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FAULT ANALYSIS IN SELF ALIGNING BALL BEARING BY WAVELET TRANSFORM BASED FEATURE EXTRACTION USING NEURAL NETWORKS

Kushal Goyal[*1] & Pratesh Jayaswal[2]

*[1&2]Mechanical Engineering Department, Madhav Institute of Technology and Science, Gwalior, Madhya Pradesh, India

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ABSTRACT

The objective of the present work is to classify different individual defects in case of self aligning ball bearing by using statistical tools coupled with a machine learning technique. The analysis of the generated results is then made and a better understanding of theoretical observations has been put in. To study fault in the bearing, vibration analysis procedure has been undertaken. In the present study, inner race and rough surface defects have been considered. The useful features of the vibration signal have been extracted by using Wavelet Transform which are then used as input to Neural Network algorithm for classification.

KEYWORDS: Artificial Neural Network, Fault identification and classification, Feature extraction, Self Aligning Ball Bearing, Wavelet Transform.

I. INTRODUCTION

In a production framework, a majority of item's cost represents upkeep and maintenance exercises which make the frameworks reliability a critical issue. Framework's unwavering quality relies on condition based maintenance and upkeep procedure. For an extensive number of creation frameworks, the upkeep systems like break-down and preventive maintenance does not hold as per the mark. Nowadays the predictive maintenance system has been emerged as a viable backbone of condition based maintenance. Predictive maintenance offers online as well as offline condition observing of the machine or part and guarantees the state of machine preceding any beginning disappointment or major breakdown, which causes the impromptu shutdown. It additionally gives adequate time to repair when contrasted to other maintenance techniques.

One of the most fundamental parts of any rotating machinery is rolling element bearing. Moving component bearing failures may influence the nature of product quality and make wastage from numerous points of view. Subsequently, the rolling element bearing failure brings about abatement in item quality and bringing down in consumer loyalty. It was reported that bearing fault detection has been one of the most classical problems in rotating machinery [1]. Not just bearing failures put machine on the danger of breakdown, but also the labor or manpower present in the immediate region of the machine is also put to risk. Apart from this, the fiscal and lag losses in the generation run likewise make a requirement for a framework that could affirm the smooth running of operations. Bearing failure is likewise important to recognize in time so that legitimate amendment steps and support procedures can be presented suitably. Bearings are designed to fulfill a certain life (which maybe in terms of operating time or number of revolutions made), under particular conditions and any deficiencies on that part are fundamentally a direct result of erroneous establishment and improper handling on the user end. There are also some localized defects that are created in the vicinity of setup that can induce some vibration when the rolling element passes over it [2]. There are number of ways in which a bearing can develop premature wear or failure. These include shaft misalignment, loosely connected couplings, improper lubrication, exposure to dirt etc [3].

It was also stated that among the techniques of fault identification, the most conspicuous are vibration measurement in time and frequency domain, acoustic emission and shock pulse method to measure the acoustic and vibration response from faulty bearings [1]. A frequency data is released by faulty bearings which contain a lot of information which can be used for early detection of faults. Resonance demodulation for fault diagnosis was pioneered by Burchill in the late 1970s. The defects in bearings are broadly classified on the basis of either fault location or the fault type. However, researchers mostly focus their attention to the location of fault. Defects can again be single-pointed or multi-pointed.

Until recently, Fast Fourier Transform (FFT) has been used extensively to study signals in time and frequency domain for vibration spectrum study in enveloped signal analysis [4], but in any case, it lingers behind necessities of fault determination progressively in light of the fact that it does not contain depiction of time varying patterns in the signal [5]. Wavelet Transform is advantageous comparatively on the grounds that it is competent to uncover features of information that other signal examination techniques fail to assess. It also has the capability to de-noise a signal without much attrition.

Proposition was also made that vibration in itself is not a problem but its excess is [6]. Every moving body undergoes and induces some amount of vibration and that can never be eliminated completely. But once its level goes beyond a particular acceptable value, it is an alert of developing fault and an early warning of system abnormality.

When signals are analyzed as functions of time, the procedure is called Time-domain analysis. [5] performed a comprehensive Time-domain analysis to monitor bearing health. A detailed account of the methods for time-domain analysis that includes waveform, indices (peak value, RMS level, crest factor etc.) and statistical tools (skewness, kurtosis and probability density moments) has also been discussed by [7].

In analyzing the signal in time-domain, the information regarding frequency is lost. Similarly, when analyzing the signal in frequency-domain, the information regarding frequency is lost. This resulted in a lot of difficulty as both facets are necessary for analysis. With advancement in soft computing technologies, Wavelet Transform was developed for extracting features from a given signal. This transform directly converts time domain signal into frequency without causing any attrition of information enabling the user to study both time and frequency domain simultaneously.

II. DETAILS OF EXPERIMENT

Materials and Method
The experiment was conducted on a machine fault simulator testing rig located in Madhav Institute of Technology and Science in Gwalior, India. It has been manufactured by SKF Pvt. Ltd. the setup is driven by 3-phase motor which transmits power to the driven shaft by means of a speed reducing pulley arrangement. Two bearing housings are present on the driven shaft. Out of these, one contains the healthy bearing and the other contains the bearing to be tested. The testing rig is shown in Figure 1. In this experiment, the bearing used is SKF 2207EKTN9. It is a self aligning type bearing consisting of balls as rolling elements. The faults have been generated by Electric Discharge Machining (EDM) to reduce secondary distortions and deformations. The location and dimensions of developed fault have been given in Table 1. The photographs of the fault generated components of the bearing are shown in Figure 2 and 3. The specifications of the rolling element bearing are given in Table 2.

