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ORIGINAL ARTICLE

VIBRATION BASED FAULT DETECTION OF ALTERNATOR BY FAST FOURIER TRANSFORM AND ADAPTIVE NEURO FUZZY INFERENCE SYSTEM

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ABSTRACT: Alternators are used in modern automobiles to provide the electrical power. The electrical power requirements in automobiles have been rising rapidly for many years and are expected to continue to rise. Now the alternator is one of the critical components of an automobile. If the alternator does not work properly, the automobile cannot operate. Hence, the present study tries to introduce a technique for intelligent fault diagnosis of an alternator using acquired vibration signals and ANFIS. This paper presented an adaptive network fuzzy inference system to diagnose the fault type of the alternator. The alternator conditions to be considered were healthy alternator (HA), unbalancing in driven shaft (UDS), crack in rotor body (CRB) and wear in bearing (WB). These features are extracted from vibration signals using the FFT technique. The features were fed into an adaptive neuro fuzzy inference system as input vectors. Performance of the system was validated by applying the testing data set to the trained ANFIS model. According to the result, total classification accuracy was 86.67%.
KEYWORDS: Fault Detection, Fast Fourier Transform, Neuro Fuzzy.

INTRODUCTION

Because of the increasing demand for higher performance as well as for increased safety and reliability of dynamic systems, fault diagnosis has been becoming more important for machine monitoring. Early diagnosis of machine faults while the machine is still operating in a controllable region can help to avoid abnormal event progression, which in turn can help to avoid major system breakdowns and catastrophes. Hence, fault diagnosis is a major research topic attracting considerable interest from industrial practitioners as well as academic researchers (Yang, 2004) .One of the most common applications of condition monitoring is fault diagnosis of electrical machines (Mohamadi Monavar *et al.*, 2008). During the last decade, a number of attempts have been made to diagnose machine faults using artificial intelligence techniques such as: Fuzzy Inference Systems (FISs) for external gear pumps (Mollazade *et al.*, 2009), railway wheels (Skarlatos *et al.*, 2004) and DC motors (Miguel and Blázquez, 2004); Artificial Neural Networks (ANN) for automotive generators (Wu and Kuo, 2009), internal combustion engines (Wu *et al.*, 2010) and gearboxes (Saravanan and Ramachandran, 2010); and Genetic Algorithms (GA) for rolling element bearings (Zhang and Randall, 2009) and so on. Other than these techniques, adaptive systems have been used for intelligent fault classification. Nowadays, adaptive neuro fuzzy inference systems have found a wide gamut of industrial and commercial applications that require analysis of uncertain and imprecise information. ANNs and FISs are complementary technologies in the design of adaptive intelligent systems. The integrated neuro fuzzy system combines the advantages of ANN and FIS. While the learning capability is an advantage from the viewpoint of FIS, the formation of a linguistic rule base is an advantage from the viewpoint of ANN. An integrated neuro fuzzy system shares data structures and knowledge representations (Akcayol, 2004). Alternators are used in modern automobiles to provide the electrical power. The electrical power requirements in automobiles have been rising rapidly for many years and are expected to continue to rise. Now the alternator is one of the critical components of an automobile. If the alternator does not work properly, the automobile cannot operate. Hence, the present study tries to introduce a technique for intelligent fault diagnosis of a Pride alternator that is one of

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high production vehicles in Iran, using acquired vibration signals and ANFIS.

EXPERIMENTAL SETUP

In this research, the alternator of Pride vehicle, that is one of high production vehicles in Iran, was used as case study. For this work, at first a test bed was built to mount the alternator and electromotor on it. The 1 hp electromotor was used to drive power to the alternator using a belt drive. The input shaft of alternator was driven by the electromotor and its speed was controlled by an inverter. The experiment setup is shown in Figure1.

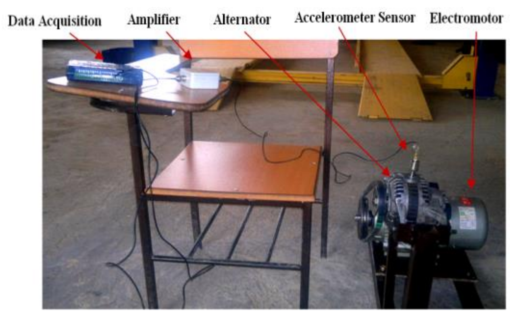

Figure 1: Experimental setup.

