International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249-8958 (Online), Volume-8 Issue-3, February 2019

Deep Groove Ball Bearing Fault Diagnosis and Classification Using Wavelet Analysis and Artificial Neural Network

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Abstract*: Now a days deep groove ball bearings are widely used to support the load of the shaft and to reduce friction in industrial machinery and domestic appliances. The major issue that arises in deep groove ball bearings is catastrophic failure which arises due to fatigue loading, electrical erosion, corrosion or spalls on various bearing components. Thus to ensure steadiness and continuous running of the machine, condition monitoring and defect detection of deep groove ball bearings are very essential. This research paper emphasizes on fault detection of deep groove ball bearings having specific defects present on various bearing elements using Debauchies Wavelet (DB-02) up to fourth level of decomposition. The vibration signals were recorded from a customized ball bearing test rig. The accelerometer and FFT analyzer is used to collect time and frequency domain vibration data and signature. Finally Artificial Neural Network (ANN) based Pattern recognition classifier is used for automatic bearing fault detection. The training of the network is done based on the collected data and the testing is done based on random data set. The highest classification rate was found to be 94%. This paper represents the implementation of Artificial Neural Network as a functional artificial intelligence tool for automatic bearing fault detection and classification without any human involvement.

Index Terms*: Artificial Neural Network, Condition Monitoring, Deep groove ball bearing, Defects, Debauchies Wavelet, Vibration Signature.

I. INTRODUCTION

Machine fault diagnosis is an important research area in today's process industry. The vital topics in the engineering arena are fault detection at early stage, diagnosis and fault classification. Early fault identification methods and appropriate condition monitoring techniques will result in reliability, safe operation and diminishing the cost involved in manufacturing. Deep groove ball bearings are mostly used in house hold and industrial applications to support the load and to reduce friction. Bearing failure is considered to be one of the vital reasons for machine breakdown. Vibration measurement, acoustic emission, motor current signature analysis, thermography analysis and wear debris analysis are used for fault detection and diagnosis of deep groove ball earings. Vibration analysis is widely used for bearing fault detection as it gives sufficient information about the abnormality of the bearing. Vibration due to fault in the bearing can be detected by using accelerometer. Frequency and amplitude are the two base parameters which are the outcome of vibration analysis technique. Time domain analysis, Frequency domain analysis and time-frequency domain analysis are three important aspects of vibration signature analysis and feature extraction. The non-stationary noisy vibration signals from rolling element bearing, makes it very much difficult to detect the fault by frequency domain and time domain analysis. In this modern era wavelet transform analysis has wide application for rolling element bearing been fault identification and diagnosis. Fault detection in a deep groove ball bearing is a type of classification issue. To classify normal and faulty bearing, artificial intelligence based classifiers can be used. The two basic steps in fault classification are feature extraction from the generated raw vibration signal and use of artificial intelligence technique like artificial neural network (ANN) and Support Vector Machine (SVM) etc. for fault identification and classification. Ali et al. [1] have proposed Empirical Mode Decomposition (EMD) energy entropy assisted feature extraction method. They have used this method to overcome the non-liner and non-stationary characteristics of rolling element bearing vibration signature. The rolling element bearing degradations are successfully identified with multiple types of defects and severities by using a developed Health Index (HI) parameter. Kankar et al. [2] have implemented wavelet-based feature extraction method for fault detection of various bearing components. They have used Minimum Shanon Entropy Criterion-a wavelet based methodology to calculate the statistical parameters required for training and testing of ANN. For fault classification, they have used three artificial intelligence techniques, i.e. learning vector quantization, support vector machine and self-organizing maps. The study shows that, rolling element bearing faults are successfully identified by support vector machine than self-organizing maps and learning vector quantization. Hemmati et al. [3] have used design of experiment method (DOE) to study the effect of operating speed, defect size and loading conditions on statistical parameters of Acoustic Emission (AE) signals. The investigation focuses on the selection of most sensitive parameter for diagnosis of fault on rolling element bearing.

Manuscript published on 28 February 2019.
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Kankar et al. [4] presents feature-recognition system by utilizing cyclic autocorrelation of raw vibration signals generated from rolling element bearing to diagnosis bearing faults. Several distinct modulating frequencies are indicated by the analysis of non-stationary signals. Finally, calculation of wavelet coefficients is done by six different base wavelets. Artificial Neural Network, Support vector machine and Self-organizing maps are used for classifying faults.

