

Automatic Fault Classification for Journal Bearings Using ANN and DNN

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Journal bearings are the most common type of bearings in which a shaft freely rotates in a metallic sleeve. They find a lot of applications in industry, especially where extremely high loads are involved. Proper analysis of the various bearing faults and predicting the modes of failure beforehand are essential to increase the working life of the bearing. In the current study, the vibration data of a journal bearing in the healthy condition and in five different fault conditions are collected. A feature extraction method is employed to classify the different fault conditions. Automatic fault classification is performed using artificial neural networks (ANN). As the probability of a correct prediction goes down for a higher number of faults in ANN, the method is made more robust by incorporating deep neural networks (DNN) with the help of autoencoders. Training was done using the scaled conjugate gradient algorithm and the performance was calculated by the cross entropy method. Due to the increased number of hidden layers in DNN, it is possible to achieve a high efficiency of 100% with the feature extraction method.

Keywords: journal bearing; fault classification; artificial neural networks; deep neural networks.

1. Introduction

A journal bearing consists of oil or grease lubricated metal sleeve within which a shaft rotates freely. Journal bearings find wide application in industrial machinery that makes use of very high loads or involving high horsepower like motors, steam turbines, compressors, and pumps. The primary purpose of a journal bearing is to reduce the friction involved and to support and guide the rotating shaft.

Major causes for defects in journal bearings include excessive load, false brinelling, true brinelling, overheating, fatigue failure, contamination, reverse loading, lubricant failure, misalignment, loose or tight fits, corrosion, etc. The vibration data have been collected for the healthy bearing in full oil condition, full loose-

ness condition, no lubrication condition, and for three different induced faults.

The study aims to develop a technique for the automatic classification and detection of various faults of journal bearings by two different methods, namely, artificial neural networks (ANN) and deep neural networks (DNN), and comparison of the results obtained thereby. Condition monitoring of the bearings is performed by feature extraction using empirical mode decomposition (EMD) followed by Hilbert-Huang transform (HHT).

KUMAR, KUMAR (2015) investigated various bearing defects with the application of neural networks. The paper presents a novel method for condition monitoring of a rolling element bearings. Implementation was done with the help of back-propagation and

the neural network toolbox in MATLAB. The back-propagation method was employed for fault classification in journal bearings in the current study.

ALI *et al.* (2015) investigated the automatic fault diagnosis of bearings using vibration signals based on the empirical mode decomposition and artificial neural techniques. This feature extraction method is based on the empirical mode decomposition and mathematical analysis of the measured data in order to select the most significant intrinsic mode functions. The feature extraction method was used to extract eighteen different features which were used for pattern recognition in ANN and DNN.

QIU *et al.* (2006) used wavelet filter based signature detection method on rolling element bearing. The performance of wavelet decomposition based de-noising and wavelet filter based de-noising methods were compared using signals of mechanical defects. The method proposed in the paper was used for the sampling of data in the current study.

HAJAR *et al.* (2013) used artificial neural networks for bearing and gear fault detection. The paper applies a feed-forward neural network to classify a large number of vibration signals. Unlike feature extraction featured in the present study, their method uses parameters extracted from power spectral density of signals for bearing fault classification.

VYAS *et al.* (2001) designed an artificial neural network for fault identification in a rotor-bearing system. Statistical moments were taken for the vibration signals which were used to train the network. The current study focuses on training the network using data obtained from feature extraction, which produces more accurate results.

GAN *et al.* (2001) constructed a hierarchical diagnosis network based on deep learning and its application in the fault recognition pattern of journal bearings. The network uses two similar networks constructed by a support vector machine and a back propagation neural network. The study highlights on the efficiency of the hierarchical deep network.

JIA *et al.* (2016) investigated the intelligent fault diagnosis of rotating machinery with massive data. Their paper highlights the advantages of using deep neural networks over shallow networks. The effectiveness of this method is further validated using data from the rolling element bearing and planetary gearboxes. This idea has been used for journal bearings in our research.

CHEN *et al.* (2016) published their work on rolling bearing fault diagnosis using deep neural networks. In their study, three different deep neural network models for fault analysis of roller bearing were employed. The accuracy in DNN method as compared with ANN was studied.

SARIDAKIS *et al.* (2008) used artificial neural networks for measurements of journal bearing performance. They introduced a fault diagnosis model that

uses ANN in order to identify the effects of increase in wear depth and increment of the misalignment angle in journal bearings. The methodology was utilised in analysing the various faults studied in our research.

JIA-LI *et al.* (2010) performed their research on gear fault diagnosis using Levenberg-Marquardt neural network. MATLAB neural network toolbox is used to model and simulate gear fault signal data. The second derivative information is used to enhance the network convergence speed and generalisation performance. This helps to reduce training epochs and improve diagnosis accuracy.

LIU and IYER (1993) investigated the use of artificial neural networks for the diagnosis of common defects in roller bearings. Here, different features were selected based on the amplitude parameter which was then used to train neural networks. A similar technique using 18 different statistically obtained features were used in the current study for neural network training.

SAMANTA *et al.* (2003) compared artificial neural networks and support vector machines for the purpose of bearing fault detection. Time-domain vibration signals were used for feature extraction which were used to train the network. The method highlighted the efficiency of artificial neural networks for neural network feature extraction.

KIM *et al.* (2003) developed a non-linear model for forecasting droughts by combining wavelet transforms and neural networks. The work highlights the efficiency of the method for correctly predicting for non-linear and non-stationary data. In the current study, empirical mode decomposition was used for feature extraction of journal bearing vibration data.

JUNSHENG *et al.* (2006) made a research of the criteria of intrinsic mode function (IMF) in empirical mode decomposition (EMD) method. The authors propose the energy difference tracking method according to the orthogonality of the IMFs. EMD condition was used in the current study for time-frequency feature extraction.

YU *et al.* (2005) studied the application of empirical mode transformation to the fault detection of roller bearings. Here, vibration signals of a roller bearing are converted into time representation using the orthogonal wavelet method. An envelope signal is then obtained by envelope spectrum analysis of the wavelet coefficients. From this, the local Hilbert spectrum is obtained using EMD method and Hilbert spectrum from which the fault pattern can be diagnosed and analysed. The authors deal with roller bearings and a similar analysis needs to be developed for fault diagnosis in journal bearings for feature extraction.

