International Journal of Engineering and Techniques - Volume 2 Issue 5, Sep – Oct 2016

RESEARCH ARTICLE OPEN ACCESS

Vibration Analysis and Fault Diagnosis of Induction Motor Bearing Using Artificial Neural Network (ANN)

Mr. Vaibhav A. Kalhapure[1], Dr.R.R.Navthar[2]
1(PG Scholar, Department of Mechanical Engg, PDVVPCOE, Ahmednagar)
2 (Associate Professor, Department of Mechanical Engg, PDVVPCOE, Ahmednagar)

Abstract:

Induction motor bearing faults are one of the main causes of catastrophic failure of machines. Thus, detection and diagnosis of faults in bearings is very crucial for the reliable. This paper focuses on fault diagnosis of induction motor bearing having localized defects using Daubechies wavelets-based feature extraction. In present study Machinery Fault Simulator (MFS) test rig used for fault diagnosis of NSK-6203 deep groove ball bearing. Vibration signals collected from the various bearing conditions- healthy bearing (HB), outer race defect (ORD), inner race defect (IRD), ball defect (BD) and combined bearing defect (CBD). The extraction of statistical features carried out using various Daubechies wavelet coefficients from raw vibration signals. Lastly, the bearing faults are classified using these statistical features as input to Artificial Neural Network (ANN) technique used for faults classifications. The test result shows that ANN identifies the fault categories of rolling element bearing more accurately for Db4 and has a better diagnosis performance as compared to other Daubechies wavelets with ANN classifier.

Keywords — **Daubechies Wavelet, Induction Motor Bearing, Artificial Neural Network (ANN).**

I. INTRODUCTION

Induction motors are electro-mechanical devices widely applicable in industrial application for conversion of electrical power to useful mechanical power. Bearing is most vulnerable component of a motor because it is often under high running speed conditions. According to survey of 6312 motors conducted by the Electric Power Research Institute (EPRI) in 1985 [1] and the survey conducted by the Motor Reliability Working Group of the IEEE-IAS, which surveyed 1141 motors, two-fifth fault of all faults occurs due to the failure in bearing [2]. Unexpected failure in bearing causes costly shutdown, lapses in production and even human casualties. To avoid these catastrophic failures it's important to monitor the condition of the bearing. To minimize machine downtimes, a sensitive and robust monitoring system is needed to detect faults in their early stages and to provide warnings of possible malfunctions. Many condition monitoring techniques is available to monitor the health of bearing; these are wear debris, motor current, noise, temperature and vibration analysis etc. The vibration signal analysis is one of the most important methods used for condition monitoring and fault diagnosis, because they always carry the dynamic information of the system. Vibration monitoring is used for continuous as well as intermittent condition monitoring with the best sensitivity and immediate response to structure change. Bearings defects may be categorized as point or local defects and distributed defects. The distributed defects are surface roughness, waviness, and misaligned. The local defects include cracks, corrosion pitting and spalls on the rolling surfaces of bearing.

Vibration analysis is by far the most prevalent method for machine condition monitoring, especially for rotating equipment. Vibration signals measured from machine can be broadly categorized as stationary and non stationary signals. To analyze vibration signals, different techniques such as time domain, frequency domain and time–frequency domain are extensively used. In time-domain, monitoring the variation in statistical features is used for identification of bearing fault, frequency-domain method be the most commonly used approach in bearing fault detection, by which the bearing defects are detected based on the analysis of spectral information of vibration signals. Time domain and frequency domain are not suitable for the analysis of non-stationary signals. Non-stationary or transient signals can be analyzed by applying different time-frequency domain techniques such as the short-time Fourier transform (STFT), the Wigner-Ville distribution and the wavelet transform (WT). WT is the most popular time-frequency domain technique because it can achieve high frequency resolutions with sharper time resolutions. The commonly used wavelets algorithms are continuous wavelet transform (CWT), discrete wavelet transform (DWT) and wavelet and packet transform (WPT).

