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Bearing Fault Diagnosis Based on Statistical Feature Extraction in Time and Frequency Domain and Neural Network

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ABSTRACT:

Bearing is an important component of almost every mechanical system used in industrial environment. Hence the defect in bearing must be detected in advance to avoid catastrophic failure. This paper aims to diagnose the defect in bearing automatically using machine intelligence. A condition monitoring setup is designed for analyzing the defects in outer race, inner race and rolling element of bearing. MATLAB is used for feature extraction and neural network is used for diagnosis. It is found that the amplitude at defect frequencies may not always clearly indicate the increment; hence statistical analysis of bearing signature is a better alternative. The work presents an experimental investigation carried out on an experimental set-up for the study of bearing fault at same angular speed and load. This paper proposes an approach of damage detection in which defects in bearing are accurately analysed using vibration signal and neural network.

KEYWORDS:

Vibration analysis; Bearing fault; Statistical feature extraction; Artificial neural network

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1. Introduction

Modern mechanical equipments are controlled automatically and with high precision. With the rapid development of science and technology, now it is required to deal with the equipment breakdown promptly and accurately which will be very helpful in terms of enhancing its reliability and decreasing downtime. Rotating machinery plays an important role in any industry while bearings are inevitable part of any rotating machinery, and their fault detection and diagnosis are of great importance. To this end, researches focused on extracting the features relevant to the bearing conditions from mechanical vibration signals which contain abundant diagnostic potential. Aim of this work is to utilize these features for automatic diagnosis. Vibration spectrums for healthy and unhealthy machines are different. All machines with different moving mechanical parts give rise to sound and vibration. Each machine has a specific vibration signature related to the construction and the state of the machine. More the number of parts, more complex will be the spectrum.

The vibration signature of the machine will also change if the state changes from static to dynamic. A change in the vibration signature can be used to detect incipient defects before they become critical. This is the basics of many condition monitoring methods. Condition monitoring using vibration measurement can save money through increased maintenance efficiency and by reducing the risk of serious accidents by preventing breakdowns. Machine parts are inherently subjected to dynamic contact forces with high amplitudes. In the region close to the contact surfaces the material stress is locally very high. Thus, after sometime of operation a localised defect growing with time will appear. The defects may be localised surface damage, wear or inadequate lubrication, etc. Vibration signatures of non-defective components are characterized by particular amplitude and frequency. If a defect/fault is present in the system, depending upon the location, it will modify the vibration signature, which is a basic assumption in machine condition monitoring.

Rolling bearings are mainly subjected to vibrations because of inherent nonlinearity, which arises due to Hertzian load deformation relationship, varying compliance, clearance, local and distributed defects, and so forth. Though the vibration studies of bearings in presence of distributed defects have been reported in depth by many researchers, still there is a scope to work in this area. Tandon et al [1] have reviewed the vibration and acoustic measurement methods for the detection of defects in rolling element bearings. Both localised and distributed defects are determined by vibration measurement. The techniques in vibration measurement are time domain and frequency domain. In time domain the different parameters covered are RMS (Root mean square) level, crest factor, probability density, mean, variance, coefficient of skewness, kurtosis, etc. Kurtosis is the most effective method and shock pulse method also gaining wide acceptance in time domain. In frequency domain wavelet transform method is useful to extract very weak signal for which Fourier transform becomes ineffective.

Acoustic measurement is used for detection of bearing defects, it involves measurement of both sound pressure and intensity but sound intensity gives better results. Also an automated interpretation of data is done by pattern recognition technique and neural network to both time and frequency domain data for detection of defects in rolling element bearings. Randall et al [2] have investigated how bearing faults can be simulated digitally, including the random fluctuations in spacing of the excitation pulses resulting from clearances in the bearing and the changing load angle experienced by each rolling element. The simulated bearing fault signals were used to investigate the efficient application of Self-Adaptive Noise Cancellation (SANC) in conjunction with envelope analysis in order to remove discrete frequency masking signals. Lin et al [3] have applied a denoising method based on wavelet analysis for feature extraction from mechanical vibration signals generated in rolling bearing diagnosis and gear-box diagnosis. For bearing-when the rollers pass through the defect, an impulse may appear.

According to the period of the impulse, we can judge the location of the defect using characteristic frequency formulae. Williams et al [4] have analysed bearing defects induced by scratching the surface, introducing debris into the lubricant or machined with an electrical discharge. They recorded root mean square, peak value, kurtosis and crest factor through the test duration from accelerometers and acoustic emission sensors and used envelop analysis for damage detection. The fatigue life of the bearing is determined experimentally. The techniques used for signal analysis are High-Frequency Resonance Technique (HFRT) and the Adaptive Line Enhancer (ALE). Randall et al [5] have given a quantitative evaluation of the degree to which information about bearing faults can be extracted by frequency analysis of raw signal. Also he demonstrated the relationship between the classical envelope analysis (and in particular, analysis of the squared envelope) and spectral correlation analysis, which is one of the tools used to characterize cyclostationary signals.

He point out how experience already gained in using envelope analysis can be used to improve results obtained by spectral correlation of cyclostationary signals more generally. Lou et al [6] have used wavelet transform to process the accelerometer signals and to generate feature vectors. An Adaptive Neural-Fuzzy Inference System (ANFIS) was trained and used as a diagnostic classifier. For comparison purposes, the Euclidean vector distance method as well as the vector correlation coefficient method was also investigated. The results demonstrate that the developed diagnostic method can reliably separate different fault conditions under the presence of load variations. Characteristic components associated with the continual increase in fault severity (fault size from 7 to 21 mils) as well as abrupt changes in defect size could be detected. Using the wavelet transform together with fuzzy logic to quantify the degree of severity of an incipient fault is a promising technique for prognostics. A more challenging task is to explore identifying simultaneous multiple faults through the smart use of time-scale analysis and other techniques in systems science and engineering.

Al-Ghamd et al [7] have applied vibration and Acoustic Emission (AE) for bearing diagnosis particularly for identifying the presence and size of a defect on a bearing loaded in radial direction using RMS and kurtosis. Comparisons between AE and vibration analysis over a range of speed and load conditions are presented. It is found that AE offers earlier fault detection and improved identification capabilities than vibration analysis. Furthermore, the AE technique also provided an indication of the defect size, allowing the user to monitor the rate of degradation on the bearing; unachievable with vibration analysis. Also, AE RMS maximum amplitude and kurtosis have all been shown to be more sensitive to the onset and growth of defects than vibration measurements. A relationship between the AE burst duration and the defect length has been presented. Tse et al [8] have worked on an effective algorithm which can be employed to recover the desired vibration out of the aggregated source of vibrations. The Blind Equalization-(BE) based Eigenvector Algorithm (EVA) has proven its effectiveness in recovering the overwhelmed vibration signal in the application of machine fault diagnosis.

