JJMIE

Volume 9 Number 2, April.2015
ISSN 1995-6665
Pages 113 - 120

Jordan Journal of Mechanical and Industrial Engineering

# Estimation of Defect Severity in Rolling Element Bearings using Vibration Signals with Artificial Neural Network

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Received 4 April 2014 Accepted 2 April 2015

**Abstract**

In condition monitoring of rotating machinery, vibration analysis is a popularly used diagnostic tool for checking the health of rolling element bearings. The vibration signal caused by bearing defects will always be contaminated and distorted by other faults and mechanical noise particularly in hostile environment. Vibration based methods are effective when the defect in the bearings has already become severe. A bearing test rig was designed and setup in a workshop to study the vibration analysis of various faults in rolling element bearings. In the literature, it was observed that researchers studied different types of seeded defects, but these defects are random in size and shape; hence the correlation between defect size and its vibration parameter is not established. In this investigation, test runs conducted with seeded defects of same type with a gradual increase of its size on outer race of radially loaded cylindrical roller bearings at different speeds and loads. Vibration data were acquired by accelerometer and processed through Fast Fouier Transform (FFT). From the data, it was found that the vibration root mean square (rms) velocity increases significantly with the increase of defect size and speed, but not with the load. Artificial Neural Networks (ANN) multilayer perception model with back-propagation algorithm was used, with input parameters of Load, Revolutions Per Minute (RPM) and vibration rms velocity and output is seeded defect size. The ANN was trained with data sets of number of test runs conducted and predicted the defect size. The predicted values were compared with the actual seeded defect size and found the error was approximately 3.90%. In this investigation, an attempt was made to predict the defect size of a specific bearing with respect to its vibration rms velocity for given conditions. This study may be useful for the monitoring of critical bearings in the industry.



**Keywords:** *Roller Bearings, Fault Detection, Defect Size , Vibrations and ANN.*

## 1. Introduction

Since structural failures in engineering field can lead to severe economic loss, structural health monitoring is essential particularly in aerospace, civil and other structures. Precise incipient structural damage identification and its location are of great interest to many researchers [1-5]. In rotating machinery, early fault detection of the rolling elements, i.e., bearing and gear faults has also been gaining importance in recent years because of its detrimental influence on the reliability of equipment. Different techniques have been developed for monitoring and diagnosis of rolling element bearings [6]. Most of the developed methods are based on vibration signals and its analysis. Vibration based methods are effective when the defect in the bearings becomes severe. Detection of the fault and its severity are two important steps or features of a condition monitoring system. The lifetime of a machine component is determined by the severity of the fault. It is crucial, especially in critical systems, where continual operation is generally indispensable. The bearing defects three types, distributed, localized and the combination of both. The distributed defects can be the surface roughness, waviness, misaligned races, and off-size rolling elements. Localized defects are developed in the raceways, rollers and cage of a bearing. The periodic impacts occur at ball-passing frequency (characteristic defect frequencies), which can be calculated from the bearing geometry and the rotational speed [7]. In vibration analysis of bearings, these defect frequencies are not observable in some cases with the help of the Fast Fourier Transform (FFT) frequency spectra, because the impulses generated by the defects are masked by mechanical noise and distorted by other faults. The vibration signal is not sensitive to the incipient defect. To overcome this problem, signal processing techniques are implemented by many researchers to detect incipient bearing local faults [8]. In this investigation, experiments are planned in a systematic way with different speed, load

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and gradual increase of defect size. The vibration signal is captured by accelerometer and processed with CSI vibration analysis software. A multi-layer perception neural network is selected and trained with the experimental data and tested to predict the approximate defect size of a damaged bearing.

## 2. Artificial Neural Networks (ANN)

Artificial Neural Networks (ANN) have been developed as generalizations of mathematical models of biological nervous systems. ANN is also kown as parallel distributed processing system. The network is referred to as a directed graph having a set of neurons (nodes) and set of connections (weights) between nodes. Each node contributes some kind of function like simple computation and each connection transfers information or signal between nodes. Each connection between two nodes is labeled with a number called the connection strength or weight. The weight represents the extent the signal is to be amplified or diminished by the connection [9].