Narendiranath et al. [5] have used Daubechies Wavelet-02 (DB-02) for fault diagnosis of journal bearing. The fast Fourier transform was used to obtain frequency domain data and it indicates the frequency having highest amplitude. Finally Artificial Neural Network is used to classify faults.

Kumar et al. [6] have implemented Discrete Wavelet Transform (DWT) method for the analysis of vibration signal. Statistical parameters extracted from the wavelet are utilized as input to Artificial Neural Network classifier. The wavelet functions like Db4, Db8, Db44 and Sym10 were implemented to analyze the vibration signals. Finally the evaluation of the performance has been done by ANN.

Nistane and Harsha [7] have used Bearing Prognostic Simulator (BPS) to examine vibration signal of rolling element bearing throughout the life span. The bearing failure evaluation was done to study the bearing defects under radial load at constant speed.

Mishra et al. [8] have proposed sigmoid function based thresholding and envelop analysis of vibration signal generated from low speed defective ball bearing to extract the statistical parameters. Here, Bayesian estimator is used to obtain an approximation of the features in the vibration signature.

Wang et al. [9] have proposed Dual-tree complex wavelet transform (DTCWT) to extract the statistical features in some special type of machine faults. It is found that DTCWT is superior than Empirical mode decomposition (EMD) and Second-generation wavelet transform (SGWT).

Nizwan et al. [10] have implemented Discrete Wavelet Transform (DWT) to study the vibration signature of ball bearing. Here, DWT was implemented to decompose the vibration signal at different levels of frequency. Then, for every decomposition level, Root Mean Square (RMS) value was calculated to detect the defect in the vibration signature of ball bearing. Here it is found that, after few level of decomposition the faulty bearings show significant deviation in retaining RMS value.

In this research, the Wavelet Transform (WT) method is implemented to overcome non-stationary vibration signals generated from deep groove ball bearing. Here the bearing analysis is done under different conditions as new bearing, ball fault, inner race and outer race fault. Daubechies Wavelet Transform (DWT) method is used to decompose the vibration signals from the deep groove ball bearings into different levels. Here Artificial Neural Network (ANN) based pattern recognition classifier was used for automatic bearing condition classification. MATLAB Neural Network Toolbox was used to create, train and test Artificial Neural Network. The results demonstrate that, by implementing a suitable Wavelet Transform method and ANN classifier, the deep groove ball bearing faults can be detected and classified at an early stage of propagation.

II. EXPERIMENTAL SETUP AND EXPERIMENTAL PROCEDURE

In the present research, the experimental setup is meant for investigation of bearing failure and vibration characteristics. By using the setup the vibration response of healthy bearing and faulty bearings are obtained. This experimental setup consists of a 3-phase induction motor with speed controller, variable frequency drive, shaft, coupling, two set of Plummer block with deep groove ball bearing, two set of pulleys, two belts, two set of self-aligned bearing with Plummer block and flywheel. The driving motor is connected with the main shaft supported by means of two sets of deep groove ball bearings. This test rig is meant for running the shaft at multiple speeds and frequencies. The bearing adjacent to coupling is taken as test bearing and the other bearings are acting as dummy. By using an accelerometer the vibration data are collected from the test bearing. The accelerometer is attached to FFT analyzer and successively to a computer system having NV-Gate software. Here NV-Gate software is used as an interface to process the vibration signal. After normal operation of the bearing for some time period, the vibration signals from FFT analyzer through accelerometer is fed to the Data Acquisition system. Normal bearing shows low amplitude peaks and high amplitude peaks are shown by faulty deep groove ball bearings.

The speed of the motor is kept constant at 1510rpm. All the bearings are properly lubricated. In the experimental process, the vibration signals are collected from fresh and the faulty bearings at the motor speed of 1510rpm. The vibration readings are recorded at the sampling frequency of 2000Hz, 1000Hz and 400Hz for the frequency domain analysis and for 60 second time period in time domain analysis. Signals and data that are collected from the magnetic base accelerometer in vertical direction are taken into consideration. Finally the signal processing was done by using MATLAB software and fault classification by ANN.