HUANG *et al.* (1998) investigated the empirical mode decomposition and the Hilbert spectrum for non-linear and non-stationary time series analysis. The authors deal with decomposing any data set into a number of intrinsic mode functions by empirical mode de-

composition method producing well-defined intrinsic mode functions (IMFs).

NARENDIRANATH BABU T. *et al.* (2017) discussed the various dynamic parameters such as stiffness or vibrations of the journal bearing. Further, the author covers fault diagnostics and automatic fault classification of journal bearings.

JEON *et al.* (2015) investigated a robust diagnosis method for a rotor system with a journal bearing. To enhance the robustness of a journal bearing diagnosis system, it is of great importance to define an optimum datum unit for featuring anomaly states of the rotor system. In this study, the authors make use of three measures for class separation, including Kullback-Leibler divergence (KLD), Fisher discriminant ratio (FDR), and a newly proposed measure: probability of separation (POS).

HASE *et al.* (2016) developed condition monitoring and maintaining machineries. It is extremely important to identify and quantify friction and wear phenomena. Due to the fact that friction and wear processes involve deformation and fracture of materials, journal bearings generate elastic stress waves that can be detected and measured as acoustic emission (AE) signals. By measuring these AE signals, it is then possible to monitor tribological processes between sliding materials.

SADEGH *et al.* (2016) identified effective frequencies and most useful features of the AE signals for classification of the lubrication types. Continuous wavelet transform (CWT) and time domain signal analysis methods are used for feature extraction of the recorded AE signals. Then, Genetic Algorithms (GAs) in combination with artificial neural networks (ANNs) are applied to select and classify the extracted features.

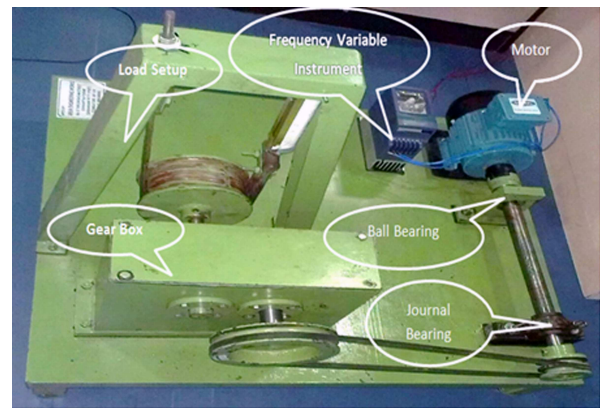
PENNACCHI *et al.* (2012) discussed misalignment in one of the most common sources of trouble of rotating machinery when rigid couplings connect the shafts. A finite element model is used for the hyperstatic shaft-line, while journal bearing characteristics are calculated by integrating Reynolds equation as a function of the instantaneous load acting on the bearings, caused also by the coupling misalignment. The results obtained by applying the proposed method are shown by means of the simulation, in the time domain, of the dynamical response of a hyperstatic shaft-line.

2. Experimental procedure

The vibrational data of the journal bearing are collected using the experimental setup shown in Fig. 1a. This is done at a shaft speed of 1200 rpm without any load being applied to the shaft.

In this study, the four channel data acquisition system (DAS) is used to collect the vibration signals on self-aligning bearing. The DAS has maximum input voltage of ± 5 V and the maximum sampling rate limit

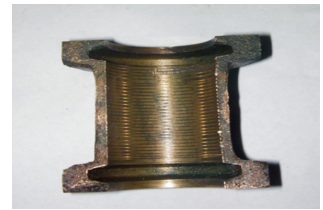
a)



b)



c)



d)



e)



Fig. 1. a) Experimental setup to record journal bearing vibrations, b) no fault on the journal bearing, c) bore fault on the bearing (fault F1), d) bore fault with hole on the bearing (fault F2), e) material removal and bore fault with hole on the bearing (fault F3).

is 51.2 ks/s per channel. The resolution of DAS is 24 bits and its input impedance is 305 k Ω . In the experimental studies, 12,800 samples per second are used to collect the vibration data. The 809K112 type accelerometer and 5020 type amplifier are used to collect the vibration signature of the bearing. The transverse sensitivity of the accelerometer is 2.5% and the operating temperature range is between 54°C to 121°C and the reference sensitivity is 100.10 mV/g. The vibration data is collected from the journal bearing through the accelerometer and the vibration signals are processed with DWESOFTE software. The vibration data obtained by running the bearing on the experimental setup produced a plot of the amplitude of vibration versus time. This was decomposed using empirical mode decomposition and Hilbert Huang spectrum, and used for automatic classification of faults.

In the vibration data collection setup, the journal bearing has been attached to a shaft that has been

connected to a motor and a frequency variable instrument which is used to vary the motor speeds while the readings are taken. The other side of the shaft closer to the motor has been attached to a ball bearing. A mono-axial sensor was attached to the bearing housing to measure the vibration data. For the purpose of this research, the vibration data of journal bearings were collected for the healthy bearing at full oil condition, bearing at full looseness condition, bearing at no lubrication condition, and for three different induced fault conditions. In the healthy condition, as shown in Fig. 1b, the shaft rotates in the healthy bearing with sufficient oil and hence the vibrations produced would be much weaker. In the full looseness condition, there is a significant clearance between the inner surface of the bearing and the shaft. This is simulated by running the shaft after loosening the fastening arrangement that fixes the shafts onto the bearing partially. In the no lubrication condition, the healthy bearing is washed, dried, and subjected to the running condition without the supply of oil. The vibrations are bound to increase due to increased friction between the running parts, which may cause earlier damage to the bearings.

Fault 1 refers to the condition in which threadlike formations are seen on the inner side of the journal bearing, as shown in Fig. 1c, which is mainly caused due to improper fits. In this case, the condition is simulated by creating threadlike impressions of pitch and depth of 1 mm using a lathe machine. Fault 2 refers to bearings with a hole formed on their surface, as shown in Fig. 1d. This can be mainly attributed to an improper lubrication system. In this case, a hole of diameter 1 mm is drilled on the bearing containing fault 1 using a drill machine. Fault 3 refers to a bearing in which a certain portion of the material has been removed from the inner surface, as shown in Fig. 1e. This is due to wearing which may be either caused by improper fits or subjecting the bearing to loads that exceed limits. This is simulated on the bearing containing fault 1 and fault 2 by removing a small portion of the surface using a lathe machine. The material hardness of the shaft and bearing, their rubbing compatibility, fatigue strength, and temperature response can also have a pronounced influence on the system response to the sliding bearing contamination, which in turn leads to faults in the bearing. These faults will lead to increase in peak amplitudes.

