International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 3 Issue 5, May - 2014

Automation of Gearbox Fault Diagnosis using Sound and Vibration Signal

Anurag Jasti
Department of Mechanical Engineering
Amrita School of Engineering
Coimbatore, India

T Praveen Kumar
Department of Mechanical Engineering
Amrita School of Engineering
Coimbatore, India

Dr. M Saimurugan
Department of Mechanical Engineering
Amrita School of Engineering
Coimbatore, India

Abstract—**Gears have wide variety of applications. They form the most important component in a power transmission system. Advances in engineering technology in recent years have brought demands for gear teeth, which can operate at ever increasing load capacities and speeds. The gears generally fail when tooth stress exceeds the safe limit. Therefore, it is essential to determine the maximum stress that a gear tooth is subjected to, under a specified loading. Analysis of gears is carried out so that these can be prevented from failure. When failure occurs, they are expensive not only in terms of the cost of replacement or repair but also the cost associated with the downtime of the system of which they are a part. Reliability is thus a critical economic factor and for designer to produce gears with high reliability they need to be able to accurately predict the stress experienced by the loaded gear teeth. This paper deals with the automation of fault diagnosis process of gearbox using sound and vibration signals obtained from the gearbox with 3 different fault conditions, 3 different speeds and 3 different loads. Sound and Vibration time domain signals are obtained for all the above conditions and the obtained signals for faults are compared with the time domain signals of good gear.**

Keywords—Fault Diagnosis, Gearbox, Decision tree, Automation

I. INTRODUCTION

All machines with moving parts give rise to sound and vibration. Each machine has a specific vibration signature related to the construction and the state of the machine. If the state of the machine changes the vibration signature will also change [1]. A change in the vibration signature can be used to detect incipient defects before they become critical [2]. This is the basics of many condition monitoring methods. Condition monitoring can save money through increased maintenance efficiency and by reducing the risk of serious accidents by preventing breakdowns. The use of vibration analysis as one of the fundamental tools for condition monitoring has been developed extensively over a period of approximately 35 years [3]. With the parallel developments in electronic equipment, transducers, computers and software nowadays machine supervision is almost completely automated. In the present work the authors present a review of a variety of diagnosis techniques for gearbox fault identification with particular regard to vibration analysis. The vibration techniques were developed with two main purposes. The first purpose is to separate the gearbox related signal from other components and to minimize the noise that may mask the gearbox signal, especially in the early stages of the fault. The second purpose is to identify the status of the gearbox, to distinguish the good and the faulty gear and to indicate the defective components. Examples of widely used techniques for gearbox are such as Waveform analysis, Time-Frequency analysis, Faster Fourier Transform (FFT), Spectral analysis, Order analysis, Time Synchronous Average, and probability density moments. These vibration based diagnosis techniques has been the most popular monitoring technique because of ease of measurement. Vibration analysis was used former mainly to determine faults and critical operation conditions. Nowadays the demands for condition monitoring and vibration analysis are no more limited trying to minimize the consequences of machine failures, but to utilize existing resources more effectively.By comparing the signals of the machine running in normal and fault conditions, the detection of faults like rotor unbalance, shaft misalignment, bearings damage, etc. is possible[4,5]. Automation of these fault diagnosis process is gaining importance in the present scenario. With the automation the breakdown time can be minimised as the failure can be detected in the early stages and the overall failure can be prevented. The pattern recognition technique was first implemented in the year 1989 to automate the fault diagnostic process [6].

The time domain methods try to analyse the amplitude and phase information of the vibration time signal to detect the fault of gear-rotor-bearing system. The time domain is a perceptive that feels natural, and provides physical insight into the vibration [7]. It is particularly useful in analysing impulsive signals from bearing and gear defects with non-steady and short transient impulses [8]. It is known that local faults in gear boxes cause impacts. As a result of this impact excitation, impulses and discontinuities may be observed in the instantaneous characteristics of the envelope and phase functions. Due to the nature of these functions, vibration signals can be considered as non-stationary and strong non-stationary events can appear in a local time period, e.g. one revolution of gear in mesh. The analysis of non-stationary signals requires specific techniques which go beyond the classical Fourier approach.Relevant features can be extracted from the vibration signal and can be classified using a

ISSN: 2278-0181
Vol. 3 Issue 5, May - 2014

classifier [9]. The commonly used technique for selection of features is decision tree [10]. This paper reports the use of decision tree for feature selection and classification. Fault diagnostic procedure is shown in the Figure I.