Author found that the enhanced EVA has more prospects for complicated vibration recovery. Shanlin et al [9] have shown through an experiment that the approach of combining wavelet transform and neural network is effective for fault diagnosis of turbine-generator set. This novel approach solved two key problems: the fault extraction and the fault pattern recognition. Rafiee et al [10] introduced an automatic feature extraction system for gear and bearing fault diagnosis using wavelet-based signal processing. Four statistical features were selected: standard deviation, variance, kurtosis, and fourth central moment of Continuous Wavelet Coefficients of Synchronized Vibration Signals (CWC-SVS). They found that the Daubechies 44 (db44) has the most similar shape across both gear and bearing vibration signals. Boumahdi et al [11] presented a methodology for the extraction of expert rules in the identification of bearing defects in rotating machinery. Data sets are collected from signals measured by piezoelectric accelerometer fixed on bearings of an experimental set-up.

Temporal and frequential analyses are then conducted to determine statistical parameters (Crest Factor (CF), kurtosis, root mean square) and spectrums (Fast Fourier Transform, envelope spectrum). The decision tree is then constructed by applying C4.5 algorithm on the dataset, and thus expert rules are established. It is experimentally proved that the J48 algorithm is a good classifier and it can offer a decision aid to accurately detect and identify bearing defects. Eftekharnejad et al [12] have attempted to investigate the comparative effectiveness of applying the kurtogram to both vibration and AE data from a naturally damaged bearing. From the observation it was evident that AE was more sensitive in detecting incipient damage than vibration, reinforcing other investigators. Wang et al

[13] have detected the multiple faults in bearing using adaptive spectral kurtosis analysis of the vibration signal from a single sensor. He proposed a multi-fault detection method based on the Adaptive Spectral Kurtosis (ASK) analysis of the vibration signal from single sensor.

The performance of the proposed method in fault detection of the rolling element bearings is validated using simulation data and experimental signals from a bearing with multiple faults and two faulty bearings. Zhang et al [14] have presented a novel procedure based on Ensemble Empirical Mode Decomposition (EEMD) and optimized Support Vector Machine (SVM) for multi-fault diagnosis of rolling element bearings. They found that the proposed method outperforms other methods and can be used for fault classification of complicated and sensitive systems. Wang et al [15] have proposed a hybrid technique to enhance health diagnosis of rotating machines under varying speed conditions. The effectiveness of the hybrid technique is demonstrated by numerical simulation and experimental studies in identifying bearing structural defects under varying operating conditions. Borghesani et al [16] have worked on the coupling of kurtosis based-indexes and envelope analysis, which is one of the most successful and widespread procedures for the diagnostics of incipient faults on rolling element bearings.

The narrow cyclic focus of the proposed index may as well entirely substitute the traditional Squared Envelope Spectrum (SES), providing as well a much simpler and fast index for an online automatic diagnostic/prognostic of rolling element bearings. Du et al [17] have utilized the multifractal features, combined with scaling exponents, multifractal spectrum, and log cumulants, to classify various fault types and severities of rolling element bearing, and the classification performance of each type features and their combinations are evaluated by using SVMs. The feature selection method based on distance evaluation technique is exploited to select the most relevant features and discard the redundant features, and therefore the reliability of the diagnosis performance is further improved. Patel et al [18] worked on the detection of local defects existing on races of deep groove ball bearing in the presence of external vibrations using an envelope analysis and Duffing oscillator.

In this work an attempt is made to make use of different statistical parameters in time and frequency domain for automatic diagnosis of bearing defects when it is not possible by observing the frequency spectrum. The literature provides the analysis in time domain, frequency domain and time-frequency domain. Here an attempt is made to make use of the important and most significant features of bearings in each domain. These features extracted from vibration signals are used by a classifier called artificial neural network for fault diagnosis.

2. Methodology

When there is a relative motion between two machine parts, one of which supports the others. The supporting member is called bearing. Generally only 10% of bearings can give design life while 40% of bearings fail by improper lubrication and 30% due to misalignment.

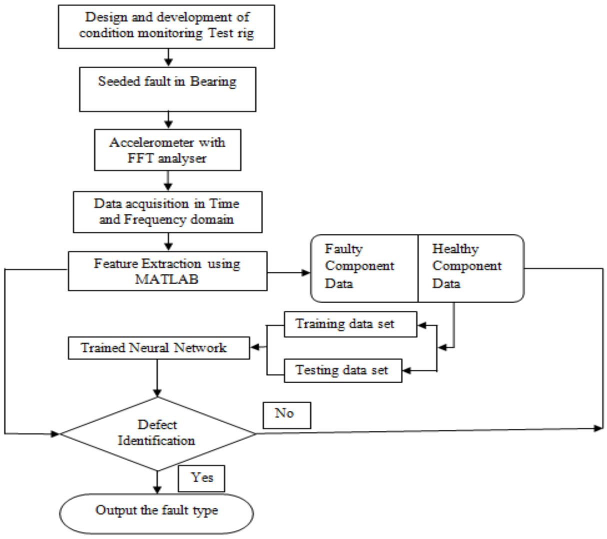


Fig. 1: A flow chart of methodology

In total 41% of mechanical system wear out failures are due to bearings [1]. Ideally, roller bearings cause little vibration. However, varying contact forces and surface roughness always give some vibration due to defect at rolling contact zone. A localised surface defect in a bearing, such as a crack or a spall, generates a vibration impulse each time it enters a contact zone. This impulse is very short compared to the time between impulses. The shape of the impulses is similar to the shape of the impulses caused by a localised surface damage. Due to the short duration, the energy from the impulse is spread over a wide frequency range and thus hard to detect in a spectrum. The impulse usually excites one or several resonances in the transfer path between the contact zone and the sensor. The impulse can be seen as an amplitude modulation of the resonant vibration. The high frequency envelope method uses resonant amplification to detect bearing defects. The different types of defects in bearings are-installation defect such as bearing race misalignment, non uniform radial or axial loading, defect developed in operation such as surface wear, crack, spall, inadequate lubrication, defect on neighbouring elements which produce dynamic load such as shaft wobbling, jointed coupling defect, gear interaction defect etc.

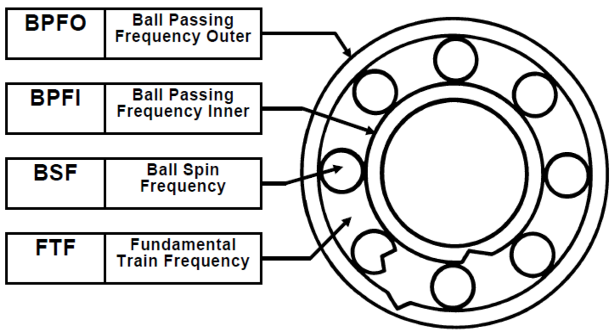


Fig. 2: Ball bearing with defect frequency

The defect in a bearing can be identified by knowing the defect frequency. The impulses from a localised bearing defect occur with a certain characteristic defect frequency as shown in Fig. 2. The characteristic frequency depends on the damage location. A bearing with finite number of rolling elements generates dynamic forces with a single characteristics frequency, called rolling element passing frequency. Whenever a rolling element passes close to a machine part vibrations are excited in part. The damaged bearing spectrum and the reference spectrum of the undamaged bearing are required to be compared for increase in amplitude at the defect frequency. This requires knowing in advance about the defect frequencies. Hence formulas defining the characteristic frequencies for damages located on the rolling elements as well as on the inner and outer races can be found as given in Eqns. (1) to (4):

$$BPFO = \frac{N \times n}{2}\left(1 - \frac{d}{D}\cos b\right) \tag{1}$$

$$BPFI = \frac{N \times n}{2}\left(1 + \frac{d}{D}\cos b\right) \tag{2}$$

$$BSF = \frac{N}{2}\frac{D}{d}\left(1 - \left(\frac{d}{D}\cos b\right)^2\right) \tag{3}$$

$$FTF = \frac{N}{2}\left(1 - \frac{d}{D}\cos b\right) \tag{4}$$

Where BPFO and BPFI denote Ball Pass Frequency Outer and Ball Pass Frequency Inner respectively. BSF and FTF denote Ball Spin Frequency and Fundamental Train Frequency respectively. N is shaft speed, n is number of rolling elements, D is pitch circle diameter of rolling elements, d is diameter of rolling element and b is contact angle.

