DETECTION AND CLASSIFICATION OF FAULTS IN ROLLER BEARING USING SIMULATED DEFECTS BY ACOUSTIC SIGNALS AND USING ADAPTIVE NEURO-FUZZY INTERFACE SYSTEM

S. Deepakkumar[1], Thiru.R.SURENDRAN[2]

[1]PG Scholar, Mechanical Engineering, Government College of Technology, Coimbatore, Tamilnadu, India.
[2]Assistant Professor, Mechanical Engineering, Government College of Technology, Coimbatore, Tamilnadu, India.

---***---

Abstract-*This paper proposes a useful method in dealing with experimental investigation of automatically monitoring and diagnosing the defects and classifying the defects by providing simulated defects in roller bearings and forming the artificial neural network by using data which is acquired by acoustic signals. This investigation consists of three essential steps: the first step is to convert the raw data extracted from the acoustic signals into useful data using statistical indicators such as root mean square, kurtosis, skew factor, crest factor. The second step is to select the more relevant indicators and to form neural network for the purpose of classifying the defects and diagnosing the severity of the defects (ball, inner, outer race defects) and combining with healthy bearing signal. The third step is to detect the unknown source signal and compare it with the acquired data and indicate its health condition and severity of its defect. The obtained results indicates that the proposed approach can reliably detects the defect and also shows the defect type at different speeds and load conditions.*

Key Words: **Fault diagnosis, bearing faults, statistical indicators, and acoustic signal.**

1. INTRODUCTION

Roller bearings are one of the important parts of rotating machineries for their purpose of controlling relative motion between the rotating and stationary parts. Transmission based machines usually uses roller bearings in controlling relative motions which are most widely used in industrial manufacturing processes because of their load carrying purposes and also for its less maintenance cost. Defect detection and its diagnosis has been an important area in the field of condition monitoring and its related researches due to importance in modern industries for their safety and manufacturing quality. The accuracy of the manufacturing process can be greatly affected even if there is small disturbances in the bearing parts and if there any defects in the bearing it will lead to severe catastrophic failure of the machine parts. So early detection of defects and the type of defect and severity of the defect can help us to deal with diagnosing its effects. So designing a good maintenance plan in condition monitoring the state of machines and also diagnosing the defects in early stage will prevent serious machine failures. Diagnosing a bearing defect may have measurement taken using various measuring techniques which can either by using temperature, electric current, thermography, or by vibration analysis using accelerometer or microphone.

Fig:-1. The Ball bearing

The spectral analysis approach is the traditional method for identifying faults in any rotating machines. This approach allows the change of the sequential signal into the frequency domain. Though, its accuracy depends on the sizes of the bearing and the speed of rotation. In this approach the details produced gives us very easy data when compared with time domain approach. Accordingly, some methods are based on the spectrum of the linear signal, such as the Hilbert transformation method [1], the high-frequency shock wave and friction forces method [2], the frequencies analysis technique [3, 4], and the envelope spectrum method [5]. This way is delicate and powerful for detecting bearing faults and diagnosing the location of damage. In totaling, all methods using the frequency domain need intelligent selection of the frequency band to be effective, as the data is often submerged in noise which is characterized by a higher energy. So in order to find defects in the traditional frequency based method is more difficult.

The time-frequency domain analysis method allows the providing of useful statistics for the stationary and non-stationary signals, and it shows its main benefit over the temporal and frequency based techniques [6]. Several methods of analysis in the time-frequency domain which have been projected, such as short-term Fourier Transform (STFT) [7], Wigner-Ville distribution (WVD), wavelet transforms [8]. It should be noted that in many of the speed variable cases the data doesn't gives reliable information in case of defects detection in bearings. This work concerns the detection and classification of faults in rotating bearing elements and its working machines with the help of artificial intelligence. Numerous methods using this approach have been used: In [9], a Neuro-Fuzzy-based (ANFIS) approach has been suggested for fault classification. The work presented in [10], showed diagnosis efficiency using multi-scale entropy and ANFIS. A summary of the progress and used choices of the wavelet was specified in [11]. In [12], they stated and found fault diagnosis based on neural networks with intelligent filters (RNFC). In [13] the journalist used neural networks for fault finding using time and frequency characteristics. In paper [14], a spectral-based diagnosis method using fuzzy logic which have been proposed. A novel method combining "Adaptive Feature Extraction" and "Multi-scale entropy" using "Support Vector Machine" (SVM) has been proposed in [15]. In [16], the approach is based on the wavelet transform and Artificial Neural Networks (ANN) for the detection and classification of faults.

The aim of this work is the integration and validation of an intelligent automated approach for the detection and classification of roller bearing faults in an industrial field using only the RMS trend signals. The approach is based on sequential statistical indicators and Adaptive Neuro-Fuzzy Inference System (ANFIS) [17]. The features are designed from the acquired signals in the form of the Root Mean Square (RMS) trend of the raw vibration signals issued from a microphone installed on a rotating bearings in operation. the above stated method takes less time to give features calculations as it comprises of simple equations when compared with several other techniques and does not require difficult deposing procedures. The experimental tests are carried out for several defected bearing sets with different states of defects and operating at various speeds of electric motor.

2. THEORY/ CALCULATION

2.1. Feature extraction and classification

The acquired vibration data shows the root mean square (RMS) of the original vibration data which is the useful and available mode of measurement from the acquisition device. These acquired signals are then subject to a moving window calculations of statistical features in order to extract intrinsic characteristics.

