An Identification of Unbalance in Rotor Bearing System and Fault Classification using Adaptive Neuro Fuzzy Interface System (ANFIS)

Prasad V. Shinde, R.G. Desavale

Mechanical Engineering Department, RIT, Sakhrale-415414, Shivaji University, Kolhapur, Maharashtra, India

prasadshinde7174@gmail.com, *ramchandra.desavale@ritindia.edu*

Abstract

In rotating machinery, unbalance creates excessive vibration and causes a catastrophic or sudden system failure. Unbalance is produced inside the system due to shaft deformation, inhomogeneity in material, and manufacturing tolerance. This current study proposed an experimental approach to identifying unbalance in the rotor-bearing system. The dominant peak is obtained at the first and multiple harmonics of the shaft frequency. It is seen from the pilot experiments the vibration amplitude increases as speed increases. Also, defect frequency corresponds to the first harmonics of the shaft's rotating speed, which conforms to the theoretical results. The Adaptive Neuro-Fuzzy Interface System (ANFIS) is implemented to classify multiple fault presents in the rolling element bearing. ANFIS reveals good fault classification over multiple fault classes of vibration data with an accuracy of 91.66 %.

Keywords: Rotor Bearing System, Unbalance, ANFIS, Defect

1. Introduction

Rotating machines are found in a wide variety of applications, including power plants, marine propulsion systems, aviation engines, machine tools, vehicles, home products, and futuristic micro- and nano machines. In modern engineering, the design trend for such systems is toward lighter weight and supersonic speeds. A precise estimate of the rotor system's dynamic properties is critical when developing any form of machinery. In real machines, rotors may display many defects at the same time, such as unbalance, rotor bow, crack, and misalignment, either during continuous operation or at the start of manufacturing of the various components due to design issues or during assembly of the rotor system setup.

Any disobedience on the part of machinery causes huge damage to the entire system as well as significant financial loss. As a result, researchers have focused their efforts on detecting defects with maximal accuracy.

At present, different fault finding techniques have been introduced for rolling bearing, such Zhang et al. [1] investigated the compound faults of vibration signatures of gearbox using genetic algorithm. Also, vibration characteristics were analyzed by energy operator demodulating, and vibration signals of bearing and gears were effectively studied. Jing [2] studied vibration signals of several defects using the blind source separation approach. This method effectively identified the compound defects. Li et al. [3] studied a vibration response of compound faults in the gears and bearing uses nonlinear feature extraction with blind source separation. The results obtained are more effective for the multi-fault diagnosis for bearings and gears. Tang et al. [4] considered the compound fault of roller bearing using the variational mode decomposition. The compound defects are separated effectively for the analysis of the individual components. Also, experimental results were carried out to validate the results, and this shows that the technique is more reliable to study compound defects. Jiang et al. [5] applied empirical wavelet transform to rolling element bearing vibration signals to identify compound faults. Experimentation was performed on rolling bearing for combine faults to validate the empirical wavelet transform-duffing oscillator results, and this shows that the method proposed was more reliable.

At present, number of methods and techniques are available for fault identification in rolling element bearing, such as Wavelet Transform-based [6-8], mode decomposition-based [9, 10] methods, and intelligent composite fault diagnosis methods [11, 12]. Many authors use the dimensional analysis approach, neural network approach, ANFIS, etc., to study the fault characteristics of rotor-bearing systems. [13-26]. Intelligent algorithms, such as neuro-fuzzy classifiers and support vector machines, are frequently used as popular methods for compound fault diagnosis since they can effectively classify different types of fault data.

From the literature findings, most of the research is going on in vibration analysis with localized defects. But there is a comprehensive scope to study multiple faults in the rotor-bearing system that needs to be investigated.

The current paper proposes a duo study of unbalance response of the vibratory system and fault classification using the Adaptive Neuro-Fuzzy Interface System (ANFIS) for the rotating system.

2. Adaptive Neuro-Fuzzy Inference System (ANFIS)

For improvement in the accuracy of complex system analysis, Jang created an ANFIS approach. ANFIS is a data-learning technique that transforms a given input into a desired output. It is based on a fuzzy inference model. This method encompasses various membership functions, fuzzy logic operators, and conditional rules.