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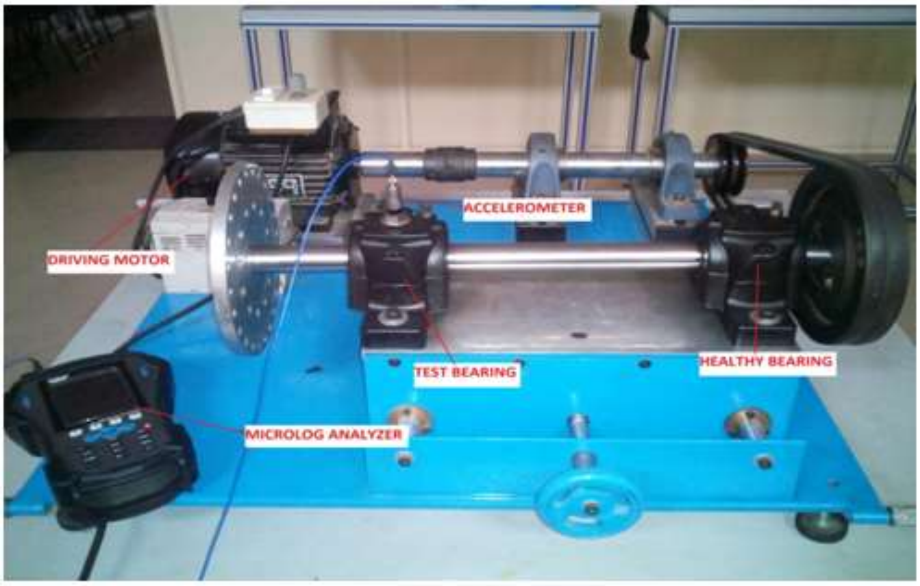

Figure 1. Fault Simulator testing rig

Figure 2. Inner race of bearing possessing inner race defect

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Figure 3. Rough surface of bearing possessing rough surface defect

Table 1. Position and dimensions of generated faults

S. No.	Type of defect/fault	Location and number of defects	Size of defect
1.	Inner race fault	3 indentations on ball path row	1mm x 0.1mm
2.	Rough surface fault	Local rough surface generated by abrasion	

Table 2. Specifications of the bearing used

Manufacturer	SKF
Bearing type	Self Aligning Ball Bearing
Number of rows	02
Balls in each row	12
Pitch diameter	53.594 mm
Ball diameter	11.5 mm
Contact angle	11.759°
Limiting speed	12000 rpm

Design of Experiment

In the experiment, the motor was made to run at 1910 rpm which gave the speed of 1500 rpm at the driven end where the bearing housings were located. The accelerometer was placed on the test bearing housing via magnetic adherence. The accelerometer is then connected to FFT (Fast Fourier Transform) Microlog analyzer CMXA 400 which records the vibration signal at a sampling rate of 6400 samples/second.

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Thirty three (33) readings were taken for the healthy bearing, inner race bearing and outer race bearing individually for the analysis. The data acquisition frequency was taken to be 30 minutes i.e the readings were taken in every 30 minutes. The vibration analysis spectrum selected was the time domain and vibration has been recorded in terms of acceleration because it was most suitable. Suitable here means that the setup was small, speed was less than 5000 rpm and the ground support was non-flexible.

Out of the 99 (i.e 33x3) readings, one acquired unprocessed signal of each bearing is shown in Figure 4, 5 and 6.

