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Condition Monitoring and Fault Diagnosis of Gearbox Using Vibration Monitoring and Adaptive Neuro-Fuzzy Inference System

Ghasem Maghsoudi Gharehbolagh[1*], Saeid Farokhzad[2], Mohammad Reza Asadi Asad Abad[3] and Mohammad Ranjbarkohan[3]

1- Department of Mechanical Engineering, Eslamshahr Branch, Islamic Azad University, Eslamshahr, Tehran, Iran
2- Ph.D Student of Mechanical Engineering of Agricultural Machinery, University of Urmia, Urmia, Iran
3- Department of Mechanical Engineering, Buinzahra branch, Islamic Azad University, Buinzahra, Iran

Corresponding author Email : Gh.maghsoudi55@gmail.com

ABSTRACT: This paper presented an adaptive network fuzzy inference system (ANFIS) to diagnose the fault type of the gearbox. The gearbox conditions to be considered were healthy, broken gear, worn gear and worn bearing. 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 95.24%. This shows that the system has great potential to serve as an intelligent fault diagnosis system in real applications.

***Keywords*:** Fast Fourier Transform, Condition Monitoring, Fault Diagnosis ,Gearbox, ANFIS.

INTRODUCTION

Gearboxes are widely used in industrial applications.An unexpected failure of the gearbox may cause significant economic losses. Tooth breakage is the most serious failure for a gearbox. Fault diagnosis of gearboxes is of crucial importance and has been studied for several decades. In modern industry, fault diagnosis plays an important role in accident prevention, human safety, maintenance, decision-making, and cost minimization. It is, therefore, very important to find early fault symptoms from gearboxes (*Lin & Zuo., 2003*). Automation, as another significant stage in industries commonly implemented to reduce the cost of production, quality control and maintenance. Based on these theories several methods are developed to automate the condition monitoring and quality control of systems (*Bagheri et al., 2010*). A faulty gear system could result in serious damage if defects occur to one of the gears during operation condition. Early detection of the defects, therefore, is crucial to prevent the system from malfunction that could cause damage or entire system halt. Diagnosing a gear system by examining the vibration signals is the most commonly used method for detecting gear failures. The conventional methods for processing measured data contain the frequency domain technique, time domain technique, and time–frequency domain technique. These methods have been widely employed to detect gear failures. The use of vibration analysis for gear fault diagnosis and monitoring has been widely investigated and its application in industry is well established (*Cameron & Stuckey., 1994; Leblanc et al., 1990*). The undeniable abilities of artificial intelligence on this way, persuades researches to use different methods of AI in their fields of study. Fuzzy Logic, Neuro-Fuzzy systems, Artificial Neural networks and Support Vector Machine algorithm are the most usual algorithms for implementing artificial Intelligence (*Bagheri et al., 2010*). Artificial neural network (ANN), support vector machine (SVM) and Fuzzy classifier are widely used as classification tool and reported in literature (*Burgess., 1998; Jack & Nandi., 2000; Nandi., 2000; Samanta & Al- Baulshi., 2003; Samanta et al., 2003; Shi & Xu., 1988*). Beside these techniques, vibration signals and signal processing are commonly used for non-destructive tests in fault diagnosis systems. Both vibration and acoustic signals carry rich and useful information about the condition of the system and it has been very popular for condition monitoring and early fault detection of gearboxes (Yang & Makis., 2010).

Experimental Setup

The test rig used for the experimentation was a gearbox. The experimental setup to collect dataset consists of gearbox, an data acquistion and four shock absorbers under the base of test-bed. Test-bed was designed and constructed to install gearbox, electromotor and four shock absorbers under bases to cancel out vibrations . The 3KW electromotor was used to drive power to the gearbox using a coupling power transmission. The input shaft of gearbox was drove by the electromotor in 1000RPM and its speed was controlled by an inverter. The experiment setup is shown in Figure 1. Vibration signals were collected from the experimental testing of Peugeot_405 gearbox using the accelerometer which was mounted on the outer surface of the bearing case of input shaft of the gearbox. For each configuration different fault conditions were tested that were medium-worn of gear, broken teeth of gear and worn bearing.