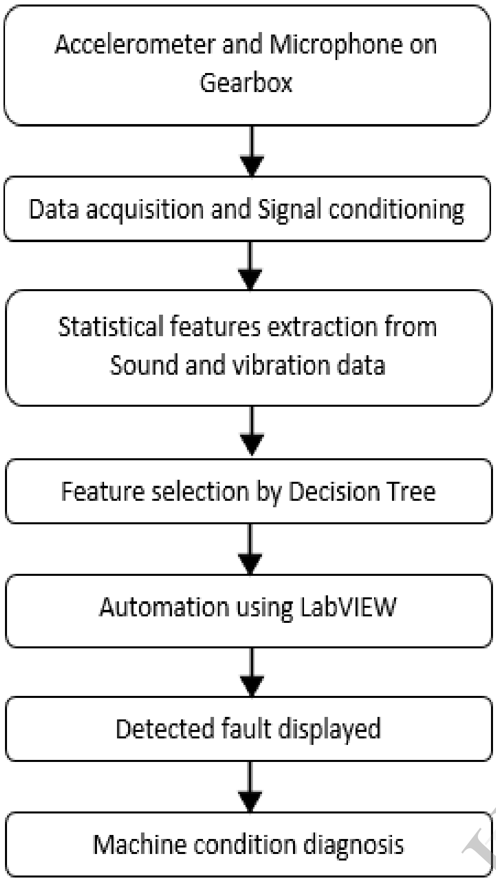

FIGURE I. FLOW CHART OF FAULT DIAGNOSTIC PROCEDURE

II. EXPERIMENTAL STUDIES

The experimental study comprises of experimental setup and experimental procedure is listed below.

A. Experimental Setup

The rotating machine fault simulator was used to conduct the experiments. This is shown in Figure II. The fault simulator has the rotational elements such as gear, shaft, bearing etc., and can be used for studying the behavior of vibration patterns by simulating the required fault(s) in these elements. The setup consists of a variable speed DC motor which is of 0.5hp power. The shaft of the motor is connected to a short shaft of 30 mm diameter. These two shafts are connected by a flexible coupling. The flexible coupling is used to minimize effects of misalignment between the shafts and to transmit the power effectively from the motor. The shaft is supported at its ends through roller bearings. From this shaft the motion is transmitted to the bevel gear box by means of a belt drive. The Gear box consists of two spur bevel gears. The two gears are inclined at an angle of 900 to each other. One gear is connected to the belt drive and the other gear is fitted with a spring loaded fail safe brake which can be used for loading the gear wheel. Motor and Gear are fitted with a speed sensing device which are connected to a control panel, where the readings can be

FIGURE II. EXPERIMENTAL SETUP

seen. Using the control panel, the brake can be controlled and also the speed of the motor which intern controls the speed of the gears. A piezoelectric accelerometer is mounted on the top flat surface of the gearbox housing using direct adhesive mounting technique as shown in Figure III. The accelerometer is connected the DAQ (Data Acquisition Card) of NI9234. In this the analogue signal is converted to digital signal. It is fed to the computer through USB

FIGURE III. ACCELEROMETER ON GEARBOX

B. Experimental Procedure

The Gears are fabricated and two different faults i.e., tooth breakage, face wear were introduced into them as shown in Figure VI. It was made sure that the lubrication level is up to the mark. Initially, the gear box containing the good gear is fitted with an accelerometer i.e. accelerometer is mounted on