The network with a single node or fewer nodes cannot solve all the problems, and the networks, which are constructed with large number of nodes, are used to solve complex problems. Some of the networks are fully connected networks, layered networks, feed forward networks. Different types of learning methods are used in ANN such as supervised learning, unsupervised learning and reinforcement learning [10]. The behavior of the network changes according to the changes in the weights of connections in the network. The changes in the weights of ANN are referred to as learning which effects the synaptic efficiencies in real ANN. Neural networks are well established and prominent in literature [11]. A neural network with back propagation supervised learning process is important and used in various applications like classification, prediction or forecasting and approximation.

Jigar patel *et al.* studied the damage identification of rolling bearings based on improved time and frequency domain features using neural networks and they successfully diagnosed up to 98% of fault cases [12]. Mahmuod Akbari *et al.* used discrete wavelets transforms along with ANN in fault diagnosis of gears and bearings in a gear box and achieved high success rate [13]. Bahaa Ibraheem implemented neural network model to optimize the turning process parameters for controlling the vibration levels in turning [14]. M. Samhouri *et al.* applied an Adaptive Neuro-Fuzzy Inference System (ANFIS) and neural networks system in machine condition monitoring and proved neural networks achieved 99% fault prediction accuracy [15].

## 3. Bearing Kinematics

When the ball or roller comes across the fault while bearing is running, the rotation of roller momentarily stops due to the impact of hitting the edge of the fault. The reaction of the force from the fault edge opposes the rotation of the roller. When a rolling element encounters a fault, a rapid localized change in the elastic deformation of the elements takes place, and a transit force imbalance occurs. A faulty rolling bearing produces certain defect frequencies depending on the rolling element bearing geometry. When the outer race is stationary, the mathematical expressions to evaluate the defect frequencies can be written as follows:

Fundamental Train Frequency,

$$FTF = \frac{1}{2}(f_i)\left[1 - \frac{d\cos\theta}{D_p}\right]$$

Ball Pass Frequency of the Outer race,

$$BPFO = \frac{N}{2}(f_i)\left[1 - \frac{d\cos\theta}{D_p}\right]$$

Ball Pass Frequency of the Inner race,

$$BPFI = \frac{N}{2}(f_i)\left[1 + \frac{d\cos\theta}{D_p}\right]$$

Ball Spin Frequency,

$$BSF = \frac{D_p}{2d}(f_i)\left[1 - \left(\frac{d\cos\theta}{D_p}\right)^2\right]$$

where $D_p$ - Pitch circle diameter, $\theta$ - contact angle, $f_i$ - Rotation frequency of inner race,

$N$ - Number of rolling elements and $d$ - diameter of rolling element.

In machinery which is running with normal speeds, these defect frequencies lie in a low frequency range up to 1000Hz. These calculated frequencies may be slightly varied from the actual values in practice due to slipping or skidding in rolling element bearings [16]. Some researchers [17] mentioned that it is difficult to obtain a significant peak at these defect frequencies in the vibration frequency spectra from a defective bearing. This is due to the noise and vibrations from other sources which mask the vibration signal from the defective bearing unless the defect is sufficiently large.

## 4. Experimental Test Set Up

Figure 1 is the schematic diagram, representing the bearing test facility and is designed to fulfill the requirements of current investigation and future research in this area. The testing involves the mounting and running of the test bearings with various sizes of seeded defects, under specific parameters of speed and load, vibration signal data acquisition through accelerometer.

The test rig (Figures 2 & 3) consists of six major parts, i.e. shaft, support bearings with plumber blocks, bearing block with test bearing, 2.2 KW-3 phase induction motor, 4 KW variable frequency drive for speed control, and a vertical hydraulic ram for applying load radially. The test set up operational speed range is up to 2800 rpm with a maximum load 16 kN via a hydraulic ram. The shaft is made up of En 18 steel; the V-pulley at one end and the test bearing at the other, and in between two support bearings with plumber blocks assembled on the shaft. Deep groove ball bearings (SKF 6212 RS2) are used as support bearings. The motor connected the shaft via a V-belt. The motor is mounted on a separate base frame to avoid transfer of vibrations of motor to test rig. The test bearing block is a square split housing and made up of with EN 24 steel. On the top of housing vibration accelerometer and hydraulic ram placed while conducting test run.

