Fuzzy-Rule-Based Faults Classification of Gearbox Tractor

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Abstract: This paper presents a fault Classification method based on a fuzzy inference system. The vibration signal from a piezoelectric transducer is captured for the following conditions of MF 285 gearbox: 'Healthy Gearbox' (H), 'Gear with tooth face worn' (W) and 'Gear with tooth face broken' (B), at three working speed (700, 1500 and 1800 rpm). The features of signal were extracted using descriptive statistic parameters. The output of the J48 algorithm is a decision tree that was employed to produce the crisp if-then rule and membership function sets. Results showed that the total classification accuracy for 700, 1500 and 1800 rpm conditions were about 79.63%, 100% and 96.3%.

Keywords: Vibration-Based Condition Monitoring, J48 Algorithm, Gearbox, Fuzzy, Tractor, Fault

1 Introduction

Condition monitoring of rotating machinery is important in terms of system maintenance and process automation. Gearboxes are widely used in industrial applications and power transmission of vehicles. An unexpected failure of the gearbox may cause significant economic losses. Condition monitoring has long been accepted as one of the most effective and cost-efficient approaches to avoid catastrophic failures of machines. It has been known for many years that the mechanical integrity of a machine can be evaluated by detailed analysis of the vibratory motion [5]. In most machine fault diagnosis and prognosis systems, the vibration of the rotating machine is directly measured by an accelerometer [17, 1]. Condition diagnosis depends largely on the feature analysis of vibration signals measured for condition diagnosis, so it is important that the feature of the signal be extracted appropriately when a fault occurs at the state change of a machine. However, the feature extraction for the fault diagnosis is difficult since the vibration signals measured at a point of the machine often contain strong noise.

Stronger noise than the actual failure signal may lead to misrecognition of the useful information for diagnosis. Therefore, it is important that the noise be suppressed from the measured signal as far as possible for sensitively identifying the failure type [11, 20].

Knowledge-based techniques [6, 3] become a suitable strategy towards automatic fault detection (AFD). Fuzzy logic is among the knowledge-based techniques to address the fault detection problem. Several researchers [8, 16] have proposed fault detection and diagnosis approaches based on a fuzzy system. Fuzzy systems are artificial intelligence techniques which have had rapid growth in the field of intelligent control (fuzzy control) [13, 14]. The fuzzy system is a rule-based approach where the rule set is usually learned from an expert's experience or prior knowledge of the system. The process of fault detection can be seen as a classification problem and hence the fuzzy system acts as a classifier to distinguish different faults according to its rules. The success of the fault detection process thus depends on the accuracy of the fuzzy rules. Typically, fuzzy rules are generated by intuition and expert's knowledge. However, for complex systems with a large amount of redundant features, the derivation of fuzzy rules is tedious and inaccurate. Researchers have continuously tried to find efficient and effective methods to generate these fuzzy rules. Neural networks have been proposed to solve the problem but they are only suitable for building fuzzy systems with a relatively small number of numerical variables. The trapping of the local optimal in the learning process is the main weakness of using neural networks [19, 12]. In this study, the decision tree is utilized as a feature selection procedure to remove irrelevant features for the purpose of reducing the amount of data needed to achieve good learning, classification accuracy, a compact and easily understood knowledge-base, and a reduction in computational time [10]. The proposed approach consists of two stages: First, the decision tree is performed as a feature selection tool to obtain the valuable features and to identify the structure of the classifier in the next iterative step. Second, the fuzzy logic classifier is used to diagnose the faults of the gearbox.

2 Material and methods

2.1 Experimental studies

The main objective of the study is to find whether the gearbox is good or faulty. If faulty, then the aim is to segregate the fault into one of the faults considered above. This paper focuses on the use of decision tree for automatic rule learning (set of 'if-then' rules) for classification and study the effectiveness of such rules through fuzzy classifier, referring to Fig. 1. In this work, the vibration signals in the frequency domain are utilized for detecting the faults of the gearbox. The proposed system consists of five procedures as shown in Fig. 1: data acquisition, the Fast Fourier transforms (FFT) of the vibration spectrum, feature extraction, feature selection, classification model extraction and fault diagnosis. These are scenically explained in the next sections. The summary role of each procedure is described as follows:

Data acquisition: this procedure is used to obtain the vibration signals. Furthermore, data processing is also carried out.