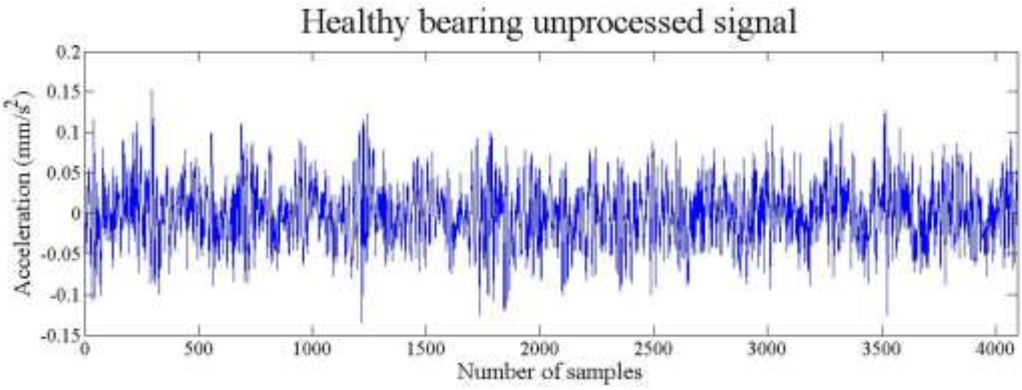

Figure 4. Unprocessed signal of healthy bearing

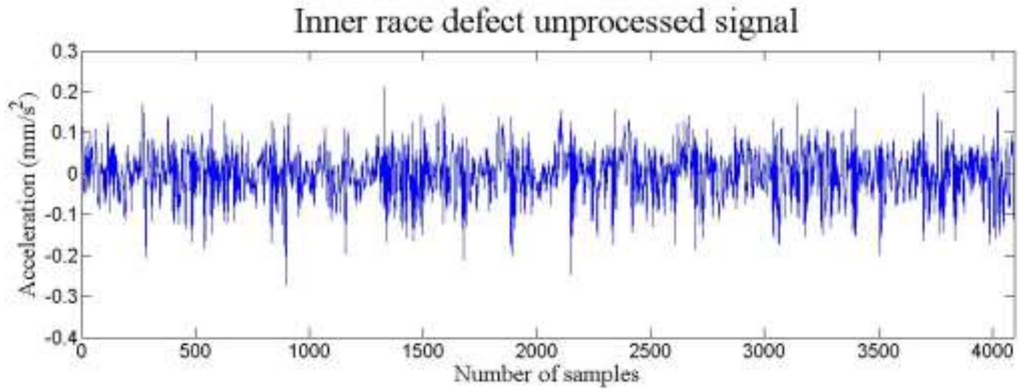

Figure 5. Unprocessed signal of Inner race fault bearing

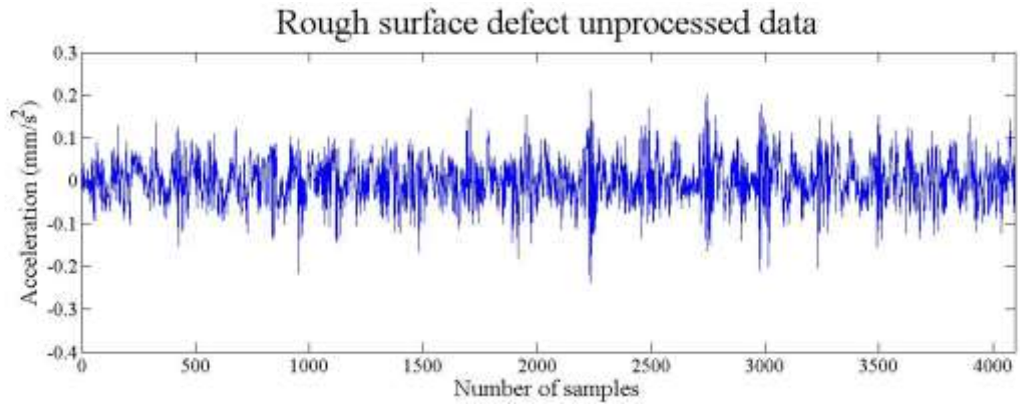

Figure 6. Unprocessed signal of bearing possessing rough surface

III. RESEARCH METHODOLOGY

After completion of data acquisition, the raw unprocessed vibration signal consists of not only our required vibration of fault generation, but also other induced vibrations as well. These include vibration of the various components attached (like the flywheel, shaft arrangement etc), vibration rebound due to bench on which the

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setup is placed. So first of all it is necessary to identify the fault frequencies, so as to know where the area of our requirement lies. The given experiment was conducted at 1500 rpm at the bearing end. The fault frequencies of the bearing are given as-

The inner race fault frequency is given by-

$$F_{\text{Inner race}} = \frac{d_b}{2}\left(\frac{N}{60}\right)\left(1 + \frac{d_b \cos\emptyset}{d_p}\right)$$

And its calculated value is 181.514Hz.

As such no exact formula exists for calculating the rough surface but according to [8] rough surface on either of the two races (inner or outer) or the ball leads to premature failure of bearings and hence it should be considered a fault. Rough surface defect can be considered as inner race/outer race fault depending on the location of rough surface. The only difference being that we have to cover a spectrum or a range of frequency instead of a pinpoint accurate frequency. In the present study, considering the non-idealness of machine setup a frequency range for both inner race fault and rough surface fault has been taken for analysis. For inner race analysis a span of 10Hz (±5 Hz) while for rough surface, a span of 20Hz (±10Hz) has been taken.

The features in the given span have been extracted by Wavelet Transform. There exists a variety to choose from the family of wavelets. In the present study Daubechies family of 8^{th} order has been chosen. After feature extraction process, this data is used as input for Artificial Neural Networks (ANN) which classified the bearings clearly.

Over the most recent 25 years, Wavelet Transform (WT) has developed at an unstable rate. Wavelets have engaged researchers and specialists of a wide range of foundations. WT has prompted energizing applications in signal analysis and numerical investigation, and numerous different applications are still being contemplated. WT is a technique used for time-frequency analysis. Because of its solid capacity in time and frequency space, it is introduced as of late by numerous specialists in rotating machinery. It disintegrates a signal in both time and frequency with respect to a wavelet, called mother wavelet. Wavelets are either continuous or discrete depending on the nature of signal. The present study includes the use of Discrete Wavelet Transform (DWT). DWT can be considered as Continuous Wavelet Transform but in parts. It is given by-

$$W(a,b) = \frac{1}{\sqrt{a}}\sum_n \sum f_n \Phi\left(\frac{n-b}{a}\right) \qquad (1)$$

Where a= scaling function

b= dilation indicating number

n= integer value

$\Phi(\frac{n-b}{a})$= mother wavelet

For a typical 3-level decomposition -:

Signal (S) = $A_3+D_1+D_2+D_3$

Where A_n and D_n stand for approximation and details at the n^{th} level. Figure 7 shows the decomposition.