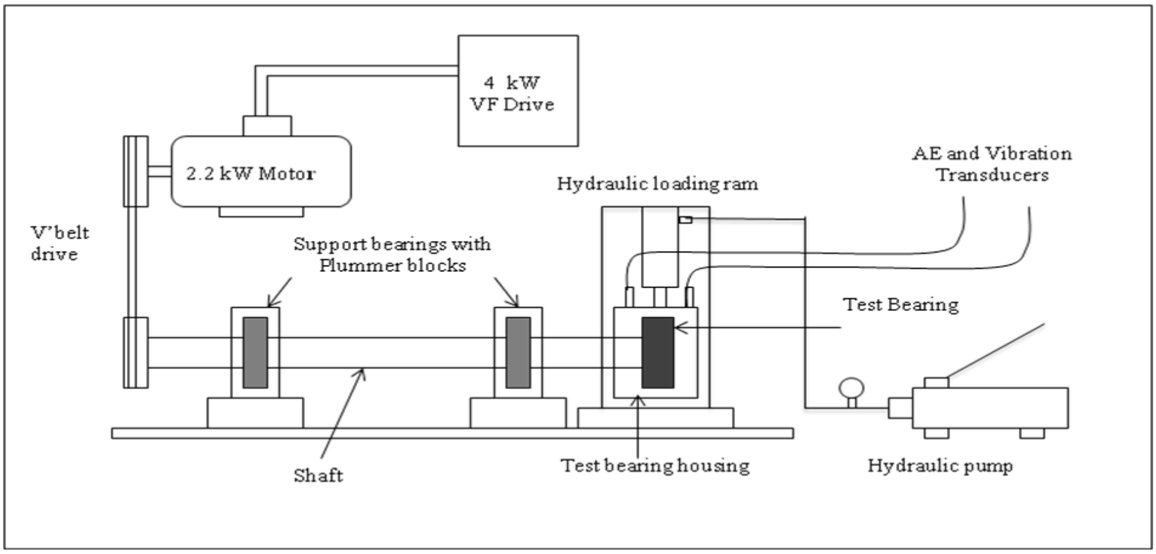


**Figure 1**. Experimental test setup schematic

**Figure 2.** Bearing Test Rig

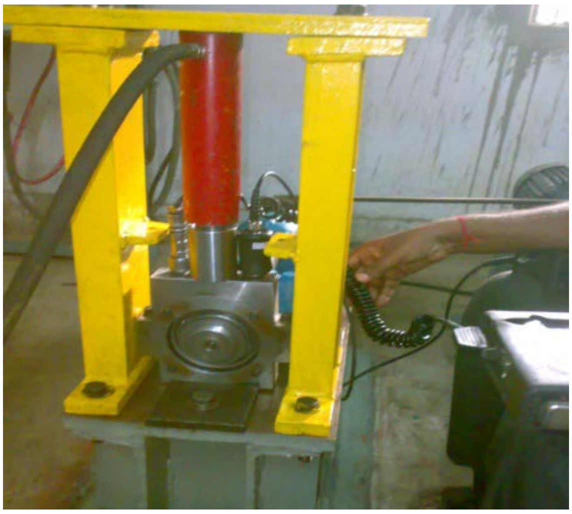

**Figure 3.** Test bearing with Probes

## 5. Test Bearing Specification

In this investigation, N312 type cylindrical roller bearing with normal clearance is considered (Figure 4). The reason behind selecting this bearing is that the defects can be created in the outer race easily as it allows easy dismantling and assembly of the outer race. The geometric details of the test bearing are as follows: Inner diameter-60mm, Outer diameter- 130mm, Width- 33mm, Number of rollers- 12, Rolling element diameter- 18mm, Pitch circle diameter ($D_p$ )- 96mm, Contact angle ($\theta$)- $0^{\circ}$.

**Figure 4.** N312 cylindrical roller bearing

The bearing characteristic defect frequencies are calculated from the dimensional parameters of N312 cylindrical roller bearing and shown in Table 1.