The Fast Fourier transforms (FFT): for to convert vibration signals of time domain to frequency domain.

Feature extraction: In this stage, we are extracted nineteen features. The most significant features are calculated by using statistical feature parameters from the frequency domain.

Feature selection and classification model extraction: method Correlation-based Feature Selection (CFS) and the J48 algorithm are used as a decision tree to select the salient features from the whole feature set. In this section the data obtained from the feature extraction procedure is split into two sets: training data and testing data. Training data is employed to build the model, whilst testing data is for validating the model.

Fault Diagnosis: Fuzzy logic inference system is used to diagnose the faults.

2.2 Experimental setup

The machine fault used for study is shown in Fig. 2. We can use that for fault diagnosis of gearbox all of tractors. It consists of: 1. Test rig for rotational machine. 2. On-line signal acquisition system. 3. Signal analysis.

It was made of five main parts: a. mechanical parts, b. pneumatic parts, c. hydraulic parts, d. lubrication system, and e. electrical and electronic parts, that each one of them was formed of many subsets.

A variable speed AC motor (30 kW) with speed up to 3000 rpm is the drive (details of electromotor are given in Table 1).

A piezoelectric accelerometer (ATLPC 259 model, Made in England, Fig. 3) is mounted on the flat surface Gearbox and is connected to the PLC (programmable logic controller).

A variable load establisher system beside rotation of Gearbox.

Eight shock absorbers (Fig. 4) under the base of test-bed to cancel out vibrations.

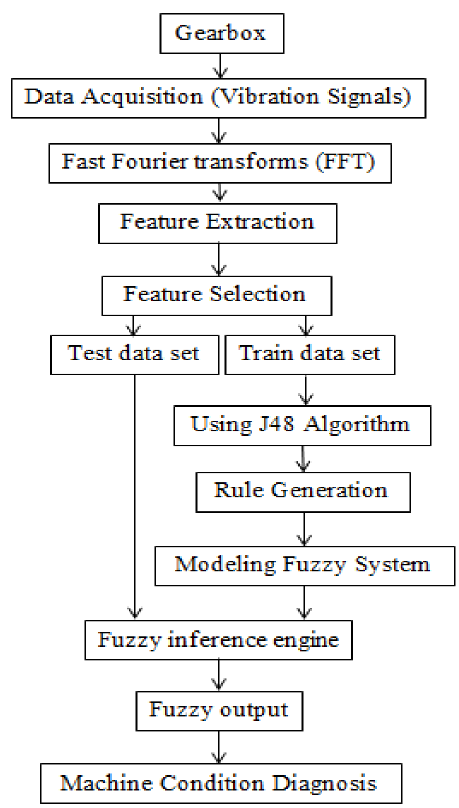

Fig.1. Flowchart of fault diagnosis system.

2.3 Experimental procedure

In the present study, gearbox of MF 285 tractor was used (Fig. 5 shows the used components and their cases). This gearbox coupled between the load establisher system and electromotor that was initially run under normal operating conditions and its speed was at three levels, 700, 1500 and 1800 rpm respectively. The vibration signal from the piezoelectric pickup mounted on the test gearbox was taken, after allowing initial running of the gearbox for some time. Where the signal is time domain and get stored directly in the computer's memory. The signal is then read from the memory, replayed and processed to convert the Fast Fourier transform (FFT) of the vibration spectrum [2].

