; and R correlation coefficient between output of model and target values.

3. Results and Discussions

3.1. Predicting Unbalance Amount by ANN

Moreover, the accuracy of achieved model in predicting of unbalance amount is shown in Fig.6. In fact, the outputs of model are compared to real unbalance amounts. For having better sense in accuracy of model the actual unbalance amount is plotted versus predicted by model and unveiled in Fig.7.

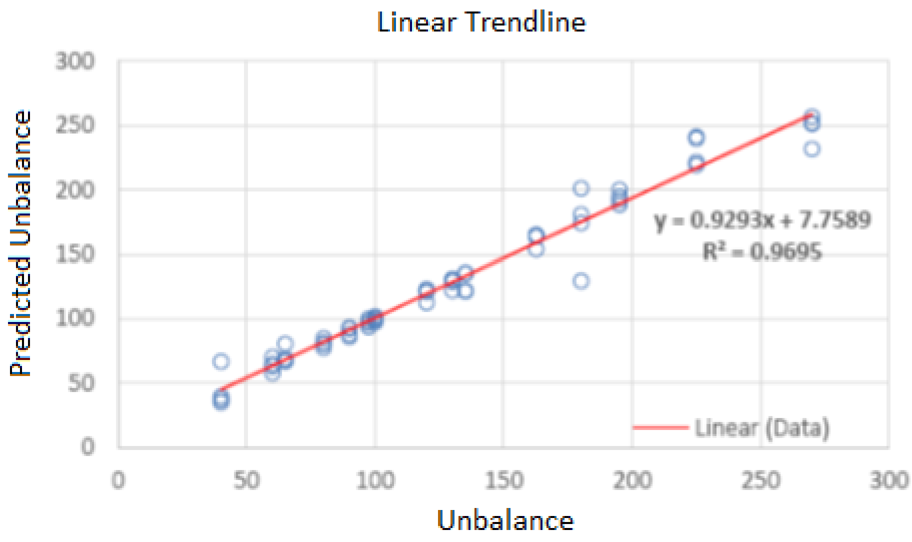


Fig.6 The correlation between outputs of achieved model and actual values in predicting of unbalance amount

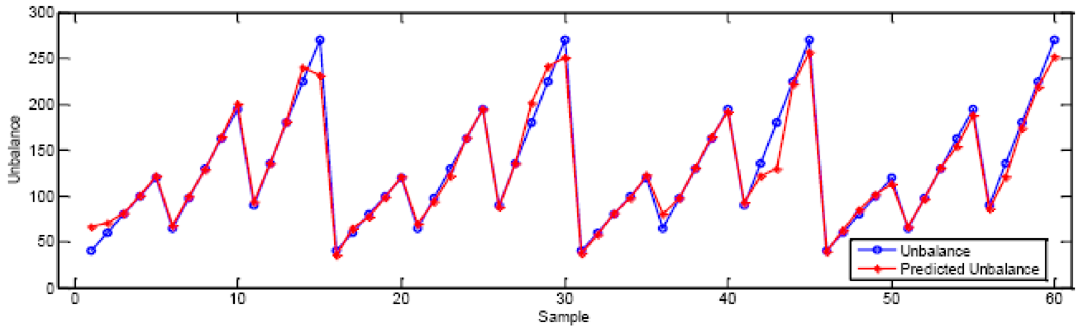


Fig.7 Predicted unbalance amount values by ANN model compared to actual values

3.2. The Performance of ANN in Unbalance Location

The second ANN model was established to identify the disc location which the unbalance mass is located on that. Same as first ANN model, inputs are mentioned statistical features from acceleration signals recorded from both bearings. The diverse vibration effects in two bearing can be used in unbalance locating. The performance diagram of ANN and correlation diagrams in different steps are depicted in Fig.8.

