

Adaptive Neuro Fuzzy Inference System for Fault Diagnosis of Feed Pump

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ABSTRACT: Rotating machinery is widely used in today's industry some of which are complex, often with extremely demanding performance criteria. Machine failures can be catastrophic resulting in costly downtime. Fault diagnosis has become increasingly more important for industrial automation. This work demonstrates the use of hybrid intelligent system in detection of vibration faults in Feed Pump. Prediction of failure in Feed Pump is based on Adaptive Neuro Fuzzy Inference System. The performance of this technique is investigated through experimental study of real online vibration signals. The results reveal that complexity analysis and velocity parameters in combination with ANFIS enable predictive maintenance and provide an effective measure for machine condition evaluation.

KEYWORDS: Fault Diagnosis, Hybrid Intelligent System, Feed Pump, ANFIS, predictive maintenance

I. INTRODUCTION

Vibration problem occurs in machinery which has sliding or rotating parts and sometimes leads to damage of components and surrounding structures. Vibrating industrial machinery comprises of motors, pumps, turbines, compressors, generators, machine tools, locomotives, diesel engines, etc. The effects of vibration are unbalanced forces in a machine, improper alignment and aero dynamic forces, etc [1]. Growing demand for higher performance, safety and reliability of industrial systems has increased the need for fault diagnosis. A vibration signature measured at the external surface of machine or at any other suitable place contains a good amount of information to reveal condition of the machine [2]. Thus, it provides very useful information about the impending failure preventing costly breakdowns. Analysis of vibration signals is widely used to detect early faults. The vibration data collected from a faulty rotating machine can exhibit different nonlinear and transient events. The analysis of such events requires specific techniques which go beyond the classical Fourier approach [3]. This paper presents application of Adaptive Neuro Fuzzy Inference system to on line fault diagnosis of critical machinery in steel plant. It considers Feed Pump as the most critical one with a criticality index of 415, highest in the category of machinery of Steel Plants [4].

II. LITERATURE SURVEY

Literature survey indicates that fault diagnosis of rotating machinery is a crucial aspect of the subject which has gained more attention. It reveals that many researchers have tried different techniques related to the fault diagnosis of rotating machineries with specific faults. The design of rotating machinery becomes increasingly complex, due to rapid progress in technology [5]. Unexpected downtime due to machinery failures has become a major issue in modern rotating machinery which is expected to run continuously for extended hours [6]. Without effective diagnosis, one is unable to make a reliable prediction of lead-time to failure. Therefore, conducting effective condition monitoring and fault diagnosis is desirable and imperative in industry. However, diagnosing faults in rotating machinery is often a labour-intensive and time-consuming practice. This makes conducting effective and efficient fault diagnosis a challenge for technicians and plant maintainers [7]. Main characteristics of neural networks are that they have ability to learn complex nonlinear input-output relationships [8]. They use sequential training procedures, and adapt themselves

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 8, August 2016

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 multiple layer 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 [9]. 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 [10]. Neuro-fuzzy system is realized as a neural network, in which fuzzy system parameters are encoded in several layers [11].

Literature survey gives an overview of vibration monitoring, rotating machinery fault diagnosis, application of artificial neural networks. Application of fuzzy logics for fault diagnosis, have been studied. The main aim of this paper is to diagnose the faults and more accurate prediction of vibration behaviour of the Feed Pump by ANFIS method.

III. EXPERIMENTAL SETUP

Feed Pump is a critical machine driven by motor running at a speed of 1450 rpm. It is connected to the pump by a flexible coupling. The shaft is supported on bearings is shown in Figure 1.