The statistical features retrieved from a vibration characteristics were used as input ANFIS classification models in this investigation.

The output of the fuzzy inference system is subjected to the first-order polynomial. Using IF-THEN rules in human cognitive systems, the ANFIS technique creates a neural-fuzzy system. Membership functions can be better represented and identified using the system's entry point. As a result, ANFIS has been developed to incorporate both the advantages of an artificial neural network and a fuzzy reasoning system.

ANFIS architecture shows two inputs and a single output with five layers of neurons in Figure1.

The first layer denotes the fuzzyfying layer, in which each neuron is an adaptable node made up of premise parameters. The second layer denotes the product layer, or the implication layer indicates a product of inputs. The normalizing layer function is to normalize the weight functions indicated by layer 3. Layer 4 is defined as a defuzzyfing layer whose nodes or neurons are adaptive. All the input is into a single neuron representing an output or results represented by layer 5.

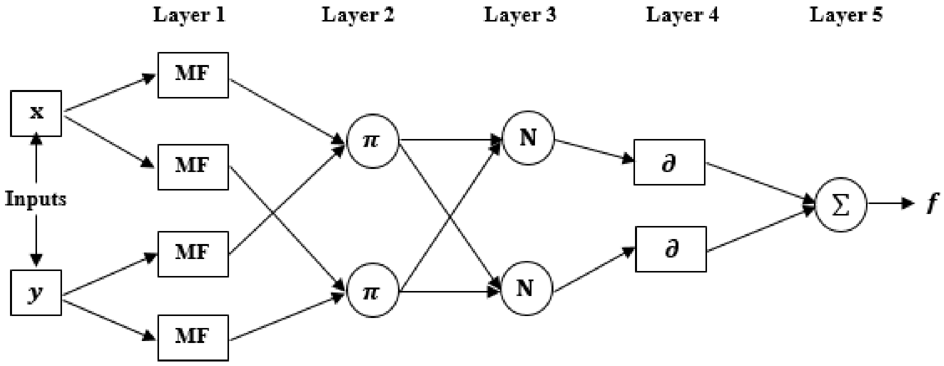

Figure 1. ANFIS Architecture

2.1 Feature Extraction

The obtained data is extracted in five features: peak value, crest factor, RMS, Range, and standard deviation.

The details of these features are given below,

- **Root mean square (RMS) -**This function measures the total level of a discrete signal.

$$\text{RMS} = \sqrt{\frac{1}{\text{M}}\sum_{\text{m}=1}^{\text{M}} f_n^2}$$

- **Peak value ($\boldsymbol{\rho}$)**
  The peak value is the highest acceleration measured in its amplitude.

$$\text{P} = \frac{1}{2}[f_{nmax} - f_{nmin}]$$

- **Crest factor(ς)**
  The crest factor is the contrast between peak and RMS acceleration. This measurement can identify accelerant bursts even though the signal RMS remains unchanged.

$$\text{Crest Factor} = \frac{\text{P}}{\text{RMS}}$$

- **Standard deviation (σ)**
  The standard deviation is a quantity that expresses the distribution's variability or the divergence of signals from the mean.

$$\sigma = \left(\frac{1}{\text{N}-1}\sum_{\text{m}=1}^{\text{M}}(f_n - f)^2\right)^2$$

- **Range (γ) -** The difference is between the high and low extremes.

3. EXPERIMENTATION

For the rotor-bearing setup, the dynamic response of the test setup is investigated by taking unbalanced mass and shaft speed into account. Figure 2 shows a schematic view of experimental. The setup consists of an unbalance disc supported by a shaft between two ball bearings driven at operating speed by a DC motor via a dimmer stat.

