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ON LINE FAULT DIAGNOSIS OF AIR COMPRESSOR USING ADAPTIVE NEURO FUZZY INFERENCE SYSTEM

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Abstract --*This paper presents a study of the use of hybrid intelligent system in detection of vibration faults in Air Compressor. It enables predictive maintenance. The performance of this technique is investigated through experimental study of real online vibration signals. The results demonstrate that complexity analysis and velocity parameters in conjunction with ANFIS provide an effective measure for machinery health evaluation.*

Index Terms -- *Hybrid Intelligent system, ANFIS, Vibration faults, Velocity parameters, Predictive maintenance*

1. INTRODUCTION

Today's production industries are facing unprecedented challenges brought about by the development of new technologies. In addition, service and maintenance are becoming more and more critical to sustain productivity and customer satisfaction at the highest possible level of global technological competence. Vibration monitoring has been used in steel, chemical, sugar, paper, and textile and other industries, for on-line condition monitoring of rotating machinery. It is necessary to avoid the break downs, which may lead to production loss in industry due to huge repair and maintenance cost and down time. Increased complexities of rotating machinery and demands for higher speeds and greater power have created complex vibration problems. The main aim of vibration monitoring is to maximize availability, reliability and efficiency of the constituent machinery of plant. Further, there is scope for diagnosis of critical machinery in steel plants.

2. LITERATURE SURVEY

A survey of literature has been carried out in the area of fault diagnosis of the rotating machinery. It reveals that many researchers have tried different techniques related to the fault diagnosis of rotating machineries with specific faults.

A study of effects of misalignment on vibration signature of rotating machinery is presented [1]. An account of study of effects of unbalance and misalignments on Rotating Machinery [2]. Truncation of the waveform during rubbing conditions was observed [3]. Orbits for light rub condition have indicated a single loop whereas multi loops observed for heavy rub. Both sub harmonics and super harmonics were exhibited in heavy rub condition above critical speed. The orbits precess in a direction opposite to the direction of the rotation of the rotor, with a shape of '8', indicating the rotor instability.

Main characteristics of neural networks are that they have ability to learn complex nonlinear input-output relationships [4]. They use sequential training procedures, and adapt themselves to the data. Characteristic features of frequency domain vibration signals have been used as inputs to ANN consisting of one input, one hidden and one-output layer each. The ANN is trained using multiplayer feed forward back propagation Marquardt Algorithm. The ANN was used for diagnosis and quantification of faults. Wavelet transform approach enables instant to instant observation of different frequency components over the full spectrum [5].

A hybrid intelligent system is one which combines at least two intelligent systems. A combination of Artificial Neural Network and Fuzzy Logic creates Neuro-fuzzy system [6]. Neuro-fuzzy system is realized as a neural network, in which fuzzy system parameters are encoded in several layers [7]. Using network learning ability the system parameters can be adapted. Hence the system is called Adaptive Neuro Fuzzy Inference System (ANFIS). Engineering judgments based on understanding of physical phenomena are needed to provide the diagnosis and methods for correcting the rotating machinery faults. The trend is to extract information about the prognostic parameters based on system analysis through various diagnostic techniques, so as to assess the health of the plant or equipment. Fault diagnosis is conducted typically in the following phases- data collection, feature extraction, and fault detection and identification.

Literature survey gives an overview of vibration monitoring, rotating machinery fault diagnosis, application of artificial neural networks. Fuzzy logics for fault diagnosis have been studied. This paper presents application of Adaptive Neuro Fuzzy Inference system to on line fault diagnosis of critical machinery in steel plant. It considers Air Compressor as the most critical one with a

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criticality index of 400, highest in the category of machinery of Steel Plants [8].

The main aim of this paper is to diagnose the faults and more accurate prediction of vibration behavior of the compressor by ANFIS method.

3. EXPERIMENTAL SETUP

Air compressor is selected as a critical machine driven by motor running at a speed of 2975 rpm. It is connected to the air compressor by a flexible coupling. The shaft is supported on bearings is shown in Figure 1. The bearing pedestals and vibration pads are provided in order to fix the tri-axial accelerometer. The dynamic vibration levels in horizontal, vertical and axial directions are measured. The frequency analysis is carried out using a Fast Fourier Transform (FFT) analyzer. The tri-axial accelerometer enables measurements of the vibration level in the horizontal, vertical and axial directions. The output of the tri-axial accelerometer was connected to a multiplexer. The output of a Multiplexer was connected to a FFT analyzer as shown in Figure 2. FFT analyzer was in turn interfaced to a computer.