The bearings with different induced faults are used to collect the vibration signature from the experimental setup. The machine was run for five seconds to collect the vibration data. After obtaining each set of readings, the machine was switched off, the bearing removed and the next fault induced before putting it back to the experimental setup.

For all the faults the bearing was run at a constant load. SAE 70 transmission oil is used in the test. The vibration data obtained by running the bearing in the

experimental setup produced a plot of the amplitude of vibration versus time. This was decomposed using empirical mode decomposition and Hilbert-Huang spectrum and used for automatic classification of faults.

The bearing was modelled with a motor of 0.5 HP, 3000 rpm connected to the rotor, through a coupling supported with one ball bearing and journal bearing at the end of the pulley. As before, different faults are induced in the bearings to collect the vibration signature from the experimental setup. The machine was run for five seconds to collect the vibration data. After obtaining each set of readings, the machine was switched off, the bearing removed and the next fault induced before putting it back to the experimental setup. The vibration data obtained by running the bearing in the experimental setup produced a plot of the amplitude of vibration versus time.

Feature extraction method was used with the vibration data to extract eighteen different features. These extracted features were used for the automatic classification of faults using artificial and deep neural networks (ANN and DNN).

3. Methodology

The automatic fault classification of journal bearing faults was performed using MATLAB Software. The software provides a numerical computing environment for matrix manipulations, plotting of data and functions, and implementation of algorithms. The programs work in an iterative manner. MATLAB has many built-in functions for data manipulation, a few of which have been utilised in the current study.

The following step by step procedure was applied for automatic fault classification of faults of journal bearings using vibration data:

3.1. Automatic fault classification using ANN

Automatic classification of the journal bearing faults is done using artificial neural networks. This enables continuous monitoring of the bearing condition and evaluating the severity of the defect online. ANN is widely considered as an effective tool for assessing the bearing performance degradation without human involvement.

The vibration signal data of the journal bearing in the healthy condition and for each of the three different fault conditions has been collected for 120 seconds. The initial 20% of the data for each second are collected and stored as a two dimensional array. The initial step comprises extracting the time domain and time-frequency domain features. Feature extraction is mainly employed to assess the bearing performance degradation over time. An increase in bearing degradation is indicated by an increase in the magnitude of time domain features. Time domain features include

eight classical features – RMS, Kurtosis, Skewness, Peak to Peak, Crest Factor, Shape Factor, Impulse Factor, Margin Factor, Add Factor 1 and Add Factor 2. These two new features are used to link different features together. All these ten factors are summarised in Eqs. (1) to (10). In the equations, the value of init is calculated as the average of RMS of healthy bearings

$$\text{RMS} = \left(\frac{1}{N} \sum_{i=1}^N x_i^2 \right)^{1/2}, \quad (1)$$

$$\text{Kurtosis} = \frac{1}{N} \sum_{i=1}^N \frac{(x_i - \bar{x})^4}{\sigma^4}, \quad (2)$$

$$\text{Skewness} = \frac{1}{N} \sum_{i=1}^N \frac{(x_i - \bar{x})^3}{\sigma^3}, \quad (3)$$

$$\text{Peak to Peak} = x_{\max} - x_{\min}, \quad (4)$$

$$\text{Crest Factor} = \frac{\max |x_i|}{\text{RMS}}, \quad (5)$$

$$\text{Shape Factor} = \frac{\text{RMS}}{\frac{1}{N} \sum_{i=1}^N |x_i|}, \quad (6)$$

$$\text{Impulse Factor} = \frac{\max |x_i|}{\frac{1}{N} \sum_{i=1}^N |x_i|}, \quad (7)$$

$$\text{Margin Factor} = \frac{\max |x_i|}{\left(\frac{1}{N} \sum_{i=1}^N |x_i|^{1/2} \right)^2}, \quad (8)$$

$$\text{Add Factor 1} = \log \left(\text{Kurtosis} + \frac{\text{RMS}}{\text{Init}} \right), \quad (9)$$

$$\text{Add Factor 2} = \log \left(\text{Kurtosis}^{(\text{Crest Factor})} + \left(\frac{\text{RMS}}{\text{Init}} \right)^{(P-P)} \right). \quad (10)$$

Other than the ten time domain features obtained above, EMD is used to extract a set of new features called time-frequency domain values to make up for a more reliable database of features. Here, the bearing vibration signal is decomposed into characteristic IMFs. In the study, only the first seven IMFs are considered. The total energy of all the IMFs are calculated as:

$$E = \sum_{i=1}^n E_i. \quad (11)$$

A feature vector is calculated as:

$$\begin{aligned} & [\text{Ent}, E_1/E, E_2/E, \dots, E_7/E] \\ & = [\text{Ent}, \text{EntIMF1}, \text{EntIMF2}, \dots, \text{EntIMF7}], \end{aligned} \quad (12)$$

where

$$\text{Ent} = \sum_{i=1}^n P_i \log(P_i). \quad (13)$$

Taking 120 samples from each of the six different available cases, the output is linked to a 4×720 matrix. This output thus formed is modelled using the pattern recognition tool in MATLAB – nprtool – which uses the 18 extracted features as inputs and 20 hidden neurons to give the output by scaled conjugate gradient method of training. 70% of the available data were employed for training, 15% data for validation, and 15% data were used for testing the neural network. The neural network performance was analysed using the cross entropy technique. The error histogram, confusion matrix, and receiver operating characteristics (ROC) plots have been used to analyse the performance of the created neural network.

3.2. Automatic fault classification using DNN

A deep learning network may be described as a group of artificial neural networks stacked together one after the other. In this research, an autoencoder has been used for realisation of deep neural networks. Also known as a Diabolo Network, it is a feed-forward, non-recurrent network with an input layer, an output layer, and one or more hidden layers connecting them. Here, for the vibrational data, an autoencoder with hidden layer size of 10 and a linear transfer function is trained for the decoder. The features are extracted in the hidden layer for the first autoencoder and these features are used to train a second autoencoder. Features are again extracted in the hidden layer for the second autoencoder. These features are then used to train a softmax layer for classification. The deep neural network is formed by stacking the encoders together with the softmax layer. The deep network is trained based on this obtained data and the network performance is measured with the aid of a confusion matrix.