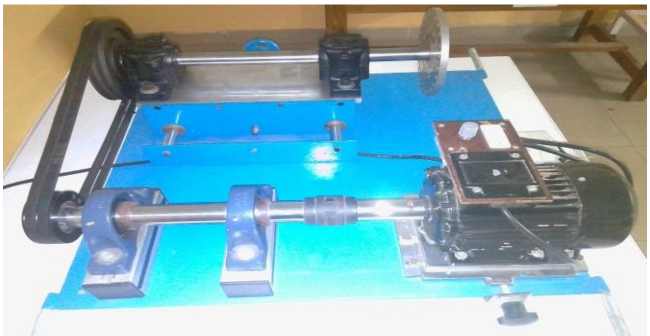

Fig. 1. Experimental setup

III. BEARING GEOMETRY AND KINEMATICS

The main purpose of the deep groove ball bearing is to support the shaft and to reduce friction. Basically ball bearings are having four different components, as, balls, cage, inner race and outer race. The main use of cage in the deep groove ball bearing is to separate different bearing elements at regular intervals and it also holds the balls at their proper position within the inner and outer race for smooth rotation.

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Fig. 2. Individual components of Deep groove ball bearing

Table 1. Specifications of the experimental bearing.

Sl. No.	Parameters	Value
1	Inner race thickness	11.8mm
2	Outer race thickness	28.2mm
3	Inner race diameter	40mm
4	Outer race diameter	80mm
5	Ball diameter (d)	12mm
6	Pitch diameter (D)	60mm
7	Number of balls (n)	09
8	Angle of contact (β)	0^0
9	Rotational speed (N)	1510rpm

Some basic assumptions are taken into consideration while deriving the bearing characteristic frequencies. They are as follows: constant angular rotation of inner and outer race, there is no slip among the bearing elements, the bearing elements are rigid in nature and throughout the working condition the pressure angle remains constant.

The characteristic frequencies of the test bearing are as follows:

- Ball Pass Frequency of Outer race (BPFO)

BPFO= $(n/2) \times (N/60)$ [1- (d/D) $Cos\beta$] = 90.6 Hz (1)

- Ball Pass Frequency of Inner race (BPFI)

BPFI= $(n/2) \times (N/60)$ [1+ (d/D) $Cos\beta$] =135.9 Hz (2)

- Ball Spin Frequency/ rolling element frequency (BSF)

BSF= $(D/d) \times (N/60)$ [1− $(d/D)^2$ $\mathrm{Cos}^2\beta$] =108.72 Hz (3)

- Fundamental train frequency (FTF)/ Cage frequency

FTF= $(1/2) \times (N/60)$ [1−$(d/D)Cos\ \beta$]=10.066Hz (4)

The above mentioned characteristic frequencies are basically needed to detect fault in ball bearings.

IV. MODES OF BEARING FAILURE AND FAULT GENERATION IN THE TEST BEARING

The faults in the ball bearing are caused by fatigue loading, wear, corrosion, electrical erosion, plastic deformation, fracture or presence of foreign particles in the lubricant. Basically these solid particles present in the contaminated lubricants cause damage to ball, inner race and outer race. There is a great change in the viscosity value of the contaminated lubricating oil. These foreign particles in the contaminated lubricating oil produce scratch mark of different size on the bearing surface and it is the prime reason for excessive vibration.

In the test bearing the artificial fault of dimensions 500 micron, 1000 micron and 1500 micron are cut circumferentially on the ball, inner race and outer race. These faults are generated by using Electro Discharge Machine (EDM) and the electrode required for the EDM to generate fault are cut by using Wire Electro Discharge Machine (Wire-EDM).

Fig. 3. Faulty bearing components (Ball, Inner race and Outer race)

These generated faults on the test bearing surface can lead to the modification and enhancement of frequency and amplitude of vibration. Thus, various types of single and combined faults created on the test bearing and the generated signals through FFT analyzer are documented and processed through MATLAB Signal processing tool to detect the severity of the fault.

V. WAVELET TRANSFORM

A wavelet series is a representation of a square-integrable (real- or complex- valued) function by a certain orthonormal series generated by a wavelet. Time-frequency representation of a signal is done by wavelet transform method. Wavelet transform is identical to the Fourier transform with different merit function. The difference in between Wavelet and Fourier transform is that: sine and cosine decomposition of the signal is done by Fourier transform, i.e. localized function in the Fourier space; in contrary the localized functions in both the real and Fourier space are used by wavelet transform. Generally the wavelet transform is represented as:

$$F(a,b) = \int_{-\infty}^{\infty} f(x)\psi^*_{(a,b)}(x)dx \qquad (5)$$

Where, * is the complex conjugate symbol

ψ is some function, that can be chosen arbitrarily by obeying certain rule.