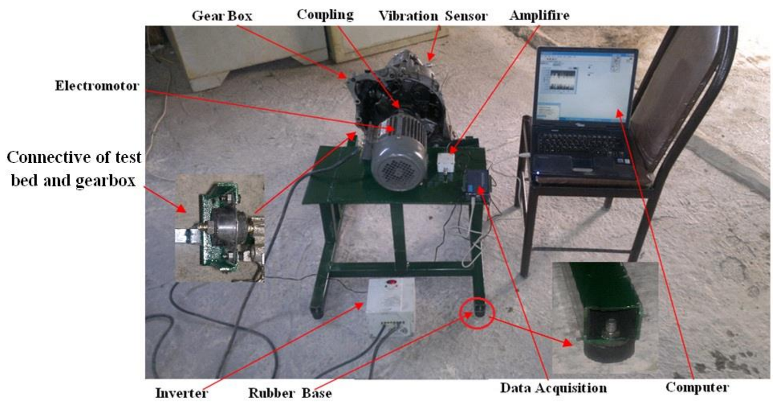

Figure 1. The experimental set-up

Four classes are studied in this work, namely, healthy, worn ogear, broken gear and worn bearing. These classes are shown in Figure 2.

Figure 2. Different conditions of gear and bearing

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*). 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 software was used for the signal processing. Each class has 70 samples that divided in two parts: 49 samples assumed for training the classifier and 21 samples for testing the system.

Fourier Transform

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

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

Where

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

$f(t)$ and $F(w)$ are a pair of fourier transforms. Eq. (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 & Kabiri., 2011*).

Feature Extraction

The time and 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 in time and frequency domain. The statistical features are explained below. These features can thoroughly describe the characteristics of the faults (*Farokhzad et al., 2012*).

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:

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

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:

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

Kurtosis

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

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

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:

$$Skewness = \frac{n}{(n-1)} \sum \left(\frac{x_i - \bar{x}}{s} \right)^3 \qquad (4)$$

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:

$$RMS = \sqrt{\frac{\sum_{n=1}^{N} \left(x(n)\right)^2}{N}} \tag{5}$$

where N is the sample size.

ANFIS Structure

An architecture of a fuzzy system with the aid of neural networks was used to make an intelligent decision for gearbox 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 modelling 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. A description of each layer follows (*Alavandar & Nigam., 2008*):

Layer 1– In the first layer each node corresponds to one linguistic term. The number of linguistic terms is determined by the expert of problem domain. In this layer for $i = 1, 2, 3, \ldots, P$; xi denotes the ith input of ANFIS and Q_i^1 is the output of node i. Here there is a node function where its rule is equal with that of fuzzy membership functions. ANFIS uses either back propagation or a combination of least squares estimation and back propagation for membership function parameter estimation:

$$Q_i^1 = M_i(x_i) \tag{8}$$

Layer 2–The output of every node in this layer, which is the product of all incoming signals, represents the firing strength of the reasoning rule. Each rule represents one fuzzy logic rule. Here, to calculate the output of the layer, AND (min) operation is used:

$$Q_i^1 = M_i(x_i) AND M_j(x_j) \tag{9}$$

Layer 3–Comparison between firing strength of the rules and the sum of all firing strength is done in this layer. The output of this layer is the normalised firing strength:

$$Q_i^3 = \frac{Q_i^2}{\sum Q_i^2} \tag{10}$$

Layer 4 – This layer is a consequent layer and implements the Sugeno-type inference system, *ie* a linear combination of the ANFIS input variables ($x_1, x_2, \ldots, x_p$) plus a constant term ($c_1, c_2, \ldots, c_p$) from the output of each fuzzy rule. The output of the node is a weighted sum of these intermediate outputs. In the following output, parameters $p_1, p_2, \ldots, P_p$ and $c_1, c_2, \ldots, c_p$ are referred to as the consequent parameters:

$$Q_i^4 = Q_i^3 \sum_{i=1}^{p} P_j x_j + c_j \tag{11}$$

Layer 5 – Defuzzification process is occurred in this layer and the outputs of layer 4 are aggregated:

$$Q_i^5 = \sum_i Q_i^4 \tag{12}$$

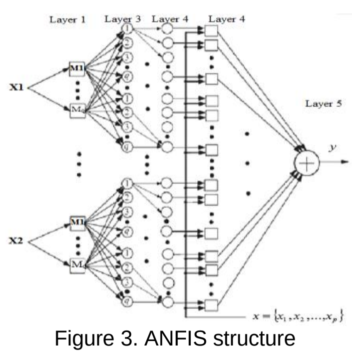

Figure 3. ANFIS structure

Fault Diagnosis

In order to evaluate the proposed approach, it was applied to the fault diagnosis of a gearbox. The data set was collected under different fault categories. The data sets were divided into two separate data sets: the training data set and the testing data set. Table 1 shows the detailed description of the data set.

Table 1. Dataset description

Label of classification	Operating condition	Number of testing samples	Number of training samples
1	Healthy	49	21
2	Broken Gear (BG)	49	21
3	Worn Gear (WG)	49	21
4	Worn Bearing (WB)	49	21

The ANFIS classifier was implemented by using the Matlab software package (Matlab version R2011b 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 gearbox fault. ANFIS used six input data sets, including a total of 1176 training data in 100 training epochs. Figure 4 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 5. 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)

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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)

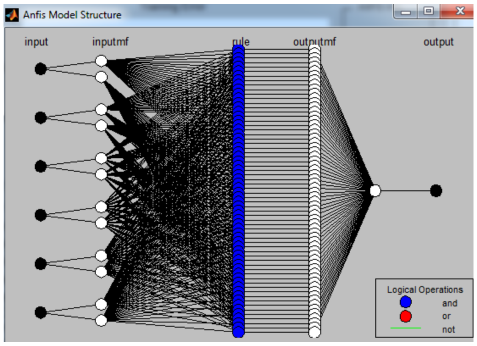

Figure 4. Topology of ANFIS for fault diagnosis of Peugeot 405 gearbox

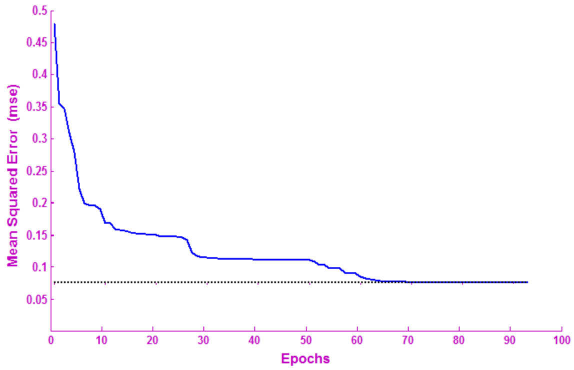

Figure 5. ANFIS curve of network error convergence

After training, 84 testing data were used to validate the accuracy of the ANFIS model for classification of the gearbox faults. The confusion matrix showing the classification results of the ANFIS model is given in Table 2. 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 BG. The third element shows the number of data points misclassified as WG and so on.

Table 2. Confusion matrix of testing data

Output/desired	Healthy	BG	WG	WG
Healthy	21	0	0	0
BG	0	20	1	0
WG	0	1	19	1
WB	0	0	1	20

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 3), ANFIS classified sets healthy, BG, WG and WB as 100, 95.24, 90.48 and 95.24%, respectively. Also, the total classification accuracy of ANFIS was obtained to be 95.24%.

Table 3. The values of classification accuracy criteria

Data Sets Label	Sensitivity(%)	Specificity (%)	Total classification accuracy (%)
Healthy	100	100	
BG	95.24	98.41	95.24
WG	90.48	96.82	
WB	95.24	98.41	

CONCULSION

This paper presented a adaptive network fuzzy inference system (ANFIS) to diagnose the fault type of the gearbox of Peugeot 405. In the present study, a fault gearbox identification system based on vibration signals using the FFT technique and ANFIS. The FFT can used to detect the transient signals of fault in a gearbox. Statistical features from the frequency domains were extracted to reflect different faults of the gearbox. 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 84 testing data and it was observed that the total classification of this technique is 95.24%. 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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