Fault diagnosis is nothing but the classification problem and artificial intelligence techniques based classifiers used to classify normal and faulty machine conditions. Machine fault classification problem consists of two main steps. First step extraction of features from raw vibration signals that demonstrate the information of fault from the raw signals and second step is to use these extracted features for fault diagnosis. This paper is mainly focused on to select the best Daubechies wavelet (db1 to db45) for statistical feature extraction and these extracted features fed to the ANN machine learning method for fault classification. Statistical features calculated by using vibration signals collected from healthy and faulty condition of induction motor bearing passed for the condition diagnosis. Statistical features are extracted from the time domain signal by using wavelet coefficients. These features are fed to a supervised attribute filter that can be used to select features. Selected features with the known output are used for training and testing of ANN. These features classifies according to the faulty and healthy condition of bearings.

II. LITERATURE REVIEW

Many researchers have been worked on vibration signal analysis techniques and numbers of research papers have been published by them. In past some decades, some study has been done in reviewing vibration techniques from a different point of view. P. D. Mcfadden and J. D. Smith developed the model to narrate the amplitude spectrum of vibration produced due to the single point defect at inner race of rolling element bearing under constant radial load, and again ext0end this model to describe the effect on vibration produced due to the multiple point defects at inner race of bearing [3-4]. Q. Sun and Y. Tang made singularity analysis across all scales of the continuous wavelet transform is performed to identify the location (in time) of defect-induced bursts in the vibration signals, modifying the intensity of the wavelet transform modulus maxima, defect-related vibration signature is highlighted and can be easily associated with the bearing defect characteristic frequencies for fault diagnosis [5]. Paya et used the Db4 wavelet to preprocess six different types of vibration signals obtained from a model drive line and ANN used to determine bearing health condition by classifying different kinds of fault [6]. S. Prabhakar et (2002) have used discrete wavelet transform as effective tool for the fault diagnosis of single and multiple bearing race faults [7]. N.G. Nikolaou and I.A. Antoniadis uses wavelet packet transform (WPT) to analyze vibration signals produced from the localised defect of bearings [8]. N. Saravanan et deals with extraction of features from the vibration data of a bevel gear box system by Morlet wavelet and classification of gear faults using support vector machine (SVM) and proximal support vector machine (PSVM) [9]. Zhitong et have carried out fault detection of induction motor using SVM technique for detecting broken rotor bars. In their experiment, induction motor was experimented with no fault, one broken bar, two broken bars and three broken bars [10]. Dong Wang et Traditional combination of Hilbert and Wavelet transforms is able to detect bearing fault, it may exhibit poor performance in identification of fault-related signatures, improvement done on this combination by using two indicators one for selection of most useful detailed signature and another for evaluation of capability of methods [11].

III. DAUBECHIES WAVELET

Calculating running averages and differences via scalar products with scaling signals and wavelets, the only difference between them consists in how these scaling signals and wavelets are defined. For the Daubechies wavelet transforms, the scaling signals and wavelets have slightly longer supports, i.e., they produce averages and differences using just a few more values from the signal. This slight change, however, provides a tremendous improvement in the capabilities of these new transforms. They provide set of powerful tools for performing basic signal processing tasks. These tasks include compression and noise removal for audio signals and for images, and include image enhancement and signal recognition. Daubechies wavelets-based element has enormous potential in the analysis of the problem with local high gradient. The scaling function Φ(x) and wavelet function β(x) of Daubechies wavelet both satisfy the following two-scaling relation:

$$\emptyset(x) = \sum_{i=0}^{N-1} P_i \emptyset(2x - i) \quad (1)$$

$$\beta(x) = \sum_{i=2-N}^{1} (-1)^i P_{1-i} \emptyset(2x - i) \quad (2)$$

Where, Pi = filter coefficients (i=0, 1, --------, N-1)