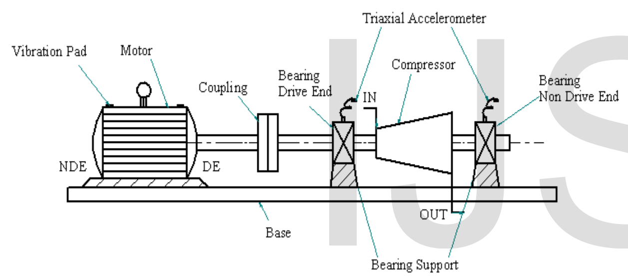

Fig.1: Experimental Set Up and Accelerometer location

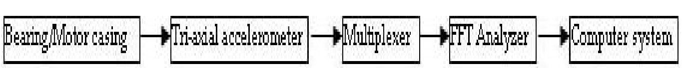

Fig. 2. Instrumentation for Vibration Analysis

4. FAULT CONDITIONS

It is essential to define normal and faulty operating conditions of the machinery in a digital form that can be used for computational purpose. This is done by representing the presence or absence of a particular fault type, with each set called membership classification (m_c). Fault state 1 is the normal state, which indicates that horizontal, vertical and axial velocity components are within ISO limit, i.e., 3.5, [9], whereas in the case of fault state 2 velocity components are beyond the limits, i.e., either < 3.5, = 3.5 or >3.5.

In order to determine the vibration severity at least two measurement locations are required. One location each on driver and driven end are considered for accurate identification of faults, in addition to First Stage. Table 1 through Table 3 gives the sample readings considered for depicting the vibration behavior.

Table 1: Frequency of RMS Velocity at MDE

Sl No	Frequency (Hz)	Speed (rpm)	RMS velocity mm/Sec.		
			v_H	v_V	v_A
1	1X	2975	2.82	3.72	2.29
2	2X	5950	2.48	3.96	2.72
3	3X	8925	2.45	2.56	2.34
4	4X	11900	3.33	1.34	2.65
5	5X	14875	2.45	3.32	2.69

Table 2: Frequency of RMS Velocity at MNDE

Sl No	Frequency (Hz)	Speed (rpm)	RMS velocity mm/Sec.		
			v_H	v_V	v_A
1	1X	2975	2.85	3.82	2.81
2	2X	5950	2.89	3.98	2.73
3	3X	8925	1.87	2.23	1.44
4	4X	11900	2.56	2.45	2.45
5	5X	14875	3.12	3.13	2.22

Table 3: Frequency of RMS Velocity at FS

Sl No	Frequency (Hz)	Speed (rpm)	RMS velocity mm/Sec.		
			v_H	v_V	v_A
1	1X	2975	2.92	3.83	2.47
2	2X	5950	2.87	3.92	2.58
3	3X	8925	2.82	2.38	2.29
4	4X	11900	3.26	3.23	3.14
5	5X	14875	2.12	2.24	2.92

Figure 3 gives the plot of velocity behavior at the Motor Drive End (MDE). Whereas, the Figures 4 and 5 give the plot of the behavior at the Motor Non Drive End (MNDE) and at the First Stage (FS) respectively. It can be observed that in all the three cases, the vertical velocity, v_V, amplitudes are high and predominating at both 1x and 2x harmonics. Specific condition can be determined by considering rotor behavior and frequency spectrum plots.