2.1.1. Feature extraction

Statistical features are then extracted from the dataset of each state of the healthy and fault bearings with a length of 2400 points. The most used features are (RMS, kurtosis, peak to peak, Skewness) which are applied to an input signal x (k) with a window of length N`

2.1.2. Adaptive neuro-fuzzy inference system

An adaptive neuro-fuzzy inference system or adaptive network-based fuzzy inference system (ANFIS) is a artificial neural network which follows Takagi–Sugeno fuzzy inference system. The ANFIS algorithm was first presented and introduced by Jang, which consists of a network characterized by input data which are fuzzified using a chosen membership functions and a training algorithm which adjusts the weighting parameters and membership functions which gives a fuzzy inference system that mimics a desired input-output data mapping. The fuzzy inference system steps which are in the following form:

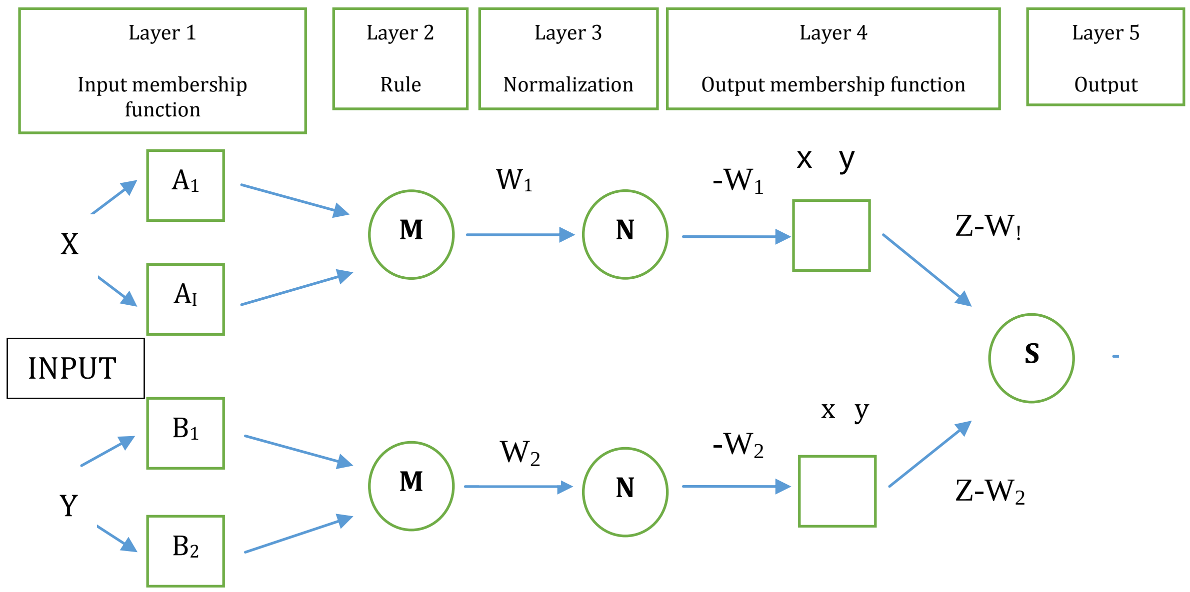


Fig-2: The structure of the ANFIS network

If x is A_i and y is B_i then $Z_i = P_i x + Q_I y + R_i$

Where A_i and B_i are fuzzy sets, x and y are system input output desired mapping, Z_i output of each rule with design parameters P_i,Q_i and R_i. The structure of the ANFIS network is given in Fig:-2.

2.1.2.2. Input membership function layer. Each and every node i in this layer is an adaptive node with node function. Hence $O_1{}^1$is a connection grade of the fuzzy set (A_1; B_i; A_2; B_2) which are given in Eqs. (1) and (2).

$O_1{}^1 = \mu_{Ai}(x)$, I = 1, 2. (1)

$O_1{}^1 = \mu_{Bi-1}(x)$, I = 3, 4. (2)

$\mu_{Ai}(x)$ and $\mu_{Bi-1}(x)$ are fuzzy membership functions given in Eq. (3). The used membership functions in the previous nodes are chosen to be the bell-shaped functions with an upper limit of one and a minimum of zero,

$\mu_{Ai}(x) = 1/\ (1+ [((x - c_i)/a_i)^2]b_i)$, i = 1, 2. (3)

Where a_i, b_i and c_i are the parameters of the bell shaped membership function.

2.1.2.2. Rule layer. Each node in this layer is a fixed node labeled M. The output is a product of all the input signals. The outputs in Eq. (4) represent the weights ω_i for each rule as:

$O_i{}^2 = \mu_{Ai}(x)\ \mu_{Bi-1}(x)$, i = 1, 2. (4)

2.1.2.3. Normalization layer. The nodes in this layer are fixed nodes labeled N. The $_i$th node calculates the ratio of the $_i$th rule's weight to the sum of all rule's weights are given as given in Eq. (5).

$\mathcal{E}^2{}_{i=1}\ w_i$, i = 1, 2. (5)

The outputs for this layer are normalized weights calculated using Eq. (6).

$O_i{}^3 = -w_i = w_I / \mathcal{E}^2{}_{i=1}\ w_i$, i =1, 2. (6)

2.1.2.4. Output membership function layer. Each node i in this layer is an adaptive node with the node function in Eq. (7).

$O_i^4 = w_i\, [P_i x + Q_I\, y + R_i]$, $i = 1, 2$. (7)

q_i, p_i and r_i are the adaptive parameters set of this node.

2.1.2.5. Output layer. The output node is labeled S, which calculates the overall output using the sum of all input signals as in Eq. (8).

