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Implementation of Neuro– Fuzzy and Multi-Layer Perceptron System Intelligent Techniques for Main Fault Diagnosis of Rotating Machinery

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ABSTRACT

Nowadays, Fault detection of rotating machinery by diagnosing sings of starting point and growth of defect using intelligent techniques, discovering the defected parts and the reason behind them and prediction of remaining working life of the machine play an important role in preserve the machine from severe defects and the high price of repairing it. The goal of this paper is using the Adaptive Neural - Fuzzy Inference Systems (ANFIS) and Multi-Layer Perceptron (MLP) for detecting the original defects in rotating machines including unbalancing, Bearing defects, Looseness and misalignment**.** So, in this study addition to the creation of this mechanism for automatic fault diagnosis, improve accuracy and speed of the network was also performed. Therefore, using the Principal Component Analysis (PCA), the input matrix was reduced to acceptable amont and the effectiveness of the ANFIS and MLP networks in detection of defects were compared with each other. To achieve this goal, mentioned networks were trained using feature vectors extracted from the spectrum frequency and waves. The obtained results showed that for 84 final measurements, the ANFIS and MLP networks have 91 and 78 averages percent successful in detecting the defects, respectively.

KEYWORDS:

Rotating Machinery, Defect Classification, Adaptive Neural - Fuzzy Inference Systems (ANFIS), Multi-Layer Perceptron (MLP).

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1- INTRODUCTION

Many techniques have been used for fault detection of rotating machineries. Among them methods based on vibration analysis are the most successful one. Vibration analysis techniques based on statistical methods, Multi-Layer Perceptron Neural Networks (MLPNN), Adaptive Neuro-Fuzzy Inference Systems (ANFIS) have been reported on literature [1,2,3,4,5]. Techniques based on artificial intelligence are expanding rapidly. In 2009 Wang et al diagnosed rotating machineries fault from time series analysis using Neural Networks. Lie et al in 2008 in their research used Neuro Fuzzy systems as well as neural networks based on statistical methods to diagnose deep grooved rolling bearings. They found that Neuro Fuzzy system shows better results than Neural Networks. In a research done by Zio et al in 2009 Neuro Fuzzy systems were used to detect rotating machineries faults. Their main goal was to improve classification precession. Their result showed that the proposed method was successful in different bearing fault classification [6].

2- METHODOLOGY

In this research some common and basic faults of rotating machineries have been diagnosed with the aid of intelligent Neuro-Fuzzy and Multi-Layer Perceptron Neural Networks (MLPNN).

To acquire the necessary data the following steps have been done:

Step 1: Design and manufacture of the machine and producing the specific faults on it

.**Step 2:** Proper vibration feature selection for fault detection. In general 12 vibration features including 10 time signal features namely: 1) Peak 2) Mean 3) Crest factor 4) Impulse Factor 5) Shape Factor 6) Free Factor 7) Kurtosis 8) Root Mean Square 9) Peak to Mean ratio 10) Absolute Mean and 2 frequency signal features namely 1) Energy 2) Optimal energy have been chosen.

$$\Delta V = \frac{1}{2}[\max\{V[n]\} - \min\{V[n]\}] \quad (1)$$

$$\bar{V} = \frac{1}{N}\sum_{n=0}^{N-1} V[n](\quad (2)$$

$$DV = \frac{1}{N}\sum_{n=0}^{N-1}|V[n]| \quad (3)$$

$$RMS = \sqrt{\frac{1}{N}\sum_{n=0}^{N-1}(V[n] - \bar{V})^2} \quad (4)$$

$$PAR = \frac{1}{|\bar{V}|}\max\{|V[n]|\} \quad (5)$$

$$Kv = \frac{\frac{1}{N}\sum_{n=0}^{N-1}(V[n] - \bar{V})^4}{RMS^4} \quad (6)$$

$$CF = \frac{\Delta V}{RMS} \quad (7)$$

$$IF = \frac{\Delta V}{|\bar{V}|} \quad (8)$$

$$SF = \frac{RMS}{|\bar{V}|} \quad (9)$$

$$CLF = \frac{\Delta V}{\frac{1}{N}\left\{\sum_{n=0}^{N-1}\sqrt{|V[n]|}\right\}^2} \quad (10)$$

$$E = \sum_{k=0}^{K-1}|S[k]|^2 \quad (11)$$

$$E_N = \frac{1}{K}\sum_{k=0}^{K-1}|S[k]| \quad (12)$$

In the above equations ΔV is the peak variation in mm/sec; $\max\{V[n]\}$ and $\min\{V[n]\}$ are peak maximum and minimum in different frequencies respectively $\bar{V}$ is the average of eigenvalues in mm/sec; N is the number of eigenvalues; $V[n]$ is eigenvalues in different frequencies; DV is absolute average eigenvalues in mm/sec; RMS is the root mean square in mm/sec; PAR is peak to average ratio; kv is kurtosis; CF is crest factor; IF is impulse factor; SF is shape factor; CLF is clearance factor; E is energy in mm per squared sec and E_N is optimal energy in mm per squared sec.