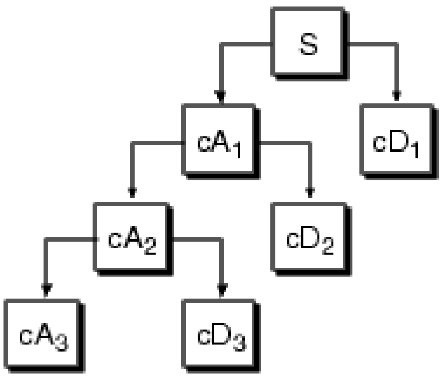

Figure 7. 3-level wavelet decomposition (MATLAB et.al)

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After feature extraction, the data is fed as input to ANN. Artificial Neural Network (ANN) approach is a very fascinating mathematical tool, which may be accustomed replicate a large type of engineering and sophisticated scientific issues into less complicated ones. Within the previous few years, this ANN approach had become a very popular tool for numerous engineering applications, attributable to its greatly reliable prediction ability. For the network to duplicate a desired behavior, the parameters of the network ought to be optimized through the suitable learning method.

An ANN could be a guided graphical arrangement, where nodes execute some computations which can be either terribly sophisticated ones (such as summary the inputs) or typically quite complicated (a node might contain another neural network). Every affiliation determines the data (signal) be due one node to a different typically associated by variety known as weight, that represents the degree to that associate data (signal) is being weaken or amplified by a affiliation. However solely those graphs area unit termed as neural network whose weights area unit primarily random and therefore the learning algorithmic rule suggests the value of weights which will attain the required task.

The type of the neural architecture depends on the ways in which nodes are connected to each other. A few node functions are sigmoid, ramp, piecewise linear function, step etc and learning algorithms like Feed Forward Back-propagation, Hebbian learning etc.

In the present study, back-propagation neural network (BPNN) has been adopted as a result of its capability of giving quick response and high learning accuracy. It provides a computationally economical technique for training the network. An optimum specification and pertinent variety of training cycles i.e. epochs at completely different input combos can be compelled to establish so as to boost the network performance.

IV. MODEL DEVELOPMENT AND TRAINING

This part will demonstrate how the classification was done on basis of Neural network architecture of extracted features by use of MATLAB. The procedure is as given -:

a. Collecting the database by conduction of experiments on SKF 2207EKTN9.
b. Feature extraction by Wavelet Transform using Daubechies level 8 (db8).
c. Developing inputs and outputs for the data.
d. Transfer of this data to MATLAB workspace.
e. Creating network architecture by selection of training algorithms, network parameters and training function.
f. Testing the network for network evaluation.
g. Simulation of the architecture by trained network.

Feature Extraction process

Single decomposition each of healthy bearing, bearing with inner race fault and bearing possessing rough surface is shown below in Figure 8, 9 and 10 respectively.

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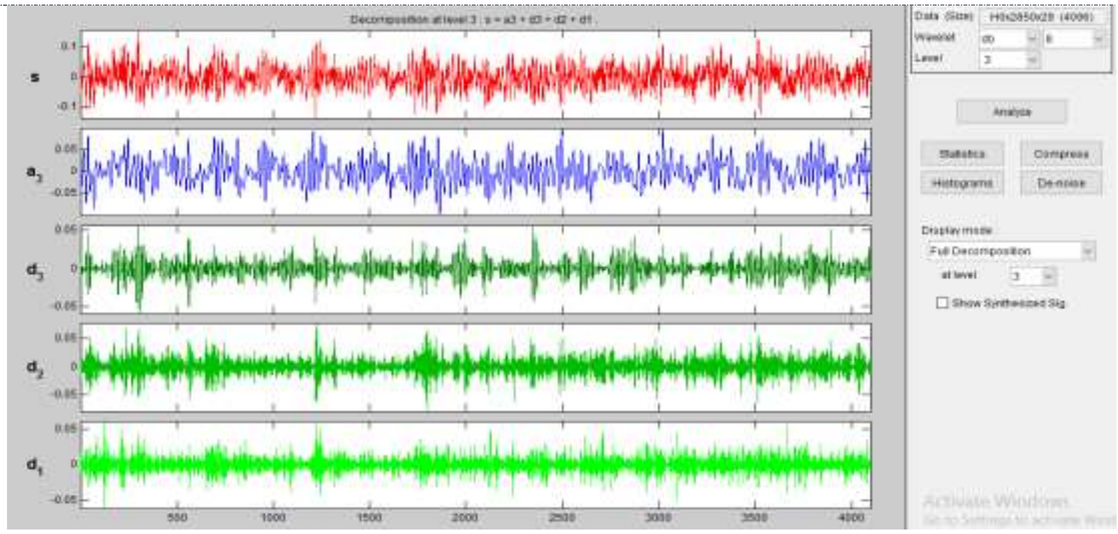