**Table 1.** Theoretical Characteristic Defect frequencies in CPM (cycles per minute) at different RPM

| | RPM → | 900 | 1100 | 1300 | 1500 |
|---|---|---|---|---|---|
| Defect frequency in CPM | FTF | 365.4 | 447.0 | 528.0 | 603.6 |
| | BSF | 2315.4 | 2829.6 | 3345.6 | 3859.2 |
| | BPFI | 6412.8 | 7836.0 | 9264.0 | 10687.8 |
| | BPFO | 4387.8 | 5361.6 | 6338.4 | 7312.8 |

## 6. Experimental Procedure

A total of five test bearings was used in this investigation. In previous studies, artificial damages were induced in bearings via several ways: scratching/engraving the surface with diamond scriber, introducing debris into the lubricant and electrical spark erosion, etc. In this investigation, defects introduced by wire cut EDM (Electro Discharge Machining) for a better accuracy. The defects were seeded in various sizes of width 0.3, 0.5, 0.7 and 0.9 mm. Depth of defect 0.3mm is maintained in all test bearings. Figure 5 shows 0.5mm width defect on bearing outer race.

**Figure 5.** Outer race seeded defect (0.5mm width)

Numbers of test runs were conducted on test rig for the consistency check of the data captured. On the first instance, a good test bearing without defect assembled to conduct a test run and was left for several hours for stabilizing and for minor adjustments of the test rig. After that, a test bearing with 0.3 mm size defect was seeded on outer race bearing assembled and the defect place(d at the top in the test bearing housing where the load was applied radially through hydraulic ram. The CSI 2120 model vibration analyzer was used for data acquisition. The same procedure was used in test runs on other bearings with different defect sizes on outer races. All the test runs were conducted at two loads in 2kN and 4kN at different speeds varying from 900 to 1500 RPM in four steps. All the speeds were adjusted with the Variable Frequency (VF) drive. The vibration signal is processed through FFT with the CSI vibration analyzer software. Time waves and frequency spectra for all the test runs were analyzed in detail for a comparative study.

A total of 32 different experiments was planned, as per the matrix (4 speeds, 4 defect sizes and 2 load conditions). It was planned to conduct many test runs for each experiment for the consistency of the measurement.

## 7. Results and Discussion

Out of the 32 experiments, in some experiments the consistency of data measurement was observed within two test runs; but for some other experiments three to four test runs were conducted. A total of 71 test runs were conducted.

In Table 2, the vibration rms velocity values were furnished for all the 32 experiments with the same parameters at different defect sizes. In this investigation, the seeded defect sizes were provided in a gradual increasing manner to observe the variation in vibration rms velocity with respective to defect size. The vibration rms velocity increases significantly with the increase of the defect size and speed, but not in the case of load.

**Table 2.** Vibration rms velocity in (mm/sec) at various defect sizes, RPM and Load

| | 2kN load | | | | 4kN load | | | |
|---|---|---|---|---|---|---|---|---|
| RPM | Defect size (width) in mm | | | | Defect size (width) in mm | | | |
| | 0.30 | 0.5 | 0.7 | 0.9 | 0.30 | 0.5 | 0.7 | 0.9 |
| 900 | 1.08 | 1.20 | 1.64 | 1.60 | 1.18 | 1.28 | 1.49 | 1.70 |
| 1100 | 1.38 | 1.53 | 2.01 | 2.27 | 1.38 | 1.72 | 1.78 | 2.13 |
| 1300 | 1.57 | 1.66 | 2.27 | 2.45 | 1.84 | 2.11 | 2.40 | 2.66 |
| 1500 | 2.01 | 2.01 | 2.90 | 2.97 | 2.09 | 2.43 | 2.70 | 3.02 |

Figure 6 shows the vibration time wave and the frequency spectrum of the test run conducted with the outer race defective bearing. A peak observed at 7312.8 CPM, ball pass outer race frequency (BPFO); some other significant peaks were also observed, but they were not related to the bearing characteristic defect frequencies.