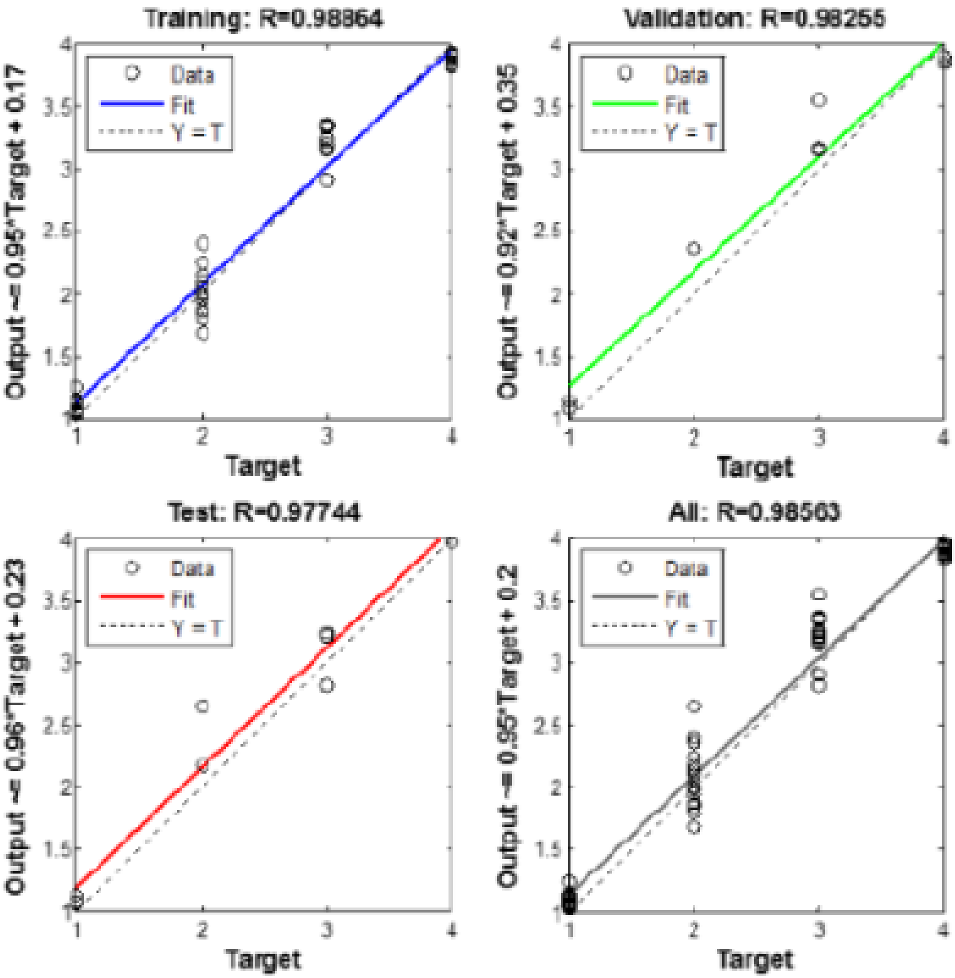


Fig.8 the correlations between output and target of model

As can be find in Fig.8, there is not overtraining in model, and it shows good accuracy in established model. Also, the real values of disc number in each sample are plotted versus predicted disc number by ANN and exemplified in Fig.9 the correlation ratio is around 0.97. Therefore, it seems that the accuracy of achieve model is proper in unbalance locating.

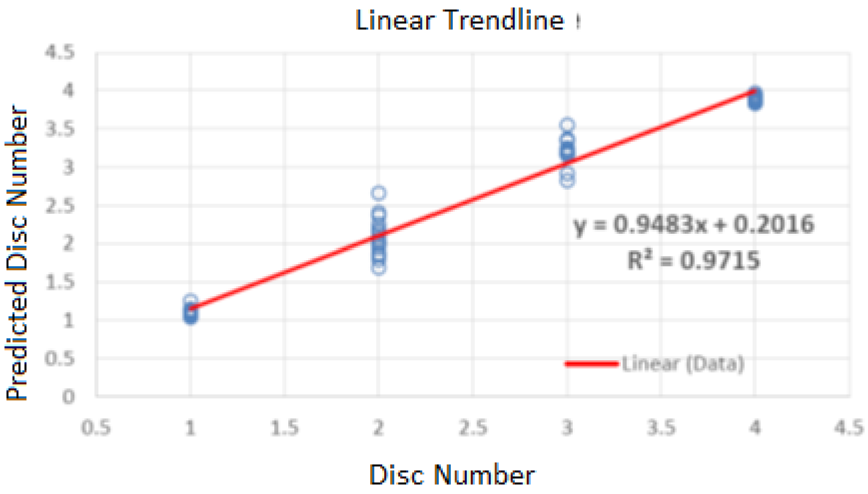


Fig.9 The correlation between outputs of achieved model and actual values in predicting of unbalance location (disc number)

For more comparison, the disc number (location of unbalance) predicted by ANN model is plotted versus to actual disc number and exemplified in Fig.10. The schematic topology of neural network is shown in Fig.11.