This needs the geometrical dimensions of bearing and speed with which it is rotating [18]. The defects to be analysed are outer race defect- bearing with crack in outer race, spall on surface, outer race severely rough to be observed at a BPFO, Inner race defect- bearing with crack in inner race, surface damage due to contamination, corrosion, electrical fluting, minor dents on races due to bearing current, inner race severely rough to be observed at BPFI, rolling element defect-one ball damaged (Minor/ Large dents on balls), crack, surface damage due to excessive load which gives rise to vibration at 3 to 10 times shaft frequency (X) and also at 1X or very high frequencies to be observed at BSF, and cage defect to be observed at FTF. The conventional methodology used for the detection of faults using vibration monitoring involves stages such as first verify the fault by preliminary analysis, then collect the further information for its analysis and evaluate the evidence of defect. If fault is not located then carry out further tests in a logical sequence to exactly locate the fault. Once the fault/defect is located rectify the problem. If required check all systems for any other fault. The knowledge needed to an analyst for accurate defect detection requires understanding of the system in which the problem exists and having the ability to apply a logical diagnostic routine. It is a need of time to change this conventional methodology of defect detection into an automatic detection of defect in a machine using machine intelligence. The methodology used for this work [19] involves stages such as design and development of a condition monitoring test rig for bearing, introduction of seeded fault in bearing, vibration measurement using FFT (Fast Fourier Transform) analyser, feature extraction using MATLAB, classification of features using neural network and identification of unknown defect using trained neural network.

The different bearing fault conditions introduced are Good Bearing (GB), Ball defect (BD), Inner race Defect (ID), and Outer race Defect (OD). The flow chart of the methodology is as shown in Fig. 1. The defects are produced on bearing and vibration measurement is done using FFT analyser in time and frequency domain. These signals are then exported to MATLAB using DDS 2011 EN software. The 23 statistical features are extracted from time and frequency domain signal using MATLAB. These features are then utilized for diagnosis of bearing defects using artificial neural network. The numbers of readings are taken for training and testing of neural network. The accuracy of detection depends upon the number of readings taken. The unknown samples are used for evaluation of trained network. The network identifies the fault condition, if any, in the given sample. In this way defect is identified by machine intelligence without vibration analyst.

3. Experimental details

Fig. 3 shows the condition monitoring test rig used for the study of effect of bearing defect on vibration signature. The test rig consists of a single stage spur gear box for applying load on bearing under test, having gears made from steel with a module of 2.11 mm, pressure angle 200, pinion teeth 26, gear teeth 46, and 20 mm face width. It also consists of a shaft with rotor disks and the support bearings. The shaft at one end is connected to a drive unit consisting of a 0.5 HP D.C. motor, 2.6 amp, 230 volt, maximum speed = 2880 rpm and voltage regulator for changing the speed through a flexible coupling. The flexible coupling connecting the main shaft to the drive unit isolates the shaft from the vibrations of the drive unit to a certain extent. The motion is transmitted to the dynamometer (an arrangement to apply load on gear box) unit by a single stage spur gearbox with a speed ratio of 1.77:1 through a V- Belt drive. The basic parameters of the test rig are fixed after considering the relations between operating speed and frequencies of vibrations along with the limitations of the measuring and analyzing equipment available.

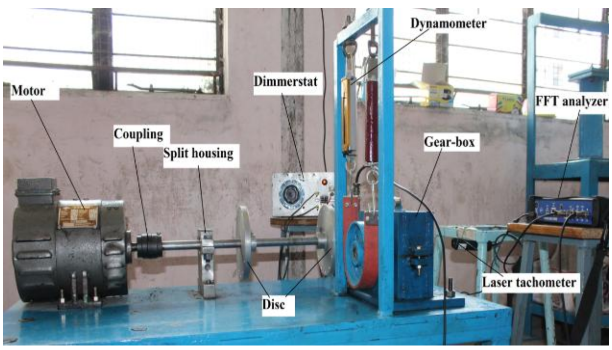


Fig. 3: Photographic view of condition monitoring test rig

General manufacturing considerations are also taken into considerations. The bearing used for analysis is 6004 type single row deep groove ball bearing, it is a high quality bearing used in axial fans, motors, drive axles, clutch, idler wheels, HVAC, snow mobiles and many other industrial applications. These are made from chrome steel, pre-lubricated with grease and have rubber seals on both sides to protect the bearings from dust or any other types of contamination. The detailed specification of this bearing with bearing characteristics defect frequencies is as indicated in Table 1.

Table 1: Specification of bearing

Parameter	Specification
Type	6004
Diameter of bore	20 mm
Outer diameter	42 mm
Width	12 mm
Basic dynamic load rating	4500 N
Basic static load rating	7350 N
Shaft rotation frequency	16.67 Hz
Number of elements	9
PCD of balls	31 mm
contact angle	0°
rolling element diameter	6.35 mm
Ball pass frequency at outer race	59.63 Hz
Ball pass frequency at inner race	90.36 Hz
Ball spin frequency	38.97 Hz
Fundamental train frequency	6.63 Hz

Fig. 4: Photographic view of accelerometer located on bearing

An accelerometer having sensitivity 100 mV/g (g = 9.81m/s^2) is placed on bearing as shown in Fig. 4, in radial vertical direction on split type of housing supporting a shaft carrying two disks to measure the vibration amplitude in displacement, velocity and acceleration with the help of a 4 channel FFT analyser. The sampling frequency used is 16384Hz and recordings of 500ms duration are obtained. Vibration readings are collected for a range of frequency 0-1600Hz, number of lines 12800, 2 averages and in the Hanning FFT window. The first channel is dedicated for the accelerometer signal, while the speed is measured by using a laser tachometer. Seeded faults in bearing are as shown in Fig. 5. Local circular defect of 0.8 mm in size on the outer and inner race of the bearing is created by electric discharge machining (EDM) as indicated in Fig. 5 (a)-(b), while the ball defect is of 0.5 mm as shown in Fig. 5 (c). The classification here is aimed to determine which type of bearing element is defective [12-15].