The wavelet transform comprises of two types of functions, such as: Scaling function and Time translation function. Scaling function is having scaling index represented as "k" and Time translation function is having time index represented as "j". Daubechies transform is mostly used for denoising of signals. The process of denoising is performed in three steps. They are: Decomposition of signal, thresholding and finally signal reconstruction. Here we have used Daubechies wavelet (DB2) to decompose the noisy signal to fourth level. Also we have used soft thresholding method. This soft thresholding method makes those values to zero, which are less than the selected threshold value. Then the values which are greater than the threshold are automatically subtracted.

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If the coefficients of the wavelets are represented as "$T_{j,k}$" and the threshold as "t", then the thresholding value can be represented as,

$D(T_{j,k}) = 1$ for $T_{j,k} \geq t$, (6)

$D(T_{j,k}) = 0$ otherwise (7)

VI. RESULTS AND DISCUSSION

6.1 Fresh Bearing

Using accelerometer and FFT analyzer, time domain and frequency domain signals are obtained from the test bearing without any defect. These signals are further processes through Daubechies wavelet analysis technique (DB02) up to fourth level. The time domain graph indicates the time in second along abscissa and amplitude (acceleration) in m/s^2 along the vertical axis. Whereas the frequency domain graph represents the frequency in Hz along abscissa and amplitude (acceleration) in m/s^2 along the vertical axis.

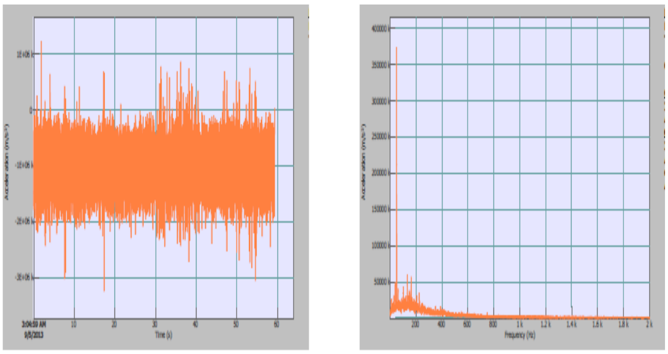

Fig. 4. Time domain and FFT signature of Fresh bearing

The above signal is decomposed by using Daubechies wavelet (DB02) up to fourth level. Then the decomposed signal was split into separate display mode to observe the defect features. The results are as follows:

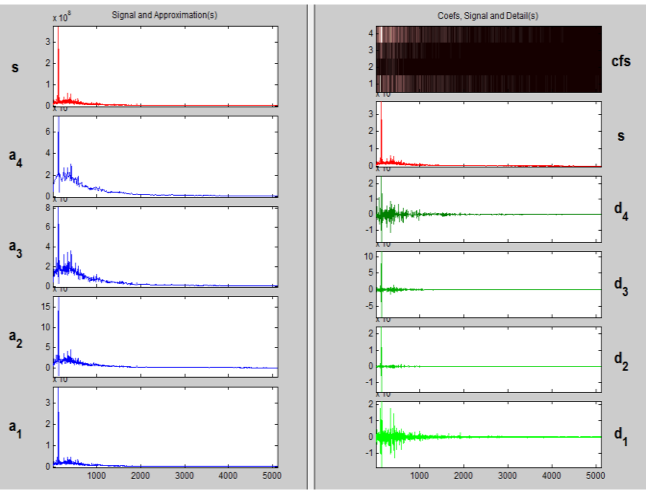

Fig. 5. Wavelet decomposition graph of fresh bearing

The above figure shows the graphical representation of Input data, signal and the corresponding approximations, detailed coefficients up to fourth level. Here "d" indicates 'detailed' and "a" indicates 'approximate' decomposition of the input signal. Here the estimation process shows regularity resulting the input data. The smoothness of the final estimation curve clearly epics that there is no fault present in the bearing. It acts as a vital tool for the fault identification of rolling element bearing.