Figure 7 shows comparative frequency spectrums of 0.5, 0.7 & 0.9 mm defects, 4kN load, and the test runs conducted at 1500RPM. It was observed that, as the defect size increased and other running conditions were the same, the peak at BPFO had an increasing trend.

Figure 8 shows Vibration root mean square (Vib.rms) velocity versus RPM for different defect sizes at 4kN load. The graph shows that the Vib.rms velocity increases with the increase of defect size and RPM.

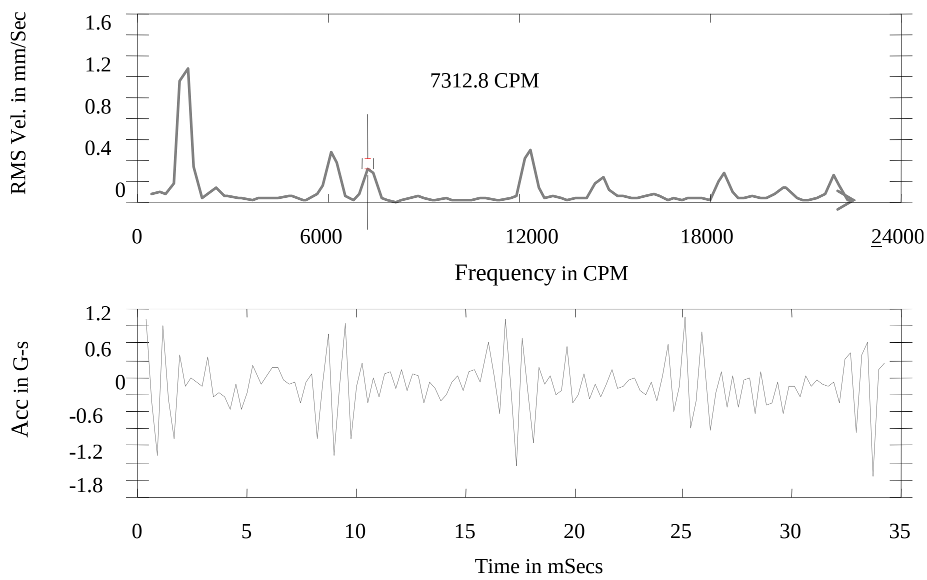


**Figure 6**. Time wave & Frequency spectrum with 0.7mm defect, 4kN load, 1500 RPM

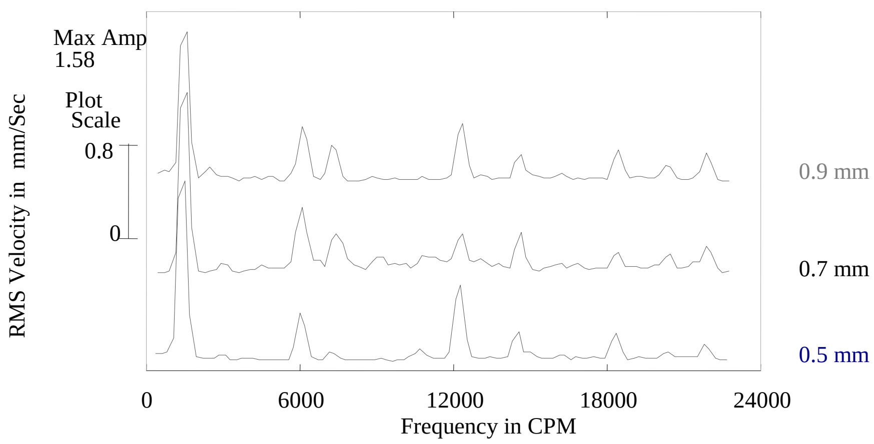


**Figure 7.** Frequency spectrums of 0.5, 0.7 & 0.9 mm defects, 4kN load, 1500 RPM

 