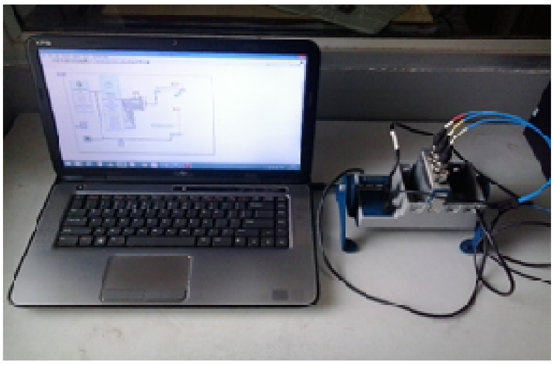

FIGURE IV. NI9234DAQ CONNECTED TO LAPTOP

ISSN: 2278-0181
Vol. 3 Issue 5, May - 2014

VIBRATION SIGNALS | **SOUND SIGNALS**

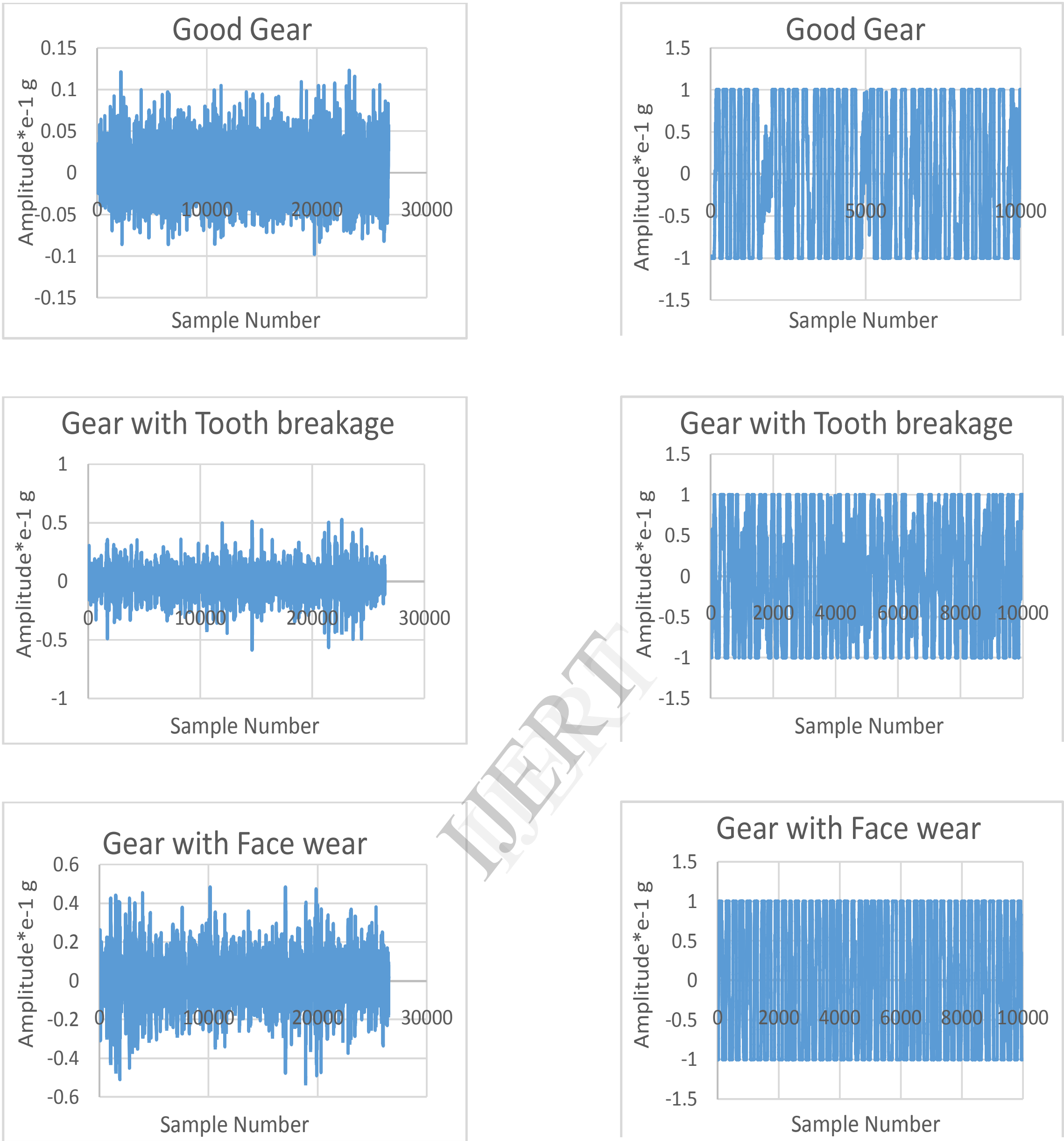

FIGURE V. TIME DOMAIN SIGNALS FOR VIBRATION AND SOUND SIGNALS AT FULL LOAD AND 1000 RPM

FIGURE VI. GEAR TOOTH BREAKAGE AND FACE WEAR

TABLE I. EXPERIMENTAL CONDITIONS

FAULT	LOAD	SPEED (RPM)
Good Gear (G1)	No Load (0 Nm)	500, 750, 1000
	Intermediate Load (5 Nm)	500, 750, 1000
	Full Load (10 Nm)	500, 750, 1000
Gear Tooth Breakage (F1)	No Load (0 Nm)	500, 750, 1000
	Intermediate Load (5 Nm)	500, 750, 1000
	Full Load (10 Nm)	500, 750, 1000
Face Wear (F2)	No Load (0 Nm)	500, 750, 1000
	Intermediate Load (5 Nm)	500, 750, 1000
	Full Load (10 Nm)	500, 750, 1000

the top of the gear box housing. Initially the brake is in off mode. The accelerometer was connected to a computer (or laptop) through NI9234 DAQ (Data Acquisition Card) as shown in Figure V. The sample length was set 26500 for all speeds and for all conditions. The experiment was conducted for the speeds of 500 rpm, 750 rpm and 1000 rpm as shown in Table If. Then the motor was switched on. The motor speed was adjusted to 500 rpm and it was allowed initial running for some time and then the LabVIEW program was started. The readings were automatically saved in spreadsheet files. Then the motor speed was changed to 750 rpm and the program was started again. After the completion of these, the same procedure was repeated for 1000 rpm. For loaded condition, the brake was on and the load was adjusted to an intermediate load of 5Nm and full load condition of 10 Nm by rotating the spring loaded fail safe Brake. Then all the readings were taken for this intermediate load. After that, the top of the gear box was removed and the lubricant was drained using the hose connected to it. Then the gear was removed and replaced with a faulty gear and the procedure was repeated. The same procedure was repeated for all the remaining gears. The same procedure was repeated for obtaining for obtaining sound signals.