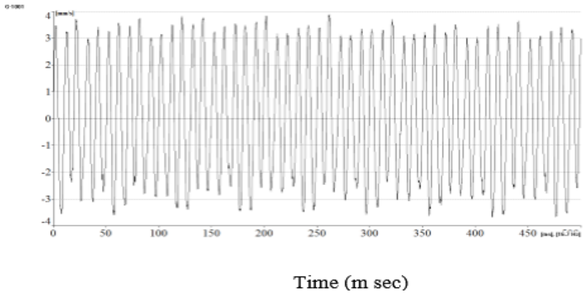
a). Outer race defect (0.8 mm hole)

(b). Inner race defect (0.8 mm hole)

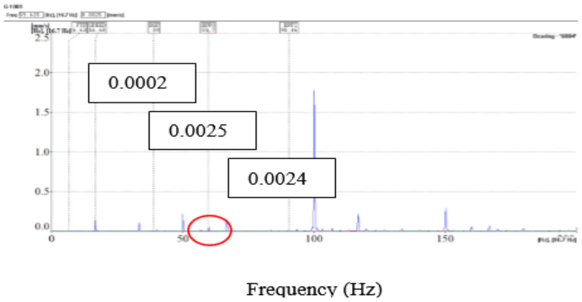
c). Ball defect (0.5 mm hole)

Fig. 5: Photographic view of seeded faults in bearing

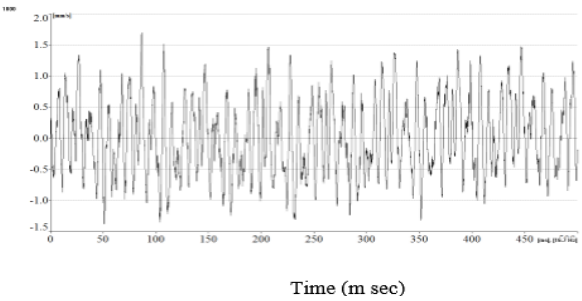
To analyse the effect of bearing fault, the data are collected for the following conditions such as Good Bearing (GB), Ball defect (BD), Inner race Defect (ID), and Outer race Defect (OD). For each condition thirty signals/ readings are acquired for a constant shaft speed of 1000 rpm (16.6Hz). In the present study results from a representative test conducted on a healthy bearing and defective bearings is presented. The vibration signals collected in time and frequency domains are as shown in Fig. 6 (a) - (b) for good bearing condition, (c) - (d) for defective outer race, (e) - (f) for defective ball condition and (g) - (h) for defective inner race. The increase in amplitude at BPFO 59.63Hz is 5 times the good condition in frequency domain Fig. 6 (b) - (d) indicates the presence of defect in outer race of bearing also the change in time domain signal Fig. 6 (a) - (c) is observed. Many times the amplitude of defect frequency will not be visible clearly even there is presence of defect in the system as indicated in frequency spectrum Fig. 6 (f) for ball defect frequency at 38.9Hz. The increase in amplitude at ball defect frequency is 4.5 times the good condition while the percentage increase in amplitude of inner race defect frequency is 3 times the good condition as indicated in Fig. 6 (h). The amplitude at defect frequency depends upon the speed and loading on bearing. Very small amplitude may not give indication of defect but there will be some change in overall the signature, which could be found by statistical analysis of it. At the same time if we compare time domain signal in Fig. 6 (a), (c), (e), and (g) we could observe the change, hence in such a case this methodology will be useful to find the defective condition more accurately. The amplitude of vibration is measured in terms of mm/s for both time and frequency domain signal.



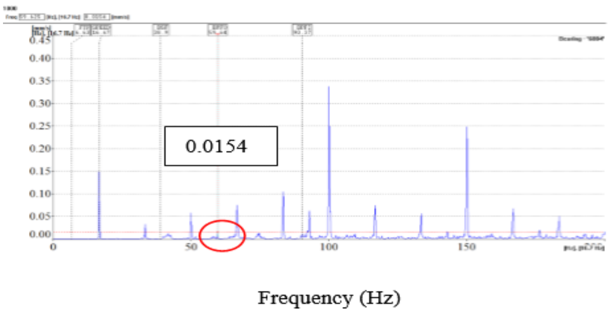
a). Time domain signal (GB)



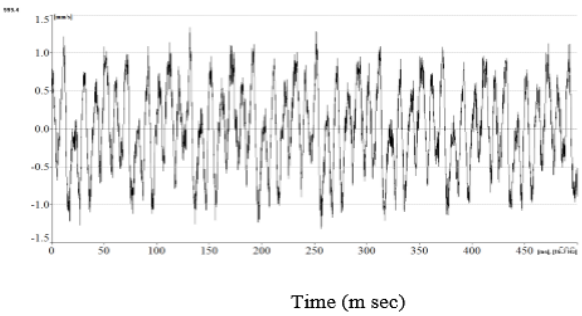
b). Frequency domain signal(GB)



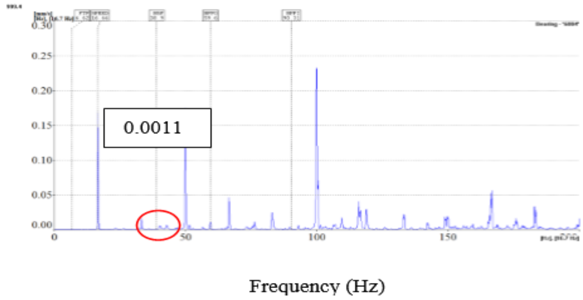
c). Time domain signal (OD)



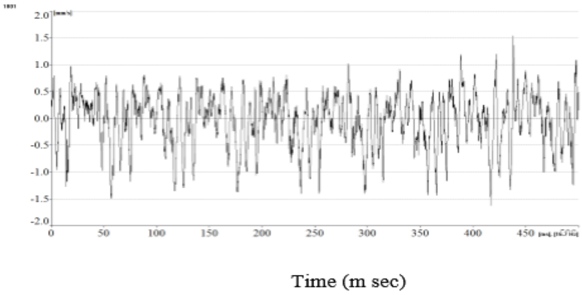
d). Frequency domain signal (OD)



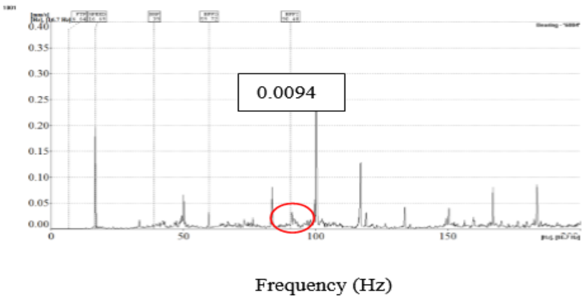
e). Time domain signal (BD)



f). Frequency domain signal (BD)



g). Time domain signal (ID)



h). Frequency domain signal (ID)

Fig. 6: Vibration response of good compared with defective bearing conditions with a shaft speed of 1000 rpm

3.1. Feature extraction

The vibration signals acquired during the tests are processed with significant efforts. The primary aim here is to calculate a number of statistical parameters in time and frequency domain and check their diagnostic capacity for the actual condition monitoring of bearings. In the literature, the research groups involved in long term bearing testing using number of sensors at different locations. They have mainly used higher order moments and their combinations to form diagnostic parameters with interesting behaviour during the tests [1-5]. In this work, various features are extracted from single sensor to save the time and money. Table 2 shows the features from the time and frequency domain that are calculated from the collected vibration waveforms. They are typical statistical moments and their combinations.