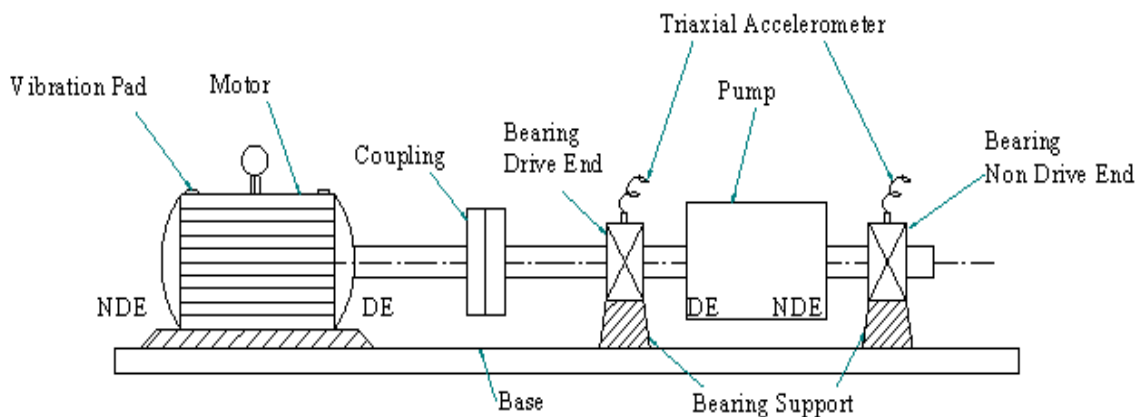


Figure 1. Experimental Set Up and Measurement Locations

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) analyser. The tri-axial accelerometer enables measurements of the vibration level in the horizontal, vertical and axial directions. In order to determine the vibration severity, measurement of at least one location each on driver and driven are required. Hence, one location each on driver-Motor (MDE & MNDE) and driven-Pump (PDE & PNDE) ends are considered for accurate identification of faults, in addition to Bearing Ends.

The Figure 2 shows the instrumentation used for vibration analysis. Motor casing or bearing location is cleaned and the tri-axial accelerometer is fixed by using either a magnet or glue.

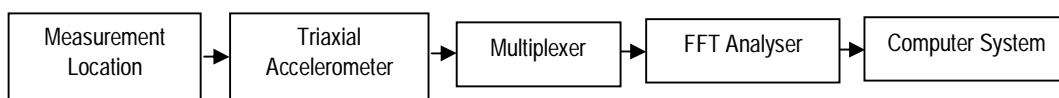


Figure 2. Instrumentation for Vibration Analysis

A tri-axial accelerometer was used to pick up RMS velocities in horizontal (v_H), vertical (v_V) and axial (v_A) directions at the measurement location. The output of the accelerometer was connected to a multiplexer. A multiplexer is used

when number of available channels is less than the number of signals to be simultaneously recorded. The output of a multiplexer was connected to a FFT analyser. FFT analyser converts time domain data into frequency domain data. FFT analyser was in turn interfaced to a computer.

IV. 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. Fault state 1 is the normal state, which indicates that horizontal, vertical and axial velocity components are within ISO limit, i.e., < 6.0 , whereas in the case of fault state 2 velocity components are beyond the limits, i.e., either ≥ 6.0 .

In order to determine the vibration severity at least two measurement locations are required. One location each on Motor Drive End (MDE) and Motor Non Driving End (MNDE), in addition to Pump Drive (PDE), are considered for accurate identification of faults. Table 1(a), (b) and (c) gives the measured velocity amplitudes v_H , v_V and v_A considered for depicting the vibration behaviours at MDE, MNDE, and PDE.

Table 1(a): RMS Velocity at MDE

Sl No	Frequency (Hz)	Speed (rpm)	RMS Velocity mm/Sec.		
			v_H	v_V	v_A
1	1X	1450	5.68	6.62	4.34
2	2X	2900	5.12	7.85	4.25
3	3X	4350	3.64	4.78	3.58
4	4X	5800	4.56	3.49	4.39
5	5X	7250	4.38	3.27	4.18
6	6x	8700	5.32	3.25	2.47
7	7x	10150	5.24	4.34	2.16
8	8x	11600	2.33	3.35	2.17

Table 1(b): RMS Velocity at MNDE

Sl No	Frequency (Hz)	Speed (rpm)	RMS Velocity mm/Sec.		
			v_H	v_V	v_A
1	1X	1450	3.45	6.38	3.96
2	2X	2900	4.12	9.75	4.19
3	3X	4350	4.51	5.62	4.87
4	4X	5800	3.69	3.65	3.54
5	5X	7250	3.78	4.84	3.31
6	6x	8700	3.56	3.24	3.54
7	7x	10150	4.12	4.42	3.25
8	8x	11600	3.85	3.81	3.67