6.2 Bearing with ball fault of 1000 micron

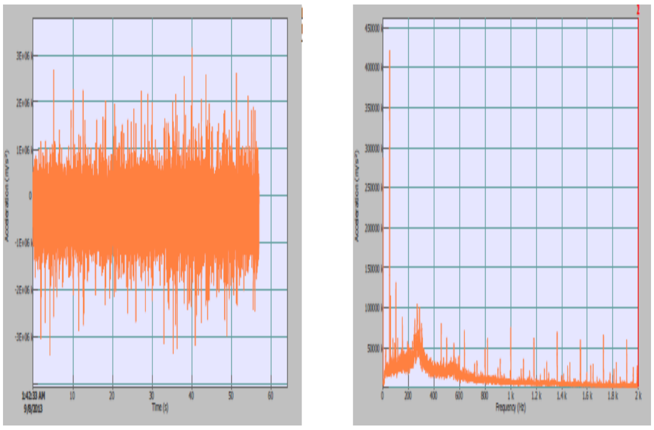

Fig. 6. Time domain and FFT signature of bearing with ball fault of 1000 micron

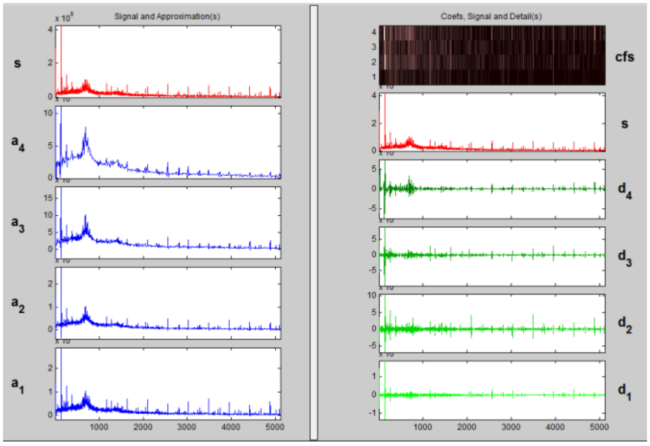

Fig. 7. Wavelet decomposition graph of bearing with ball fault of 1000 micron

Here the estimation process shows non-regularity resulting the input data. The harshness of the final estimation curve clearly epics the indication of fault in the bearing.

6.3 Bearing with inner race fault of 1000 micron

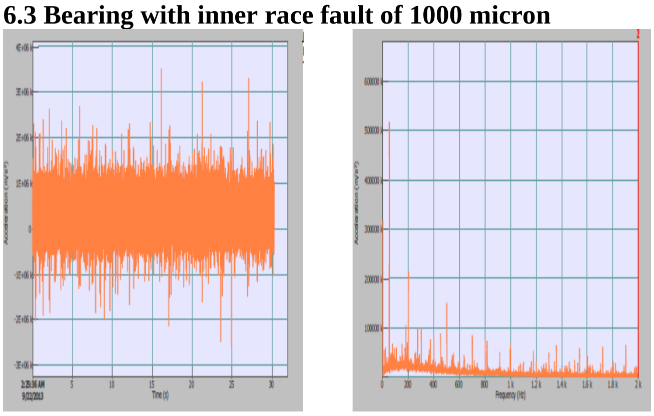

Fig. 8. Time domain and FFT signature of bearing with inner race fault of 1000 micron

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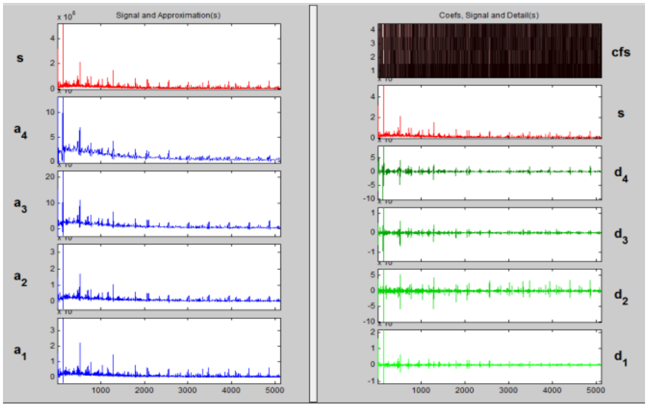

Fig. 9. Wavelet decomposition graph of bearing with inner race fault of 1000 micron

Here the estimation process shows non-regularity resulting the input data. The harshness of the final estimation curve clearly epics the indication of fault in the bearing.