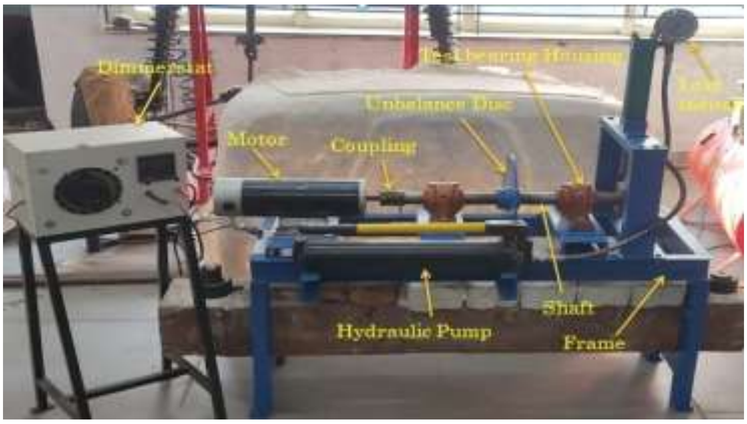

Figure 2. Experimental Setup

To measure vibration signals, Adash VAPro 4400 Fast Fourier transforms (FFT) with an accelerometer of the piezoelectric type was placed on the test bearing housing. The ball bearing specifications mentioned in Table 1 are used for experimentation. The deep groove ball bearing is mounted on the pedestal carrying a shaft. The mild steel shaft of 600 mm in length and 40 mm in diameter is used for experimentation. The unbalance disk is attached to the shaft, and variable unbalances are created throughout the experiment. The 1 HP DC motor is used to rotate the shaft with the help of a dimmer stat. Stat jaw coupling is used to attach the motor shaft and bearing shaft. The proximity sensor is used for the speed measurement of the shaft.

The different combination of bearing speed and unbalanced mass was simulated between 500 rpm to 1300 rpm. A total of 25 trials were conducted to acquire vibration signals and defect frequencies.

Table 1. Bearing Specifications
Bearing - SKF 6209-K
d- Bearing Inner Dia. - 45 mm
D- Bearing Outer Dia. - 85 mm
No. of Balls (N)- 9
Diameter of balls- 9 mm

4. Results And Discussion

4.1 Influence of Unbalance on Vibration Characteristics

The figure 3 to 6 shows frequency response spectra of vibratory setup under the influence of unbalance present in system. The unbalance of 25 gm to 125 gm is considered for experimentation.

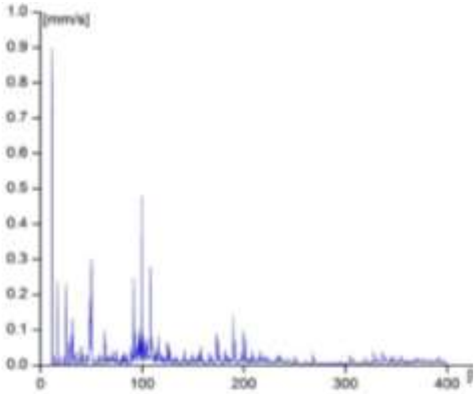

Figure 3. Vibration response at 700 rpm and 25 gm of unbalance mass

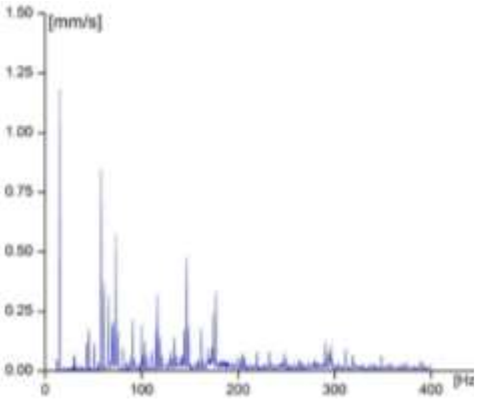

Figure 4. Vibration response at 900 rpm and 75 gm of unbalance mass

Figure 3 shows a vibratory response at 25 gm unbalance and 700 rpm speed of shaft. The vibration amplitude recorded at the first harmonics of the shaft frequency is 0.898 mm/s, which corresponds to the first harmonic of the shaft frequency. The defect frequency is closely matches with the experimentally obtained frequency. Figure 4 shows a vibration response for trial 75 gm of unbalanced mass and shaft rotational speed of 900 rpm. The peak amplitude of vibration is obtained at 1×fs is 1.18 mm/s. The significant peak is obtained at 15 Hz, matching the theoretical study.