N = even integer

Daubechies scaling function can exactly represent any polynomial whose order is up to, but not greater than N/2 – 1 can be exactly represented as,

$$f(x) = \sum_{k=-\infty}^{\infty} C_k \emptyset(x - k) \quad (3)$$

IV. ARTIFICIAL NEURAL NETWORK

Artificial intelligence techniques such as fuzzy logic, artificial neural network (ANN) have been continuously and successfully applied for bearing fault detection and diagnosis. ANNs are made up of interconnected processing units known as neurons and it is adaptively changes its structure during learning phase. Artificial neural networks provide a parameterized class of nonlinear functions to learn nonlinear classifiers. Nonlinear functions are built up through composition of summation and sigmoid. ANN used to solve a variety of problems of pattern recognition, prediction, optimization and control. Back propagation algorithm is used for training purpose during which weights are adjusted for error minimization between ANN predictions and outputs. ANN is an adaptive system that changes its structure based on information that flows through the network. ANN perform a specific function during training by adjusting the interconnection weights and the process goes until the error between the network output and the desired output falls below the predetermined value, while the error is minimized by modifying the weights and biases. Having various architectures of ANN, multilayer feed forward Back Propagation algorithm is widely used for rotary machine elements.

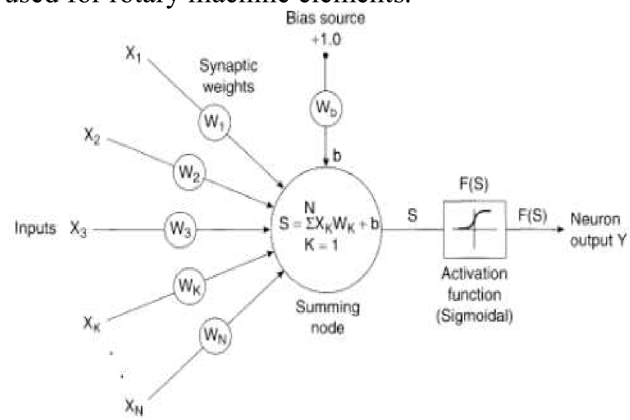


Fig.1. Model of a single non-linear neuron.

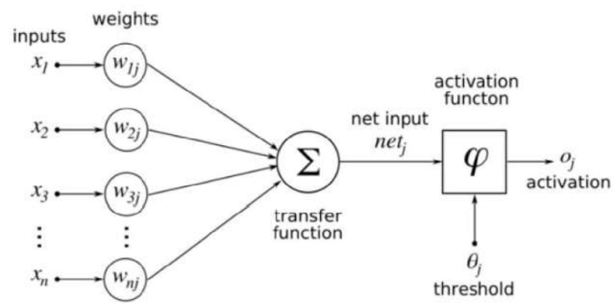


Fig.2. Artificial Neural Network (ANN)

A single neuron consists of synapses, adder and activation function. Bias is an external parameter of neural network. Model of a neuron shown in Fig. 1 can be represented by following mathematical model

$$y(k) = \emptyset\left(\sum_{i=1}^{p} W_{ki} X_I + W_{ko}\right) \quad (4)$$

Input vector comprising of 'p' inputs multiplied by their respective synaptic weights, and sum off all weighted inputs. A threshold (bias) is used with constant input. Activation function converts output into a limited range output.