The time domain represents the display of the vibration magnitude as a function of time. This is represented in the following Figure. The main advantage of this technique is that there is no data lost prior to the inspection and it allows a great deal of detailed analysis. The amplitude of vibration increases from a new machine to a faulty machine and it also varies with the severity of fault. Simple signal metrics applied to the measured time domain signal can give some information regarding the potential defects. The instrumentation of time domain metrics is cost effective and simple to implement. There are many values in the time domain signal, which will be difficult to analyze. So, in order to analyze a time domain signal, the amplitude of the time domain signal is converted into various forms using statistical formulae such as Mean, RMS, Variance, Kurtosis etc., which are called as features of signal which will give more information of the monitored machine.

Feature extraction is a special form of dimensionality reduction. When the input to be analyzed is too large to be processed, then the input data will be transformed into a reduced representation set of features also named as features vector. Transforming the input data into a set of features is called feature extraction. When performing analysis of complex data one of the major problems is the no. of variables involved. Feature extraction is a general term for methods of constructing combinations of the variables to get around these problems.

The features extracted are

1. Mean – It refers to the average of all the data points in a set of data. The following formula was used for computation of mean.

$$\text{Mean} = \frac{\sum_{i=1}^{n} x_i}{n} \tag{3.1}$$

2. Median – It refers to the middle value of the ordered signal point values in a given signal.

3. Mode – It refers the value that appears most often in a set of data.

4. Root Mean Square – It is the square root of the arithmetic mean of the squares of the original values. Root Mean Square can be calculated by the following formula.

$$\text{RMS} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}({x_i}^2)} \tag{3.2}$$

5. Standard Deviation – It shows how much variation or dispersion from the average exists.

   Let X be a random variable with mean value μ:

   $E[X] = \mu$

   Here the operator E denotes the average or expected value of X.