Figure 8. Decomposition for healthy bearing

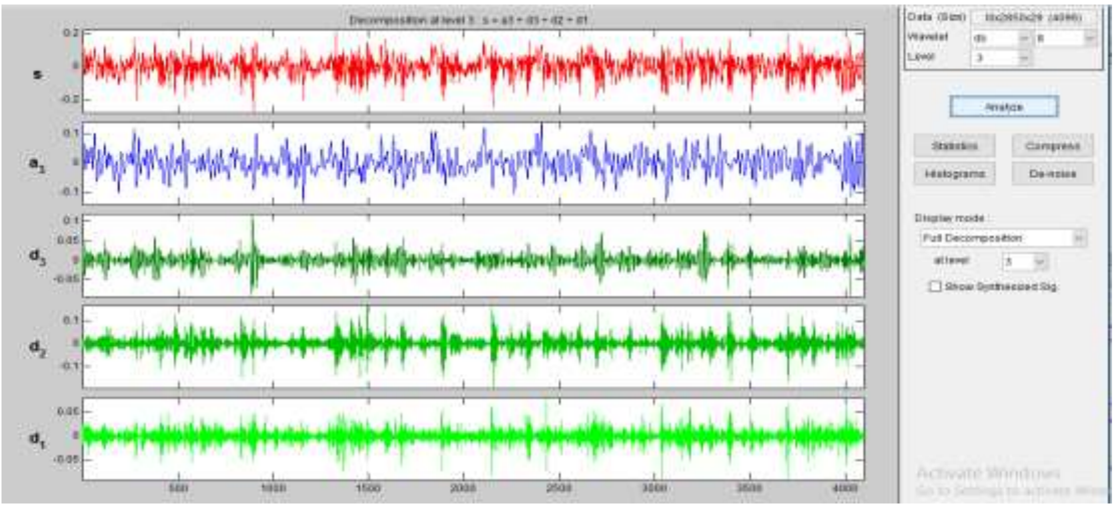

Figure 9. Decomposition for inner race fault bearing

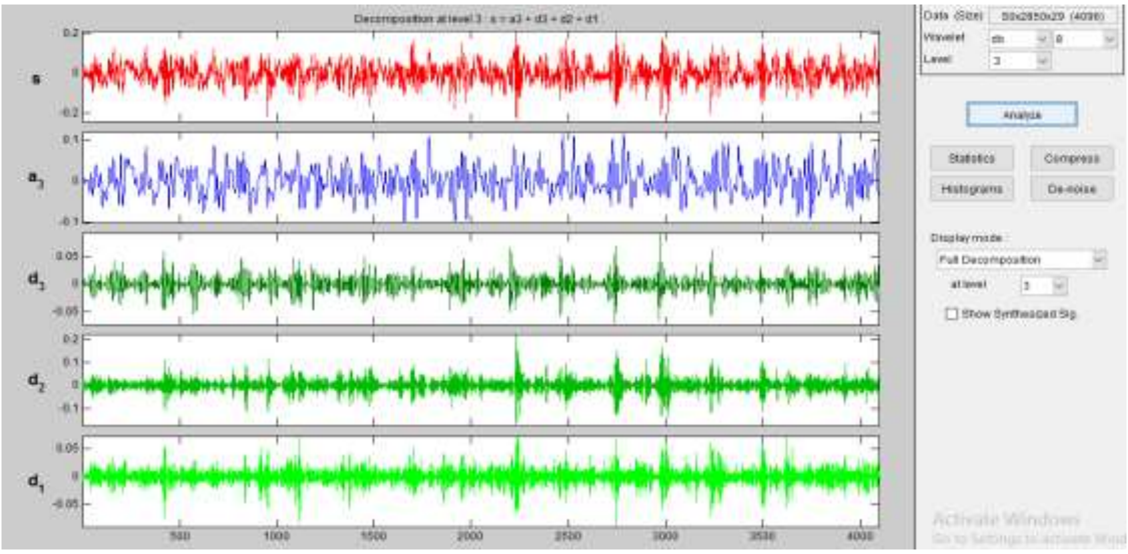

Figure 10. Decomposition for bearing having rough surface

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Feed Forward Back-propagation model

In Feed Forward Networks, the neurons are organized in layers, with the primary layer accepting the information and the last layer creating the output. These systems have the output layer of one-dimensional linear neurons, all the more regularly gone before by at least one hidden layers of sigmoid neurons. The linear output layer lets the system to create the results outside the range - 1 to +1. The information in these systems are continually pushed forward starting with one layer then onto the next and this legitimizes their name as feed forward network.

Learning in these Feed-Forward Networks has a place with the class of supervised learning, where the sets of information and outputs are fed into the system for some cycles, thus as a result of the network 'learns' the association between the input and output [9]. Back-propagation learning algorithmic program is employed for learning these networks. In training, calculations are made out from input layer directed to the output layer, and therefore the errors are then propagated from the output layer to the preceding layers. These networks are very quick in recognizing linear and non-linear relationships between inputs and outputs.

For achieving desired results, different training algorithms are developed like Cascade forward back-propagation, Hopfield, Competitive etc. The present study employs the use of Levenberg-Marquardt back-propagation (trainlm) algorithm. A Feed Forward network is as shown in Figure11.

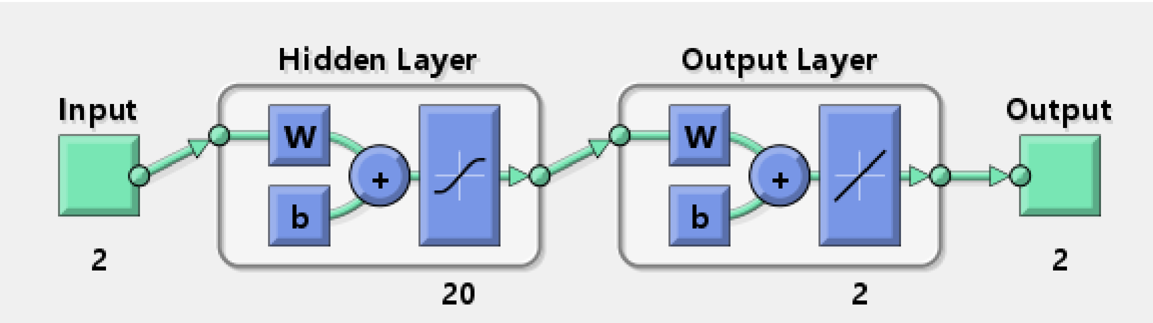

Figure 11. Feed Forward Back Propagation Network (MATLAB et.al)

The training set is divided into 3 sets of data. 70% used for testing, 15% for validation and 15% for testing. Biases and weights have been initialized randomly. The network was trained for reaching minimum gradient.