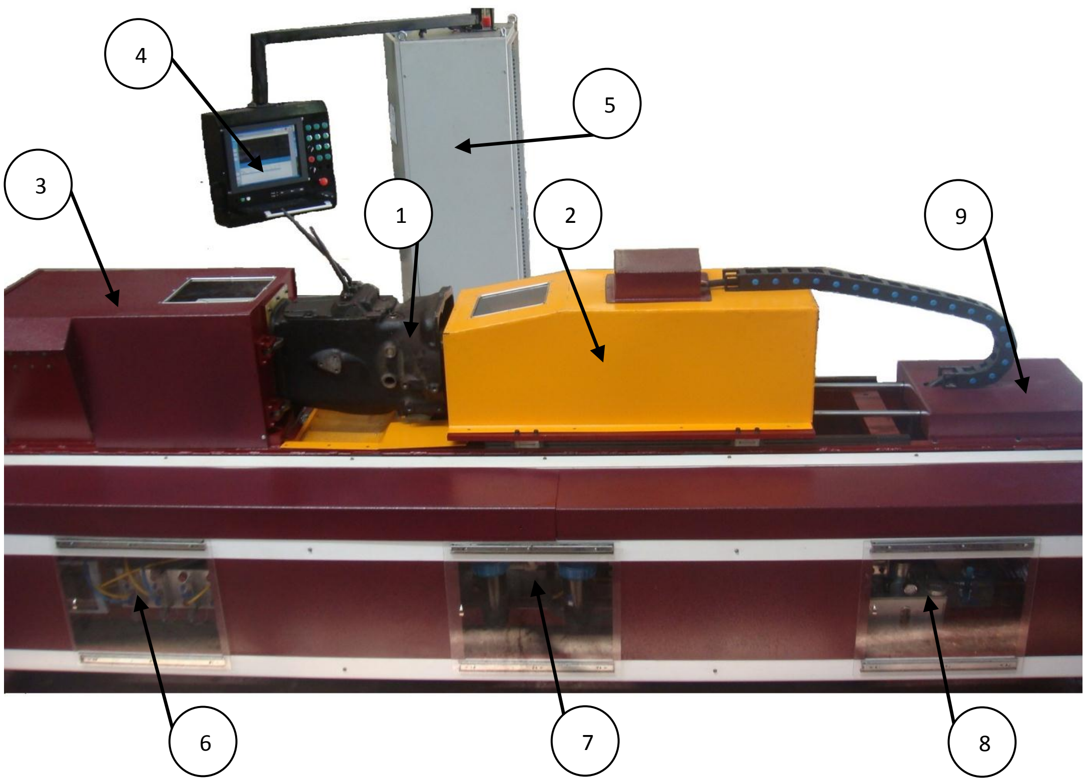

Fig.2: Test-Bed

1. Gearbox 2. Electrical motor 3. Load establisher system 4. Controller keys and touch panel 5. Electrical and electronic Toolbox 6. Electrical and pneumatic valves 7. Hydraulic system 8. Lubrication system 9. Power cylinder for to move electromotor

Fig.3: Accelerometers ATLPC 259

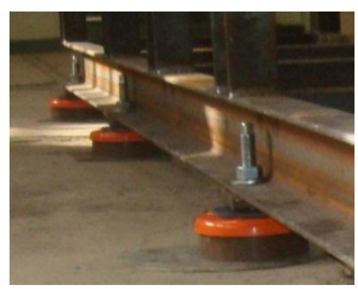

Fig.4: Shock absorber

Fig.5: Healthy gear (left) – Broken gear (middle) - Worn tooth face gear (right)

Table 1: Detail of Electromotor

Electromotor	Description
Electromotor capacity(kW)	30
Motor driving speed (rpm)	Variable
Voltage	380 v
Phase	Three phase

2.4 Feature extraction

The measured signals obtained from the experiment were calculated to obtain the most significant features by feature extraction. The accuracy of feature extraction is of great importance since it directly affects the final diagnosis results. In this paper, we are extracted nineteen features. The feature extraction using descriptive statistics on the frequency domain data. Research works have reported the use of this method [17, 9, 15]. We selected a fairly wide set of these parameters as the basis for our study. The statistical features are explained below:

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

$$f_1 = \frac{\sum_{n=1}^{N} x(n)}{N} \tag{1}$$

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.

$$f_2 = \sqrt{\frac{\sum_{n=1}^{N} (x(n)-f_1)^2}{N}} \tag{2}$$

Where 'N' is the sample size.

Mean square root amplitude signal:

$$f_3 = \left(\frac{\sum_{n=1}^{N} \sqrt{|x(n)|}}{N}\right)^2 \tag{3}$$

RMS (root mean square): The RMS value of a set of values (or a continuous-time waveform) is the square root of the arithmetic mean (average) of the squares of the original values (or the square of the function that defines the continuous waveform).

$$f_4 = \sqrt{\frac{\sum_{n=1}^{N} (x(n))^2}{N}} \tag{4}$$

Maximum value: It refers to the maximum signal point value in a given signal.