V. METHODOLOGY

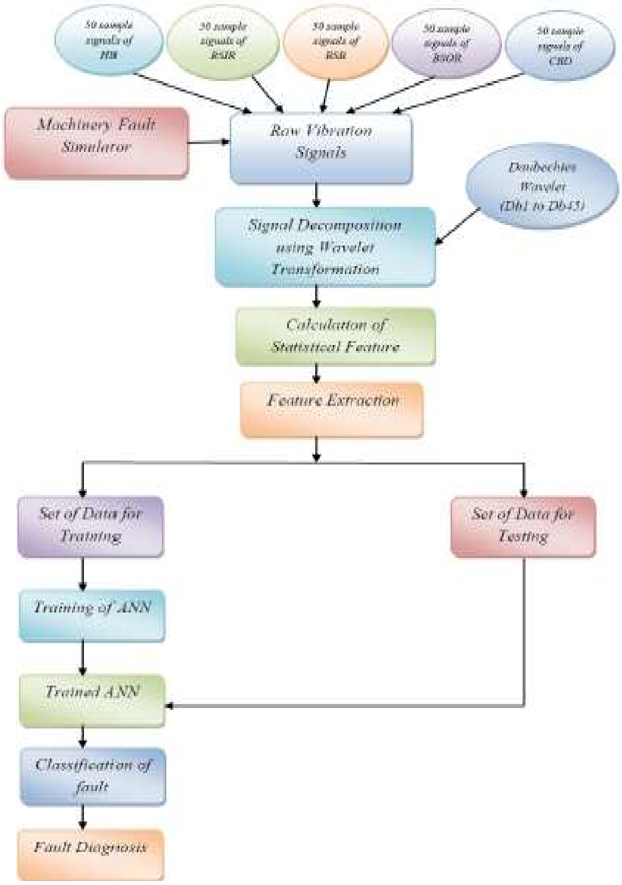


Fig.3.Flow chart of Bearing Fault Diagnosis

VI. EXPERIMENTAL SETUP

Test rig is used for experimentation to generate training and test data. Vibration response for bearing with no defect and bearing with faults are obtained. The rig is connected to OROS data acquisition system through proper instrumentation. Bearing used for experimental study is NSK-6203 and values of various parameters of bearing are given in table I. Data acquisition and analysis done by NVGate software. Data acquisition hardware consists of 8 input channels, for simultaneous high speed data acquisition sampling rate (51.2 k Samples/sec). A remote optical sensor with a visible red LED light source is used to measure rotor speed. Piezoelectric accelerometers are used for picking up the vibration signals from various stations on the rig. The data are collected for healthy and faulty bearing conditions in induction motor as shown in fig.4, fig.5, fig.6 and fig.7. A variety of faults on bearings are simulated on the rig at different speeds of 600, 1200 and 1800 rpm. Following four different bearing conditions are considered:

1. Healthy bearings (HB)
2. Spall on outer race of bearing (BSOR)
3. Spall on inner race of bearing (BSIR)
4. Spall on ball of bearing (BSB)
5. Combined bearing defect (CBD)

Tab.1. Parameters of bearing used for experiment

Parameter	**Value**
Bearing Number	6203
Bearing Type	Deep Groove Ball Bearing
Outer race diameter	40 mm
Inner race diameter	15.875 mm
Ball diameter	6.75 mm
No of balls	8
Width	12 mm
Contact Angle	0º

Fig.4. (a) Spall at inner race (b) Spall at ball (c) Spall at outer race (d) Healthy bearing

VII. FEATURE EXTRACTION

A set of statistical features are calculated from various Daubechies wavelet coefficients of raw vibration signals. These statistical features are as follows. The statistical features are elaborated as follows:

1) Kurtosis:

Kurtosis is normalized the fourth statistical moment of the signal. Kurtosis is a measure of whether the data are peaked or flat relative to a normal distribution.

$$K_{kur} = \frac{1}{n}\sum_{i=1}^{n}\left(k(t) - \bar{k}\right)^4 \quad (5)$$

2) Skewness:

Skewness is a measure of symmetry, or more precisely, the lack of symmetry

$$K_{skew} = \frac{1}{n}\sum_{i=1}^{n}\left(k(t) - \bar{k}\right)^3 \quad (6)$$

3) Variance:

Variance is the expectation of the squared deviation of a random variable from its mean, and it informally measures how far a set of (random) numbers are spread out from their mean.

$$K_{var} = \frac{1}{n}\sum_{i=1}^{n}\left(k(t) - \bar{k}\right)^2 \quad (7)$$

4) Standard Deviation (SD):

Standard deviation is measure of energy content in the vibration signal

$$K_{sd} = \sqrt{\left(\frac{1}{n-1}\sum_{i=1}^{n}(k_i - \mu)^2\right)} \quad (8)$$

5) Root Mean Square (RMS):

Root mean square (RMS), measures the overall level of a discrete signal.

$$K_{rms} = \sqrt{\left(\frac{1}{n}\sum_{i=1}^{n}k^2\right)} \quad (9)$$

Where, k= mean value of the discrete time signal
n= sample size
s= standard deviation.