4. Results and discussion

4.1. Automatic fault classification using artificial neural network (ANN)

Various performance characteristics have been extracted for accurate assessing bearing performance degradation in an online condition monitoring platform. The ten different features extracted are RMS, Kurtosis, Skewness, Peak to Peak, Crest Factor, Shape Factor, Impulse Factor, Margin Factor, Add Factor 1, and Add Factor 2. Add Factor 1 and Add Factor 2 are

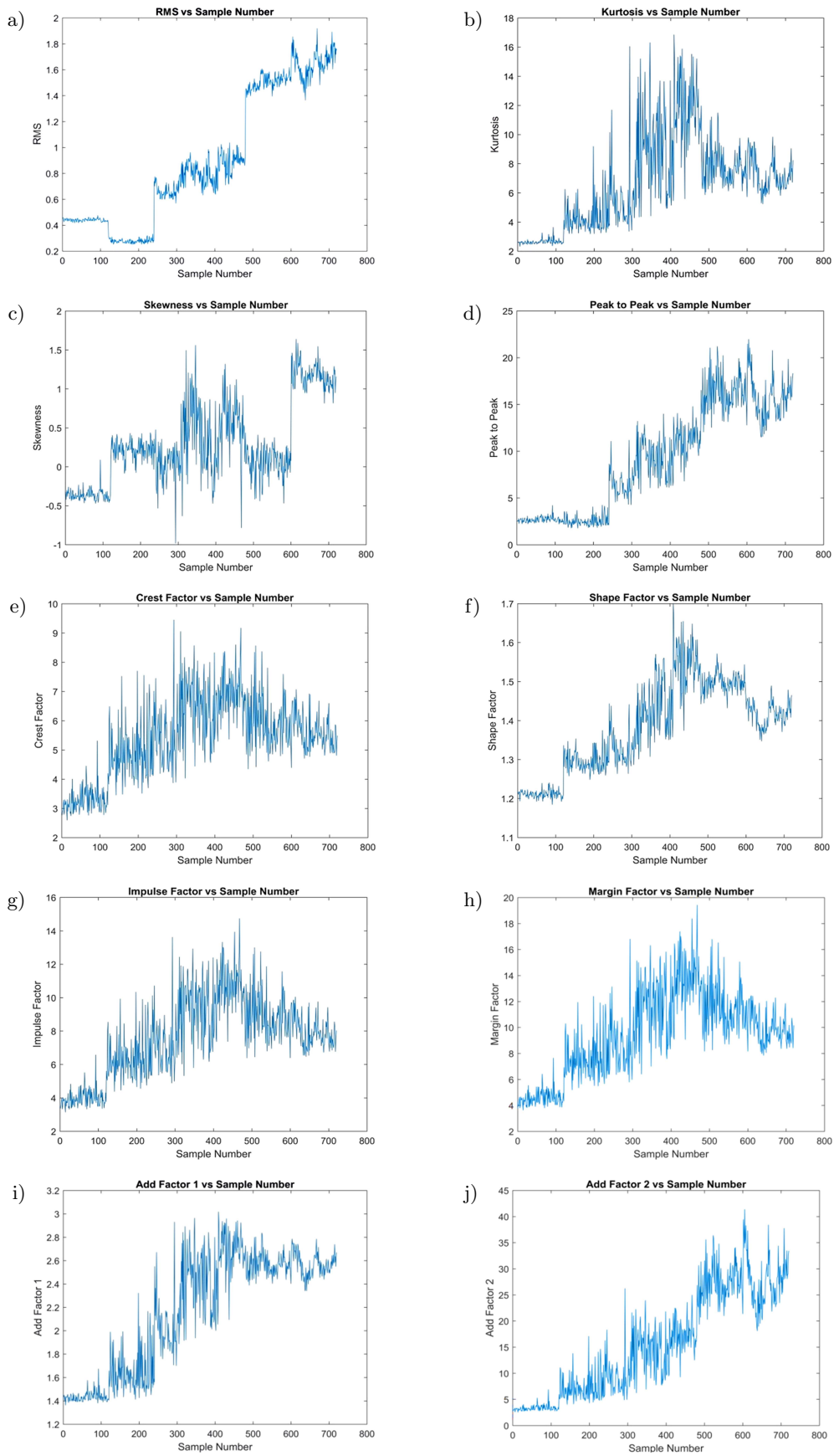


Fig. 2. Variation of statistical features: a) RMS, b) Kurtosis, c) Skewness, d) Peak to Peak (P_P), e) Crest Factor, f) Shape Factor, g) Impulse Factor, h) Margin Factor, i) Add Factor 1, j) Add Factor 2.

used to link various different factors together. The various time domain features increase in magnitude with increase in bearing damage. In the graphs, each consecutive groups of 120 samples represent accordingly: healthy bearing, full looseness condition, no lubrication condition, fault 1, fault 2, and fault 3. As the bearing defects are induced on the same bearing one after the other, the magnitude of the different faults keeps increasing and drops to its lowest value in the last 180 readings as it represents the healthy bearing

without any faults. As sudden degradation of bearings is usually associated with industrial environments, the plot may not always depict a monotonous behaviour. As noise and various other excitations are usually involved with rotating machinery, it is usually difficult to establish a deterministic model based on a single feature or assign a threshold value to accurately assess bearing damage.

The variation of the above discussed ten factors with time has been obtained and is shown in Fig. 2.

