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Development of Asynchronous Motor Bearing Fault Diagnosis Method using TDA and FFNN

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Abstract: ***Asynchronous motors (AM) are life line of any process industry. Malfunctioning of AM at any stage of process leads the cost of finish product and decrease the efficiency of plant. Hence detection and diagnosis of AM failure at early stage is essential for timely maintenance and enhance the overall efficiency of the plant. The work present in this paper focuses on the bearing faults of AM. For this purpose experimental setup is developed in laboratory and results are based on experimental study carried out in laboratory by analysing AM generated vibration signals using time domain analysis (TDA) and feed forward neural network (FFNN).***

Index Terms: ***Bearing Failure, Induction Motor, Neural Network, Time Domain Analysis, Vibration Signals.***

I. INTRODUCTION

Industries are incumbent on AM. AM are key element of every industry. As per a review, AM consumes about 40 to 50% of generated electricity in a nation state [1]. It is shown in earlier study that malfunctioning in AM causes huge loss due to stopping production in industry. AM malfunctioning in industries increases repairing and production cost. The mostly adopt upholding schemes in industries are curative, periodic and condition based [2]. The selection of upholding scheme is generally focused on minimization of cost of final product and repairing. The condition monitoring system consist of Sensors, Data acquisition card, Fault detection system, Fault classification system and Fault diagnosis system [3].

Sensors collect the desired signals. The data acquisition device is used for amplification, conditioning and sampling the signal data acquired by sensors. The acquired data is then processed by fault detection scheme, which selects the features, sensitive to AM malfunctioning cause [4]. The fault cataloging scheme is of threshold model type and predictive model type. Predictive model fault cataloging system is a model which detect the fault and state of AM by using output signals based on artificial neutral network (ANN) and fuzzy logic (FL) [5, 6]. The threshold fault cataloging system model works on fault features characteristics to be recorded. Finally fault diagnosis system acts its role and send information to the operator about fault with resolution of problem. With increasing of operating time parts of AM decays slowly and converts into fault after a time [7, 8]. Due to faults in AM components, changes in AM parameters can be noticed and by analysis of such changes, fault can be detected at early stage. The key restraint in this process is requirement of expert man power for understanding and logical interpretation of the data, which can be conquering by automatic intelligent diagnostic scheme. The application of ANN may be a solution for detection and diagnosis of AM fault; however it requires a great number of training data which is directly related to the computation time.

II. EXPERIMENTAL SETUP AND PROCESS

The designed and developed experimental setup used in present study is given in figure 1. The specimen bearing with artificially generated faults on inner ring ball race way (IRBF) and outer ring ball race way (ORBF) were used in this study and shown in figure 2. In developed condition monitoring (CM) of AM for acquiring the current signals, vibration signals under normal and abnormal condition Hall Effect Current Transducer, Accelerometer and a data acquirement circuit is used. The CM setup is kept in a box containing two portions. The first portion is reserved for power supply and voltage regulators and the next portion contains signal conditioning board and data acquiring board.

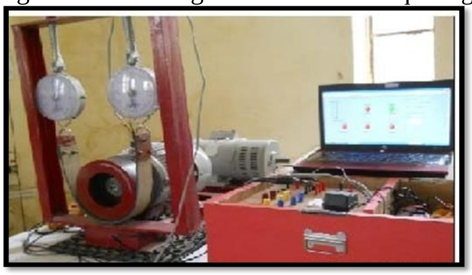

Fig.1 Experimental Setup

Fig.2 Bearing Specimens used in Experimental Study

The data of experiments were recorded on developed test bench in laboratory. The sampling frequency of vibration signals were set at 4 kHz with resolution 12 bit/sample recorded. The vibration samples signals for good bearing (GB), rolling part fault (RPBF), IRBF and ORBF bearing condition were recorded with 50000 data point length of signal in each case.

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Then the recorded signals were separated into five non overlapping segments to reduce the computation time. The span of every segment selected cautiously to have information and seize contained features of the signal. Total 1000 data sets were generated for all bearing conditions, out of which 20 percent data sets were utilized in training the NN and remaining 80 present were used in testing of NN.

While train NN, the first, second, third and fourth outputs were sets to show GB, RPBF, IRBF and ORBF respectively. Features for GB, RPBF, IRBF and ORBF condition were squeezed from recorded vibration signals in time domain for automatic fault cataloging. In the present work for extraction of features statistical parameters such as, Peak value (PV), RMS value, Crest factor (CF), Kurtosis value (KV), Skewness, Impulse factor (IF), Shape factor (SF), Clearance factor (Cl F), Upper bound (UBVH) and Lower bound value of histogram (LBVH) were selected.

A stored signal of vibration for a GB is shown in Figure 3 and for RPBF, IRBF and ORBF given in Figure 4-6 respectively.