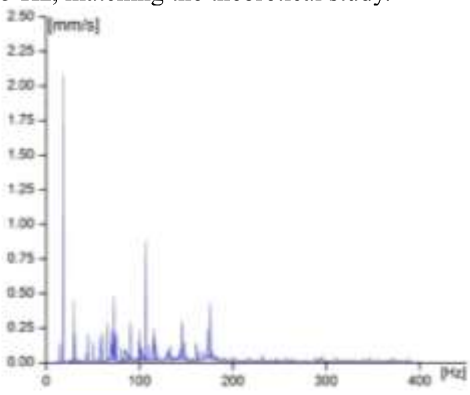

Figure 5. Vibration response at 1100 rpm and 100 gm of unbalance mass

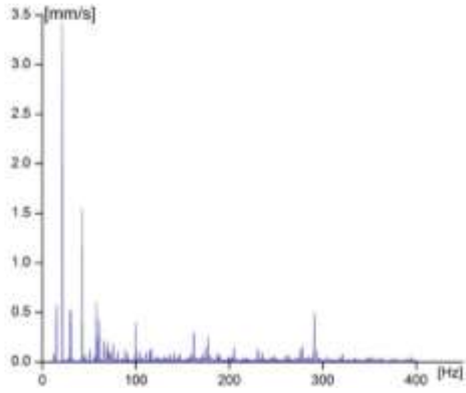

Figure 6. Vibration response at 1300 rpm and 125 gm of unbalance mass

This trial was conducted with a shaft unbalance of 100 gm and a 1100 rotor speed. The vibration plot for the above test is given in Figure 5. The dominant peak occurs around 18.3 Hz, close to the first harmonic of the shaft frequency. Other distinct low amplitude spikes are also observed at different frequencies.

The frequency response plot for unbalance mass of 125 gm and shaft speed of 1300 rpm is observed in Figure 6. The significant peak is observed at 21.5 Hz which is of amplitude of 3.4 mm/s.

Table 2. Vibration Response of all trials

Speed	**25 gm**	**50 gm**	**75 gm**	**100 gm**	**125 gm**
RPM	**Vibration Amplitude (mm/s)**				
500	0.566	0.598	0.784	0.854	0.902
700	0.898	0.927	0.997	1.09	1.29
900	0.945	1.02	1.18	1.49	1.58
1100	1.415	1.59	1.65	2.07	2.35
1300	1.894	2.354	2.89	3.17	3.4

Similarly all other trials are conducted for various speeds and unbalance mass and vibration amplitude is reported in Table 2.

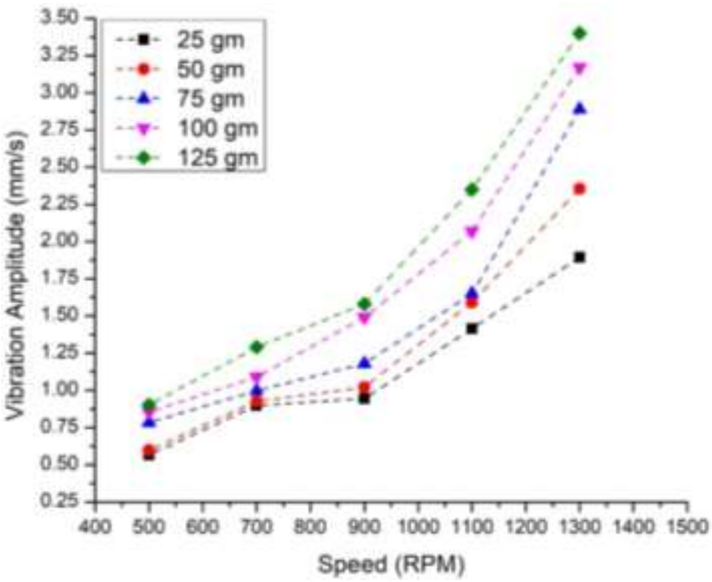

Figure 7 Influence of unbalance mass on vibration amplitude

Preliminary experimentation was performed successfully in the range of 25gm-125gm and the speed range of 500 rpm to 1300 rpm, as shown in Table 3. It is observed from the pilot experiments that amplitude of vibration increases as speed increases. Also, defect frequency corresponds to the shaft's rotating speed fs, which conforms to the theoretical results.