$O_i^3 = \mathcal{E}^2_{i=1}\, z\, \mathcal{E}^2_{i=1}\, z, i \,/\, \mathcal{E}^2_{i=1}\, w_i\, i$. (8)

The training of the ANFIS network is besed on the algorithm which combines both the least squares and the gradient descent estimation and the methods which includes two training stages for better efficiency and to escape from the data of local minima. In the initial stage, the parameters are required to be fixed. The resulting parameters are introduced into the least squares estimation algorithm. In the following stage, the parameters are also supposed to be fixed. The parameters are then rationalized using the back propagation gradient descent method, and in the form of the error values. The used classification algorithm is based on a modified faster version of the original ANFIS classifier [18] that has been proposed in [19]. The first order gradients are used in order to speed up the learning algorithm without the use training data. To calculate the gradient, a least square error estimator has been introduced. The time needed to estimator execution are proved to be very less in comparison to the computation difficulty of the initial algorithm in large scale data.

Transmission based machines usually uses roller bearings in controlling relative motions which are most widely used in industrial manufacturing processes because of their load carrying purposes and also for its less maintenance cost. So designing a good maintenance plan in condition monitoring the state of machines and also diagnosing the defects in early stage will prevent serious machine failures. Diagnosing a bearing defect may have measurement taken using various measuring techniques which can either by using temperature, electric current, thermography, or by vibration analysis using accelerometer or microphone. It is important to have checking data that fully represents the features of the data the FIS is intended to model. If the checking data is significantly different from the training data and does not cover the same data features to model as the training data, then the training results will be poor. The objective of this project is to improve bearing monitoring using by acoustic signal indicators separately and evaluating the acquired signals using MATLAB. The methodology of the present work is shown in Fig. Initially, the bearing defects, causes and its effects are analyzed rigorously by performing literature review.

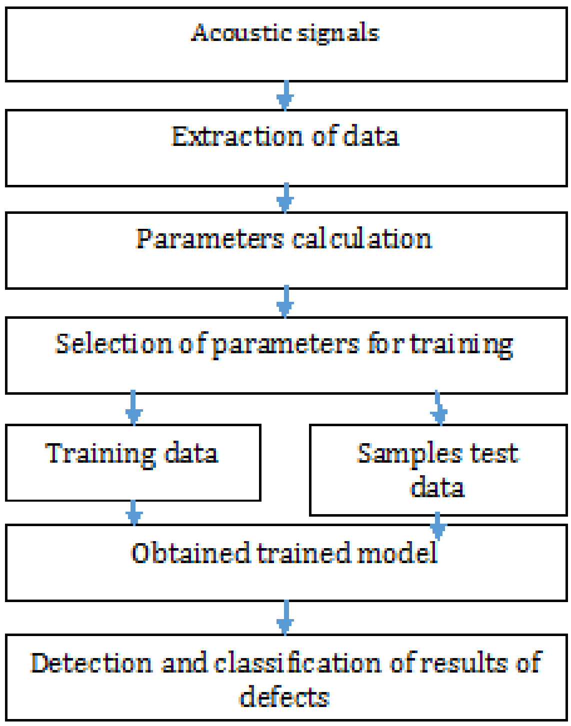


Fig-3: The steps for detection and classification of defects

3. EXPERIMENTAL INVESTIGATION

3.1. Experimental setup

From the review it is well known that the occurrence of rotating machine damages are more due to the faults and defects of the bearings than any other type of sources. So in order to prevent the effects of the defects industrially used bearings are taken into consideration and the experimental setup is prepared according to industrial need and the tests are done and the data is prepared to form fault diagnosis algorithm for the defected bearing components. The test rig for carrying out the experiment is shown in the Fig. 4. This investigation conducted a series of experimental tests on the behavior of the bearing of the in different states (without defects and faulted). These tests are carried out at different speeds of the electric motor which is used.

The experiment is by simulating three types of defect: outer bearing defect, inner bearing defect and ball defect on an UC205-16, which is a UC 200 wide inner ring ball bearings. Experimentally simulated defects are created in the inner race and outer races and in the bearing balls. The UC205-16, which is cylindrical ball type bearing which is used in this investigation. The bearing which is selected having an inner diameter of 25mm and an outer diameter of 52mm and the calculated weight of the bearing is 0.50lb or 0.2Kg and it has set screw type locking. The bearing has dynamic load rating of 14000N and the static load rating of 7850N.