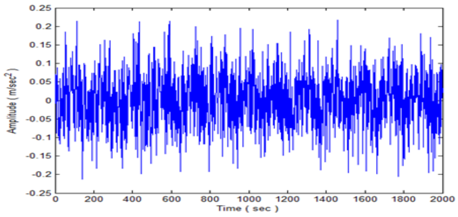

Fig 3 Recorded Vibration Signature Of Good Bearing

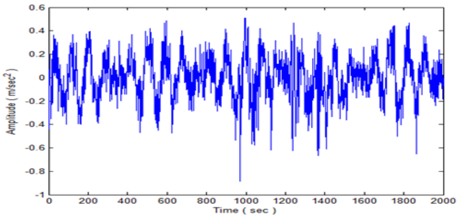

Fig. 4 Recorded Vibration Signature Of Rolling Part Faulty Bearing

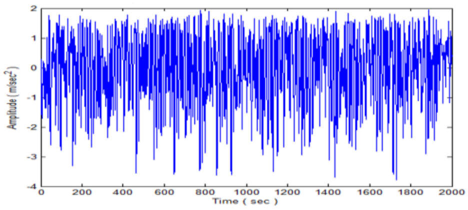

Fig. 5 Recorded Vibration Signature Of Inner Ring Ball Race Faulty Bearing

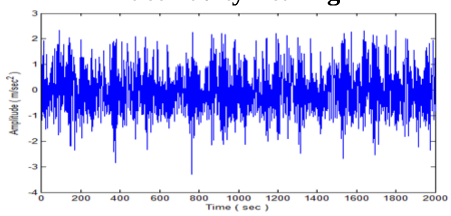

Fig. 6 Recorded Vibration Signature Of Outer Race Faulty Bearing

The squeeze features from vibration signals are presented graphically in figure 7-16. In graphs blue colour represents GB, red colour represents RPBF, green colour represents IRBF and purple colour f represents ORBF. The ranges of these features are given in figure 17. The separation between GB and ORBF are greatest in the plots of PV and UBVH. The plot of Cl F, IF, SF, LBVH shows the difference between GB and IRBF. Similarly the difference between GB and RPBF is shown in plot of RMS value and skewness.

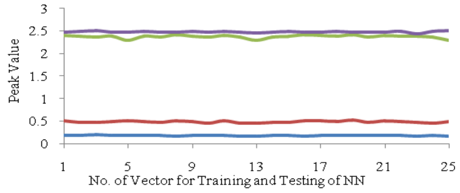

Fig. 7 Features Based on TDA - Peak Value

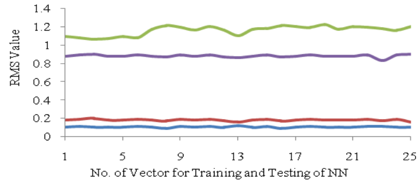

Fig. 8 Features Based on TDA – RMS Value

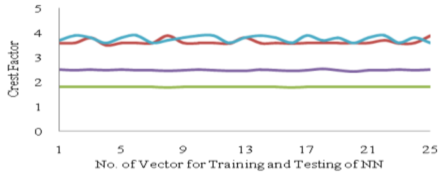

Fig. 9 Features Based on TDA – Crest Factor

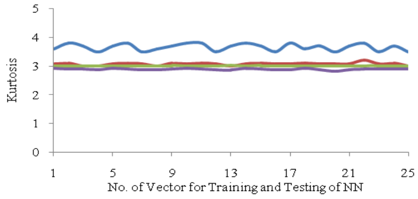

Fig. 10 Features Based on TDA – Kurtosis

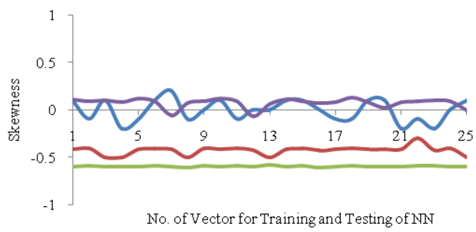

Fig. 11 Features Based on TDA – Skewness

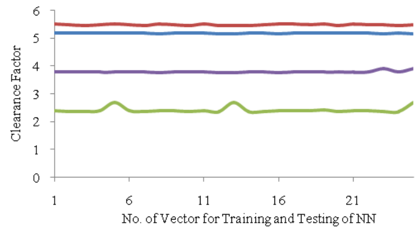

Fig. 12 Features Based on TDA–Cl Factor

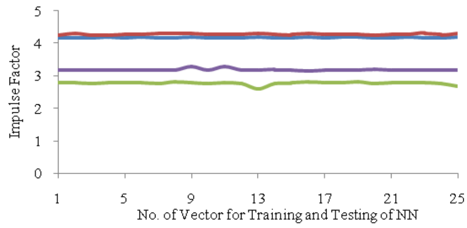

Fig. 13 Features Based on TDA– Impulse Factor

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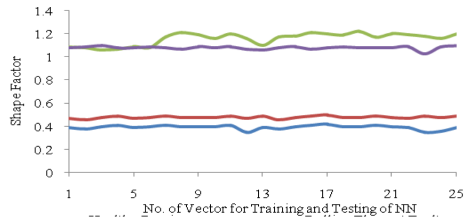