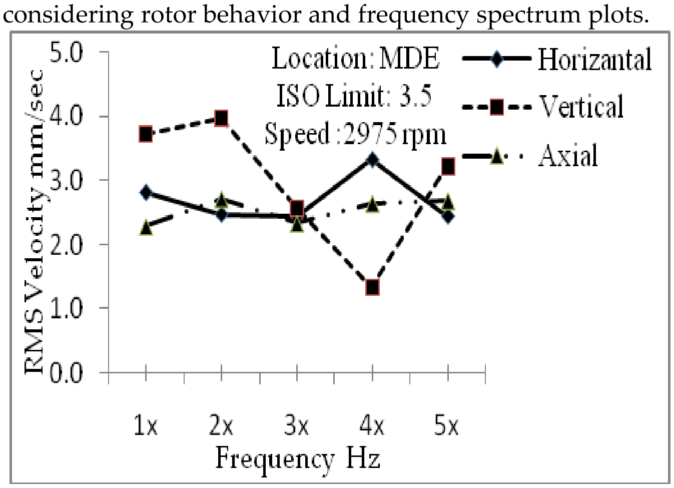

Figure 3. Plot of Rotor Behavior at MDE

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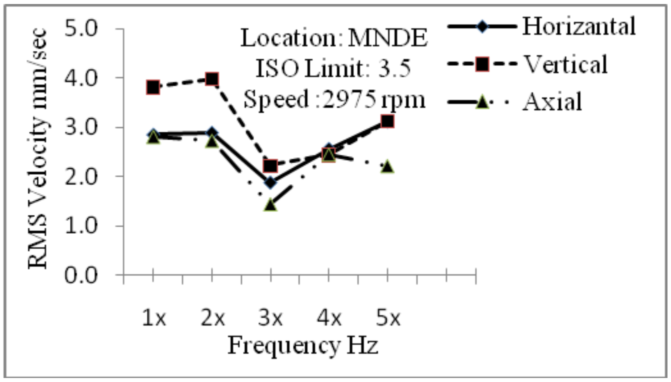


Figure 4. Plot of Rotor Behavior at MNDE

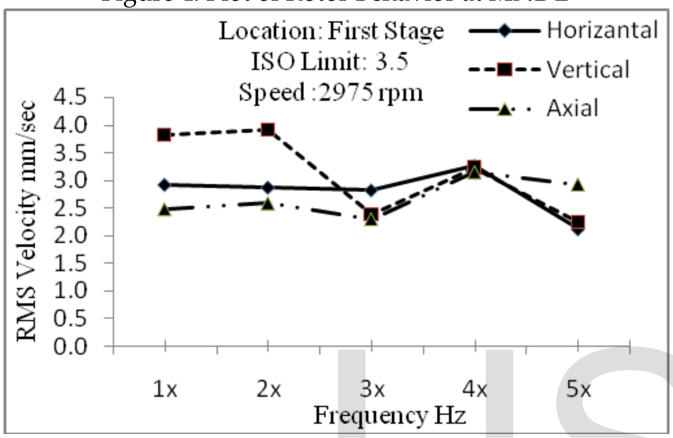


Figure 5 Plot of Rotor Behavior First Stage

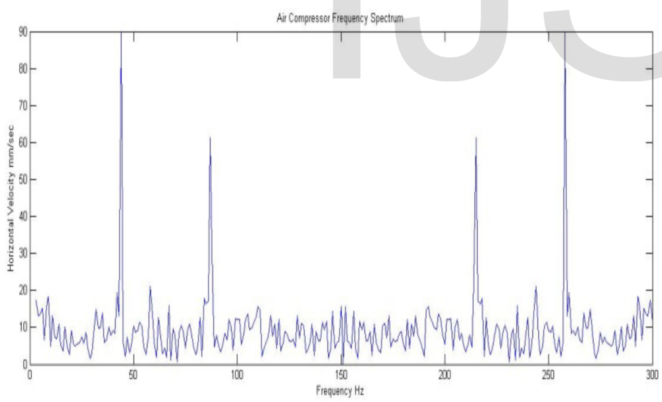


Figure 6. Frequency Spectrum of Air Compressor

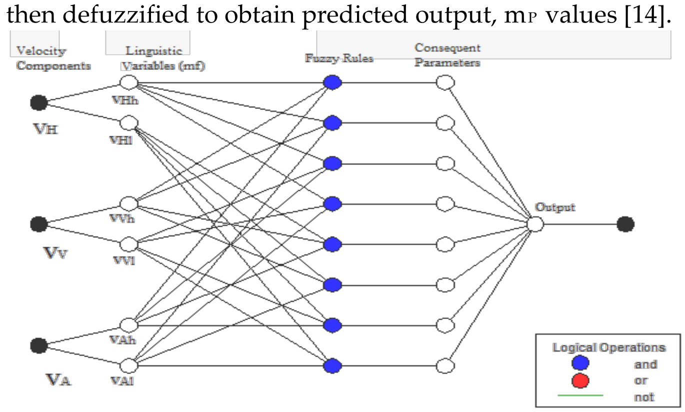
The vibration signals of Air Compressor were transferred to FFT signal processor. Figure 6 shows the frequency spectrum. In the present study, fault identification is done using the FFT technique and ANFIS.