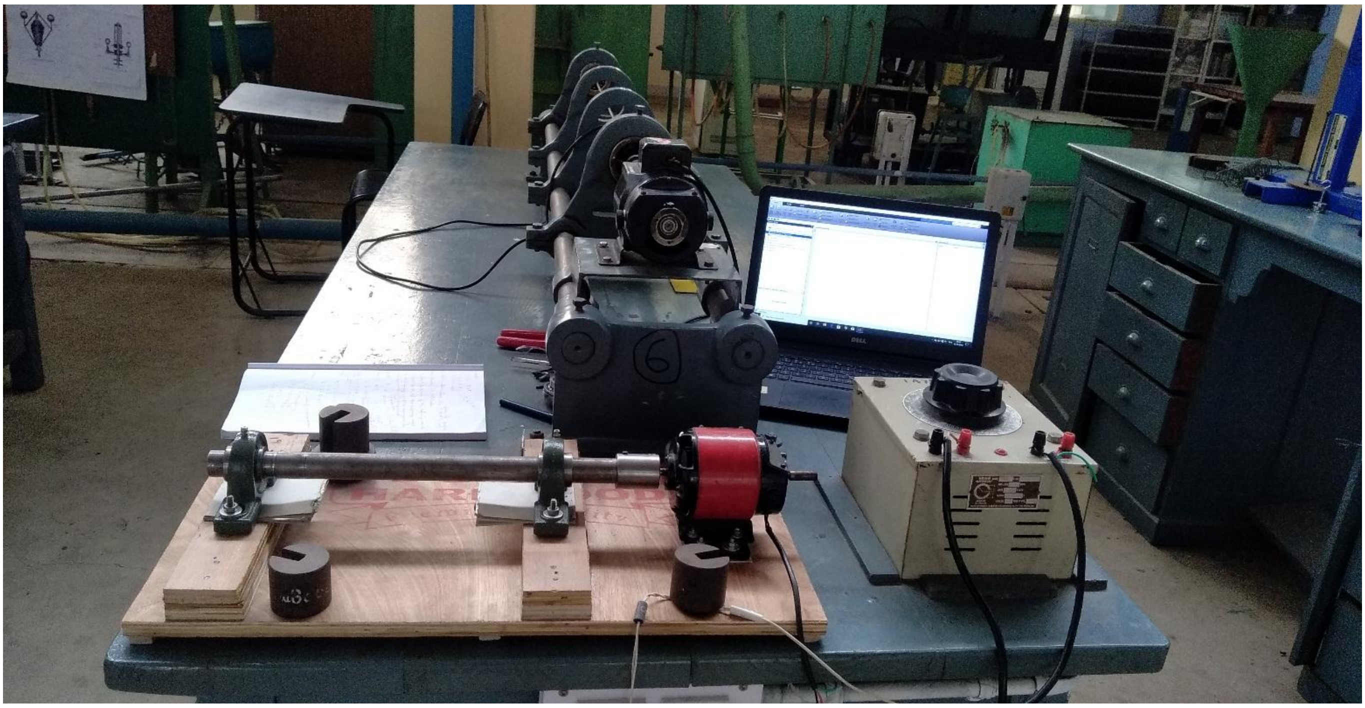


Fig -4: Experimental setup

The tests were carried out on the four bearings in which one is healthy bearing and other three are defected bearing in which the defects are purposefully created and then it is connected through the electric motor by a hollow shaft which weighs 0.5 Kg and the experiment is carried out different states (healthy and in the presence of defects) and at variable speeds (100, 200, 300 rpm). The defects (Ø 4.5mm cut) are created artificially on three different places in three bearings. The first bearing has a defect on the outer race, the second on the inner race and the third on the ball. Acoustic analysis is used technique for fault and defect detection. The acoustic experiment were acquired at a variable acquisition frequency using a microphone interfaced with a computer.. The acoustic variables measured by the acquisition device are expressed as the RMS value of the acceleration. Numeric data is collected for each state of the bearing with an acquisition length of 2400 samples which represents the concatenation of 600 samples of the acoustic signals for a fixed operation condition and rotating speed.

4. RESULT AND DISCUSSION

For studying the defects of the defected bearings the acoustic signals from various rotational speeds are collected changing the speed of the motor by controlling the voltage. The raw signals are taken for a period of ten seconds and for the evaluation the 2400 samples are selected in the MATLAB. The collected acoustic data contains the data which is initially contains noises which are removed using the necessary filters. The obtained results shows that the vibration in case of defected bearings are higher when compared to the healthy bearing at various rotational speeds which is a valid statement due to different rotational speeds and due to the defects.

The frequency of rotation of the bearings tends to increase the vibration of the machine. From the previous analysis of data the impact of the defects causes change in RMS value when the speed is varied which shows the considerable influence of speed in increasing the intensity of vibration. The visual representation of the data in time domain is difficult so the data is changed from time domain to frequency domain using fast fourier transform in MATLAB. The analyzed data is then characterized according with various statistical indicators such as RMS, kurtosis, peak to peak ratio and Skewness. This helps in classifying the defects and also detection the defects when comparing with the values of normal bearing.

The traditional indicators for the different defected bearing conditions are to be studied which are extracted from the acoustic signals in order to verify the signals ability to detect the various defects. The in-depth analysis of the scalar indicators shows that only the skewness has an overlap between the outer race defect and the defect of the inner race which confirms the analysis previously discussed.