   Then the standard deviation of X is the quantity.

   $$\text{Standard Deviation } (\sigma) = \sqrt{E[X^2] - (E[X])^2} \tag{3.3}$$

6. Variance – It measures how far a set of numbers is spread out.

   $$\text{Variance } (X) = E[X^2] - (E[X])^2 \tag{3.4}$$

7. Skewness – The coefficient of Skewness is a measure for the degree of symmetry in the variable distribution. The following formula was used for computation of skewness.

$$\text{Skewness} = \frac{n}{(n-1)}\sum\left(\frac{x_i-\bar{x}}{s}\right)^3 \qquad (3.5)$$

where 's' is the standard deviation.

8. Kurtosis – The coefficient of Kurtosis is a measure for the degree of peakedness/flatness in the variable distribution. The following formula was used for computation of kurtosis.

$$\text{Kurtosis} = \left\{\frac{n(n+1)}{(n-1)(n-2)(n-3)}\sum\left(\frac{x-\bar{x}}{s}\right)^4\right\} - \frac{3(n-1)^2}{(n-2)(n-3)} \qquad (3.6)$$

9. Maximum Value – It refers to the maximum signal point value in a given signal.
10. Minimum Value – It refers to the minimum signal point value in a given signal.

These ten statistical features were extracted from sound and vibration signals.

III. RESULTS AND DISCUSSION

The extracted statistical features were given as an input of the J48 decision tree algorithm. The obtained decision tree for the vibration signals at 1000 rpm is shown in Figure VII

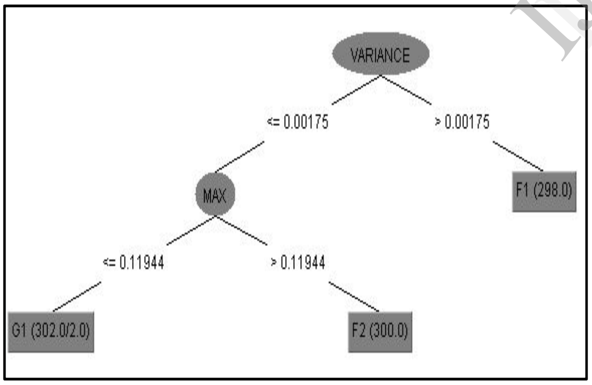

FIGURE VII. DECISION TREE FOR VIBRATION SIGNAL AT FULL LOAD AND 1000 RPM

The above decision tree represents the classification of gears at 1000 rpm. From the above decision tree, we can say that if the value of Variance is greater than 0.00175, then it is classified as class 'F1' i.e. Gear with Tooth breakage. If it is less than or equal to 0.00175, then we should consider Maximum value. If the Maximum value is greater than 0.11944 then it is classified as class 'F2' i.e. Gear with Face wear and if the Maximum value is less than or equal to 0.11944, then it is classified as class 'G1' i.e. Good gear.

The decision tree for the sound signals at 1000 rpm is shown in Figure VIII.

As we can see from the Figure VIII the decision tree for vibration signal is much simpler than decision tree for sound signal. As there are so many branches in sound signal, it will be difficult for classifying. So, vibration signal is dominant feature. The classification results of the vibration signals at 500 rpm is shown in Table. 2 in the form of confusion matrix.

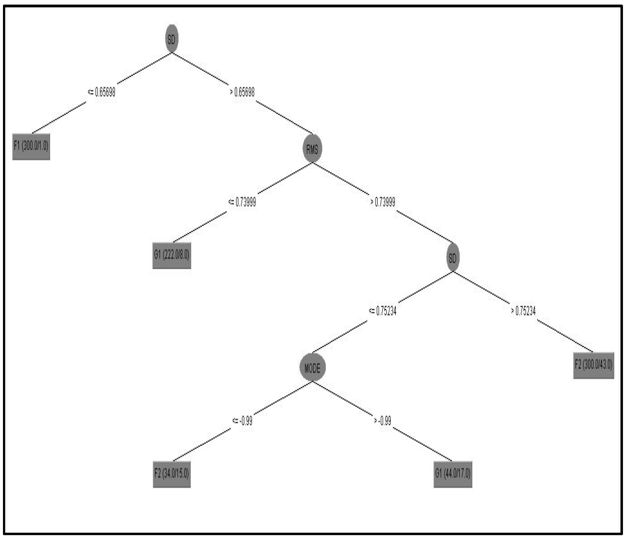

FIGURE VIII. DECISION TREE FOR SOUND SIGNAL AT FULL LOAD AND 1000 RPM

TABLE II. THE CONFUSION MATRIX OF DECISION TREE FOR VIBRATION SIGNAL AT 1000 RPM

	G1	*F1*	*F2*
G1	299	0	1
F1	0	297	3
F2	0	6	294

The sample testing result of the classifier for 500 rpm is represented in the form of the confusion matrix in Table. In the above confusion matrix 'G1' denotes Good Gear, 'F1' denotes Gear with Tooth breakage, 'F2' denoted Gear with Face wear. The following were interpreted from the confusion matrix