3.1.1. Statistical parameters

The statistical parameters from the time and frequency domain are calculated, as explained below with reference to Table 2. For time domain signal, X (n) is a signal series for n = 1, 2, . . . , N, where N is the number of signal samples. The probability density of acceleration of a bearing in good condition has a Gaussian distribution, whereas a damaged bearing results in non-Gaussian distribution with dominant tails because of a relative increase in the number of high levels of acceleration.

Table 2: Statistical parameters

Time domain parameters	Frequency domain parameters
$p1=\frac{\sum_{n-1}^{N}x(n)}{N}$, $p2=\sqrt{\frac{\sum_{n-1}^{N}(x(n)-p_1)^2}{N-1}}$	$p12=\frac{\sum_{m-1}^{M}y(m)}{N}$, $p13=\frac{\sum_{m-1}^{M}(y(m)-p_{12})^2}{(M-1)}$
$p3=\left(\frac{\sum_{n-1}^{N}\sqrt{\lvert x(n)\rvert}}{N-1}\right)^2$, $p4=\sqrt{\frac{\sum_{n-1}^{N}(x(n))^2}{N}}$	$p14=\frac{\sum_{m-1}^{M}(y(m)-p_{12})^3}{M\left(\sqrt{p_{13}}\right)^3}$
$p5=\max\lvert x(n)\rvert$	$p15=\frac{\sum_{m-1}^{M}(y(m)-p_{12})^4}{M\left(\sqrt{p_{13}}\right)^2}$, $p16=\frac{\sum_{m-1}^{M}f_m y(m)}{\sum_{m-1}^{M}y(m)}$
$p6=\frac{\sum_{n-1}^{N}(x(n)-p_1)^3}{(N-1)p_2^3}$	$p17=\sqrt{\frac{\sum_{m-1}^{M}(f_m-p_{16})^2 y(m)}{M}}$
$p7=\frac{\sum_{n-1}^{N}(x(n)-p_1)^4}{(N-1)p_2^4}$	$p18=\sqrt{\frac{\sum_{m-1}^{M}f_m^2 y(m)}{\sum_{m-1}^{M}y(m)}}$, $p19=\sqrt{\frac{\sum_{m-1}^{M}f_m^4 y(m)}{\sum_{m-1}^{M}f_m^2 y(m)}}$
$p8=\frac{p_5}{p_4}$, $p9=\frac{p_5}{p_3}$	$p20=\frac{\sum_{m-1}^{M}f_m^2 y(m)}{\sqrt{\sum_{m-1}^{M}y(m)\sum_{m-1}^{M}f_m^4 y(m)}}$, $p21=\frac{p_{17}}{p_{16}}$
$p10=\frac{p_4}{\frac{1}{N}\sum_{n-1}^{N}\lvert x(n)\rvert}$	$p22=\frac{\sum_{m-1}^{M}(f_m-p_{16})^3 y(m)}{Mp_{17}^3}$
$p11=\frac{p_5}{\frac{1}{N}\sum_{n-1}^{N}\lvert x(n)\rvert}$	$p23=\frac{\sum_{m-1}^{M}(f_m-p_{16})^4 y(m)}{Mp_{17}^4}$

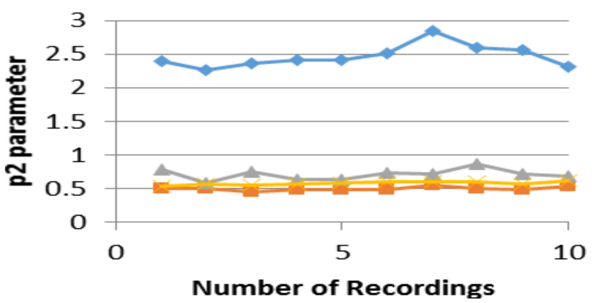
Instead of studying the probability density curves, it is often more informative to examine the statistical moments of the data. The first moment called mean value p1, standard deviation p2, variance p3, and p4 is the root mean square (RMS) value of signal are measure of central tendency, while p5 is the absolute maximum of the signal. The third moment normalized with respect to the cube of standard deviation is known as the coefficient of skewness p6, is a measure of unsymmetry about the mean. The fourth moment, normalized with respect to the fourth power of standard deviation, is quite useful, called kurtosis p7 whilst the crest factor p8, i.e., the ratio of peak value to RMS value of amplitude, these are measure of variation from mean. The parameter p9 to p11 results as a combination of previous parameters. For an undamaged bearing with Gaussian distribution, the kurtosis value is close to 3. A value greater than 3 is judged by itself to be an indication of impending failure and no prior history is required.

However, one disadvantage is that the kurtosis value comes down to the level of an undamaged bearing (i.e., 3) when the damage is well advanced. Therefore, it has been suggested to measure kurtosis in selected frequency bands. Local defects can also be detected in the time domain by displaying the vibration signal observing the presence of periodic peaks due to impact of the rolling element with the defects. Similarly y (m) is the Fourier transform for m = 1, 2, ... M, where M is the number of spectrum lines, f_m is the frequency value of the m^{th} spectrum line. The parameter which is, a measure of central tendency in frequency domain is p12 the mean. The parameter which is measure of variation from mean is p13 the variance, p14 the third moment, and p15 the forth moment. While p16 is the grand mean, p17 standard deviation with respect to grand mean, p22 and p23 third and forth moments with respect to grand mean and p18, p19, p20, p21 combination of previous parameters in the frequency domain [10,11].

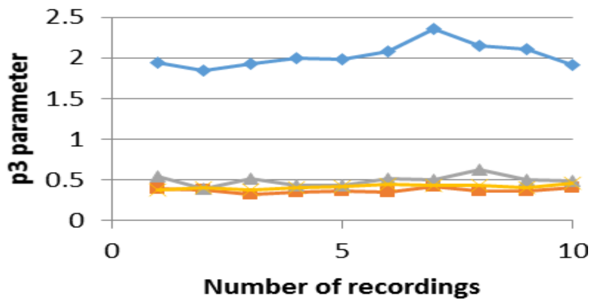
According to the set of signals collected, each bearing defect condition is represented by a set of vibration signals. The twenty three statistical features are calculated from time and frequency domain signal. Finally, 30 data sets are collected in, for twenty three statistical features which means 23×30 data set is available for each faults. For four different faults (i.e., GB, BD, ID and OD), there is total 23×4×30 data sets available. This total data set is divided and used for the training, testing and for evaluation. These signals are processed in order to be replaced by a vector of parameters to simplify the classification procedure.