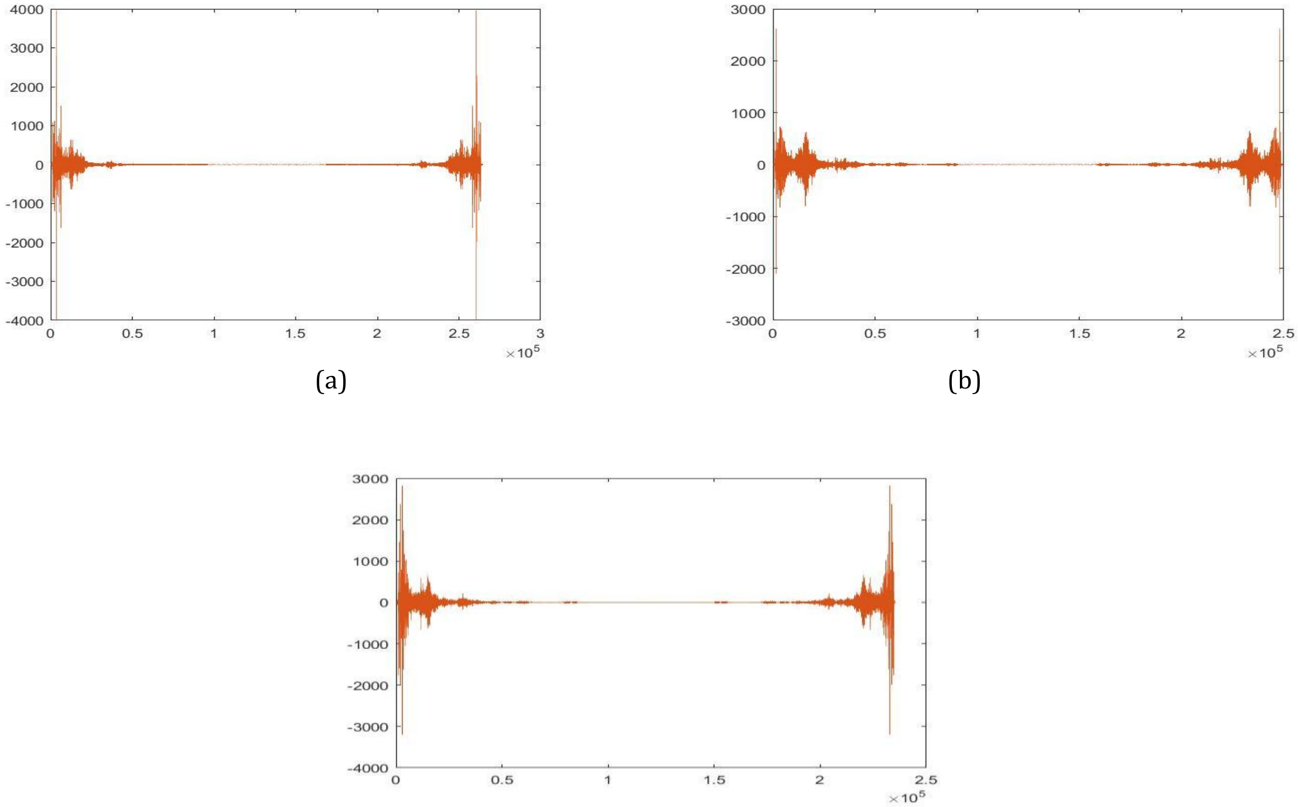
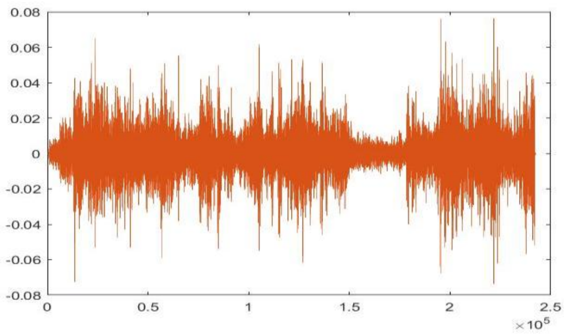
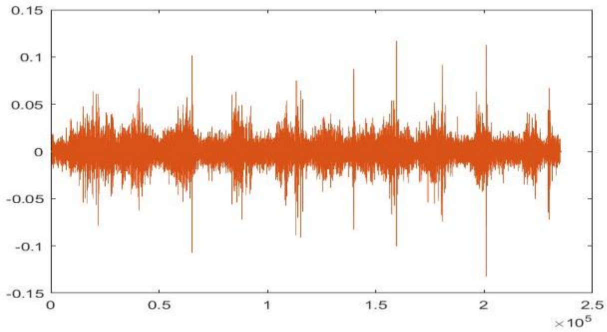


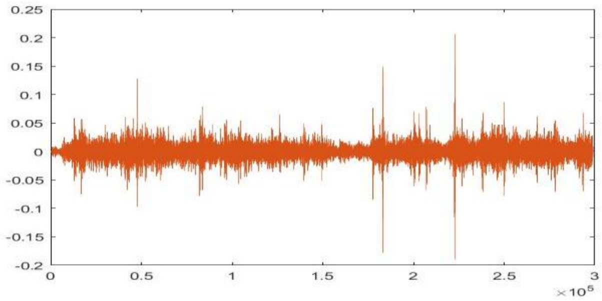
Fig -5: Healthy bearing acoustic signal at (a) 100 rpm, (b) 200 rpm, (c) 300 rpm



(d)

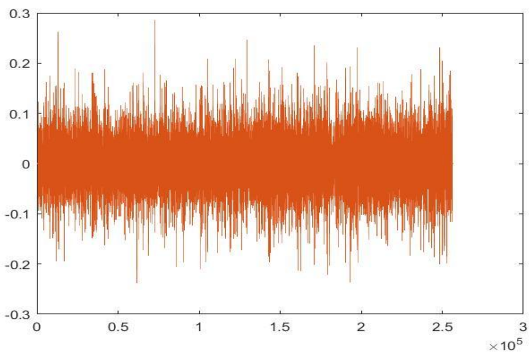


(e)

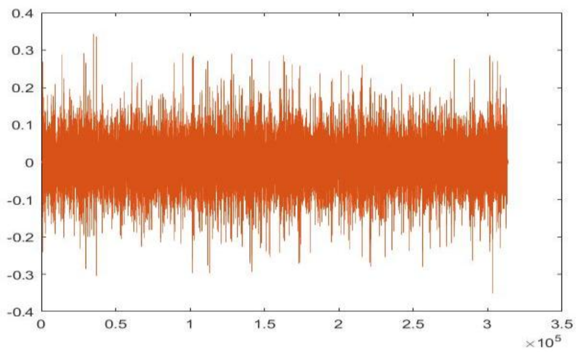


(f)