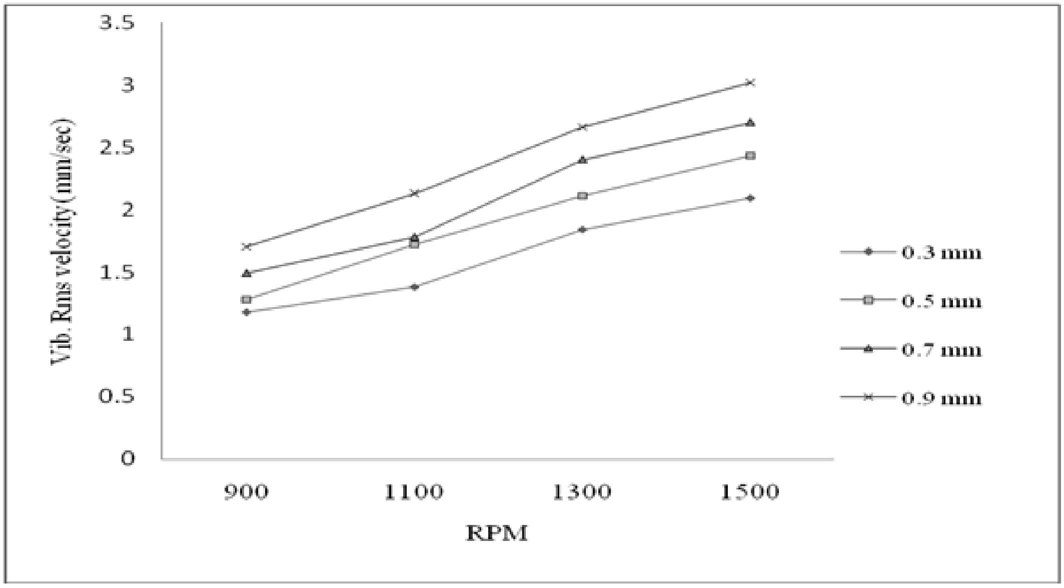


**Figure 8**. Vib.rms velocity (mm/sec) at different defect sizes and RPM at 4kN load

A feed-forward back propagation neural network is constructed with four layers including input, output and two hidden layers (Figure 9). The ANN with one hidden layer gave significantly high errors. Hence, a two-layer network was considered. The input neurons were load, RPM and Vibration rms velocity whereas the output neuron was defect size. Neurons, in the hidden layers, were determined by examining different neural networks. An easy Neural Networks (NN) plus software is used for training this network with back propagation algorithm (Figure 10). Weights of network connections were randomly selected by the software itself.

As per ref. [18], the advantage of the usage of neural networks for prediction is that they are able to learn from examples only, and that after their learning is accomplished, they can recognize hidden and strong non-linear dependencies, even when there is a significant noise in the training set. When input data are adjusted to designate shape, it is divided into three sets; a training set (learning), a validation set and a testing set. The default setting of the ratio, as per statistical program, is: 70% of the input data is a training set, 15% a validation set and 15% a testing set. To sum up, the training set is used for creating a model, the validation set for verifying the model, and the testing set for testing the usability of the model.