V. RESULTS AND DISCUSSIONS

After the networks are trained, tested and validated; the experimental results are explained in this chapter. The predicted values of the experiment indicate the ANNs ability to predict responses is excellent. During training the neural network, some windows open which are shown in Figure 12-15.

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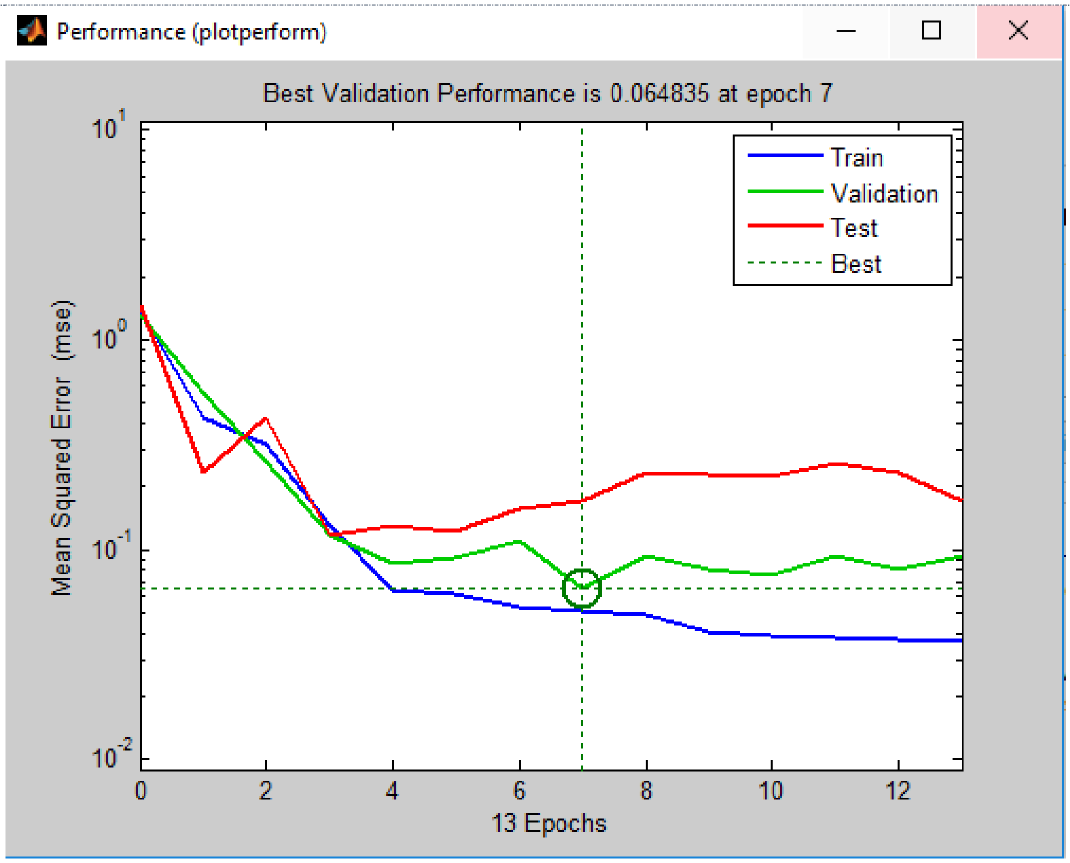