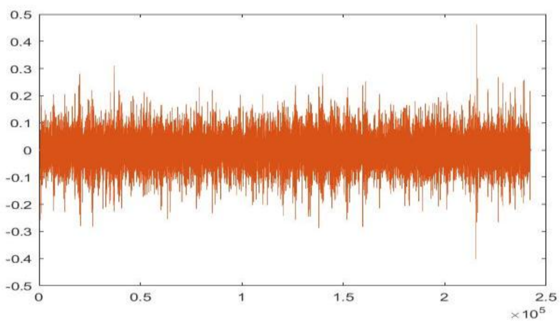
Fig-6: Outer race defected bearing acoustic signal at (d) 100 rpm, (e) 200 rpm, (f) 300 rpm



(g)

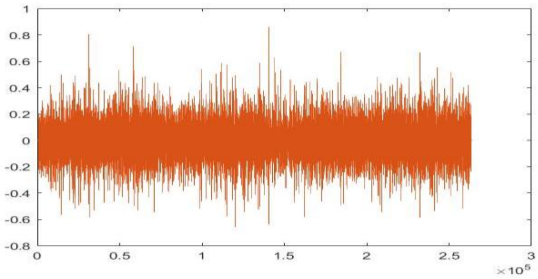


(h)

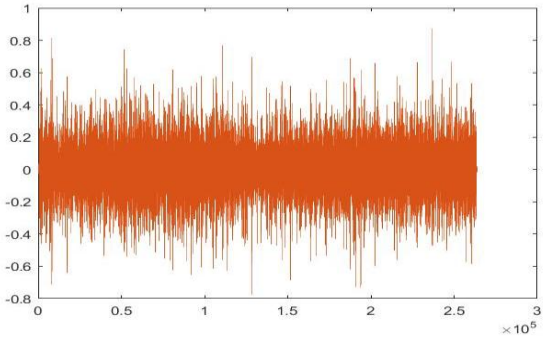


(i)

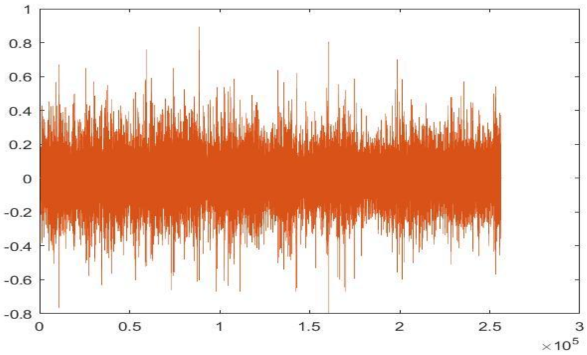
Fig-7: Inner race defected bearing acoustic signal at (g) 100 rpm, (h) 200 rpm, (i) 300 rpm



(j)



(k)



(l)

Fig-8: Ball defected bearing acoustic signal at (j) 100 rpm, (k) 200 rpm, (l) 300 rpm

Table 1:- RMS values of defected bearing acoustic signal at 100 rpm, 200 rpm, 300 rpm

rpm	Outer race defect	Inner race defect	Ball defect	Healthy
100	0.0121	0.011	0.011	0.0034
200	0.0472	0.0587	0.0292	0.002
300	0.1186	0.1334	0.0379	0.0017

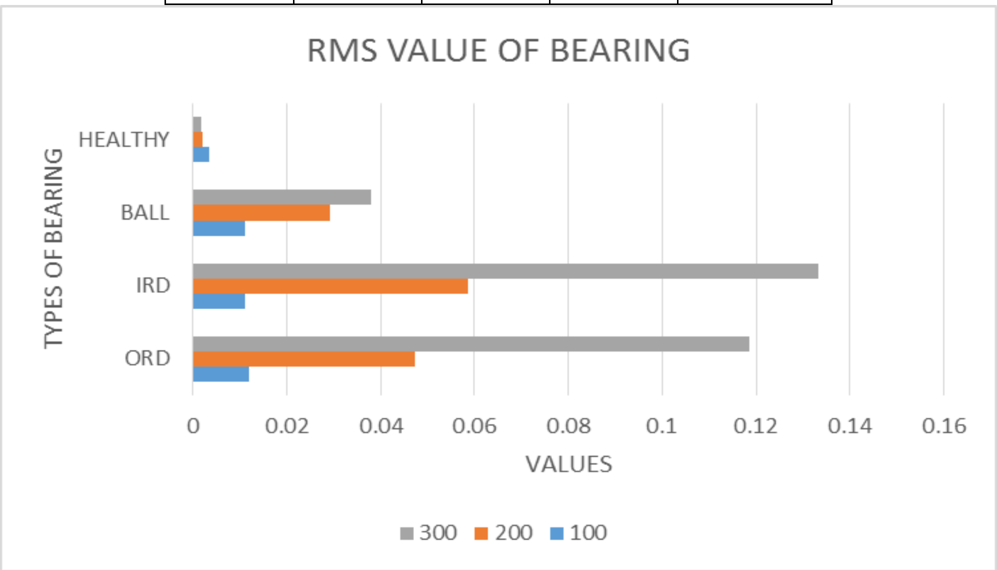


Chart -1: RMS values of defected bearing acoustic signal at 100 rpm, 200 rpm, and 300 rpm

Table 2:- Skewness values of defected bearing acoustic signal at 100 rpm, 200 rpm, 300 rpm

rpm	Outer race defect	Inner race defect	Ball defect	Healthy
100	-0.0267	-0.0384	-0.0267	-0.001
200	-0.03	-0.079	-0.0468	-0.002
300	-0.0255	-0.023	-0.05	-0.0012