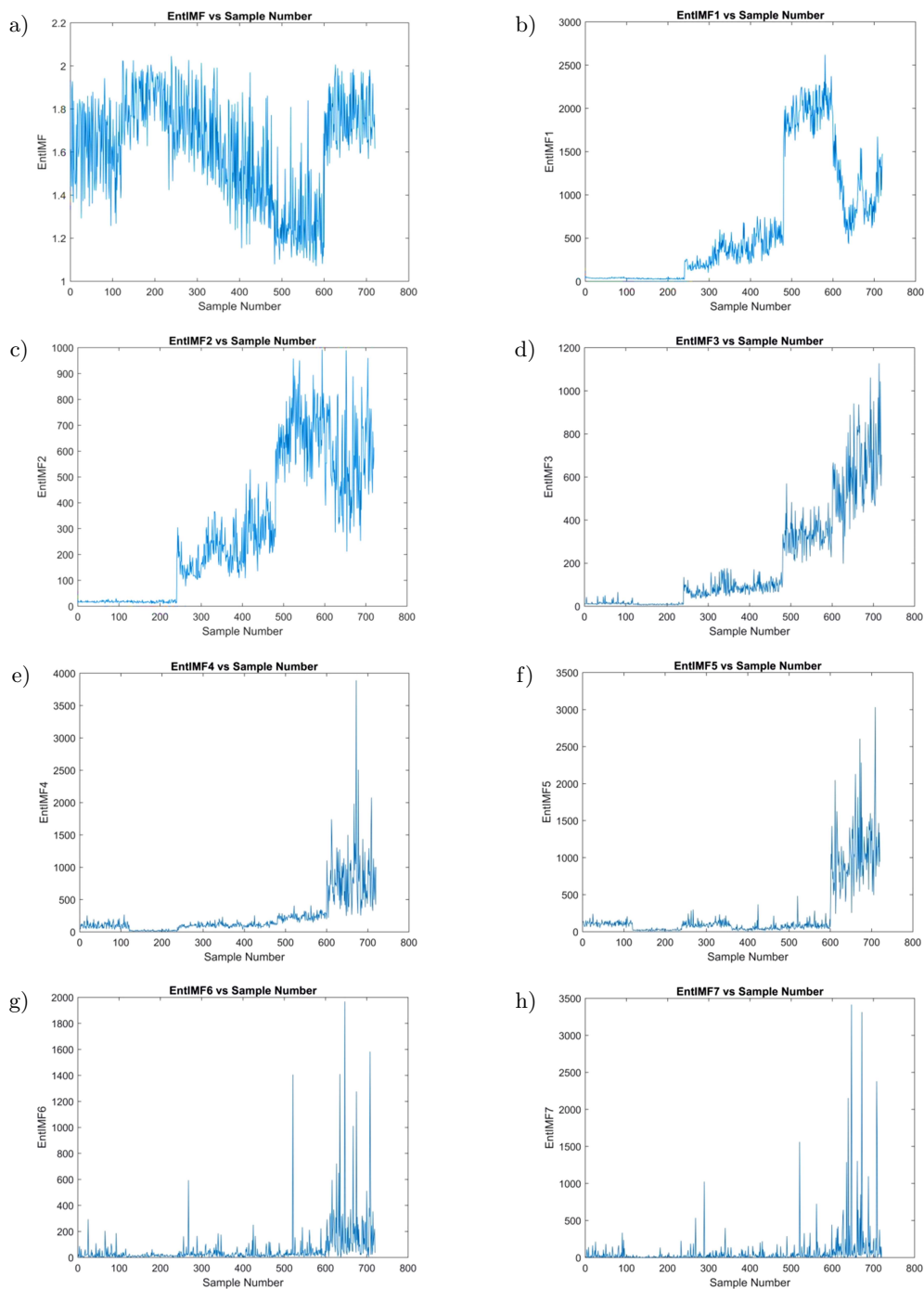


Fig. 3. Variation of features based on EMD: a) EntIMF, b) EntIMF1, c) EntIMF2, d) EntIMF3, e) EntIMF4, f) EntIMF5, g) EntIMF6, h) EntIMF7.

The time domain and time-frequency domain features are extracted which are used to implement the neural networks through the pattern recognition tool in MATLAB. The vibration signal data of the self-aligning bearing in the healthy condition and for each of the three different fault conditions were collected for 120 seconds. The following factors have been obtained by considering the first twenty percent of the data of each second of vibration of the journal bearing. The initial 20% of the data for each second are collected and stored as a two-dimensional array. The initial step comprises of extracting the time domain and time-frequency domain features. Feature extraction is mainly employed to assess the bearing performance degradation over time. An increase in bearing degradation is indicated by an increase in the magnitude of time domain features. Time domain features include eight classical features – RMS, Kurtosis, Skewness, Peak to Peak, Crest Factor, Shape Factor, Impulse Factor, Margin Factor – and two new features – Add Factor 1 and Add Factor 2. These two new features are used to link different features together. Based on the ten factors obtained, we get a 1x10 vector for each second of data.

In addition to the time-domain features extracted above, EMD is used to extract certain other features known as time frequency domain features which are used to build a more reliable and robust database. Here, we obtain the EMD energy entropy of each IMF which varies with variation in energy of vibration signals. In our study, we have only considered the energy entropy of the first seven IMFs.

The time frequency domain features thus extracted have been illustrated in Fig. 3.

ANN implementation has been performed at the no load condition of the various fault conditions for the above mentioned criterion. The input for ANN comprises of the eighteen features that were extracted earlier. The number of hidden neurons was set to 10. The number of outputs was 6 – healthy bearing, full looseness, no lubrication, fault 1, fault 2, and fault 3. Training was done using the scaled conjugate gradient method and an epoch of 55 iterations was obtained for 100% accuracy of ANN. 70% of the total data available was used for training, 15% for validation, and 15% was used for testing. Cross entropy feature was employed for validating the performance of the neural network. The error histogram showed an error concentration very close to zero indicating the efficiency of the neural network. The receiver operating characteristics (ROC) is defined as the probability of detection in machine learning. In the neural network obtained, the ROC plot was close to the idea, as it shows the performance of a neural network. For a good performance, area under true positive rate should be bigger and it should not overlap with the false positive rate. Thus, according to

the Fig. 4, the employed method can be considered good.

Various ANN performance validation parameters have been obtained and are shown in Figs. 5 to 9.