3.1.2. Diagnostic potential

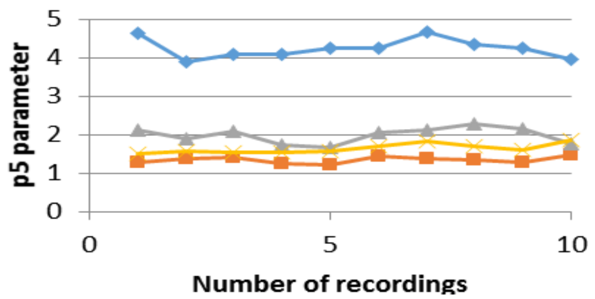
The statistical features extracted from time and frequency domain signals using MATLAB program are compared for their diagnostic potential as shown in Fig. 7 and Fig. 8. The variation of five time domain parameters from p1 to p11 for defective conditions of bearing for 10 numbers of recordings is as shown in Fig. 7(a) to (e). It is observed that for every defective condition (GB, BD, ID, OD) as marked in Fig. 7 (e), each parameter shows a different reading, but the parameter p1, p3, p6 p7, p8, p9 and p11 is having a poor diagnostic potential compared to parameters p2, p4, p5, and p10 for individual defect. While p2, p3, p4, p5, p7, p8 and p10 have good diagnostic potential for defective bearing since the lines drawn using number of recordings for different faulty conditions such as GB, BD, ID, OD for these parameters are having clear differentiation from each other. The decrement in the value of parameters p2, p3, and p4 for defective ball condition is 80%, for defective inner race is 75%, for defective outer race is 76% of the good bearing condition. The decrement in p5 parameter is 70%, 60% and 60% for the respective defective condition. The parameter p7 and p8 increases by 45% and 50% for BD, 70% and 60% for ID, and 60% for OD. The potential of p2, p4, p5 and p10 is quite better for individual bearing defect.



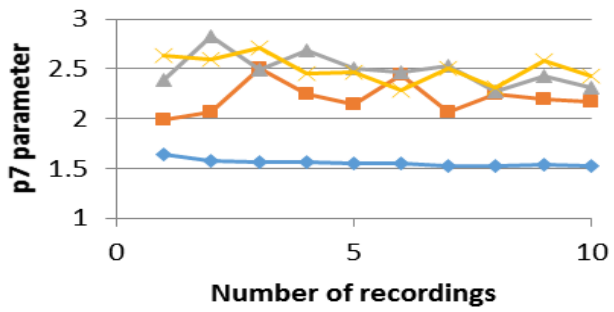
a). p2 parameter



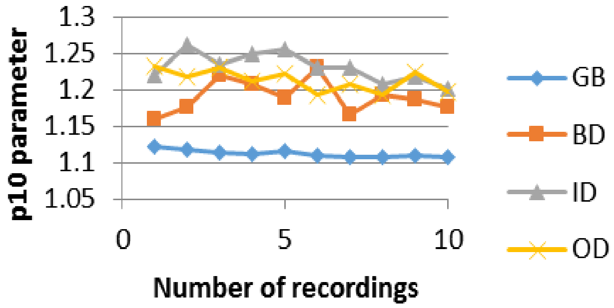
b). p3 parameter



c). p5 parameter



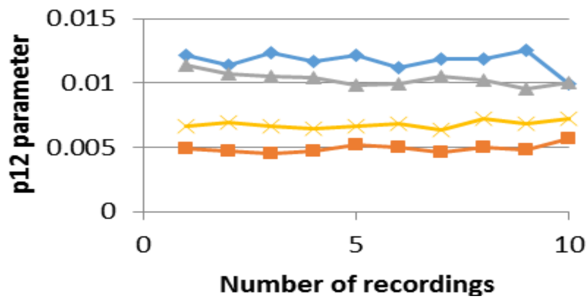
d). p7 parameter



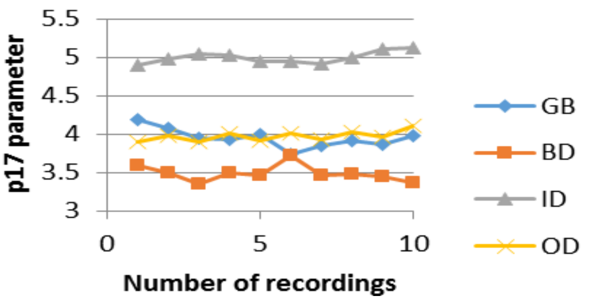
e). p10 parameter

Fig. 7: Diagnostic potential of time domain parameters p2 (a) to p10 (e) for different fault conditions

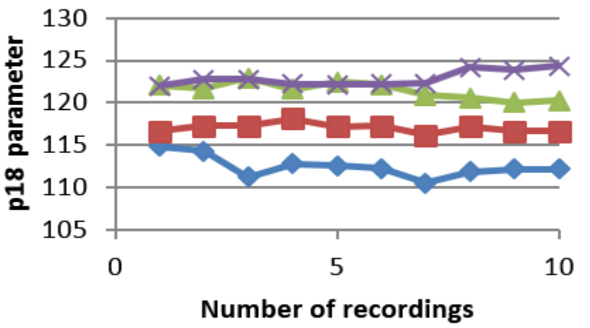
Similarly Fig. 8 (a) to (e) shows the variation of five frequency domain parameters from p12 to p23 for defective conditions of bearing for 10 numbers of recordings. It is observed that for every defective condition (GB, BD, ID, OD) as marked in Fig. 8 (f), each parameter shows a different reading, but the parameter p13, and p14 is having a poor diagnostic potential. The diagnostic potential of p12, p15 and p22 is lower than the parameters p16, p17, p18, p19, p20 and 23 since the lines drawn using number of recordings for different faulty conditions such as GB, BD, ID, OD for parameters p16, p17, p18, p19, p20 and p23 are having clear differentiation from each other. The increment in the value of parameter p16 for defective ball condition is 0.4%, for defective inner race condition is 4% and for defective outer race condition is 6% of the good condition. The value of parameter p18, p19, and p23 shows increment while p20 shows decrement for different defective conditions. An appreciable change in the value of parameter p17 and p23 is observed and these parameters have good diagnostics potential.



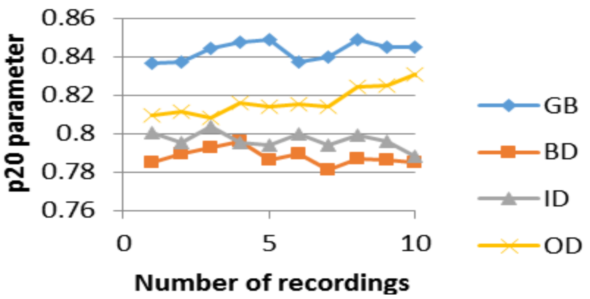
a). p12 parameter



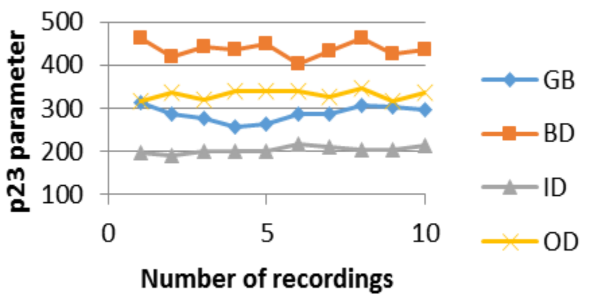
b). p17 parameter



c). p18 parameter



d). p20 parameter



e). p23 parameter

Fig. 8: Diagnostic potential of frequency domain parameters p12 (a) to p23 (e) for different fault conditions

Thus it is found that the parameters in frequency domain have better diagnostic potential than time domain parameters. These features which include the most important information about the defect, contained in the signal are extracted in order to prepare the matrices of learning and testing for the neural networks. It shows that frequency analysis has become a fundamental tool for vibration signal processing [16].