Step 3: To reduce the amount of input data and hence increase the efficiency of the classification techniques, the Principle Coordinate Analysis (PCA) have been used. Mathematical and statistical concepts related to this method are: variance; covariance; eigenvalues and eigenvectors of an array. The averages of these data are computed by equations (13) and (14).

$$\bar{X} = \frac{1}{n}\sum_{i=1}^{n} x_i \quad (13)$$

In the above equation $\bar{X}$ is data average in x direction; n is the total number of data; x_i is value of each data in x direction. Variance is computed using Eq 14.

$$V(X) = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2 \quad (14)$$

Step 4: Use of MLPNN and ANFIS for fault classification. MATLAB software has been used for Classifier design.

Multi layer neuro fuzzy and neural network have been designed by the following stages:

Stage 1: Multi layer neural network design.

The following points have been considered in MLPNN design.

a) Initial weights and biases have been chosen from small random numbers,
b) Introducing proper inputs and outputs to the network.

Stage 2: Neuro fuzzy network design.

ANFIS structure consists of 5 layers which are: First layer: Input nodes; Second layer: Rule nodes; Third layer: Averaging nodes; Fourth layer: Conclusion nodes; Fifth layer: Output nodes.

In ANFIS like neural network 512 data points have been used for classification as follows:

First defect (unbalance) 128 data points.

Second defect (angular misalignment) 128 data points.
Third defect (looseness) 128 data points.
Fourth defect (bearing) 128 data points.
For improving training process performance the data were normalized between [-1, 1]. Some data were used for training and some were used for test. From total of 512 data points 342 data points were used for training and the remaining 170 were used for test.
PCA have been used for reducing input vector dimension. By using this method the input vector dimension have been reduced from 12 to 4.
The input vector dimension for training is 342×5 and output vector dimension is 170×5. The last columns of the aforementioned matrices are related to the associated faults.
For optimizing training process in ANFIS the fault number associated to each are introduced to network as follows:

First fault = [rand(1,128)]

Second fault = [rand (1,128)+3]

Third fault = [rand(1,128)+6]

Fourth fault = [rand(1,128)+9]

In designing ANFIS, forward multi-layer perceptron neural network with back propagation algorithm for training have been used. Sugeno inference system with three sigmoid functions for input have been used.

3- RESULTS

The NN structure is 4-10-4. The number of hidden layer neurons is 10 which is determined by trial and error. In the designed MLPNN 2/3 of the whole data were used for training and validation and the remaining 1/3 of data were used for test.
Figure 2 compares all of 512 measured data points for different faults as well as ANFIS output. As is shown in this figure ANFIS has classified different faults fairly well.

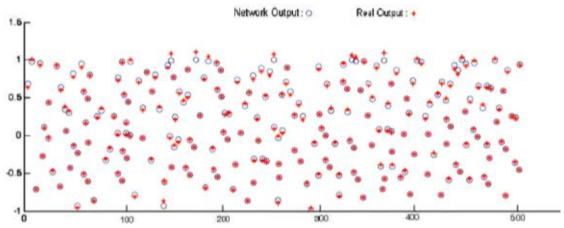

Fig 2 Comparison of real output and ANFIS output for training and test

ANFIS showed better results than MLPNN. The same percentage of data was used for training and testing. The simulation results showed the designed ANFIS could predict the fault correctly with 91 percentages.
The results from this research were in agreement with Ref [1, 2] which showed better performance of ANFIS over MLPNN.

4- CONCLUSION

Using random numbers for classification and fault detection by ANFIS as well as using decimal numbers for fault classification in MLPNN was one of the main contributions of this research. The results showed using this technique improved the ANFIS and MLPNN performance by letting the presence of all the neurons in the training process. Using decimal numbers for fault classification in Neural Networks (NN) prevents the process of neuron death which degrades Neural Network performance. Using Principle Coordinate Analysis (PCA) is the other contribution of this research. PCA is a technique to determine the most influential features and thereby reduce the input matrix dimension of NN thus improving Network performance. By using PCA technique the input dimension reduced from 12 to 4.

5- REFERENCES

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