$$f_5 = \max(|x(n)|) \tag{5}$$

Product of division 3^th^ moment on the cube mean:

$$f_6 = \frac{\sum_{n=1}^{N} (x(n)-f_1)^3}{N.{f_2}^3} \tag{6}$$

Product of division 4^th^ moment on the fourth power mean:

$$f_7 = \frac{\sum_{n=1}^{N} (x(n)-f_1)^4}{N.{f_2}^4} \tag{7}$$

Crest Factor: is a measurement of a waveform, calculated from the peak amplitude of the waveform divided by the RMS value of the waveform.

$$f_8 = \frac{f_5}{f_4} \tag{8}$$

Product of division maximum on the mean square root amplitude signal:

$$f_9 = \frac{f_5}{f_3} \tag{9}$$

Product of division root mean square on the mean amplitude signal:

$$f_{10} = \frac{N.f_4}{\sum_{n=1}^{N} |x(n)|} \tag{10}$$

Product of division maximum on the mean amplitude signal:

$$f_{11} = \frac{N.f_5}{\sum_{n=1}^{N} |x(n)|} \tag{11}$$

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

$$f_{12} = \frac{\sum_{n=1}^{N}(x(n) - f_1)^2}{N} \tag{12}$$

Harmonic mean:

$$f_{13} = \frac{N}{\sum_{n=1}^{N}\frac{1}{x(n)}} \tag{13}$$

Geometric mean:

$$f_{14} = \sqrt[N]{\prod_{n=1}^{N} x(n)} \tag{14}$$

Diffusion coefficient:

$$f_{15} = \frac{f_2}{f_1} \times 100 \tag{15}$$

Average division from mean:

$$f_{16} = \frac{\sum_{n=1}^{N}|x(n) - f_1|}{N} \tag{16}$$

Skid:

$$f_{17} = \frac{\frac{1}{N}\sum_{n=1}^{N}(x(n) - f_1)^3}{(\sqrt{\frac{1}{N}\sum_{n=1}^{N}(x(n) - f_1)^2})^3} \tag{17}$$

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

$$f_{18} = \sqrt{\frac{N-1}{N}} \times \frac{1}{(N-2).{f_{12}}^{1.5}} \times \sum_{n=1}^{N}(x(n) - f_1)^3 \tag{18}$$

Kurtosis: Kurtosis indicates the flatness or the spikiness of the signal. The following formula was used for computation of Kurtosis:

$$f_{19} = \frac{(N-1)\times(N+1)}{(N-3)\times(N-2)\times N\times {f_{12}}^2} \times \sum_{n=1}^{N}(x(n) - f_1)^4 - \frac{3\times(N-1)^2}{(N-2)(N-3)} + 3 \tag{19}$$

In all up formulas, x(n) is amplitude of signal and 'N' is sample rate of signal.

2.5 Feature selection and classification model extraction

A 'divide-and-conquer' approach to the problem of learning from a set of independent instances leads naturally to a style of representation called a decision tree. A decision tree is a tree-based knowledge representation methodology used to represent classification rules. A standard tree induced with c5.0 (or possibly ID3 or c4.5) consists of a number of branches, one root, a number of nodes and a number of leaves. One branch is a chain of nodes from root to a leaf, and each node involves one attribute. The occurrence of an attribute in a tree provides the information about the importance of the associated attribute. In a decision tree, the top node is the best node for classification. The other features in the nodes of a decision tree appear in descending order of importance. It is to be stressed here that only features that contribute to the classification appear in the decision tree and others do not. Features that have less discriminating capability can be consciously discarded by deciding on the threshold. This concept is made use of for selecting good features. In this research, Method Correlation-based Feature Selection (CFS) and the J48 algorithm (A WEKA implementation of c4.5 Algorithm) are used as a decision tree to select the salient features from the whole feature set [18]. In this section the data obtained from the feature extraction procedure is split into two sets: training data and testing data. Training data is employed to build the model, whilst testing data is for validating the model. Input to the algorithm was the set of statistical features extracted from raw vibration signatures. The data sets of the features for each condition have 60 samples. In each operating condition, %70 of samples is employed for the training process and the remaining samples for testing purposes. The detailed descriptions of those data sets are given in Table 2. Based on the output of the J48 algorithm, various statistical parameters are selected for the various conditions of the gearbox. Selected statistical features are used as membership functions and the values appearing between various nodes in the decision tree are used for generating the fuzzy rules to classify the various conditions of the gearbox under study.