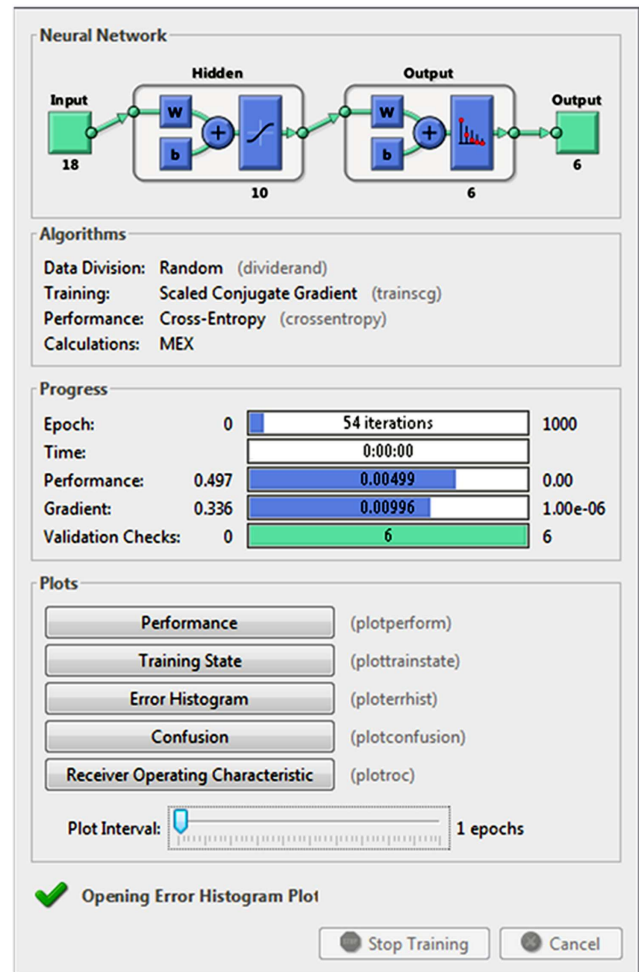


Fig. 4. ANN data.

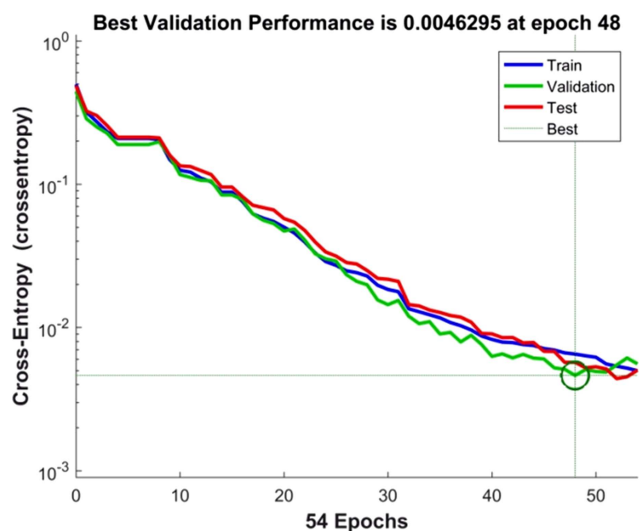


Fig. 5. Performance diagram.

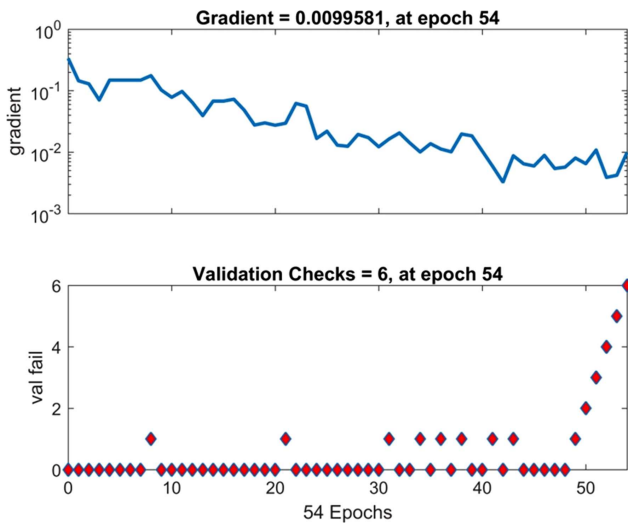


Fig. 6. Training state epochs performance.

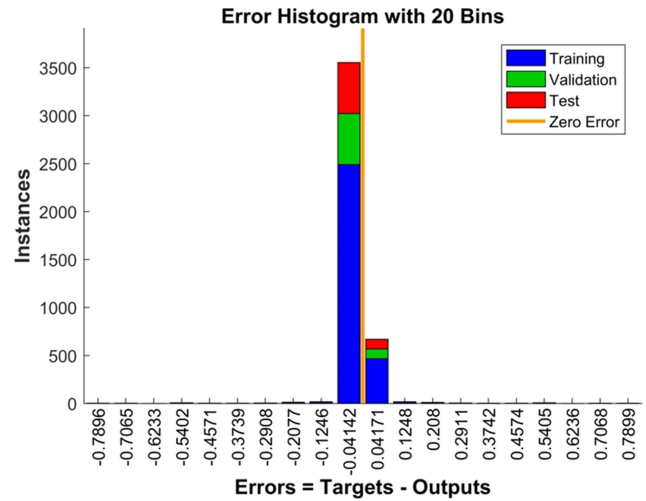


Fig. 9. Error histogram.

		Confusion Matrix						
		1	2	3	4	5	6	
Output Class	1	119 16.5%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
	2	0 0.0%	120 16.7%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
	3	1 0.1%	0 0.0%	117 16.3%	7 1.0%	0 0.0%	0 0.0%	93.6% 6.4%
	4	0 0.0%	0 0.0%	3 0.4%	113 15.7%	0 0.0%	0 0.0%	97.4% 2.6%
	5	0 0.0%	0 0.0%	0 0.0%	0 0.0%	120 16.7%	0 0.0%	100% 0.0%
	6	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	120 16.7%	100% 0.0%
		99.2% 0.8%	100% 0.0%	97.5% 2.5%	94.2% 5.8%	100% 0.0%	100% 0.0%	98.5% 1.5%
		1	2	3	4	5	6	
		Target Class						

Fig. 7. Confusion matrix summary.