5. DIAGNOSIS OF FAULT USING ANFIS

Fuzzy modeling has found numerous practical applications in control and prediction. ANFIS is a new inference system, in which a universal approximate is introduced to represent highly non-linear functions [10]. An adaptive neural network is a network structure consisting of a number of nodes connected through directional links. Each node is characterized by a node function with fixed or adjustable parameters. Learning or training phase of a neural network is a process to determine parameter values to sufficiently fit the training data. ANFIS is a fuzzy Sugeno model put in the framework of adaptive systems to facilitate learning and adaptation [11].

A Sugeno type Adaptive Neuro Fuzzy Inference System with three input nodes Horizontal (v_H), Vertical (v_V) and Axial (v_A) velocities and one output node was used. The input consists of the velocity vector obtained by extraction of amplitudes for the characteristic velocities of the machinery used in our experimental setup, with the fault state as the output [12]. Three inputs in their vector order are v_H, v_V and v_A rms velocity amplitudes.

300 data sets were collected for training. Out of these 300, 20 data sets were randomly selected for testing. A separate set of 24 data sets were collected for checking and characterization of faults. Thus total of 324 data sets were considered for the purpose of analysis. Figure 7 shows the network structure of the system and the membership functions when the number of membership function for each input node is set to 2. The network first fuzzifies each input with two membership functions that can be classified as low and high depending on the value of the velocity amplitudes. The input membership functions v_{Hl}, v_{Hh} v_{Vl}, $v_{Vh,}$ v_{Al} and v_{Ah} velocities and their types (i.e., Gaussian) are then combined to form the rule base [13]. The network selects an output membership function depending on the rules fired by the fuzzy logical combination of input membership functions. Output membership functions are then defuzzified to obtain predicted output, m_P values [14].



(v_{Hl}-Low horizontal, v_{Hh}-High horizontal, v_{Vl}-Low vertical, v_{Vh}-High vertical, v_{Al} -Low axial, v_{Ah}-High axial velocities)
Figure 7. Structure of the System and Membership Functions

Experimental data was collected from Air Compressor in v_H, v_V and v_A directions. The data obtained were classified according to ISO limit as m_C, (1's and 2's) and m_P and listed in Table 4.

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Table 4: Experimental Data and Predicted Values

Sl.No	Velocity mm/sec			m_C	m_P	Rounded off m_P
	v_H	v_V	v_A			
1	3.36	3.95	3.22	2	2.0109	2
2	2.86	3.18	3.32	1	0.99887	1
3	2.67	3.25	3.35	1	0.99984	1
4	2.87	3.26	3.14	1	1	1
5	3.19	3.85	3.29	2	1.9914	2
6	3.15	3.35	2.92	1	0.99572	1
7	2.27	3.36	2.78	1	0.99064	1
8	3.15	2.87	2.85	1	1.0006	1
9	3.35	3.98	3.36	2	2.0094	2
10	2.58	2.55	2.87	1	1.0007	1
11	3.25	2.87	2.23	1	0.99898	1
12	2.88	3.28	2.25	1	1.001	1
13	3.27	3.86	3.39	2	1.9951	2
14	3.36	2.45	1.82	1	0.988	1
15	3.38	1.67	2.57	1	0.98808	1
16	3.23	1.59	1.98	1	1.0008	1
17	3.28	3.92	3.38	2	1.9956	2
18	3.12	1.34	2.23	1	1.0007	1
19	1.34	1.22	3.23	1	1.0015	1
20	2.54	3.34	2.22	1	0.9999	1

The system was loaded with the 300 data sets for training and allowed to iterate through the data sets for 100 epochs. Figure 8 shows the training error at each epoch. The error descended steeply from the second epoch and leveled off to an acceptable level 0.043. It was also attested by the command line output of the system.