Table 2: Descriptions of data sets in each condition

Label of classification	Number of training samples	Number of testing samples
Healthy (H)	42	18
Worn (W)	42	18
Broken (B)	42	18
Total Samples	126	54

2.6 Fault diagnosis using fuzzy inference system

Fuzzy logic makes use of the knowledge of experts through its transformation into linguistic terms. Fuzzy logic is a rule-based system that successfully combines fuzzy set theory with the inference capability of human beings. As rules, linguistic terms are used and are modeled through membership functions that represent simulation of the comprehension of an expert. Membership functions give the scaled value of definite number values that are defined by linguistic labels. Rules are defined such as IF (condition) THEN (result). The conditions and results are linguistic terms that represent the input and output variables, respectively. The rule base of the fuzzy logic classifier consists of many rules. A rule base is used to obtain a definite output value according to the input value [4]. After defining membership functions and generating the 'if-then' rules by J48 algorithm, the next step is to build the fuzzy inference engine. The fuzzy toolbox available in MATLAB 7.6 [7] was used for building the fuzzy inference engine. Each rule was taken at a time and using membership functions and fuzzy operators the rules were entered.

3 Results and discussion

3.1 Vibration signals

Fig. 6 shows the samples of vibration signal acquired for various experimental conditions of the gearbox using FFT. According to this Figure, it is obvious that the vibration amplitude value is increased by increasing the working speed. Also, in each working speed of the gearbox, the vibration amplitude value is increased by increasing the severity of gearbox faults. Results show that fault diagnosis of gearbox is difficult using a spectrum of vibration signals alone. Therefore it is necessary to utilize an automatic signal classification system in order to increase accuracy and reduce errors caused by subjective human judgment.

3.2 Decision trees

The outcomes of the J48 algorithm are shown in Fig. 7, 8 and 9. Decision trees show the relation between features and the condition of the gearbox. Tracing a branch from the root node leads to a condition of the gearbox and decoding the information available in a branch in the form of the 'if - then' statement gives the rules for classification using fuzzy for various conditions of gearbox. Hence, the usefulness of the decision tree in forming the rules for fuzzy classification is established. The top node of the decision tree is the best node for classification [15]. The other features appear in the nodes of the decision tree in descending order of importance. It is to be stressed here that only features that contribute to the classification appear in the decision tree and others do not. The level of contribution is not the same and all statistical features are not equally important. The level of contribution by an individual feature is given by a statistical measure within the parenthesis in the decision tree. The first number in the parenthesis indicates the number of data points that can be classified using that feature set. The second number indicates the number of samples against this action. If the first number is very small compared to the total number of samples, then the corresponding features can be considered as outliers and hence ignored. Features that have less discriminating capability can be consciously discarded by deciding on the threshold. This concept is used in selecting good features. The algorithm identifies the good features for the purpose of classification from the given training data set and thus reduces the domain knowledge required to select good features for the pattern classification problem.

3.3 Accuracy of decision trees

The classification results based on decision trees are calculated using a 'use training set, evaluation where the data set to be evaluated is randomly partitioned so that in each condition 42 samples are used for training. The process is iterated with different random partitions and the results are averaged. Obtained confusion matrices from the decision trees are given in Table 3. In a confusion matrix, each cell contains the number of samples that was classified corresponding to actual algorithm outputs. The diagonal elements in the confusion matrix show the number of correctly classified instances. Results show that the accuracy of decision trees produced for 700, 1500 and 1800 rpm is about 87.3%, 100% and 99.21%, respectively.

3.4 Membership functions
A membership function (MF) is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. Observing the values of the feature, based on which the branches of the decision tree are created for different conditions of the gearbox, the MFs for the corresponding features are defined.