VIII. RESULTS

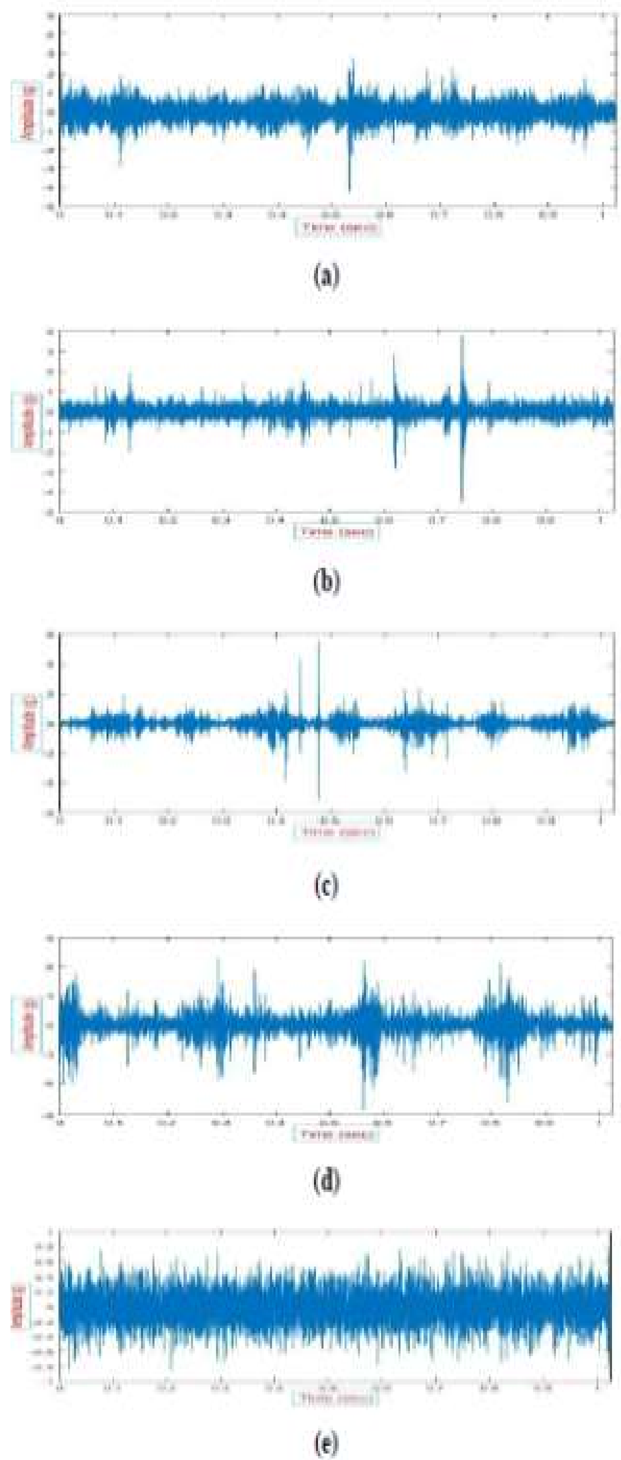
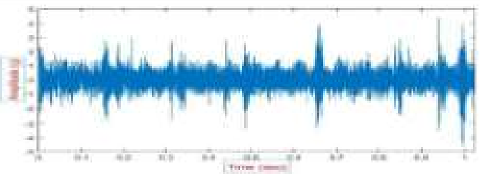
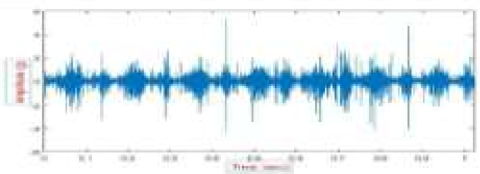