Four classes are studied in this work, namely: healthy alternator (HA), unbalancing in driven shaft (UDS), crack in rotor body (CRB) and wear in bearing (WB). These classes have been shown in Figure 2. The vibration signals are measured from the alternator working under normal condition and faulty conditions at a constant rotation speed of 3000 rpm. Piezoelectric type accelerometer (VMI-102 model) is used to measure the vibration signals. Accelerometer specification is provided in Table 1. The accelerometer location is shown in Figure 1; it is mounted on alternator body in the vertical direction. The accelerometer is connected to the signal-conditioning unit (Easy-Viber FFT analyzer). The vibration signal in digital form is fed to the computer through a USB port. The software Spectrapro[4] that accompanies the signal conditioning unit is used for recording the signals directly in the computer's secondary memory. The signal is then read from the memory and processed to extract the FFT of vibration spectrum.

Figure 2: Alternator faults.

Table 1: Accelerometer specification

Accelerometer type VMI-102	
Sensitivity	100mv/g
Frequency response (+/-3db)	0.7-15000Hz
Resonant frequency	30000Hz
Temperature range	-50 ^{o}C ... +120 ^{o}C

2.1. Signal Processing

Many signal processing techniques are presented for processing the signals aim to have a better feature extraction and selection. In recent articles, advanced non-parametric approaches have been considered for signal processing such as wavelets, fast Fourier transform (FFT), short time Fourier transform (STFT) (Schoen *et al.,* 1995; Omid, 2010). In this study the fast Fourier transform was used as signal processor technique that suitable for the steady conditions and stationary behaviors. The velocity time signals were transferred into frequency domain by FFT. This process is done for every sample. The FFT toolbox in MATLAB^{R2011a} software was used for the signal processing. The data sets were divided into two separate data sets: the training data set and the testing data set. Table 2 shows the detailed description of the data set.

Table 2: Dataset description

Label of classification	Operating condition	Number of testing samples	Number of training samples
1	HA	15	35
2	UDS	15	35
3	CRB	15	35
4	WB	15	35

2.2. Fourier Transform

An energy-limited signal $f(t)$ can be decomposed by its Fourier transform$F(w)$, namely

$$f(t) = \frac{1}{2\pi}\int_{-\infty}^{+\infty} F(w)e^{iwt}dw \quad (1)$$

$$F(w) = \int_{-\infty}^{+\infty} f(t)e^{-iwt}dt \quad (2)$$

Where, $f(t)$ and $F(w)$ are a pair of Fourier transforms. Equation (1) implies that $f(t)$ signal can be decomposed into a group with harmonics e^{iwt}. The weighting coefficients $F(w)$ represent the amplitudes of the harmonics in $f(t)$. $F(w)$ Is time independent and it represents the frequency composition of a random process, which is assumed that its statistics do not change with time. The fast Fourier transform (FFT) is a faster version of the discrete Fourier transform (DFT). The FFT utilizes some clever algorithms to do the same thing as the DTF, but in much less time (Ghaderi and Kabiri, 2011).

2.3. Feature Extraction

The frequency domain signal can be used to perform fault diagnosis by analyzing vibration signals obtained from the experiment. The measured FFT values of signal were calculated to obtain the most significant features by feature extraction. Statistical methods have been widely used to provide the physical characteristics of frequency domain data. Statistical analysis of vibration signals yields different descriptive statistical parameters. A wide set of parameters were selected as the basis for the study. They are mean, standard deviation, sample variance, kurtosis, skewness and root mean square. These features were extracted from vibration signals. The statistical features are explained below. These features can thoroughly describe the characteristics of the faults.

Mean: It is the average of all signal point values in a given signal.

Standard deviation: This is a measure of the effective energy or power content of the vibration signal. The following formula was used for computation of standard deviation:

$$Stdv = \sqrt{\frac{n\sum x^2 - \left(\sum x\right)^2}{n(n-1)}} \quad (3)$$

Where, n is the sample size.

Sample variance: It is variance of the signal points and the following formula was used for computation of sample variance:

$$Variance = \frac{n\sum x^2 - \left(\sum x\right)^2}{n(n-1)} \quad (4)$$

Kurtosis: Kurtosis indicates the flatness of the signal. Its value is very low for normal condition of the alternator and high for faulty condition of the alternator due to the spiky nature of the signal:

$$Kurtosis = \left\{\frac{n(n+1)}{(n-1)(n-2)(n-3)}\sum\left(\frac{x_i - \bar{x}}{s}\right)^4\right\} - \frac{3(n-1)^2}{(n-2)(n-3)} \quad (5)$$

Where, s is the sample standard deviation.