Factor **Fig. 14 Features Based on TDA – Shape**

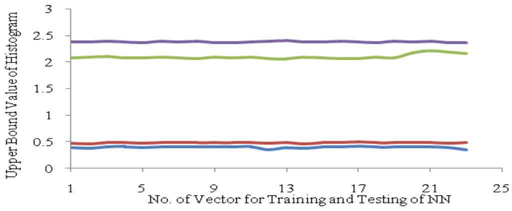

Fig. 15 Features Based on TDA–Upper Bound Value of Histogram

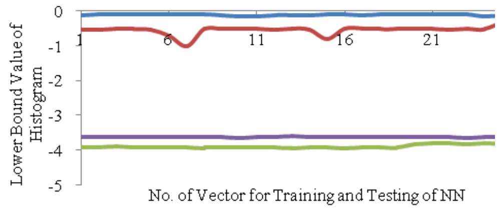

Fig. 16 Features Based on TDA–Lower Bound Value of Histogram

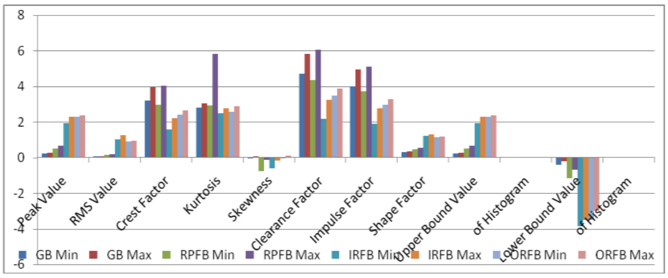

Figure 17: Statistical parameter of Time Domain Analysis

III. FAULT CLASSIFICATION USING FFNN

In the present work for classification of faults in AM, FFNN was designed using squeeze features of TDA. Before feeding data to developed FFNN all the squeeze features were normalised. The process of training and testing of the FFNN is shown in Figure 18 for GB, ORBF, IRBF and RPBF state.

The FFNN are trained and tested based on the features discussed in previous section. Out of 1000 data set of input vectors 200 sets are used for training purpose and rest 800 set for testing of FFNN. The classification rates of input vectors based on squeeze out statistical features are shown in Table 1.

Table 1: Overall Classification Rate of Bearing Conditions

S.No.	Bearing Conditions	Individual Classification Rate %	Overall Classification Rate %
1	GB	99.80%	97.45%
	RPBF	96.40%	
3	IRBF	95.60%	
4	ORBF	98.00%	

IV. CONCLUSION

The time domain analysis technique is best method for AM bearing fault detection and classification. The benefit of TDA is that it straightforwardly centers around the time domain

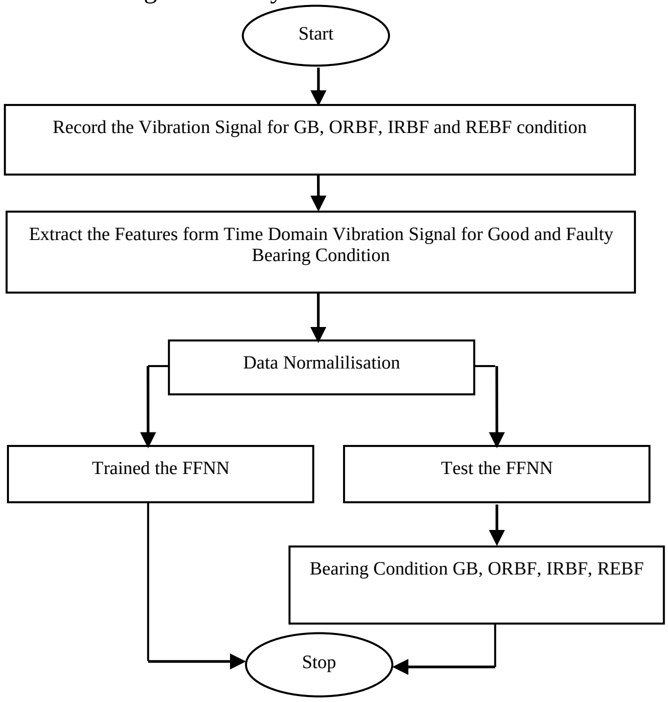

Fig.16 Process of Training and Testing of the Neural

waveform of vibration signals. The features crush out from vibration signals can be utilized to sustain into NN classifiers to recognize good and faulty bearing conditions. In the present research work classification rates of individual bearing condition are 99.80%, 96.40%, 95.60% and 98.00% for GB, RPBF, IRBF and ORBF separately. The general fault classification rate of various bearing fault in AM is 97.45%. Result demonstrates the adequacy and use of presented technique for detection and diagnosis of induction motor bearing faults.

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