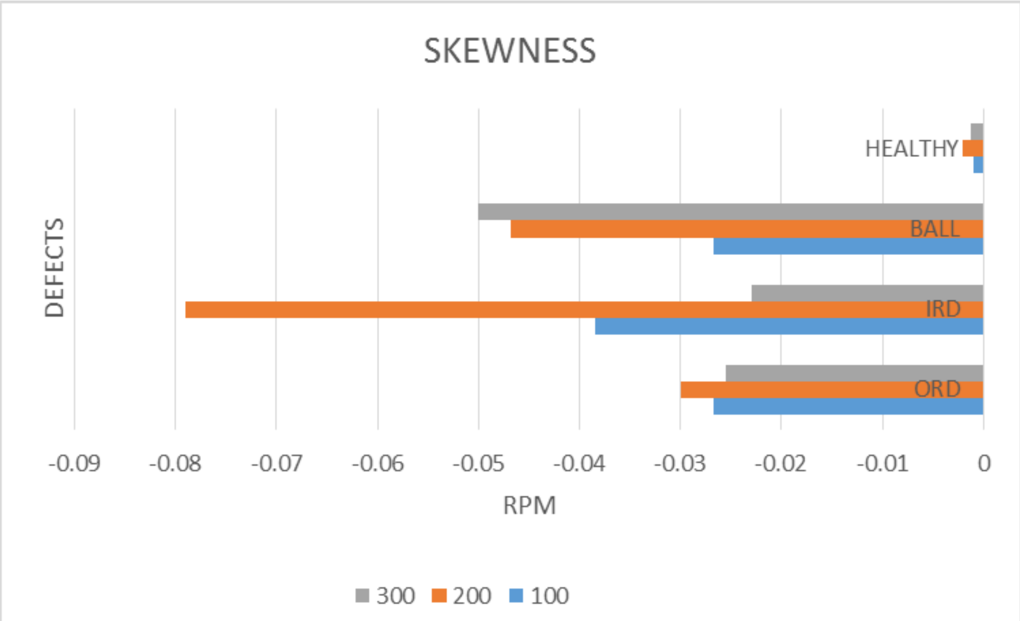


Chart -2: Skewness values of defected bearing acoustic signal at 100 rpm, 200 rpm, and 300 rpm.

Table 2:- Kurtosis values of defected bearing acoustic signal at 100 rpm, 200 rpm, 300 rpm.

rpm	Outer race defect	Inner race defect	Ball defect	Healthy
100	4.0192	25.8205	3.0192	3.0001
200	6.8205	21.9803	3.2043	3.0075
300	5.2244	34.119	3.4109	3.0021

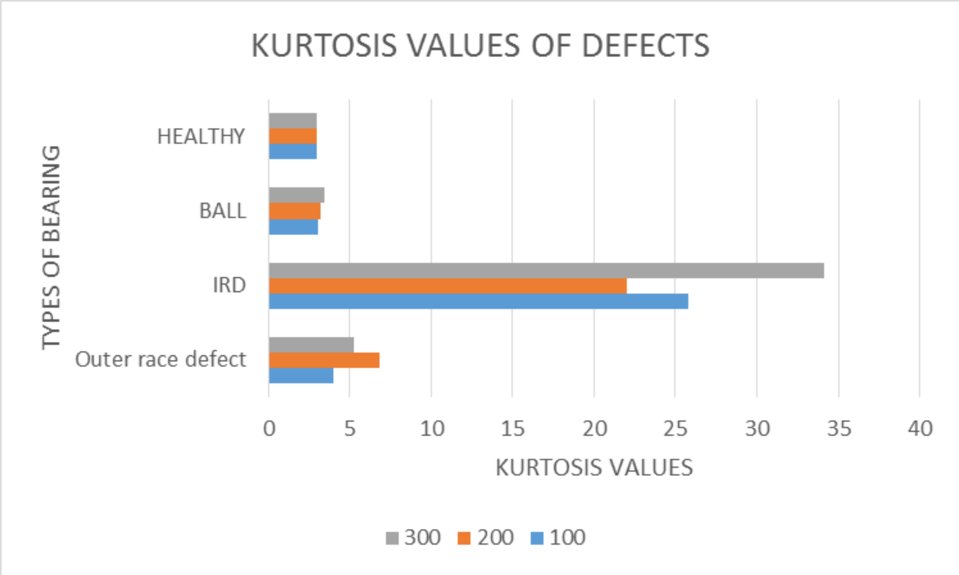


Chart -3: Kurtosis values of defected bearing acoustic signal at 100 rpm, 200 rpm, and 300 rpm

From the chart 1 it is clear that the RMS value the defects vary according to the speed and the type of defect and for the inner race defect it is shown that that value increases due to its highest vibrational frequency and from the chart 2 it is shown that skewness value is also high for inner race defect when compared with other types of defects and also from healthy bearing and from the chart 3 kurtosis value is more than 30 for inner race defects which shows that the method gives required and absolute value because the inner race defect tends to give kurtosis value in the range of 30 to 60.

From the indicator analysis results shown it is clear that the statistical indicator is unreliable for fault detection and identification due to the overlapping curves. On the other hand, the remaining indicators allow the detection and identification of the studied defects. After identifying relevant indicators as feature vectors and for the aim of facilitating industrial exploitation, an adaptive neuro-fuzzy inference system (ANFIS) will be configured to perform automated fault diagnosis in order to minimize uncertainty in the diagnosis process. The ANFIS model is trained using the training data set, so that the fuzzy logic inference is able to give the expected results.