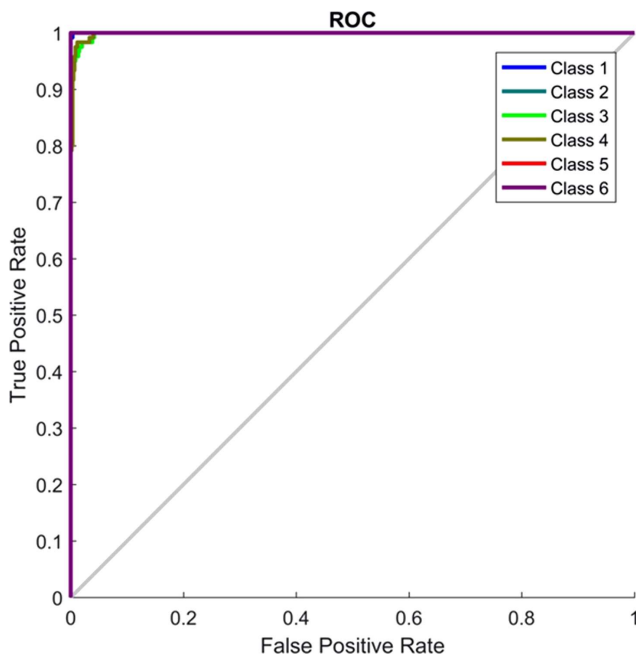


Fig. 8. ROC plots.

4.2. Automatic Fault Classification Using Deep Neural Network (DNN)

A better approach for the automatic classification of faults when the number of types of faults is higher is the deep neural network. In this case, the deep neural network is realised with the aid of autoencoders. Multiple number of hidden layers is employed to improve the accuracy of the output. The dataset is initially used to train an autoencoder. The features extracted from the hidden layer are used to train a second autoencoder. Again, new features are extracted which are used to train a softmax layer for fault classification. The encoders and the softmax layer were stacked together to form the deep network. The confusion matrix plotted to estimate the efficiency of the neural network showed the efficiency of 100%. This shows that the neural network was able to classify all the different types of faults that were present accurately. The training parameters and various performance plots obtained for the journal bearing at no load condition at 1200 rpm have been plotted below. The training was done using the scaled conjugate gradient algorithm and the performance was calculated by the cross entropy method. Due to the increased number of hidden layers in DNN, it is possible to achieve a high efficiency of 100% with the feature extraction method.

In the confusion matrix, the output class refers to the output that was obtained while the target class refers to the output that should have been obtained. Here, unlike in ANN, all the faults have been classified correctly and hence an accuracy of 100% has been obtained, which proves the advantage of DNN in comparison with ANN. Also, it may be noted that the epoch and the number of iterations obtained in this case is way higher than in ANN. By virtue of this, DNN is able to identify minor changes in a pattern that cannot be recorded by ANN. However, a higher number of itera-

tions points to a higher cycle time, which means that DNN may be used only if the number of faults is very high and ANN is unable to give a highly accurate prediction.

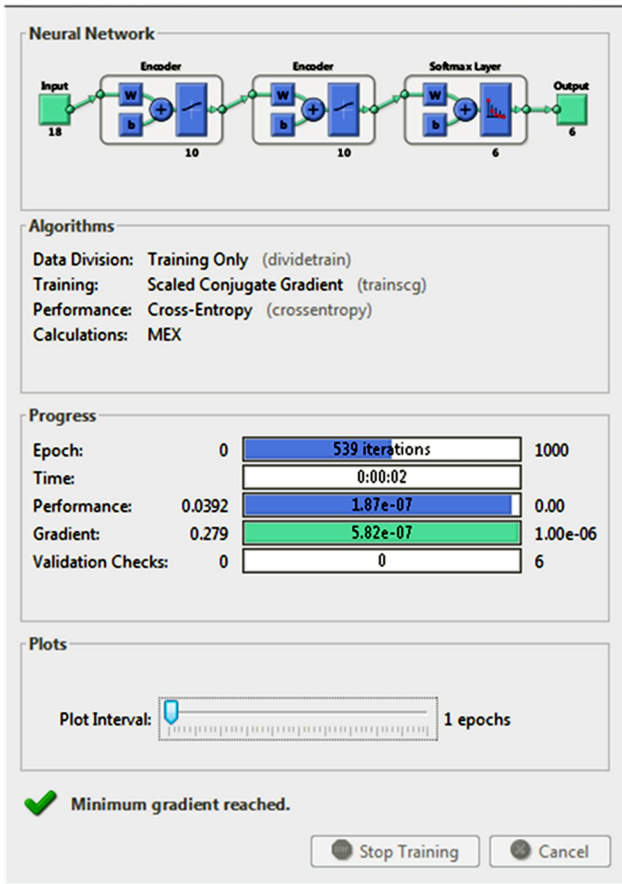


Fig. 10. Journal bearing neural training parameters.

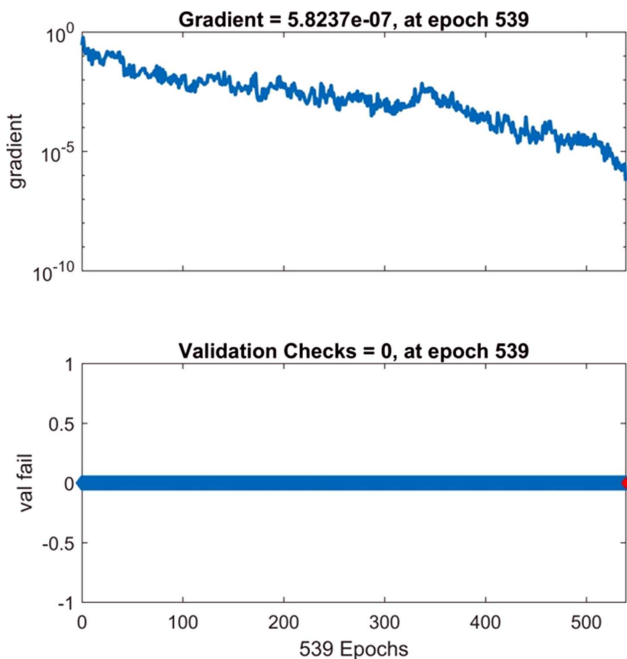


Fig. 11. Deep network training state parameters.