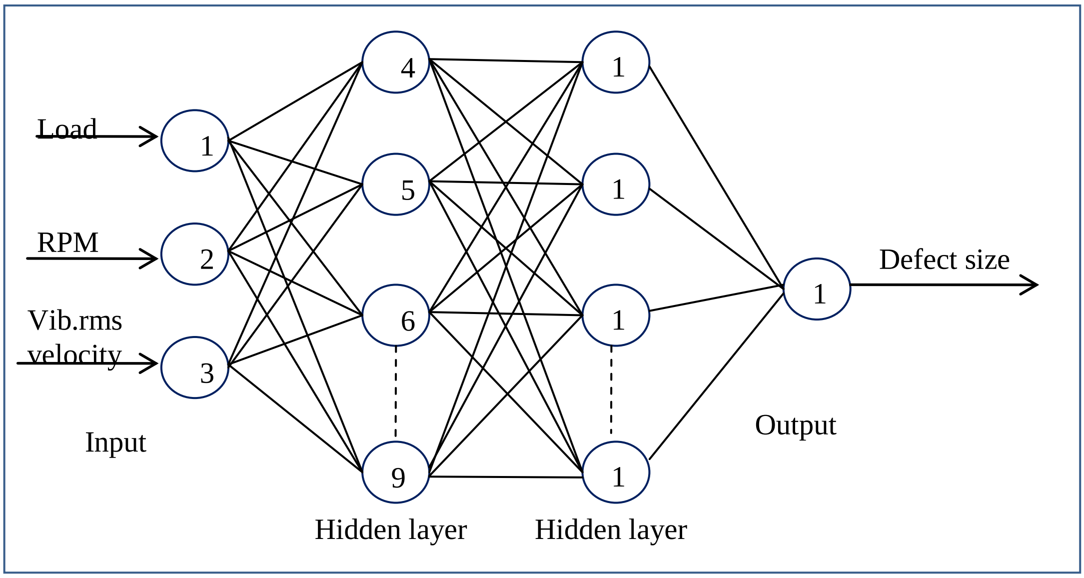


**Figure 9.** Neural network architecture

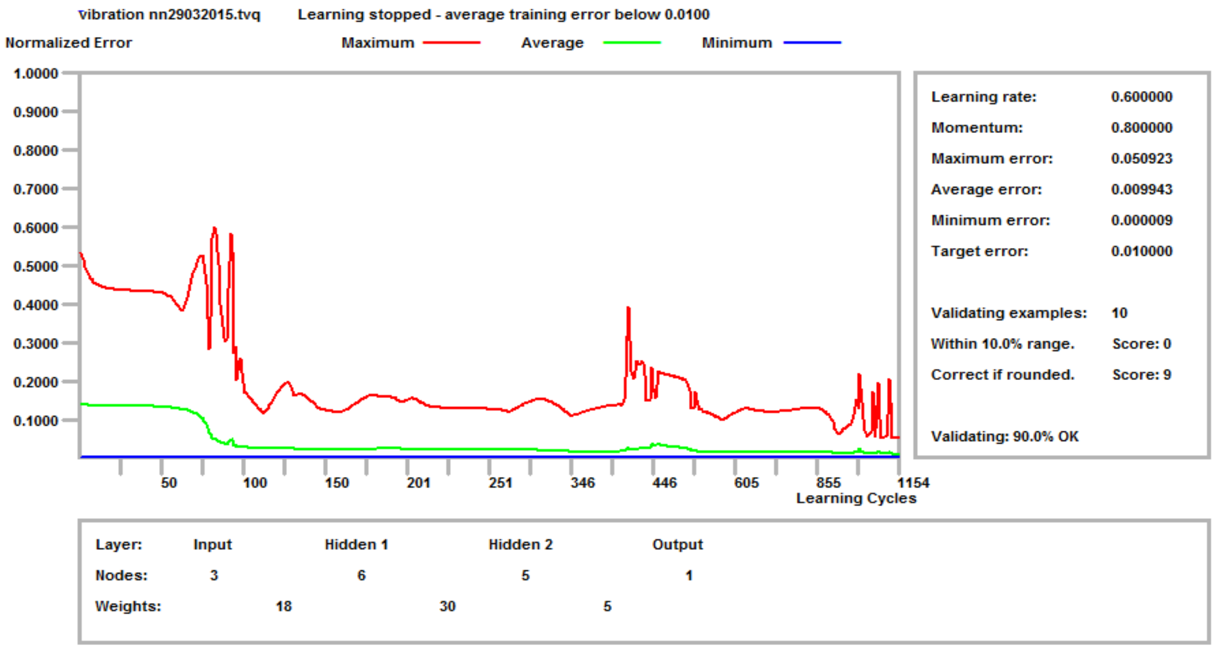


**Figure 10**. Learning progress graph with maximum, average and minimum training error.

Out of the 71 test runs data, the neural network was trained with 51 data sets, validated with 10 data sets and tested for 10 data sets, which were selected in a random manner. Predicted values of the defect size through testing are given in the Table 3. The percentage of the error between the actual defect size and the predicted values are calculated. The mean error percentage was found as 3.75% of defect size.