4. Bearing fault identification system

The main intention of this work is to generate a neural network that can detect the defects in bearing automatically without the vibration analyst. It is difficult for an analyst to diagnose the defect when the amplitude of defect frequency is not visible clearly in the frequency spectrum. If a defect is present in the system then the vibration signature obtained from it will be different than the good bearing. This change in signature, which could be found by statistical analysis, is used as an input to neural network. Here the supervised network is utilized, called a feed-forward network trained with back propagation, which uses a set of input vectors and a set of associated desired output vectors called target vectors [6-9, 17].

4.1. Neural network classification

Many vibration analysis techniques are available for identification of defects in mechanical systems, but it requires a good deal of expertise to apply them successfully. Simpler approaches are needed, which allow relatively unskilled operators to make reliable decisions without a diagnostic specialist to examine data and diagnose problems. Therefore, there is a demand for techniques that can make a decision on the running health of the machine automatically and reliably. Nowadays intelligent vibration monitoring is on-going research for automatic fault detection and diagnosis of mechanical systems, particularly to identify the incipient failures because of the complexity of the vibration signals. Currently, industrial applications of intelligent monitoring systems have been increased with the progress of intelligent systems. Artificial neural network-based, genetic algorithm-based, fuzzy logic-based, support vector machine-based, various similar classifiers, expert systems and combined algorithms have been successfully applied to automated detection and diagnosis of machine conditions.

They largely increase the reliability of fault detection and diagnosis systems. Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. A neural network can be trained to perform a particular function by adjusting the values of the connections (weights) between elements. The network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Typically, many such input/target pairs are needed to train a network. Neural networks have been trained to perform complex functions in various fields, including pattern recognition, identification, classification, speech, vision, and control systems. Back propagation is the generalization of the Widrow-Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer functions. Standard back propagation is a gradient descent algorithm, in which the network weights move along the negative of the gradient of the performance function.

The term back propagation refers to the manner in which the gradient is computed for nonlinear multilayer networks. An artificial neuron is composed for some connections, which receive and transfer information, also there is a net function designed for collecting all information (weights - inputs + bias) and sends it to the transfer function, which process it and produces an output. The process is illustrated in Fig. 9.

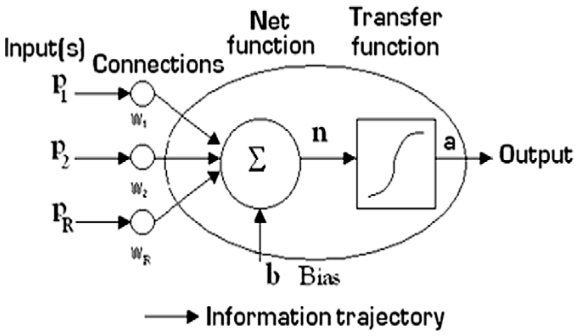


Fig. 9: Artificial neuron diagram

There are two main phases in the ANN's application: the learning or training phase and the testing phase. The learning phase is critical because it determines the type of future tasks it is able to solve. Once trained the network, the testing phase is followed, in which the representative features of the inputs are processed. After calculating the weights of the network, the values of the last layer neurons are compared with the wished output to verify the suitability of the design.

4.2. Feed forward neural network

The back propagation of an ANN assumes that there is a supervision of learning of the network. The method of adjusting weights is designed to minimize the sum of the squared errors for a given training data set. The derivation of the back propagation formula involves the use of the chain rule of partial derivatives. The sum of squared errors is calculated from the output of output node and input to input node is decided also the weights are updated. For the hidden layers, the calculations are similar. The only change is how the ANN output error is back propagated to the hidden layer nodes. The output error at the i^{th} hidden node depends on the output errors of all nodes in the output layer. After calculating the output error for the hidden layer, the update rules for the weights in that layer are the same as the previous update. A critical parameter is the speed of convergence, which is determined by the learning coefficient. In general, it is desirable to have fast learning, but not so fast as to cause instability of learning iterations. The stopping criteria are based on the minimum error reached.

The network training is also limited to 1000 epochs and the validation dataset may affect the training, with a maximum of 6 iterations failed. By changing the weights given to these signals, the network learns in a process that seems similar to that found in nature. i.e., neurons in ANN receive signals or information from other neurons or external sources, perform transformations on the signals, and then pass those signals on to other neurons. The way information is processed and intelligence is stored depends on the architecture and algorithms of ANN as shown in Fig. 10. The basic training process consists of four steps as, assemble the training data, create the network object, train the network, and simulate the network response to new inputs. The Features extracted from vibration signals are stored as a set of input vectors and depending upon the condition of bearing a set of target vectors. These two vectors are stored as input matrix and the target matrix in MATLAB workspace a sample of which is as shown in Table 3 and Table 4 respectively.

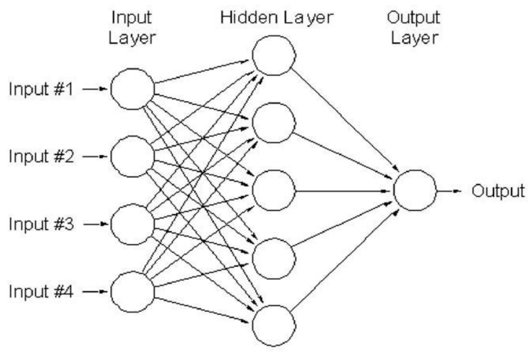


Fig. 10: ANN architecture

Table 3: Input vector with all parameters

Extracted Features	Condition of bearing GB	BD	ID	OD
p1	0.0171	0.0443	0.0179	0.0029
p2	1.8365	0.5245	0.6072	0.5395
p3	1.4927	0.3847	0.4038	0.3674
p4	1.8364	0.5264	0.6074	0.5394
p5	3.2789	1.5632	1.8428	1.6777
p6	0.0974	0.2922	-0.2317	0.4270
p7	1.5771	2.2486	2.8413	2.8628
p8	1.7855	2.9698	3.0338	3.1100
p9	2.1967	4.0639	4.5632	4.5665
p10	1.1192	1.1966	1.2598	1.2469
p11	1.9982	3.5537	3.8219	3.8781
p12	0.0102	0.0046	0.0107	0.0066
p13	0.0074	0.0004	0.0009	0.0004
p14	22.9693	15.6936	16.2826	14.2433
p15	610.4695	306.3975	349.2166	275.752
p16	110.1181	104.3188	109.0024	110.938
p17	4.0500	3.4349	5.0058	3.922
p18	117.2182	115.9806	119.3022	121.0025
p19	141.3138	149.3545	150.2601	150.5903
p20	0.8295	0.7765	0.794	0.8035
p21	0.0368	0.0329	0.0459	0.0354
p22	0.5736	-0.0341	0.1124	-0.95
p23	311.847	462.2423	203.1632	335.5247