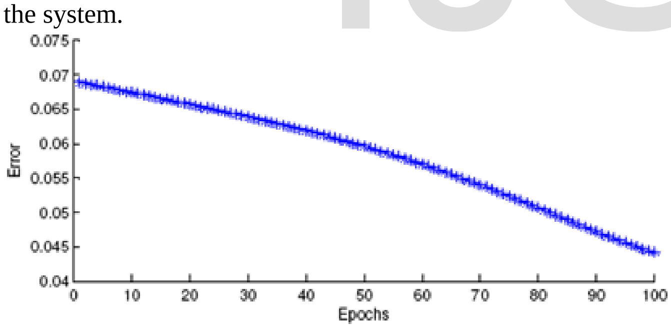

Figure 8: Trend of Training Error

Figure 9. Shows the comparison between training and checking data trends. 24 data sets loaded to the trained network for checking. Checking data need not be from the training data set.

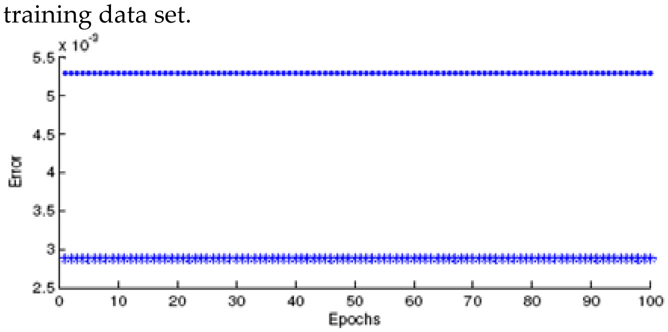

Figure 9. Comparison of Training and Checking Data.

The structure of error level for the training and checking data sets is very similar at the beginning and ending. The error values are shown in Table 5. Thus a validation of the structural stability of the system can be done. The model simulates correctly for any set of data obtained in the same way as that of training and checking data. ANFIS system simulation information is given in Table 6.

Table 5: Training and Checking Data Errors.

Process Points	Errors	
	Training	Checking
Beginning	0.00288418	0.00592692
End	0.00288622	0.00651582

Table 6: ANFIS System Simulation Information

Sl. No.	Particulars	No
1.	Nodes	34
2.	Linear Parameter	32
3.	Nonlinear Parameters	12
4.	Total Parameters	44
5.	Training Data Sets (Pairs)	300
6.	Testing Data Sets (pairs)	20
7.	Checking Data Sets (Pairs)	24
8.	Epochs Reached	2
9.	Fuzzy Rules	8

After training, 20 testing data were used to validate the accuracy of the ANFIS for classification of the air compressor faults. Confusion Matrix (3x3) showing the classification results of the ANFIS model is given in Table 7. The diagonal elements in the confusion matrix show the number of correctly classified instances. In the first column, the first element ('3') shows the number of data points belonging to the horizontal and classified by ANFIS as Horizontal Class (or Class H). The second element ('0') shows the number of data points belonging to the horizontal class but misclassified by ANFIS as Vertical Class (or Class V). The third element ('1') shows the number of data points misclassified as Axial Class (or Class A) and so on [15].

Table 7: Confusion Matrix of Testing Data

Output/Desired	Class H	Class V	Class A
Class H	3	0	0
Class V	0	15	0
Class A	1	0	1

The multistage confusion matrix (3x3) given in Table 7 is converted into (2x2) matrix by combining the cell elements with different classes is shown in Table 8, where, N = Total Number of Testing Data Sets, TNC= Total Number of Classification, TN= True Negative Decisions, FP= False Positives Decisions, FN= False Negative Decisions and, TP= True Positives Decisions.

Table 8: Confusion Matrix (2x2)

N=20		Predicted		TNC
		No	Yes	
Actual	No	TN	FP	3
		3	0	
	Yes	FN	TP	17
		1	16	

There are three criteria to determine the test performance of classifier. These criteria are Sensitivity (*ST*), Specificity (*SP*) and Total Classification Accuracy (*TCA*) [15]. Sensitivity can be obtained as, $ST=TP/AP$, where *TP* is the Number of True Positive Decisions and *AP* is the Number of Actual Positive Cases. i.e., $ST=16/17=0.941$ or 94.1%. Specificity can be obtained as, $SP=TN/AN$, where *TN* is the Number of True Negative Decisions and *AN* is the Number of Actually Negative Cases. i.e., $SP=3/3=1$ or 100%. Total Classification Accuracy can be obtained as, $TCA=TCD/TN$, where *TCD* is the Number of Correct Decisions and *TN* is the Total Number of Cases i.e., $TCA=19/20=0.95$ or 95%.