Fig.5.Vibration signals of different bearing condition at 600 rpm (a) inner race fault (b) outer race fault (c) ball fault (d) combined bearing fault (e) healthy bearing

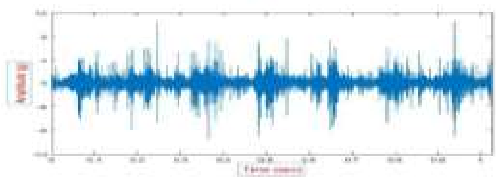
(a)



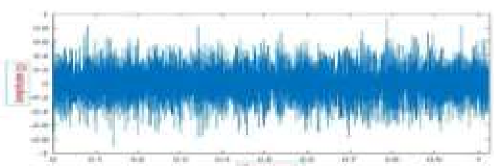
(b)



(c)

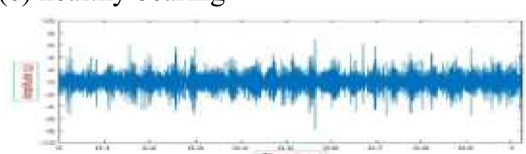


(d)

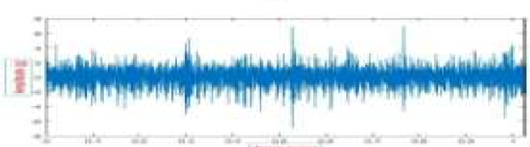


(e)

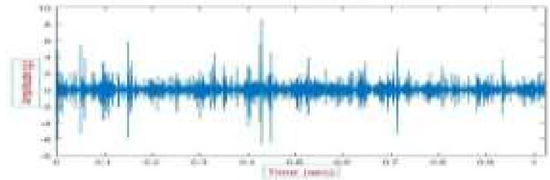
Fig.6.Vibration signals of different bearing condition at 1200 rpm (a) inner race fault (b) outer race fault (c) ball fault (d) combined bearing fault (e) healthy bearing



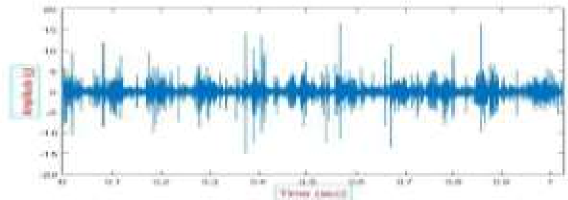
(a)



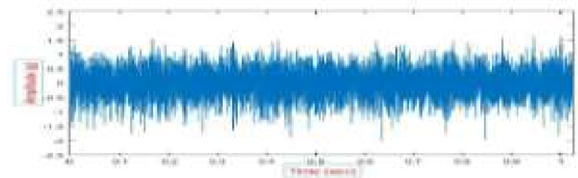
(b)



(c)



(d)



(e)

Fig.7.Vibration signals of different bearing condition at 1800 rpm (a) inner race fault (b) outer race fault (c) ball fault (d) combined bearing fault (e) healthy bearing

The vibration response at rotor speed 600, 1200 and 1800 rpm with different defects conditions without loader is shown in figs.5, 6 and 7 respectively. The five different bearing conditions are used as (a) bearing with spall on inner race surface (BSIR) (b) bearing with spall on outer race surface (BSOR) (c) spall on ball (BSB (d) combined bearing defect (CBD) (e) healthy bearing (HB). From the obtained response, it can analyzed that with healthy bearings the periodic responses are observed with low magnitude as shown in fig. 5, 6 and 7(e). When the spall has been introduced in the outer race of bearings, the time response is of non-periodic in nature with intermittency (with vertical response) as shown in figs.5, 6 and 7 (b). The more severe vibrations are appeared in the spectra with defect in inner race and balls as shown in figs.5, 6 and 7 (a) and (c). The combined defect has more impact on vibration spectra and response shows anarchy and beat like structure in fig. figs.5, 6 and 7 (d).