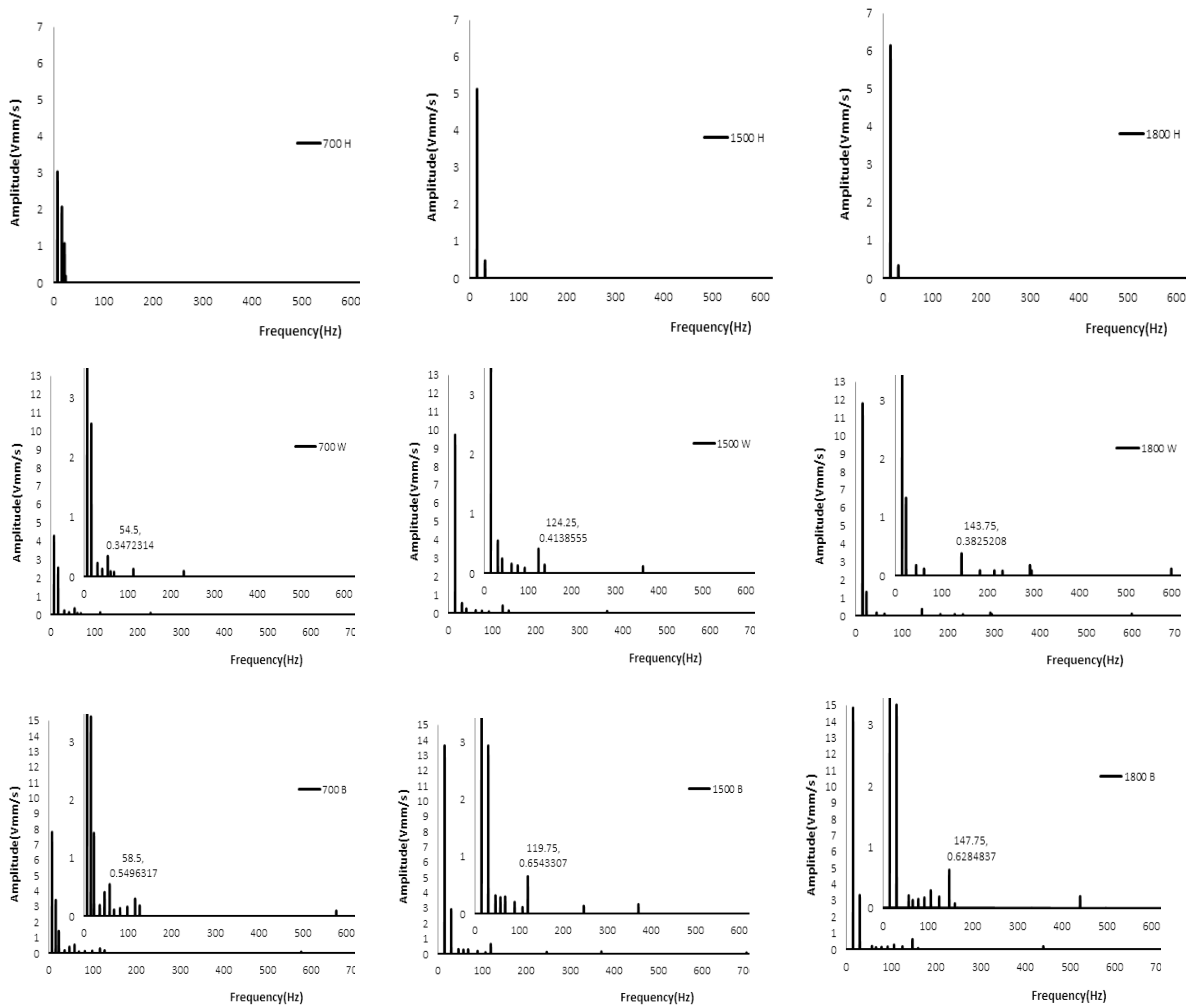

Fig.6: Vibration signals of gearbox in 700, 1500 and 1800 rpm

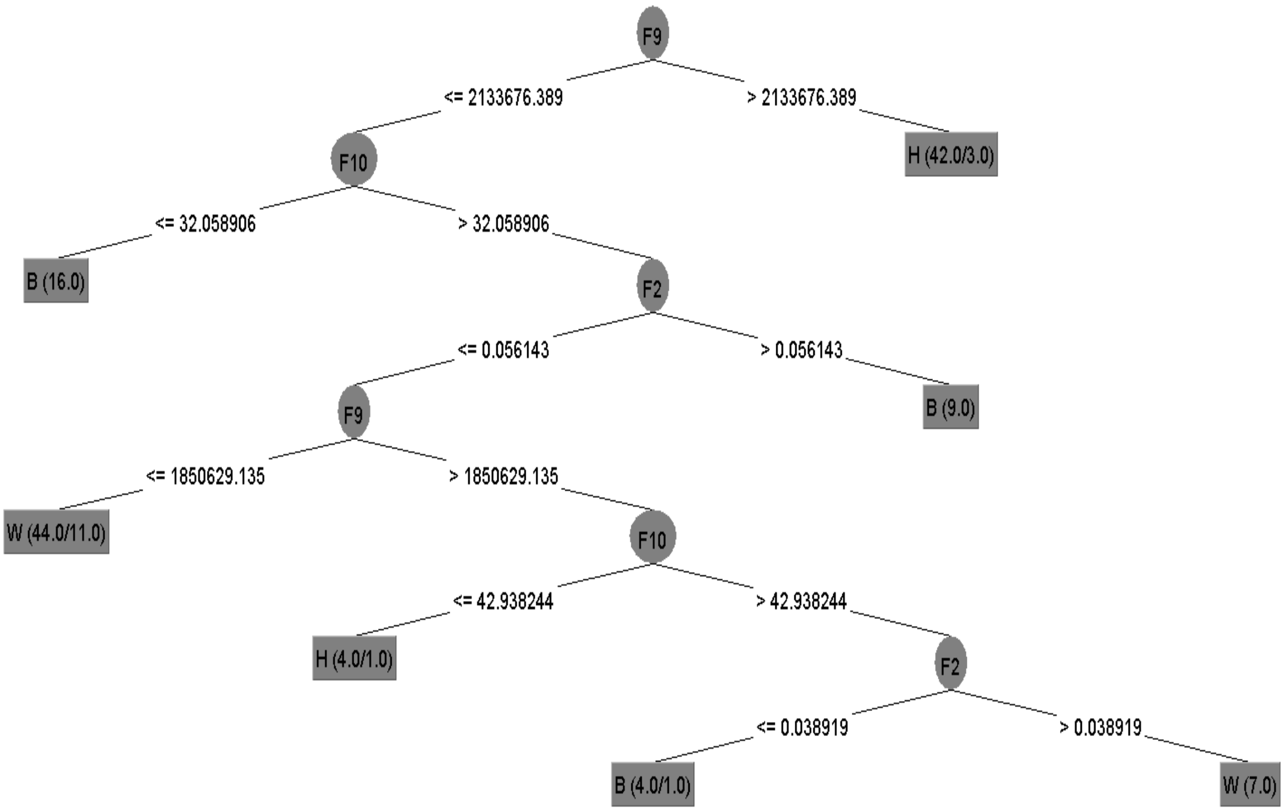

Fig.7: Decision tree from J48 algorithm for 700 rpm condition

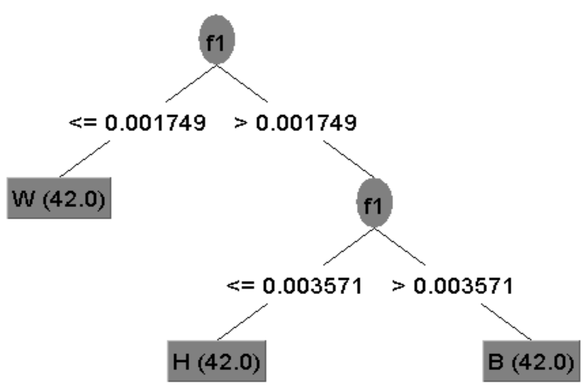

Fig.8: Decision tree from J48 algorithm for 1500 rpm condition

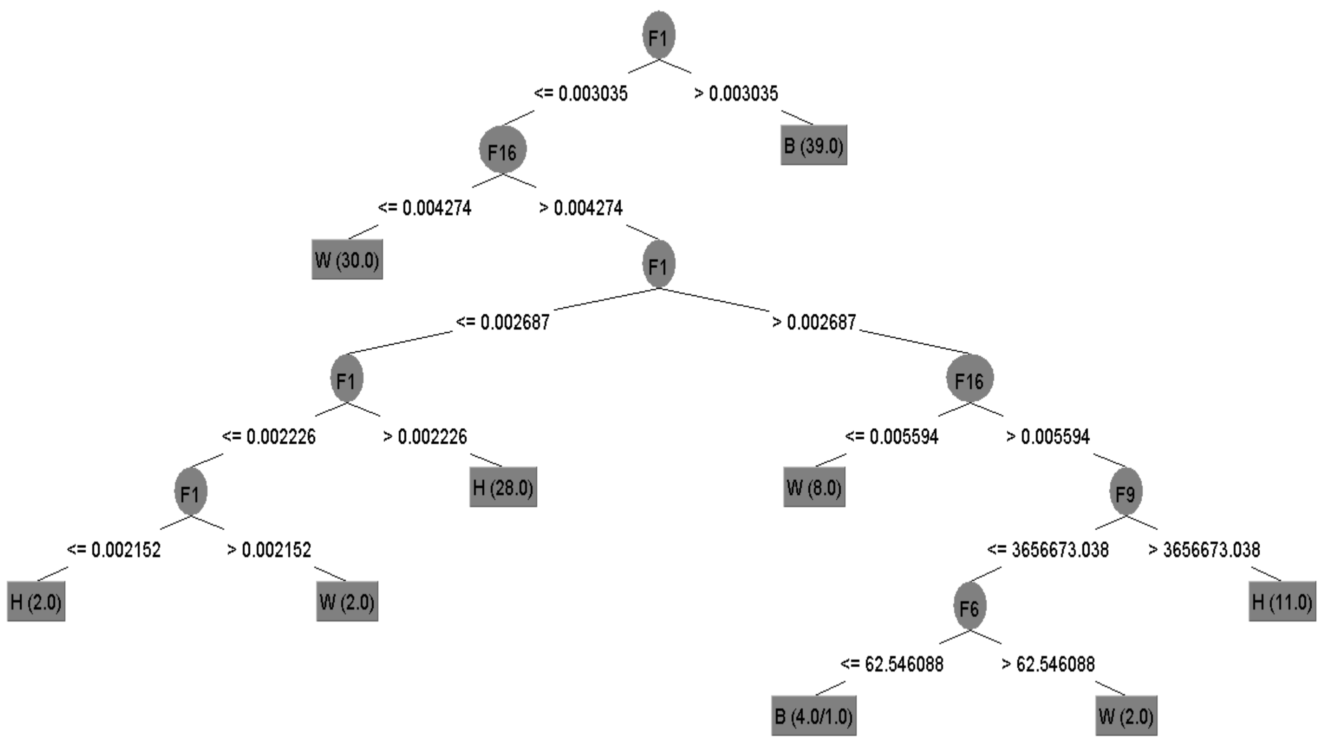

Fig.9: Decision tree from J48 algorithm for 1800 rpm condition

700 rpm condition:

From Fig. 10 we can see that f2, f9 and f10 play decisive roles in classifying the various gearbox faults for this condition. This output of the decision tree is used to design the MFs for the fuzzy classifier as shown in Fig. 11. In the present study, trapezoidal MF is used. The selection of this MF is to some extent arbitrary. However, the