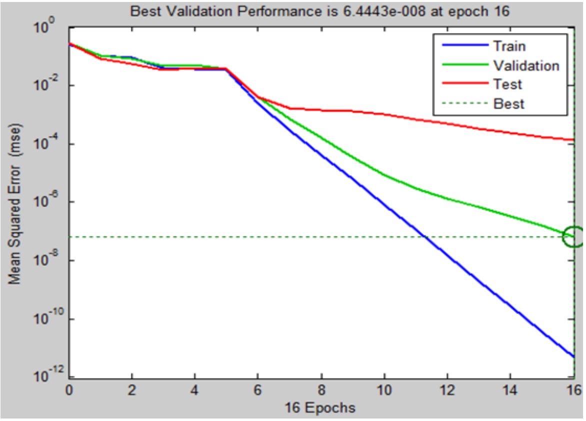
Table 4: Target vector for output layer

Sr. No.	Bearing condition	Target Node 1	Node 2	Node 3	Node 4
1	GB	1	0	0	0
2	BD	0	1	0	0
3	ID	0	0	1	0
4	OD	0	0	0	1

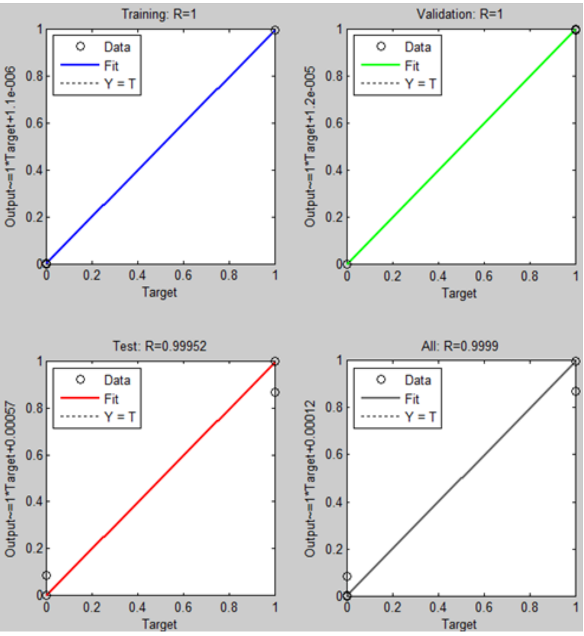
The next step is to create a network and train it until it has learned the relationship between the given inputs and targets. The network used with back propagation is the three-layer feed-forward network. For each faults namely Good Bearing (GB), Ball Defect (BD), Inner Race Defect (ID), and Outer Race Defect (OD) in bearing, a total of 120 samples, thirty feature vectors consisting of twenty three feature value sets are collected from the experiment for each condition. Twenty-five samples in each class are used for training and 5 samples are reserved for testing network. Training is done by selecting three layers neural network, of that one is an input layer, one hidden layer and one output layer. The numbers of neurons in the hidden layer are varied and the values of number of neurons, RMS error and number of epochs along with the percentage efficiency of classification of various faults using ANN are computed. The neural network is designed with MATLAB and ANN tool box with twenty three neurons, one hidden layer and four output neurons. The architecture of the artificial neural network is as follows:

- Network type: Forward neural network trained with feedback - propagation,
- Number of neurons in hidden layer: 2 to 30.
- Transfer function: TANSIGMOID - Sigmoid transfer function in hidden and output layer.
- Training function: TRAINLM (Levenberg - Marquardt).
- Adaption learning function : TRAINGDM.
- Performance function: MSE (Mean Squared Error).
- Number of hidden layers: 2.
- Number of neurons in hidden layer: 4.

The network is created with above parameters and the training parameters used are as follows: Show: 25, Epochs: 1000, Goal: 0, Max fail: 6 etc. To check the results of network after training, the performance plot is drawn as shown in Fig. 11 (a).



a). Performance plot



b). Regression plot

Fig. 11: Neural network training output

The plot shows the mean squared error of the network starting at a large value and decreasing to a smaller value. In other words, it shows that the network is learning. The plot has three lines, because the 120 input and target vectors are randomly divided into three sets. 60% of the vectors are used to train the network. 20% of the vectors are used to validate how well the network is generalized. Training on the training vectors continues as long as the training reduces the network error on the validation vectors. After the network memorizes the training set, training is stopped. This technique avoids the problem of over fitting, which plagues many optimizations and learning algorithms. Finally, the last 20% of the vectors provide an independent test of network generalization to data that the network has never seen. The regression of the network is as shown in Fig. 11 (b). The overall training, testing and validation found to be the best fit with R = 0.9999 while the only 16 number of iterations is required.

5. Results and discussion

Many tests are conducted on an experimental set up to detect the defects in bearing. Results in terms of various 23 parameters are calculated from time and frequency domain signal. From the recorded vibration waveforms in time and frequency domain the whole set of parameters (features) as described earlier are calculated utilizing in-house algorithms developed in MATLAB environment. In the following sections the behaviour of the best from a diagnostic point of view, parameters is analytically presented. The diagnostic potential of time and frequency domain parameters for different conditions such as GB, BD, ID, OD are as shown in Fig. 7 (a)-(f) and Fig. 8 (a)-(f) respectively. From a total set of about 23 parameters, about 14 of them seem to have a clear diagnostic potential. For the vibration recordings, time domain parameters standard deviation (p2), root mean square (RMS) value (p4), absolute maximum of the signal (p5) and p10 while frequency domain parameters mean (p12), forth moment (p15), grand mean (p16), standard deviation with respect to grand mean (p17), p18, p19, p20, p21, p22 and p23, proved capable of attending the damage accumulation upon the defective bearing and have shown an almost monotonic behaviour during the tests.

These 14 parameters are used for training the network. After training the network, it is used for testing the samples using simulation of the network. To improve the accuracy of results the number of hidden neurons is increased from 2 to 30. The better results are obtained from a network created with 4 neurons in the hidden layer, the performance of which for different fault conditions are as reported in Table 5 for four new samples. Performance of ANN in the percentage prediction of bearing faults using above networks is found successful for classifying the faults namely good bearing, ball defect, inner race defect, and outer race defect respectively. The overall average efficiency of the entire classification using ANN is found to be 99.37%. Using this neural network it is possible to detect the defects in bearing with 99.37% accuracy.

Table 5: Performance of ANN in % prediction of defect type

Condition	G	BD	ID	OD
Sample 1	100.00	90.01	99.98	99.99
Sample 2	100.00	100.00	100.00	99.99
Sample 3	100.00	100.00	100.00	99.99
Sample 4	100.00	100.00	99.99	99.99

6. Conclusion

Experimental vibration studies for locally defective deep groove ball bearing have been carried out and reported in this paper by applying radial loading on the bearing test rig. Based on the studies reported herein, it is observed that the set up prepared for analyzing the defects in bearing is working satisfactorily. The frequency domain parameters are having more diagnostic potential compared to time domain parameters. The ANN based defect classifier using the above mentioned statistical parameters as neurons are effective in defect identification. With this methodology the defects in bearing can be detected automatically without the vibration analyst. This is a novel thing that the defects in bearing which cannot be detected using spectrum analysis by vibration analyst can be detected using the trained neural network automatically.

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