Table 1(c): RMS Velocity at PDE

Sl No	Frequency (Hz)	Speed (rpm)	RMS velocity mm/Sec.		
			v_H	v_V	v_A
1	1X	1450	5.37	7.14	3.92
2	2X	2900	3.19	8.82	3.24
3	3X	4350	3.22	3.29	3.38
4	4X	5800	3.66	3.42	4.11
5	5X	7250	3.12	3.21	3.11
6	6x	8700	4.13	4.19	4.21
7	7x	10150	3.95	3.76	3.81
8	8x	11600	3.51	3.99	3.21

The velocity amplitudes are plotted against frequency in Figure 3(a) to (c). Figure 3(a) gives the velocity behaviour at the Motor Drive End (MDE). Figure 3(b) gives the behaviour at the Motor Non Drive End (MNDE) and Figure 3(c) shows that of the Pump Drive End (PDE) respectively.

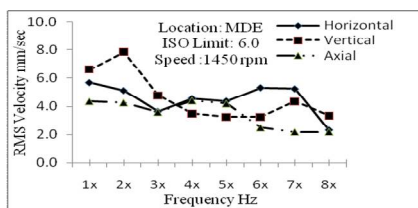


Figure 3(a). Rotor Behaviour at MDE

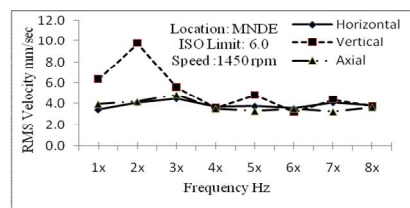


Figure 3(b). Rotor Behaviour at MNDE

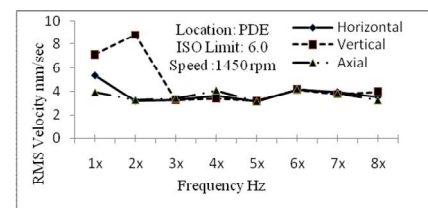


Figure 3(c). Rotor Behaviour at PDE

It can be observed that in all the three cases, the amplitudes of vertical velocity, v_V , are high at both 1x and 2x harmonics, v_V at 2x being is slightly higher than 1x indicates the parallel misalignment. The looseness will often cause sub harmonic multiples at 0.5x, 1.5x, 2.5x, 3x, 3.5x and 4x. Thus combined faults of parallel misalignment and mechanical looseness occurred in a feed pump [12]. The findings were verified from the maintenance log book of the host Industry and found correct.

However, the velocity amplitudes collected continuously from FFT analyser used to plot time wave form and frequency spectrum. The specific condition can be determined by considering rotor behaviour and frequency spectrum plots. The vibration signals of structures and machines are captured in time domain waveforms. If the excitation of vibrations is multiple due to the existence of combined faults, then the wave form consisting of multiple sub harmonics will become clumsy as shown in Figure 4 (a). Hence, it becomes difficult to extract any useful information about the faults. The

complexity of the time waveform can be minimised by changing the spectrum into FFT [13]. This reduces the very complex shape to easier form of vibration amplitude (mm/sec) vs frequency (Hz). The vibration signals were recorded periodically at MDE, MNDE and PDE. The plots of RMS velocity v/s frequency have been drawn in Matlab. FFT Tool reveals high velocity amplitudes at 1x and 2x with multiple sub harmonics as shown in Figure 4 (b).

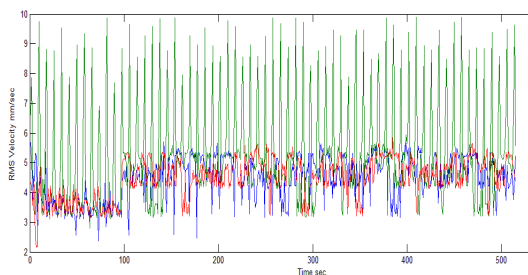


Figure 4(a). Time Waveform Signal of Feed Pump

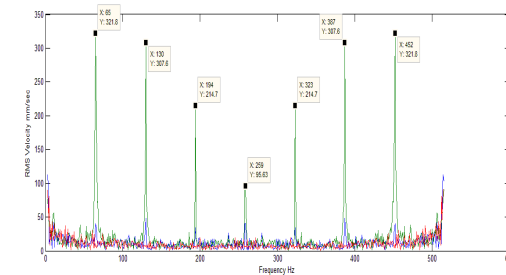


Figure 4(b). Frequency Spectrum of Feed Pump

In the present study, fault identification is done using the FFT technique and validated in ANFIS, so as to prove that ANFIS can be more effective and easy to adopt for online monitoring.