6.4 Bearing with outer race fault of 1000 micron

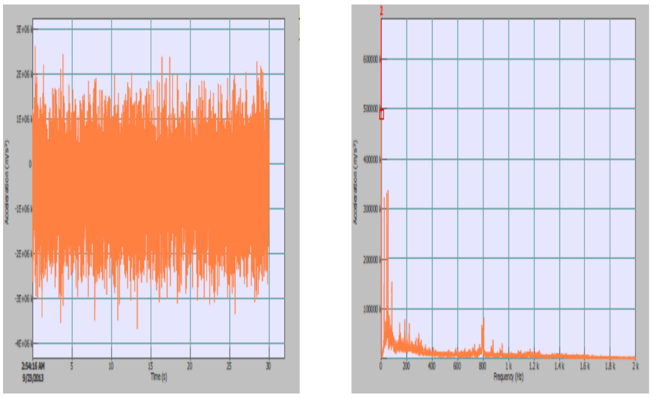

Fig. 10. Time domain and FFT signature of bearing with outer race fault of 1000 micron

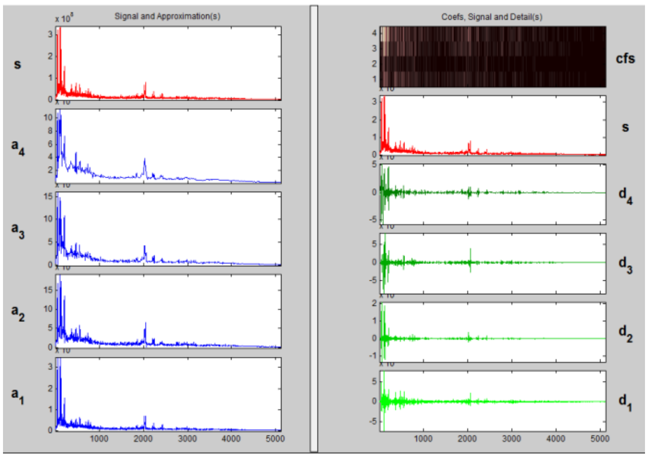

Fig. 11. Wavelet decomposition graph of bearing with outer race fault of 1000 micron

Here the estimation process shows non-regularity resulting the input data. The harshness of the final estimation curve clearly epics that there is fault present in the bearing. It acts as a vital tool for the fault identification of rolling element bearing.

VII. ARTIFICIAL NEURAL NETWORK

It is a subfield of artificial intelligence. ANN consists of several layers such as input, hidden and output layer. The various neurons are present in each layer. The neurons present in the input layer represent the raw data provided to the system. The input layer is attached to the hidden layer through some weights. Finally the hidden layer is attached to the output layer which receives the desired output, which can be represented as,

$$Y = f\left(\sum_{i=1}^{n} a_i w_i + b\right)$$
(8)

Where,

Y= Output of the neuron

b= Bias

a_i= Input of a neuron

w_i= Weight associated with the corresponding inputs.

Neural network can be used as a tool for prediction and classification of faults. Pattern recognition tool can be used as a classifier to classify the faults and recognize a followed pattern.

The inputs and outputs are imported in the MATLAB workspace and "nptool" is used and data are trained. Here, training algorithms used is scaled conjugate gradient (trainscg) back propagation. The performance function is mean square error (MSE). The connection weights are modified to train the network and to optimize the performance criterion the network is biased iteratively. The network is trained repetitively and the network which produces the lowest validation error during training was selected as the optimum network. A MSE of 10^{-3}, a minimum gradient of 10^{-10}, and maximum of 1000 numbers of epoch are used and if any one of these conditions is met then the training process would stop automatically.

Here, in the present research, classification based on binary scheme is implemented to represent the condition of the bearing in the pattern recognition classifier, as Fresh bearing (1 0 0), Inner race fault (0 1 0) and Outer race fault (0 0 1) to indicate the conditions of the bearing.

7.1 All confusion matrix and Performance graph for fresh and inner race fault of 1000 micron

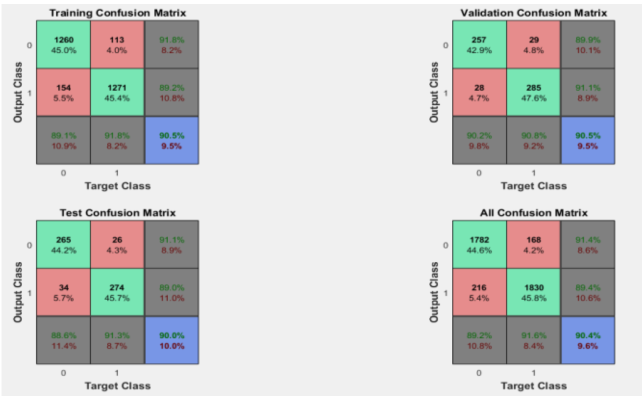

Fig. 12. All confusion matrix of fresh bearing and inner race fault of 1000 micron

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The above figure shows the confusion matrix for fresh and inner race fault of 1000 micron. The all confusion matrix shows that 90.4% of bearing faults were classified successfully. Hence we can say that, pattern recognition tool of ANN is having higher level of accuracy in the classification of bearing faults.