From the Table 3, it is found that the predicted values are very close to the experimental values. From these results, it can be deemed that the proposed network model is capable of predicting the defect size

The graph, shown in Figure 11, gives a comparison between the actual defect size and the predicted defect size for all the 71 sets of data. According to the values obtained, the overall calculated average error was 4.83%

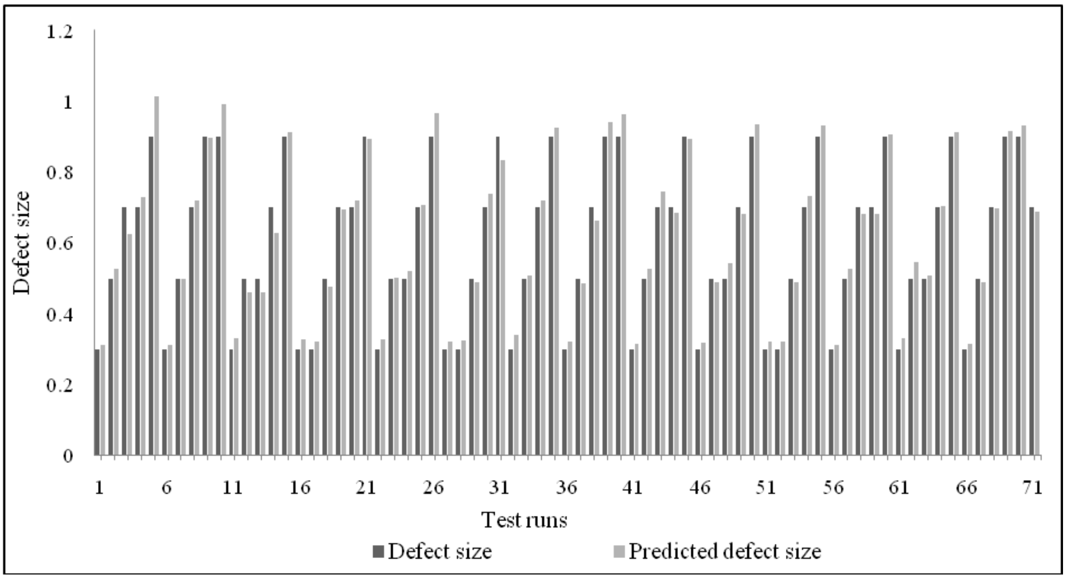


**Figure 11.** Comparision of actual verses predicted defect sizes for all test runs

.

 

**Table 3**. Experimental results and its predicted values of defect size in testing

| Exp. No | Load (kN) | RPM | Vib. rms velocity (mm/sec) | Defect size in (mm) | Predicted Defect size in (mm) | % error |
|---|---|---|---|---|---|---|
| 1 | 2 | 900 | 1.20 | 0.5 | 0.485 | 2.82 |
| 2 | 2 | 900 | 1.60 | 0.9 | 0.892 | 0.82 |
| 3 | 2 | 1100 | 1.78 | 0.7 | 0.708 | 1.15 |
| 4 | 2 | 1300 | 1.57 | 0.3 | 0.317 | 5.70 |
| 5 | 2 | 1500 | 2.01 | 0.3 | 0.324 | 8.26 |
| 6 | 4 | 900 | 1.70 | 0.9 | 0.932 | 3.57 |
| 7 | 4 | 1100 | 1.72 | 0.5 | 0.526 | 5.26 |
| 8 | 4 | 1300 | 1.84 | 0.3 | 0.291 | 3.00 |
| 9 | 4 | 1300 | 2.40 | 0.7 | 0.734 | 4.98 |
| 10 | 4 | 1500 | 3.02 | 0.9 | 0.917 | 1.84 |
| Average error : 3.75 | | | | | | |

## 8. Conclusions

In the present work, 71 test runs are conducted for planned 32 experiments with four levels of speed, defect size and two levels of load. A feed-forward four layered back propagation neural network (3-6-5-1) was used to train the collected experimental data. The ANN was trained with 51 data sets, validated with 10 data sets and tested for 10 data sets taken from the total test runs. The trained ANN was used to predict the defect size. It is found that there is an agreement between the experimental data and the predicted values for the defect size is (3.75% of error). With this ANN model, it is possible to monitor the condition of the bearings of important equipment in the industry to predict the severity of defect size, which will help in proper maintenance action to avoid the sudden failure of the equipment.

Hence, from these experimental investigations, it is revealed that the vibration data along with ANN model give a better analysis to diagnose the defect size of a particular bearing.

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