- The diagonal elements in the confusion matrix represents the number of correctly classified instances. The element in the first row and first column represents the number of data points belongs to class 'G1' i.e. Good gear and has been classified as Good Gear.
- The second element in the first column shows the number of data points belonging to class 'G1' but has been misclassified as class 'F1' i.e. Gear with tooth breakage. Similarly the third element shows the data points belonging to class 'G1' but misclassified as class 'F2' i.e. Gear with Face wear.

The classification results of both sound and vibration signals for all the speeds are presented in Table III for fault diagnosis of gearbox.

TABLE III. EFFICIENCIES OF SOUND AND VIBRATION SIGNALS

	LOAD	**SPEED** (RPM)	**EFFICIENCY** (%)
Vibration	No Load (0 Nm)	500	99.556
		750	99.667
		1000	99.556
	Intermediate Load (5 Nm)	500	99.667
		750	99.667
		1000	99.778
	Full load (10 Nm)	500	99.444
		750	97.444
		1000	98.889
Sound	No Load (0 Nm)	500	94.334
		750	73.334
		1000	83.334
	Intermediate Load (5 Nm)	500	86.667
		750	90.889
		1000	89
	Full load (10 Nm)	500	94.334
		750	73.334
		1000	83.334

The fault diagnosis process can be automated using LabVIEW. From the obtained Decision trees ofvarious fault conditions, a program can be designed in LabVIEW, which would make the fault diagnosis process automatic. Figure IX shows the block diagram of the program for vibration signal at 5 Nm load condition. Figure X shows the control panel for automation.

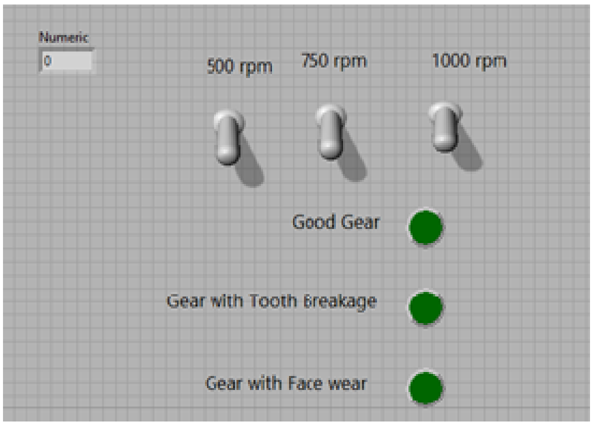

FIGURE X. CONTROL PANEL

IV. CONCLUSION

Decision trees were obtained from the sound and vibration signals. From the decision trees obtained, it was known that vibration is the dominant feature for fault diagnosis and this can be used for automating the process. The efficiency of vibration signals for three different speed conditions were determined. The dominant statistical feature and decision rule was obtained using decision tree algorithm. Automation of gearbox fault is a major area of study in condition monitoring of rotation machinery. The gearbox fault diagnosis process was automated using LabVIEW program.