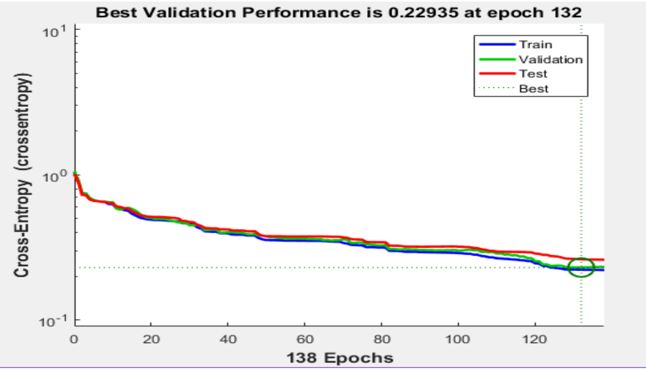

Fig. 13. Best validation performance graph for fresh bearing and inner race fault of 1000 micron

The above graph indicates that 132 epochs are required by ANN to achieve the required target. We know that a mean square error (MSE) of zero value indicates no error in the training process of artificial neural network. On the contrary, a higher error percentage is shown during the training process of the neural network, if the MSE is greater than 0.5. Hence for a better training result the mean square error should be within the acceptable range of 0.5. In the above graphical representation, MSE is 0.22935, which is within the acceptable range. It represents that, the artificial neural network implemented for the bearing fault diagnosis was correct and being used successfully for the allotted task.

7.2 All confusion matrix and Performance graph for fresh and outer race fault of 1000 micron

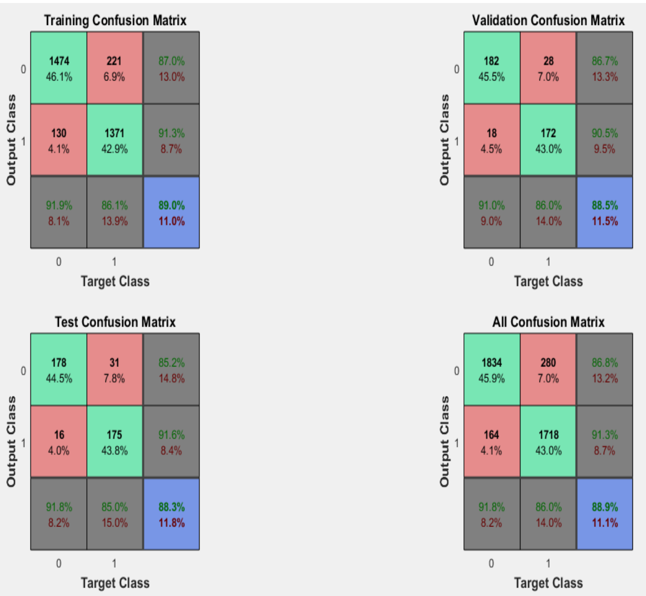

Fig. 14. All confusion matrix of fresh bearing and outer race fault of 1000 micron

The above figure shows the confusion matrix for fresh and outer race fault of 1000 micron. The all confusion matrix shows that 88.9% of bearing faults were classified successfully. Hence we can say that, pattern recognition tool of ANN is having higher level of accuracy in the classification of bearing faults.

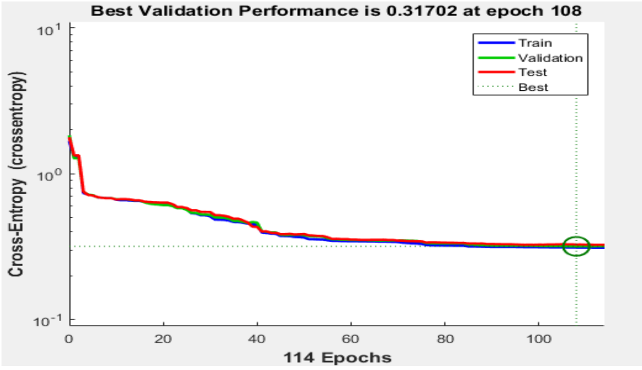

Fig. 15. Best validation performance graph for fresh bearing and outer race fault of 1000 micron

The above graph indicates that 108 epochs are required by ANN to achieve the required target. In the above graphical representation, MSE is 0.31702, which is within the acceptable range of 0.5.