Figure 12. Performance plot of trained, tested and validation data

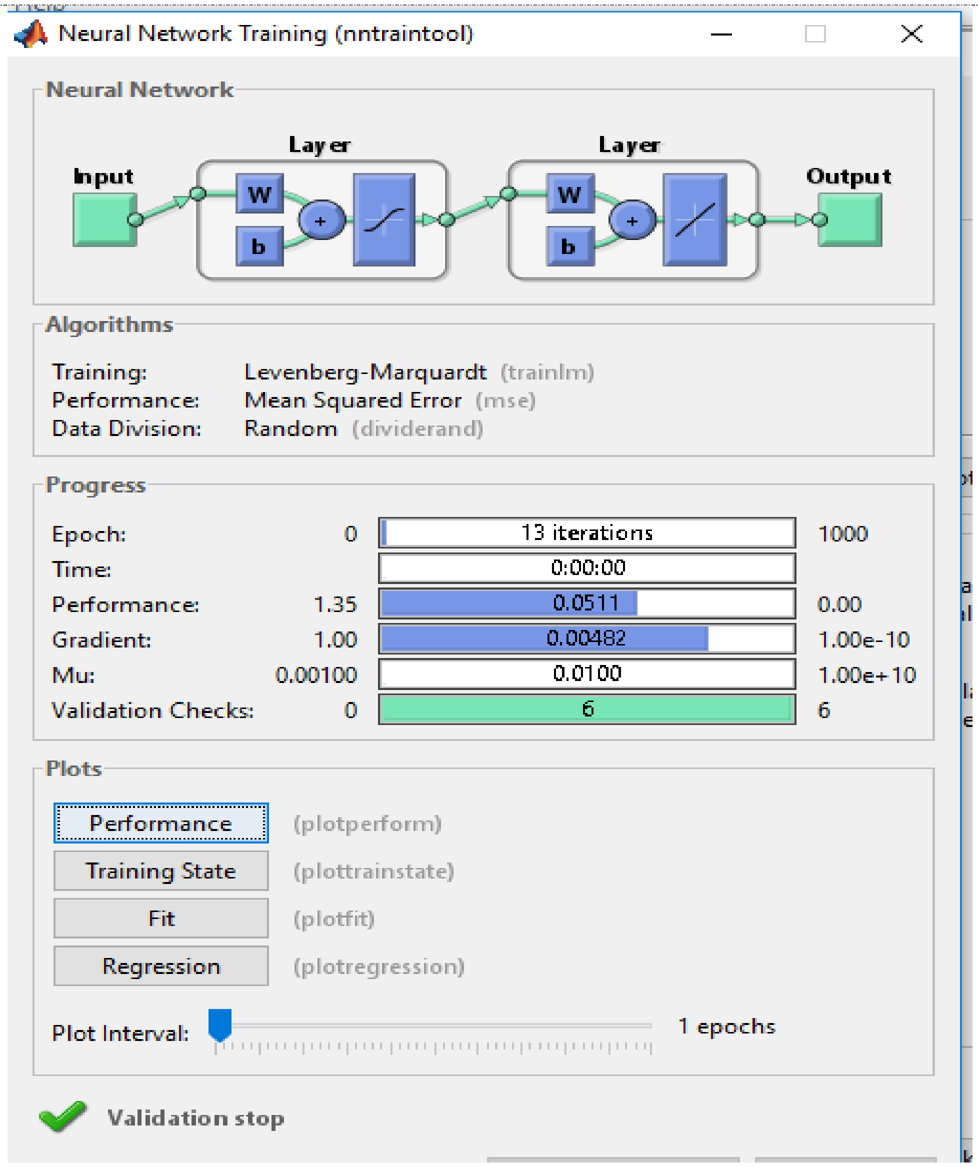

Figure 13. Figure depicting the training window

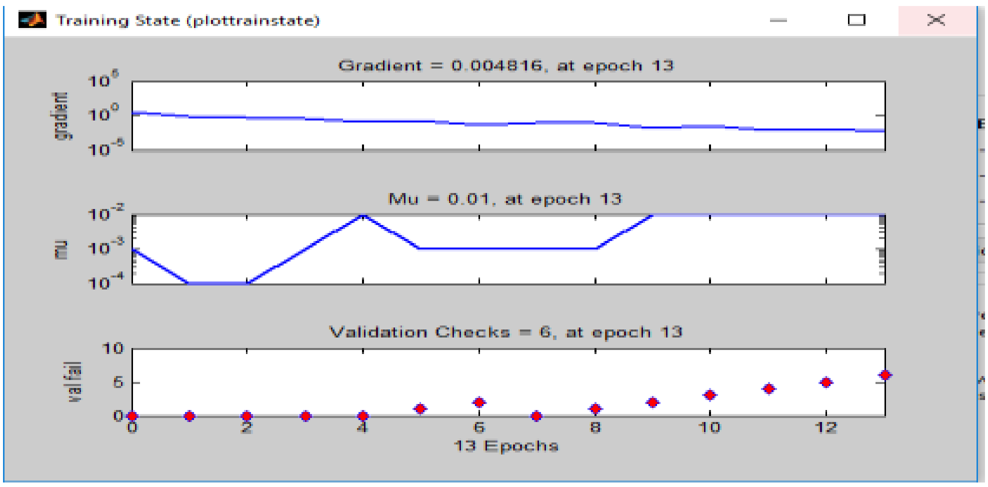

Figure 14. Training state of neural network

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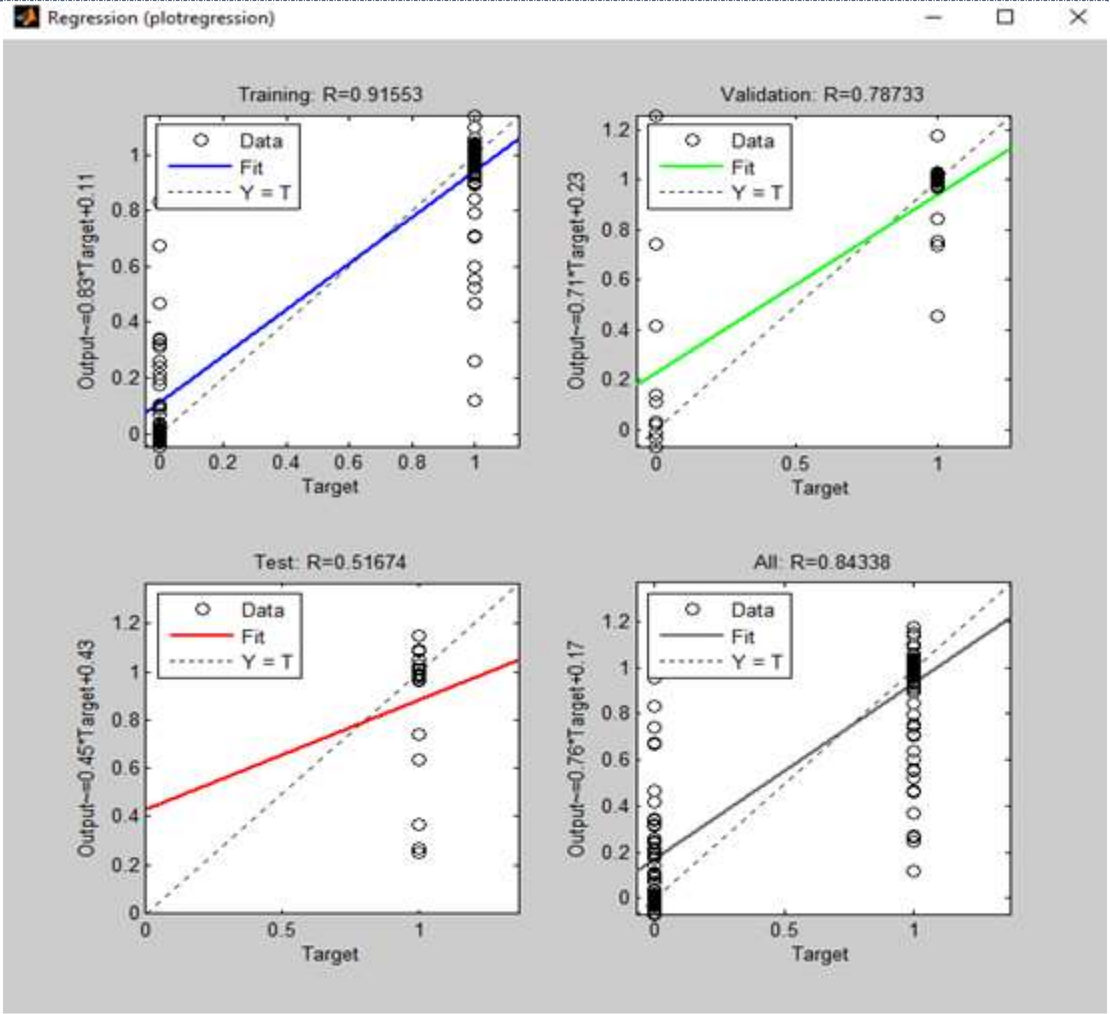

Figure 15. Regression analysis of Feed forward network

The statistical output of the iterations is as shown below in Table 3.

Table 3. Statistical iterations output

	No. of samples	Mean Squared Error	Regression
Training	69	5.11421e-2	7.29070e-1
Validation	15	6.48353e-2	7.38919e-1
Testing	15	1.6891e-2	9.59141e-1

Training state and regression plot is shown in Figure 14 and 15 respectively. Validation is used to judge the network generalization & to hinder the training once generalization ceases to boost. Validation tends to a halt once GRADIENT performance decreases and also the validation performance (VAL FAIL) will increase. The minimum gradient for the experiment came out to be 0.004816 at epoch 13. The point at which validation halts, the best validation was observed to be 0.064835 at epoch 7 as shown in Figure 12. Mean Squared Error (MSE) is the mean of square of difference between actual and target outputs. Lower MSE values denote higher performance and nil signifies no error. Outputs predicted by the used learning functions were plotted on y-axis against the given target values. It can be clearly seen that the outputs trace the targets fairly during training.

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Training continues until network's error starts reducing in respect of validation set. Different networks deviate from one another in terms of training functions used. Thus, such networks will fix the multi-dimensional riddle at random well, provided congruent knowledge and enough neurons in its hidden layer are available. Levenberg-Marquardt (trainlm) back propagation algorithmic program used for the model, wherever training ceases automatically once generalization stops, as implicit by a rise in mean squared error (MSE) of the validation samples. Then the networks were simulated within the testing set.