Skewness: Skewness characterizes the degree of asymmetry of a distribution around its mean. The following formula was used for computation of skewness:

$$Skewness = \frac{n}{(n-1)}\sum\left(\frac{x_i - \bar{x}}{s}\right)^3 \quad (6)$$

Root Mean Square: It is the root of mean square of all signal point values in a given signal and the following formula was used for computation of root mean square:

$$RMS = \sqrt{\frac{\sum_{n=1}^{N}(x(n))^2}{N}} \quad (7)$$

Where, N is the sample size (Farokhzad *et al.*, 2012).

2.4. ANFIS Structure

Architecture of a fuzzy system with the aid of neural networks was used to make an intelligent decision for alternator faults. The Neuro fuzzy system combines the learning capabilities of neural networks with the linguistic rule interpretation of a fuzzy inference system. Fuzzy systems are suitable for uncertain knowledge representation, while neural networks are efficient structures capable of learning from examples. The hybrid technique brings the learning capability of neural networks to the fuzzy inference system. The parameters associated with the membership functions of a Sugeno-type FIS will change through the learning algorithm of the neural network. The computation and adjustment of these parameters are facilitated by a gradient vector, which provides a measure of how well the FIS is modeling the input/output data for a given set of parameters. From the topology point of view, ANFIS is an implementation of a representative fuzzy inference system using a back propagation (BP) neural network-like structure. Figure 3 shows the topology of ANFIS with ***q*** node for each input, which consists of five layers (Alavandar and Nigam, 2008).

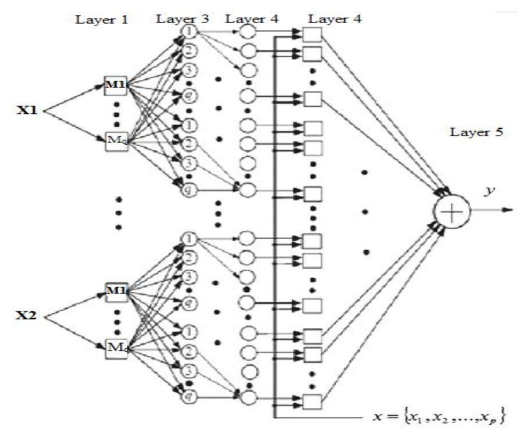

Figure 3: ANFIS structure.

RESULTS AND DISCUSSION

The vibration signals of alternator were transferred to frequency domain by FFT signal processor. Figure 4 shows the time signal and Figure 5 show the frequency domain of one sample of each class that was studied in this research.

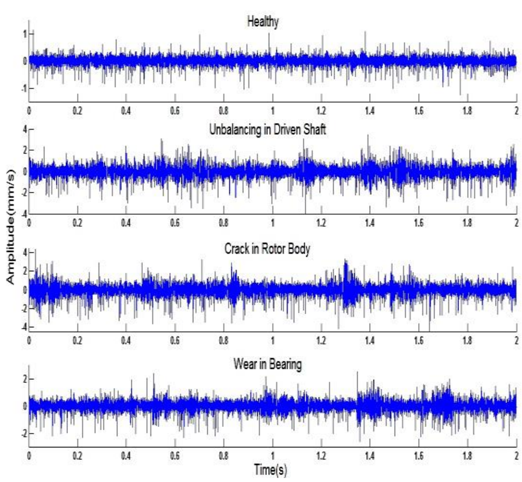

Figure 4: Time signal of each class**.**

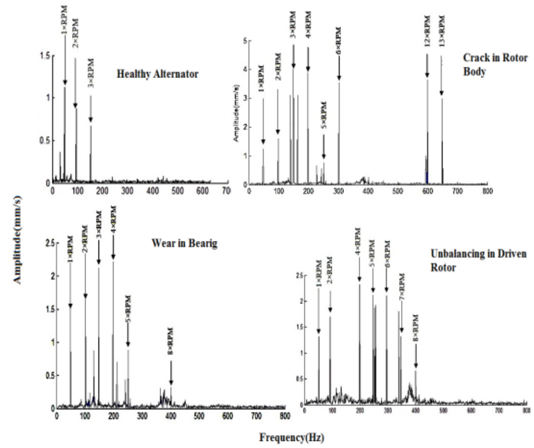

Figure 5: Frequency domain of each class.