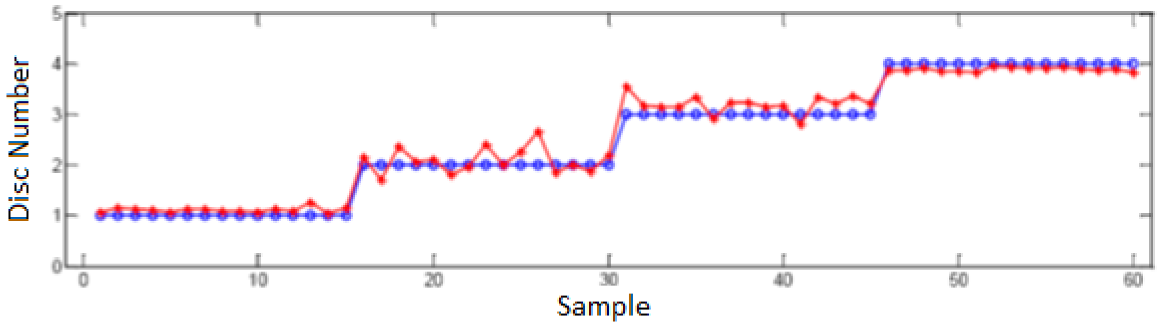


Fig.10 Predicted unbalance location (disc number) by ANN model compared to actual values

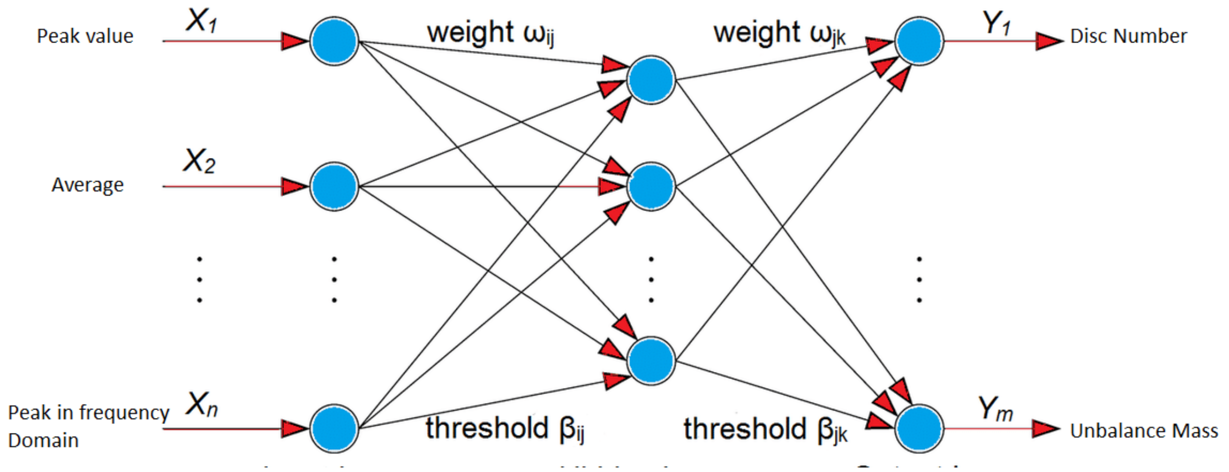


Fig.11 schematic topology of established ANN

Moreover, in another study, the K-Nearest Neighbor Algorithm (KNN) and Decision Tree Algorithm (DT) were performed to identify unbalance parameters includes unbalance mass value, location of unbalance mass and distance unbalance mass to the shaft center in which the accuracy was acquired by KNN as 87%, 85% and 88% for disc number, the unbalance mass value and distance unbalance mass to the shaft center line, respectively [15]. Accuracy of DT in proposed parameters identifying are 71%, 65%, and 74%, respectively. The current work (ANN) presents the disc location and unbalance amount with more accuracy in comparison to KNN and DT. Moreover, the hybridized wavelet transformation to ANN to detect unbalance of shaft presents accuracy as 95%, 97.26%, and 96.28% for disc number, eccentric radius, and eccentric mass, respectively [24]. So, current method shows better performance in unbalance location identifying.

4. Conclusion

The main interest of current work is detecting unbalance characteristics such as unbalance amount and location of that by means of ANN. The statistical features were employed to extract proper data of acceleration signals recorded from bearings. These features were used in ANN increased the accuracy of model up to 96.95% in predicting unbalance amount generated by eccentric mass. Moreover, the performance of ANN model in unbalance location was reached as 97.15%. To sum up, this experimental tests and modeling exploited that ANN has potential to use in unbalance fault attributes predicting which may be utilized in unbalance corrections.

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