Prediction performance calculation tools

This section discusses the numerical calculations for the developed neural network model. The analysis was made by using MSE and Coefficient of Determination (R^2). Some researchers [10] postulated (R^2) determines variance interpreted by the model that is a parameter for reduction of variance in the model. These performance scales are the nice measure of overall prognosticative accuracy. RMSE & R^2 yields the concept measures of prognosticative accuracy. All results recorded square measure for the training set and testing set. The expressions of all the measures are as given below-

$$\text{MSE} = \sum_{i=1}^{n}\left(\frac{Q_{experimental}-Q_{predicted}}{n}\right) \tag{1}$$

$$R^2 = 1-\left[\sum_{i}^{n}\left(\frac{Q_{experimental}-Q_{predicted}}{Q_{experimental}^2}\right)^2\right] \tag{2}$$

Equation (1) is used to evaluate performance of developed models. The obtained MSE and R^2 values of the trained model are highly significant.

VI. CONCLUSIONS AND FUTURE SCOPE

In this paper, efforts have been made to compare and classify the healthy bearing and faulty bearing. The experimental work presents associate degree approach for diagnostics of moving element bearing faults in the scope of moving component bearing faults and Back-propagation ANN calculation. Distinctive vibration signs were analyzed directive a number of tests and applying a series of signal process techniques.

The grouping execution was successfully extended by testing from modifying the amount of hidden layers and neurons giving the perfect regression values and low errors.

Higher relationship coefficients and low MSE values exhibit that the ANN expectations and target fault appraisals are close. With the advances of soft computing methods like ANN and Wavelet Transform, it has turned out to be a lot easier to analyze faults.

The present research has also tried to extend its scope to identify the nature of faulty bearing. With more research and use of better soft computing technologies this study can also be used to diagnose individual faults in a single rolling element bearing with more accurate results.

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