During ANFIS training 8 designated rules were generated based on the fault state defined for combination of inputs. The rule base generated by the system is shown in Figure 10.

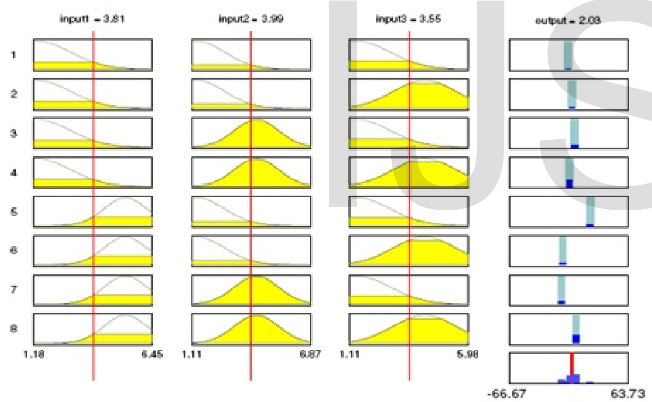

Figure 10: Rule Base of the System

If horizontal velocity, v_H is of first parameter, vertical velocity, v_V is of second parameter and axial velocity, v_A is of third parameter, then the output parameter is one which is mapped with membership function as shown in Figure 11. Similarly remaining rules were defined.

1. If (vH is in 1mf1) and (vV is in 2mf1) and (vA is in 3mf1) then (o/p is out1mf1) (1)
2. If (vH is in 1mf1) and (vV is in 2mf1) and (vA is in 3mf2) then (o/p is out1mf2) (1)
3. If (vH is in 1mf1) and (vV is in 2mf2) and (vA is in 3mf1) then (o/p is out1mf3) (1)
4. If (vH is in 1mf1) and (vV is in 2mf2) and (vA is in 3mf2) then (o/p is out1mf4) (1)
5. If (vH is in 1mf2) and (vV is in 2mf1) and (vA is in 3mf1) then (o/p is out1mf5) (1)
6. If (vH is in 1mf2) and (vV is in 2mf1) and (vA is in 3mf2) then (o/p is out1mf6) (1)
7. If (vH is in 1mf2) and (vV is in 2mf2) and (vA is in 3mf1) then (o/p is out1mf7) (1)
8. If (vH is in 1mf2) and (vV is in 2mf2) and (vA is in 3mf2) then (o/p is out1mf8) (1)

Figure 11. Verbal Rule Set of the ANFIS System

6. ANALYSIS OF RESULTS

Velocity components measured in v_H, v_V and v_A directions by tri axial accelerometer. They were processed through FFT. The 1x and 2x vertical velocity v_V components are high and predominating. This indicates the presence of misalignment and unbalance in the Air Compressor. These velocity components processed in ANFIS indicates the predictions shown in Table 1.

The ANFIS system was trained till the results obtained with minimum error 0.00288418. 20 data sets were used to test trained ANFIS. For the proper data set, the testing error 0.00592692 decreases with the training, proceeding until a jump point. The error generated while training the ANFIS begins with 0.00288418 and ends with 0.00288622 when epoch number reaches 2. This validates the structural stability of the system and will perform correctly for any set of data obtained in the same way as that of training and checking.

7. SCOPE FOR FURTHER WORK

Although much progress has been made on intelligent fault diagnosis of rotating machinery, there is a significant scope for additional research into intelligent real-time fault diagnosis techniques for industry in a reliable, efficient and precise manner.

8. APPLICATION OF WORK

Fault diagnosis can be applied to a wide variety of machinery across industries. All types of machines need to be tested during design, assembly, and normal operation by applying intelligent fault diagnostic techniques.

9. CONCLUSION

The main motivation for applying a Neuro-fuzzy computing approach is that it combines the generalization capabilities of Neural Networks with the ease of interpretability and high expressive power of fuzzy rules in an effective way. Vibration signals were obtained from the Air Compressor using Tri-axial Accelerometer and FFT. These signals were processed in MATLAB using ANFIS tool for training, testing and checking to simulate the Air Compressor. The performance criterion of the ANFIS classifier was evaluated using confusion matrix. The total classification accuracy of 95% obtained proves the validation of the Air Compressor model. Neuro-Fuzzy Systems have high potential in diagnosis of machinery. The proposed ANFIS model has been found to be an effective tool for diagnosing faults.

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