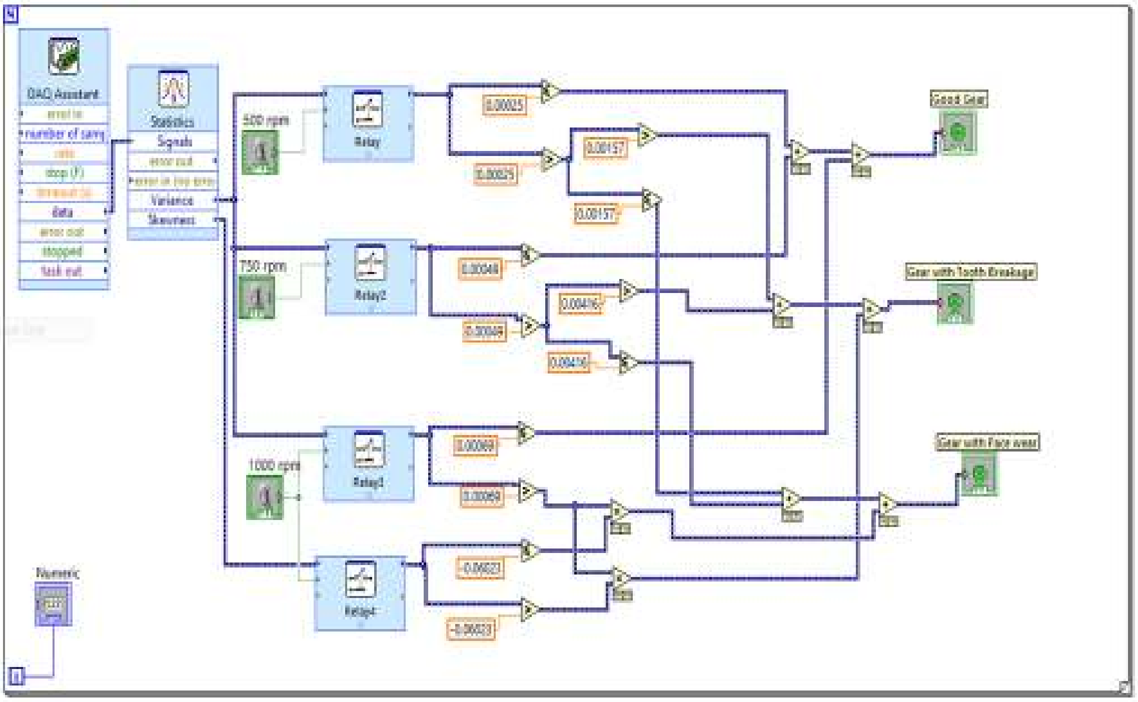

FIGURE IX. BLOCK DIAGRAM FOR AUTOMATON OF FAULT DIAGNOSIS OF GEARBOX

REFERENCES

[1] Amit. Aherwar and Md. Saifullah. Khalid, "Vibration Analysis Techniques for GearboxDiagnostic: A Review", International Journalof Advanced Engineering Technology, vol. III, April-June, 2012, pp. 04-12

[2] Choy. F. K, "Damage Identification of aGear Transmission Using Vibration Signatures",Journal of Mechanical Design, Vol. 125, 2003, pp.394-403,

[3] J. Miettinen, and P. Pataniitty."Acoustic Emission in Monitoring Extremely Slowly Rotating Machine Rolling Bearing" Tampere University Technology, Tampere, Finland, 2000

[4] J. Miettinen, and P. Pataniitty. 2000. Acoustic Emission in Monitoring Extremely Slowly Rotating Machine Rolling Bearing. Tampere University Technology, Tampere, Finland

[5] R.I. Raja, "Gearbox diagnosis and prognosis using Acoustic Emission", School of engineering, Cranfield University, Oct. 2005

[6] Cao, L. J., Chua, K. S., Chong, W. K., Lee, H. P. and Gu, Q. M., " A comparison of PCA, KPCA and ICA for dimensional reduction in support vector machine", Neurocomputing, 55, 2003, pp.321-336

[7] B.D. Forrester, Advanced Vibration Analysis Techniques for Fault Detection and Diagnosis inGeared Transmission Systems, Ph.D. Thesis, Swinburne University of Technology, Australia, 1996.

[8] P.D. McFadden, "A revised model for the extraction of periodic waveforms by time domain averaging", Mechanical systems and signal processing, vol. 1(1), pp. 83-95, 1987.

[9] Koo, I.S., and Kim, W.W., "The development of reactor coolant pump vibration monitoring and a diagnostic system in the nuclear power plant," *ISA Transactions*, 39, 309-316, 2000.

[10] Sakthivel, N.R., Nair, B.B. and Sugumaran, V. (2012), "Soft computing approach to fault diagnosis of centrifugal pump", Applied Soft Computing, 12, pp.1574-1581.