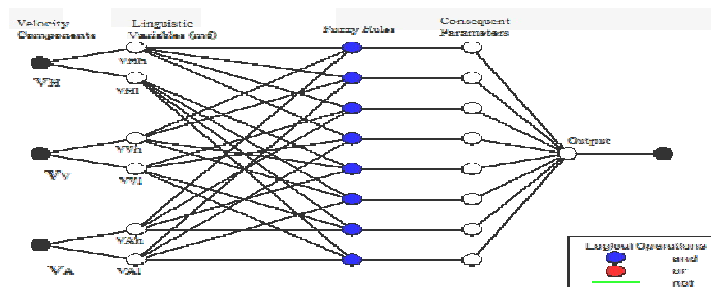
V. DIAGNOSIS OF FAULT USING ANFIS

Fuzzy modelling 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. Hybrid intelligent system enabled predictive maintenance of Air Compressor by detection of vibration faults. The performance of ANFIS technique is investigated through experimental study of real online vibration signals. Analysis of velocity parameters in conjunction with ANFIS provides an effective measure for machinery health evaluation [14].

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 sufficiently to fit the training data. ANFIS is a fuzzy Sugeno model put in the framework of adaptive systems to facilitate learning and adaptation [15].

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 experimental setup, with the fault state as the output [16]. Three inputs in their vector order are rms velocity amplitudes v_H , v_V and v_A .

515 data sets were collected for training. Out of these 515, 60 data sets were randomly selected for testing. A separate set of 30 data sets were collected for checking and characterization of faults. Thus total of 545 data sets were considered for the purpose of analysis. Figure 5 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.



(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 5: Structure of the System and Membership Functions

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 8, August 2016

The network first fuzzifies each input with two membership functions that can be classified as low (1's) and high (2's) depending on the value of the velocity amplitudes. The input membership functions v_{Hh} , v_{Vh} , v_{Vl} , v_{Vh} , v_{Al} and v_{Ah} velocities and their types (i.e., Gaussian) are then combined to form the rule base [17]. 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 values [18]. The ANFIS method was found suitable for nonlinear vibration measurements obtained from accelerometer [19]. ANFIS system simulation information is given in Table 2.

Table 2 : 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)	515
6.	Testing Data Sets (pairs)	60
7.	Checking Data Sets (Pairs)	30
8.	Epochs Reached	2
9.	Fuzzy Rules	8

Checking data were used for testing the generalization capability of the fuzzy inference system at each epoch and validate. The checking data and the training data have identical formats. The FIS membership function parameters were computed when both training and checking data were loaded. The checking data error decreased as the training begun. The checking error is the difference between the checking data output value and the output of the fuzzy inference system corresponding to the same checking data input value. The checking error records the RMSE for the checking data at each epoch. The ANFIS Editor plots the checking error versus epochs curve as the system is trained [20]. Experimental data collected from Feed Pump in v_H , v_V and v_A directions were classified according to ISO limit < 6.0 or ≥ 6.0). The system was loaded with the 515 data sets for training and allowed to iterate for 100 epochs. Figure 6(a) shows the training error at each epoch. The error descended steeply from the second epoch and levelled off to an acceptable level 0.0897921. It was also attested by the command line output of the system.