In order to evaluate the proposed approach, it was applied to the fault diagnosis of an alternator. The data set was collected under different fault categories. The ANFIS classifier was implemented by using the Matlab software package (MATLAB^{R2011a} with Fuzzy Logic Toolbox). The training data set was used to train the ANFIS model, whereas the testing data set was used to verify the accuracy and the effectiveness of the trained ANFIS model for classification of the four classes of alternator fault. ANFIS used six input data sets, including a total of 840 training data in 100 training epochs. Figure 6 shows the topology of ANFIS designed for fault diagnosis. At the end of 100 training epochs, the network error (mean square error) convergence curve of ANFIS was derived as shown in Figure 7. From the curve, the final convergence value is 0.078. Also, the 64 rules were obtained as follows:

- Rule 1. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf1) and (input5 is in5mf1) and (input6 is in6mf1) then (output is out1mf1) (1)
- Rule 2. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf1) and (input5 is in5mf1) and (input6 is in6mf2) then (output is out1mf2) (1)
- ……………………………………………………………………
- ……………………………………………………………………
- 64. If (input1 is in1mf2) and (input2 is in2mf2) and (input3 is in3mf2) and (input4 is in4mf2) and (input5 is in5mf2) and (input6 is in6mf2) then (output is out1mf64) (1)

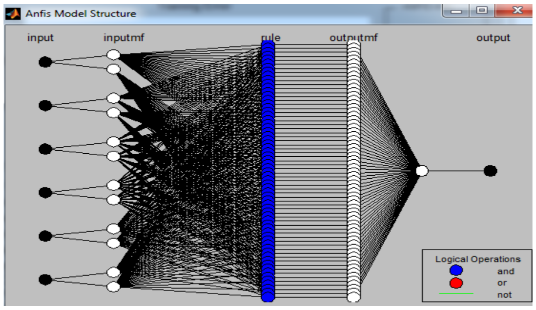

Figure 6: Topology of ANFIS for fault diagnosis of alternator.

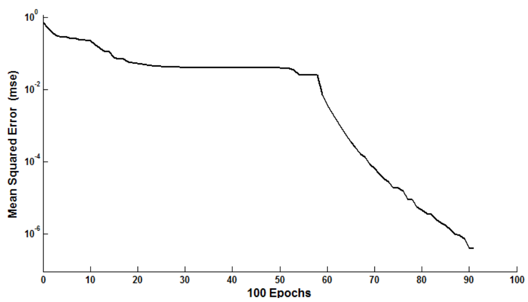

Figure 7: ANFIS curve of network error convergence.

After training, 60 testing data were used to validate the accuracy of the ANFIS model for classification of the alternator faults. The confusion matrix showing the classification results of the ANFIS model is given in Table 3. The diagonal elements in the confusion matrix show the number of correctly classified instances. In the first column, the first element shows the number of data points belonging to the healthy class and classified by ANFIS as healthy. The second element shows the number of data points belonging to the healthy class but misclassified as UDS. The third element shows the number of data points misclassified as CRB and so on.

Table 3: Confusion matrix of testing data

Output/desired	HA	UDS	CRB	WB
HA	13	1	0	2
UDS	0	13	0	1
CRB	1	1	14	0
WB	1	0	1	12

Sensitivity, specificity and total classification accuracy are three criteria to determine the test performance of classifiers. These criteria are defined as:

- **Sensitivity**: number of true positive decisions/number of actually positive cases.
- **Specificity**: number of true negative decisions/number of actually negative cases.
- **Total classification accuracy**: number of correct decisions/ total number of cases.

According to the values of statistical parameters (see Table 4), ANFIS classified sets healthy alternator, unbalancing in driven shaft, crack in rotor body and wear in bearing as 86.67, 86.67, 93.33 and 80 respectively. Also, the total classification accuracy of ANFIS was obtained to be 86.67%.

Table 4: The values of classification accuracy criteria

Data Sets Label	Sensitivity (%)	Specificity (%)	Total classification accuracy (%)
HA	86.67	93.33	86.67
UDS	86.67	97.78	
CRB	93.33	95.56	
WB	80	95.56	

CONCLUSION

This paper presented an adaptive network fuzzy inference system (ANFIS) to diagnose the fault type of the alternator. In the present study, a fault alternator identification system was used based on vibration signals using the FFT technique and ANFIS. The FFT can used to detect the transient signals of fault in an alternator. Statistical features from the frequency domains were extracted to reflect different faults of the alternator. Input vectors to the ANFIS are six features. The final ANFIS model has 64 rules with a network error convergence of 0.078. The trained ANFIS model was evaluated using 75 testing data and it was observed that the total classification of this technique is 86.67%. The method of fault diagnosis provides an accurate and automatic classification technique. The results show the applicability and effectiveness of this method to detect faults in starter motors.

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