A. ANN Training and Testing

	Features					Speed (rpm)	Load (kg)	Class
	Standard deviation	Skewness	Kurtosis	Variance	RMS			
Amplitude Of features	0.09473	0.145294	1.063082	0.010321	0.2915	600	0	BSIR
	0.08620	0.017941	2.537462	0.397325	0.3217	1200	0	BSIR
	0.12840	0.215249	3.844771	0.246216	0.4124	1800	0	BSIR
	0.01666	-0.03742	2.311480	0.002483	0.1392	600	1	BSB
	0.05959	0.021045	1.801679	0.003682	0.1920	1200	1	BSB
	0.21858	-0.15215	2.725587	0.008312	0.2125	1800	1	BSB
	0.04061	-0.15895	3.603718	0.007932	0.0663	600	2	HB
	0.18732	0.014883	2.820007	0.002019	0.0853	1200	2	HB
	0.20612	0.09722	1.98393	0.003945	0.0958	1800	2	HB
	0.04934	0.175769	2.306253	0.012650	0.6695	600	3	BSOR
	0.01661	-0.08057	2.201347	0.003592	0.5919	1200	3	BSOR
	0.09606	0.158955	1.906349	0.052467	0.5590	1800	3	BSOR
	0.02484	-0.07319	1.532006	0.009011	0.3929	600	0	CBD
	0.03804	0.01658	2.659621	0.013566	0.7250	1200	0	CBD
	0.14526	0.213391	2.971920	0.019454	0.8778	1800	0	CBD

Tab.2 Input Data for ANN Training/Testing

Parameters	Details
Network type	Forward neural network
No of neurons in input layer	05
No of neurons in hidden layer	18
No of neurons in output layer	1
Transfer function	Sigmoid transfer function
Training rule	Back propagation
Train ratio	70%
Validation ratio	15%
Test ratio	15%

Tab.3 Detailed Parameters of ANN

Total 250 vibration signals are obtained by considering healthy and faulty bearing conditions. To convert the complex vibration signals into simplified signals with more resolution in time and frequency domain i.e. wavelet transformation, these raw signals are divided into sub-signals.Features selected by best Daubechies wavelet are used for training and testing of ANN. A sample of input vector data for ANN training/testing is shown in table. Total 75 instances and 7 features are used for study. These features include standard deviation, skewness, kurtosis, variance, RMS, load and speed. The details of neural network used for classification of faults given in below table.

Parameters	ANN
	Daubechies wavelet (Db4)
Correctly classified instances	71 (94.67%)
Incorrectly classified instances	04 (5.33%)
Total number of instances	75

Tab.4 Evaluation of the success of numeric prediction

ANN has correctly predicted 14, 15, 15, 14 and 13 cases, for a (a) bearing with spall on inner race surface (BSIR) (b) bearing with spall on outer race surface (BSOR) (c) spall on ball (BSB) (d) combined bearing defect (CBD) (e) healthy bearing (HB. Artificial Neural network efficiency of Daubechies wavelet (Db1to Db45) family shown in fig.8, from this graph get maximum efficiency at Db4 i.e. 94.67%. The values of various measures of correctly classification of faults are given in tab.4.