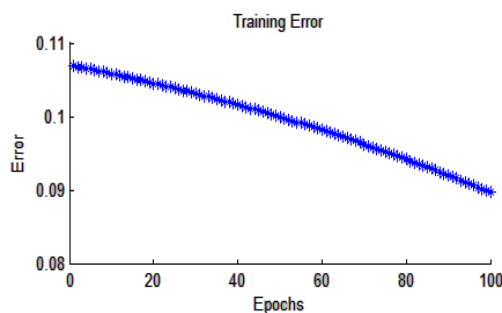


Figure 6(a): Trend of Training Error

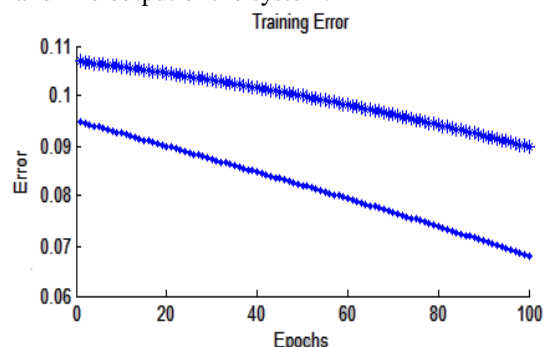


Figure 6(b). Comparison of Training and Checking Data.

Figure 6(b) shows the comparison between training and checking data trends. 30 data sets loaded to the trained network for checking. Checking data need not be from the training data set. The training error records the Root Mean Squared Error (RMSE) of the training data set at each epoch.

The ANFIS network classified the testing and checking data sets. The testing data were selected randomly from training data. After testing the testing data in a trained ANFIS network, the trend shows some of the data sets beyond the ISO limit, i.e. ≥ 6.0 and was classified as 2's as shown in figure 7(a). Checking data collected after training and testing separately, were fed into the trained ANFIS network. Some of the data sets fall beyond ISO limit, i.e. ≥ 6.0 and

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 8, August 2016

were classified as 2's as shown in Figure 7(b). The average testing error for the checking data set is 0.0680809. When checking data were tested against the trained FIS, they were almost similar and satisfactory.

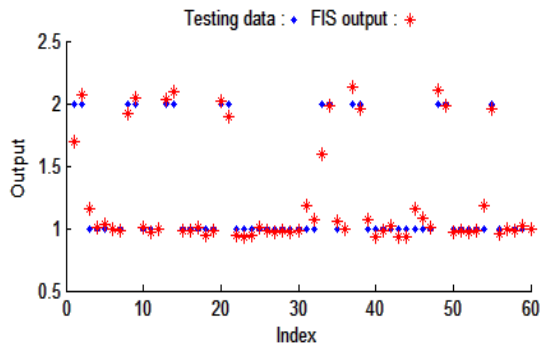


Figure 7(a): Testing the FIS with Training Data Set

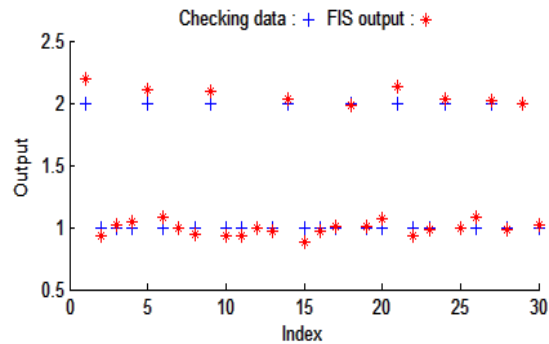


Figure 7(b): Testing the Checking Data Set

The error levels for the training and checking data sets were very similar at the beginning and as well as at ending, as depicted in Table 6. The FIS outputs obtained establishes the structural stability of the system and simultaneously ensures that the model simulates correctly for any set of data obtained.

Table 6: Training and Checking Data Errors

Process Points	Errors	
	Training	Checking
Beginning	0.0900271	0.0683758
End	0.0897921	0.0680809

After training, 60 testing data were used to validate the accuracy of the ANFIS for classification of the Feed Pump faults. Confusion Matrix (3x3) showing the classification results of the ANFIS model is given in Table 7(a). The diagonal elements in the confusion matrix show the number of correctly classified instances. In the first column, the first element ('4') 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 ('2') shows the number of data points misclassified as Axial Class (or Class A) and so on [21].

Table 7(a): Confusion Matrix of Testing Data

Output/Desired	Class H	Class V	Class A
Class H	4	0	1
Class V	0	8	0
Class A	2	0	45

Table 7(b): Confusion Matrix (2x2)

N=60		Predicted		TNC
		No	Yes	
Actual	No	TN 4	FP 1	5
	Yes	FN 2	TP 53	

The multistage confusion matrix (3x3) given in Table 7(a) was converted into (2x2) matrix by combining the cell elements with different classes as shown in Table 7(b), 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.