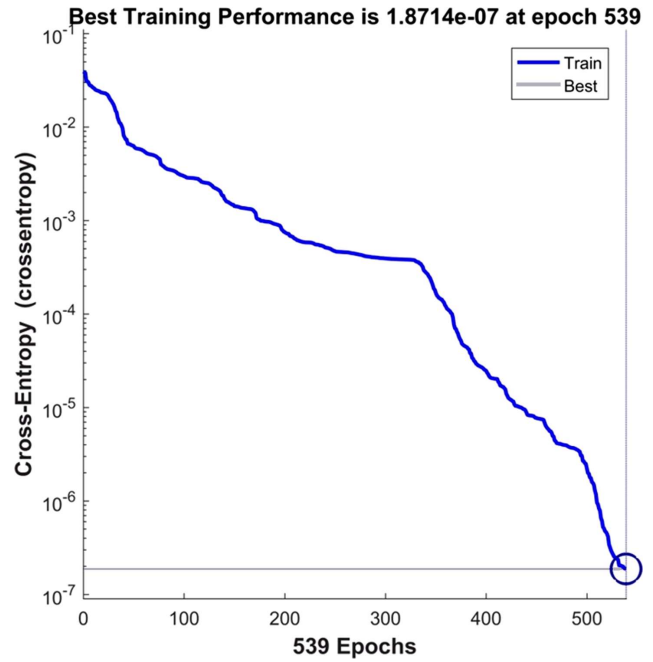


Fig. 12. Deep network performance.

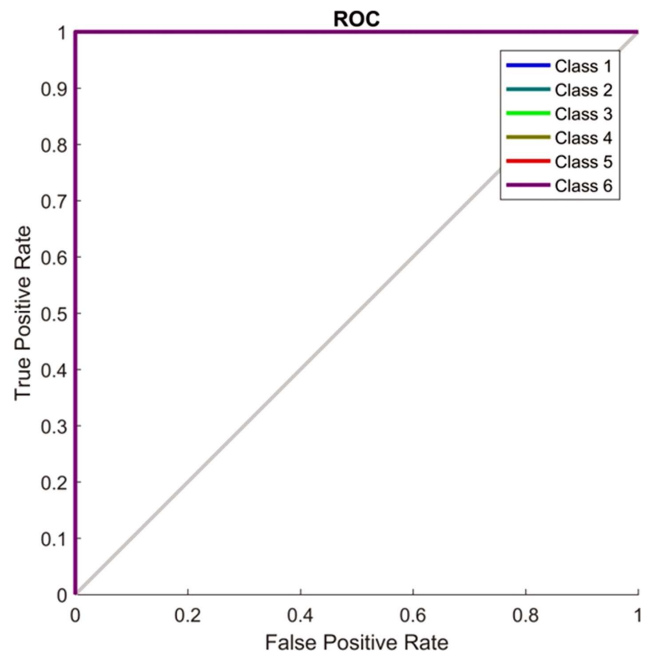


Fig. 13. Deep network ROC.

5. Conclusions

The advantage of the proposed method lies in the ability to handle real time data from bearings for condition monitoring and fault prediction. Since the confusion matrix allows visualisation of the performance of an algorithm, a supervised learning has good percentage of probability. Therefore this method can be concluded as a good one to process real time data due to prediction above 90%. Also the feature extraction scheme including time domain, frequency, and time-

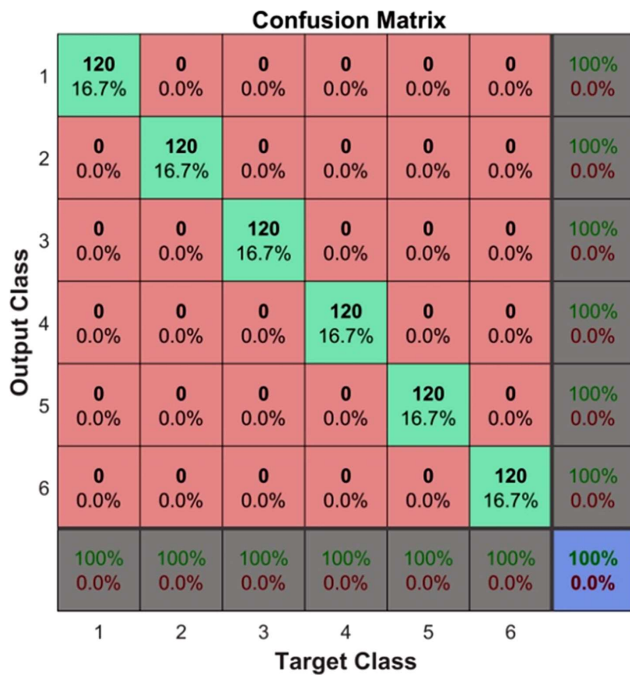


Fig. 14. Deep network confusion matrix.

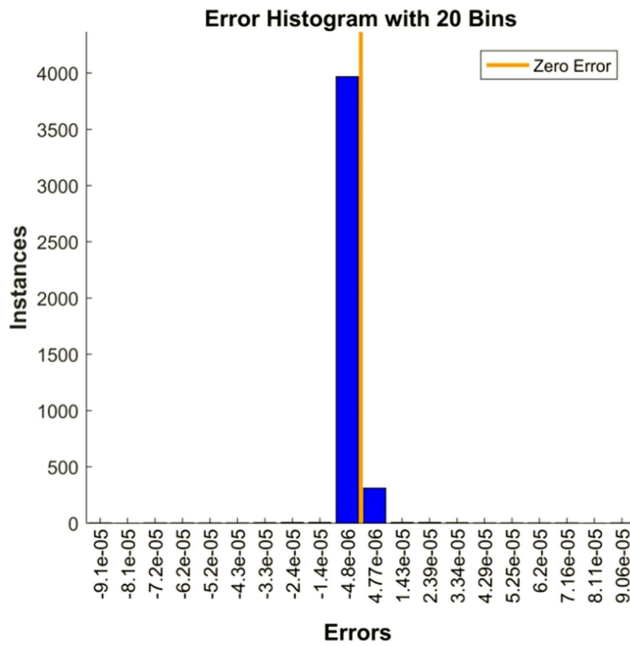


Fig. 15. Error histogram.

frequency domain feature is superior to the single mode schemes.

Neural network training was done with a standard neural toolbox of neural pattern recognition which is a two-layer feed-forward network with a sigmoid transfer function in the hidden layer, and a softmax transfer function in the output layer. The number of hidden neurons is set to 20. This can be changed depending on the performance of the network.

In ANN, an error histogram close to zero percentage was attained. Thus this adds to the success of the

methodology that was used in the study. The statistical features used are a powerful tool which characterises the change of bearing vibration signals when faults occur. The benefits of these features are the simplicity of implementation and low computational time.

However, as the number of faults increases, the overlap of fault types begins to occur. In this case, it becomes difficult to distinguish one fault from the other accurately. In such a scenario, a deep neural network can be implemented to increase the precision with which errors are determined and distinguished from one another.

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