The total precision of the classification of the proposed approach for all of the training and test data is in the order of 87.67% and it shows detailed classification results for the training data. The developed method shows the absolute error of the ANFIS output relative to the desired output which is equal to 4.45 %. As a result, the total accuracy of the proposed approach classification for the test data set is 90.45%. A comparison with previous research works that uses the ANFIS classifier for bearing faults diagnosis has stated that the current study uses a time-based approach that accelerates the processing of the feature extraction procedure as it does not require the calculation of the spectrum of the raw data as in other spectral based methods. In addition the features used in this work are characterized by simple formulas which do not require long processing time compared to entropy-based techniques. The obtained results show excellent performance for a variable speed drive operating in industrial production line.

5. CONCLUSIONS

In this approach it is proposed that using acoustic signals gives best results in case un accessible areas of the rotating machines and the method gives less computing approach which helps in finding the type of defect and its severity and also gives valid results. The method is based on the extraction of statistical indicators from the acquired acoustic signals and then the classification of faults using a trained adaptive neuro-fuzz inference system ANFIS and also the level of the defect.

The experimental results obtained at various defected bearing states (healthy and defected bearings) which show that the proposed ANFIS approach which is used in the detection and classification of bearing state is more reliable. The accuracy of the total classification and detection proposed approach for all the training and testing data is in the order of 90.45%.

REFERENCES

[1] M.A. Minnicino II, H.J. Sommer III, Detecting and Quantifying Friction Nonlinearity Using the Hilbert Transform, 2004, p. 419.

[2] K. Gyorgy Lipovszky, G. Solyomvari, Vibration Testing of Machines and Their Maintenance, 1990.

[3] R.A. Collacott, Vibration Monitoring and Diagnosis, 1979.

[4] A. Dimarogonas, Vibration for Engineers, Prentice-Hall, Upper Saddle River, N.J., 1996.

[5] R.B. Randall, J. Antoni, Rolling element bearing diagnostics—a tutorial, Mech. Syst.Signal Process. 25 (2) (Feb. 2011) 485–520.

[6] I. Attoui, N. Fergani, N. Boutasseta, B. Oudjani, A. Deliou, A new time–frequency method for identification and classification of ball bearing faults, J. Sound Vib. 397 (Jun. 2017) 241–265.

[7] E. Cabal-Yepez, A.G. Garcia-Ramirez, R.J. Romero-Troncoso, A. Garcia-Perez, R.A. Osornio-Rios, Reconfigurable monitoring system for time-frequency analysis on industrial equipment through STFT and DWT, IEEE Trans. Ind. Inf. 9 (2) (May 2013) 760–771.

[8] J. Seshadrinath, B. Singh, B.K. Panigrahi, Investigation of vibration signatures for multiple fault diagnosis in variable frequency drives using complex wavelets, IEEE Trans. Power Electron. 29 (2) (Feb. 2014) 936–945.

[9] Y. Lei, Z. He, Y. Zi, A new approach to intelligent fault diagnosis of rotating machinery, Expert Syst. Appl. 35 (4) (Nov. 2008) 1593–1600.

[10] L. Zhang, G. Xiong, H. Liu, H. Zou, W. Guo, Bearing fault diagnosis using multi-scale entropy and adaptive neuro-fuzzy inference, Expert Syst. Appl. 37 (8) (Aug. 2010) 6077–6085.

[11] R. Yan, R.X. Gao, X. Chen, Wavelets for fault diagnosis of rotary machines: a review with applications, Signal Process. 96 (Mar. 2014) 1–15.

[12] J. Zarei, M.A. Tajeddini, H.R. Karimi, Vibration analysis for bearing fault detection and classification using an intelligent filter, Mechatronics 24 (2) (Mar. 2014) 151–157.

[13] B. Li, M.-Y. Chow, Y. Tipsuwan, J.C. Hung, Neural-network-based motor rolling bearing fault diagnosis, IEEE Trans. Ind. Electron. 47 (5) (2000) 1060–1069.

[14] G. Goddu, Bo Li, Mo-Yuen Chow, J.C. Hung, Motor bearing fault diagnosis by a fundamental frequency amplitude based fuzzy decision system, in: IECON '98. Proceedings of the 24th Annual Conference of the IEEE Industrial Electronics Society (Cat. No.98CH36200), vol. 4, 1998, pp. 1961–1965.

[15] Q. Li, Q. Zhang, X. Liao, Adaptive feature extraction algorithms and SVM with optimal parameters on fault diagnosis of bearing, in: 2016 35th Chinese Control Conference (CCC), 2016, pp. 5133–5137.

[16] A.B. Patil, J.A. Gaikwad, J.V. Kulkarni, bearing fault diagnosis using discrete wavelet transform and artificialneural network, in: 2016 2nd International Conference on Applied and Theoretical Computing and Communication Technology (iCATccT), 2016, pp. 399–405.

[17] Q. Fu, B. Jing, P. He, S. Si, Y. Wang, Fault feature selection and diagnosis of rolling bearings based on EEMD and optimized Elman_AdaBoost algorithm, IEEE Sens. J.18 (12) (Jun. 2018) 5024–5034.

[18] J.-S. Jang, ANFIS: adaptive-network-based fuzzy inference system, Syst. Man Cybern. IEEE Trans 23 (3) (1993) 665–685.

[19] B. Cetis¸li, A. Barkana, Speeding up the scaled conjugate gradient algorithm and its application in neuro- fuzzy classifier training, Soft Comput. 14 (4) (Feb. 2010) 365–378.