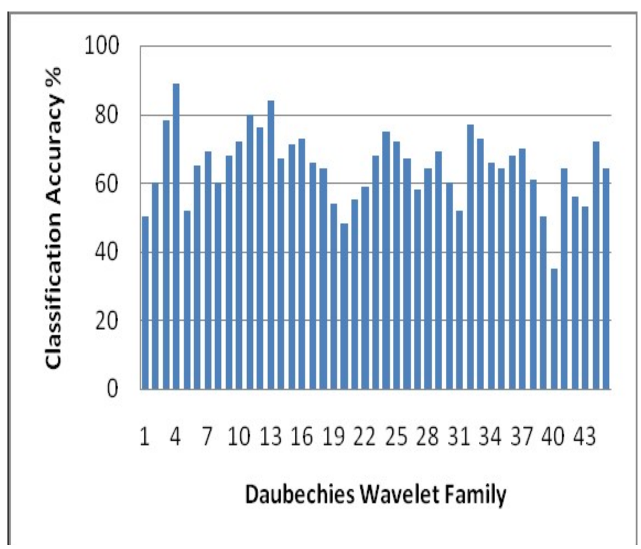


Fig.8 Classification Accuracy for Daubechies wavelet family

IX. CONCLUSION

This study presents Features are extracted from Wavelet Coefficient vibration signals using statistical techniques. The roles of different vibration signals, obtained without loader and at various speeds are investigated Wavelet features were extracted for all the wavelet coefficients on the basis of maximum energy of signal and for all the signals using the Daubechies wavelets 'db1' to 'db45'.It has been found that db4 gives best efficiency i.e. 94.67%.The results show the potential application of ANN for developing a knowledge base system which can be useful for early diagnosis of fault for applying condition based maintenance to prevent catastrophic failure and reduce operating cost of induction motor.

ACKNOWLEDGMENT

I am highly greatly thankful to the Principal, Dr. H. N. Kudal and Dr. K. B. Kale, Head of Department of Mechanical Engineering, P.D.V.V.P.COE, Ahmednagar for their kind support and guidance.

REFERENCES

1) *'IEEE recommended practice for the design of reliable industrial and commercial power systems', IEEE Std. 493-(1997)[IEEE Gold Book], Appendix H. [12]*
2) *P. F Allbrecht. J. C. Appiarius. and R. M. McCoy, 'Assessment of the reliability of motors in utility applications – updated', IEEE Transactions on Energy Conversion. Vol. I. No. I. pp. 39-46, 1986.*
3) *McFadden, P. D., & Smith, J. D. (1984). Model for the vibration produced by a single point defect in a rolling element bearing. Journal of Sound and Vibration, 96(1),69–82.*
4) *McFadden, P. D., & Smith, J. D. (1985). The vibration produced by multiple point defects in a rolling element bearing. Journal of Sound and Vibration, 98(2), 263–273.*
5) *Q. Du and S.Yang, "Improvement of the EMD method and applications in defect diagnosis of ball bearings," Measurement Science and Technology, 17, pp. 2355-2361, 2006.*
6) *Paya, B.A., Esat, I.I. and Badi, M.N.M., 1997, "Artificial neural networks based fault diagnostics of rotating machinery using wavelet transforms as a preprocessor", Mechanical Systems and Signal Processing, Vol 11, pp.751–765.*
7) *Prabhakar, S., Mohanty, A. R., & Sekhar, A. S. (2002). Application of discrete wavelet transform for detection of ball bearing race faults. Tribology International, 35, 793–800.*
8) *N. Tandon, "A comparison of some vibration parameters for the condition monitoring of rolling element bearings," Measurement, 12, pp. 285-289, 1994.*
9) *Saravanan, N., Siddabattuni, V.N.S Kumar and Ramachandran, K.I., 2008, "A comparative study on classification of features by SVM and PSVM extracted using Morlet Wavelet for fault diagnosis", Expert systems with applications, Vol. 35, pp. 1351-1366.*
10) *R. Heng and M. Nor, "Statistical analysis of sound and vibration signals for monitoring rolling element bearing condition," Applied Acoustics, 53, pp. 211-226, 1998.*
11) *R. Randall, J. Antoni, and S. Chobsaard, "The relationship between spectral correlation and envelope analysis in the diagnostics of bearing faults and other cyclostationary machine signals," Mechanical Systems and Signal Processing, 15, pp. 945-962, 2001.*
12) *J. Stack, T. Habetler, and R. Harley, "Fault-signature modeling and detection of inner-race bearing faults," IEEE Transactions on Industrial Application, 42, pp. 61-68, 2006.*
13) *G. Luo, D. Osypiw, and M. Irle, "On-line vibration analysis with fast continuous wavelet algorithm for condition monitoring of bearing," Journal of Vibration and Control, 9, pp. 931 947, 2003.*