7.3 All confusion matrix and Performance graph for fresh and ball fault of 1000 micron

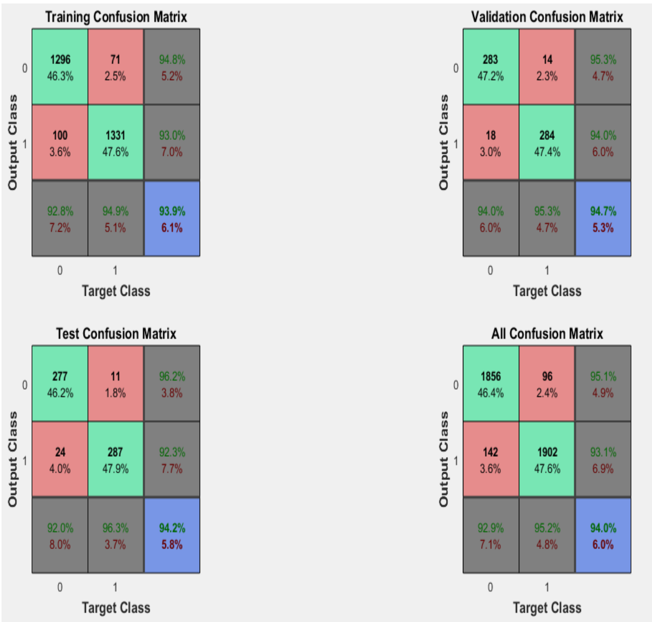

Fig. 16. All confusion matrix of fresh bearing and ball fault of 1000 micron

The above figure shows the confusion matrix for fresh and ball fault of 1000 micron. The all confusion matrix shows that 94% of bearing faults were classified successfully. Hence we can say that, pattern recognition tool of ANN is having higher level of accuracy in the classification of bearing faults.

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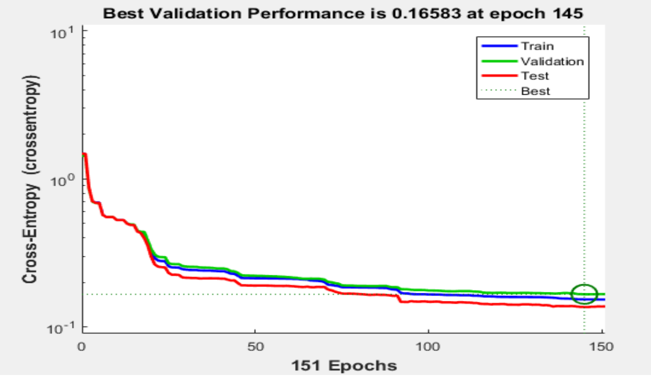

Fig. 17. Best validation performance graph for fresh bearing and ball fault of 1000 micron

The above graph indicates that 145 epochs are required by ANN to achieve the required target. In the above graphical representation, MSE is 0.16583, which is within the acceptable range of 0.5.

Consequently, the results clearly indicate that the proposed method is suitable for automatic online bearing fault detection and classification.

VIII. CONCLUSION

Aiming at the rolling element bearing vibration signature characteristics, the Daubechies wavelet (DB-02) is selected to obtain the fault features in this research paper. The Daubechies wavelet shown to be a vital tool in connection with FFT analyzer vibration data to indicate a comprehensive picture regarding the health of the deep groove ball bearing. Thus, this early detection of bearing fault indicates the effectiveness of the proposed condition monitoring technique. The artificial neural network was created, trained and tested using ANN tool box in MATLAB. Finally Artificial Neural Network (ANN) based Pattern recognition classifier is used for automatic bearing fault detection. The training of the network is done based on the collected data and the testing is done based on random data set. The highest classification rate was found to be 94%. Therefore, this paper emphasizes an application step of wavelet analysis technique and Artificial Neural Network based classifier for automatic bearing fault detection and classification for bearing prognostics.

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