There are three criteria, to determine test performance of the classifier. These criteria are Sensitivity (ST), Specificity (SP) and Total Classification Accuracy (TCA) [21]. 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. Therefore, $ST = 53/55 = 0.9636$ or 96.36%. 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. Therefore, $SP = 4/5 = 0.8$ or 80%. Total Classification Accuracy can be obtained as,

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 8, August 2016

$TCA = TCD/TN$, where TCD is the Number of Correct Decisions and TN is the Total Number of Cases. Hence, $TCA = 57/60 = 0.95$ or 95%.

During ANFIS training eight designated rules were generated based on the fault state defined for combination of inputs. The rule base generated by the system is as shown in Figure 8(a). The system divides equally input and output spaces of the numerical data into linguistic terms and generates IF-THEN rules covering the training data. It is determine a degree for each rule by aggregating degrees of membership functions in the antecedent and consequent parts. Finally, defuzzifies by converting a fuzzy answer into a crisp value and an output.

If horizontal velocity, v_H is the first parameter, vertical velocity, v_V is the second parameter and axial velocity, v_A is the third parameter, then the output parameter is one which maps with membership function as shown in Figure 8(b). Similarly remaining rules were defined [22].

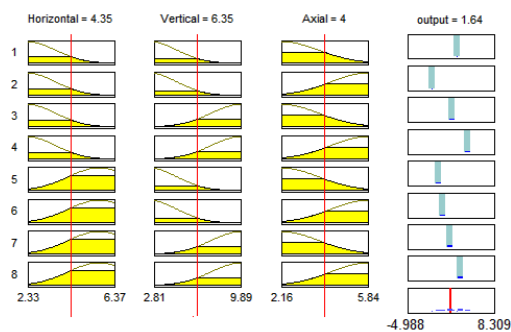


Figure 8(a): Rule Base of the System

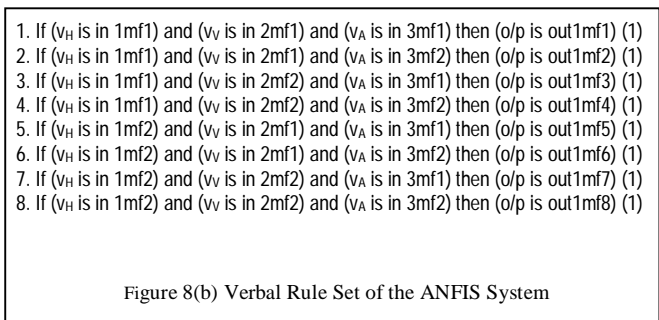


Figure 8(b) Verbal Rule Set of the ANFIS System

Fuzzy logic maps an input space to an output space. All the IF-THEN rules are evaluated in parallel. The rules themselves are useful because they refer to variables and the adjectives that describe those variables as shown Figure 8(b).

VI. 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 mechanical looseness in the Feed Pump.

The ANFIS system was trained till the results obtained with minimum error 0.0897921. 60 data sets were used to test trained ANFIS. For the proper data set, the testing error 0.0897731 decreases with the training, proceeding until a jump point. The error generated while training the ANFIS begins with 0.0900271 and ends with 0.0897921 when epoch number reaches 2. This validates the structural stability of the system and proves that the model perform correctly for any set of data obtained in the same way as that of training and checking.

VII. 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. This research work can be extended to various critical machines.

VIII. 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. ANFIS is used for

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 8, August 2016

simulation and modelling of mechanical, electrical, electronic systems. Adaptive Neuro Fuzzy Inference System finds application with the performance of a chemical process plant due to rapid deterioration of the process equipment and characteristic variable deviations. ANFIS is used to forecast the environmental conditions such as humidity, temperature, atmosphere pressure, etc.

IX. 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 Feed Pump using Tri-axial Accelerometer and FFT. These signals were processed in MATLAB using ANFIS tool for training, testing and checking to simulate the Feed Pump. The performance criterion of the ANFIS classifier was evaluated using confusion matrix. The total classification accuracy of 95% obtained, proves the validation of the Feed Pump 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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Vol. 5, Issue 8, August 2016

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BIOGRAPHY



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