4.2 Fault Classification

A five bearing faults classes are considered for ANFIS, viz. unbalance, outer race fault, misalignment, inner race fault, and clearance. Overall, 60 fault cases are trained and tested in ANFIS. 80% of data is used for training, and 20% is utilized for testing. The details of ANFIS parameters are provided in table 3.

Table 3. ANFIS Parameter

No of Membership functions	5
Optimization method	Linear
Type of membership functions	Trimf

Table 4 compares the performance of the ANFIS using statistical measures such as root mean square error (RMSE) and correlation coefficient (R). These characteristics are typically expressed in terms of predicting error, which is defined as the difference between the observed and predicted values.

Table 4. ANFIS Results

Accuracy	91.67
R	0.9775
RMSE	0.4978

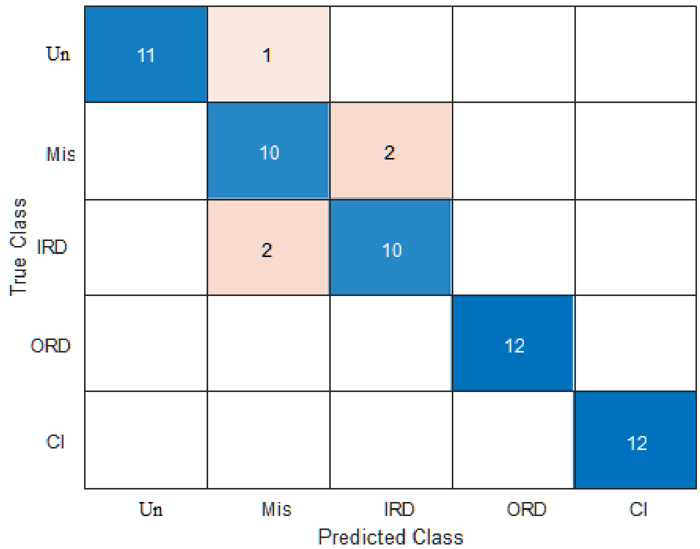

Figure 8. Confusion Matrix

The correlation coefficient (R) of 0.9775 and root mean square error (RMSE) of 0.4978 is acquired using data classification. Figure 7 shows a confusion matrix that offers an actual class vs. a predicted class. The 60 fault cases are considered, 55 fault cases are predicted correctly, and five are wrongly classified. ANFIS gives a 91.66 % of fault classification accuracy.

5. CONCLUSION

The current study proposes a duo study of unbalance response of the vibratory system and fault classification using the Adaptive Neuro-Fuzzy Interface System (ANFIS) for the rotating system.

The results obtained are summarized as follows,

1. It is observed that as unbalanced mass with shaft speed increases, the amplitude of vibration increases.
2. Experimental defect frequencies closely match the theoretical defect frequencies that validate the experimental investigation.
3. The linear nature of vibration is observed as an increase in unbalanced mass, which changes the system's dynamics.
4. Adaptive Neuro-Fuzzy Interface System (ANFIS) classified 55 fault cases out of 60 fault cases with a 91.66 % of classification accuracy over multiple fault cases.

The current work can be extended with the application of convolutional neural network (CNN), support vector machine (SVM), K- nearest neibour network (KNN).

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Biographies

Mr. Prasad Vishwasrao Shinde received the bachelor's degree in mechanical engineering from D. Y. Patil College of Engineering, Kolhapur in 2013, the master's degree in mechanical engineering from Shivaji University, Kolhapur in 2016, and pursuing the philosophy of doctorate degree in mechanical engineering from Shivaji University, Kolhapur, respectively. He is currently working as a Research Scholar at the Department of Mechanical Engineering, Rajarambapu Institute of Technology, Islampur. His research areas include bearing vibration, machine learning, and acoustic analysis.

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Dr. R. G. Desavale received the bachelor's degree in Automobile engineering from Rajarambapu Institute of Technology, Islampur in 2005, the master's degree in mechanical engineering from Shivaji University, Kolhapur in 2008, and the philosophy of doctorate degree in mechanical engineering from National Institute of Technology, Warangal respectively. He is currently working as an associate professor at the Department of Mechanical Engineering, Rajarambapu Institute of Technology, Islampur. His research areas include bearing vibration, FEA, and signal analysis.