following points were considered while selecting the MF. Observing the values of the feature, based on which the branches of the decision tree are created, the MFs for all three features are defined for f2, f9 and f10, respectively. From Fig. 10 it is obvious that 0.038919 is a threshold for a membership value of f2. Up to this threshold value the MF generates the value ‘0’, which means that it is not f2-1 and afterwards it increases linearly (assumption). The trapezoidal MF suits this phenomenon and hence it was selected to map each point in the input space to a membership value (Fig. 10). To review, the threshold values are given by the decision tree and the slope is defined by the user through heuristics. The threshold value (0.038919) is defined based on the representative training dataset. If the f2 value is less than or equal to 0.038919, an MF which is defined on a 0–1 scale gives a value of 1, which means that it is f2-1. If the threshold value is greater than 0.038919, the MF generates a value of 0. MFs for other features are designed accordingly and shown in Fig. 10. There are three possible outcomes from a fuzzy classifier, namely: Healthy (H), Worn (W) and Broken (B). Hence, three MFs are defined with equal range as shown in Fig. 11.

Table 3: Confusion matrices of decision trees for three working speeds of gearbox

Condition	700 rpm			1500 rpm			1800 rpm		
	Healthy	Worn	Broken	Healthy	Worn	Broken	Healthy	Worn	Broken
Healthy(H)	42	0	0	42	0	0	41	0	1
Worn(W)	1	40	1	0	42	0	0	42	0
Broken(B)	3	11	28	0	0	42	0	0	42

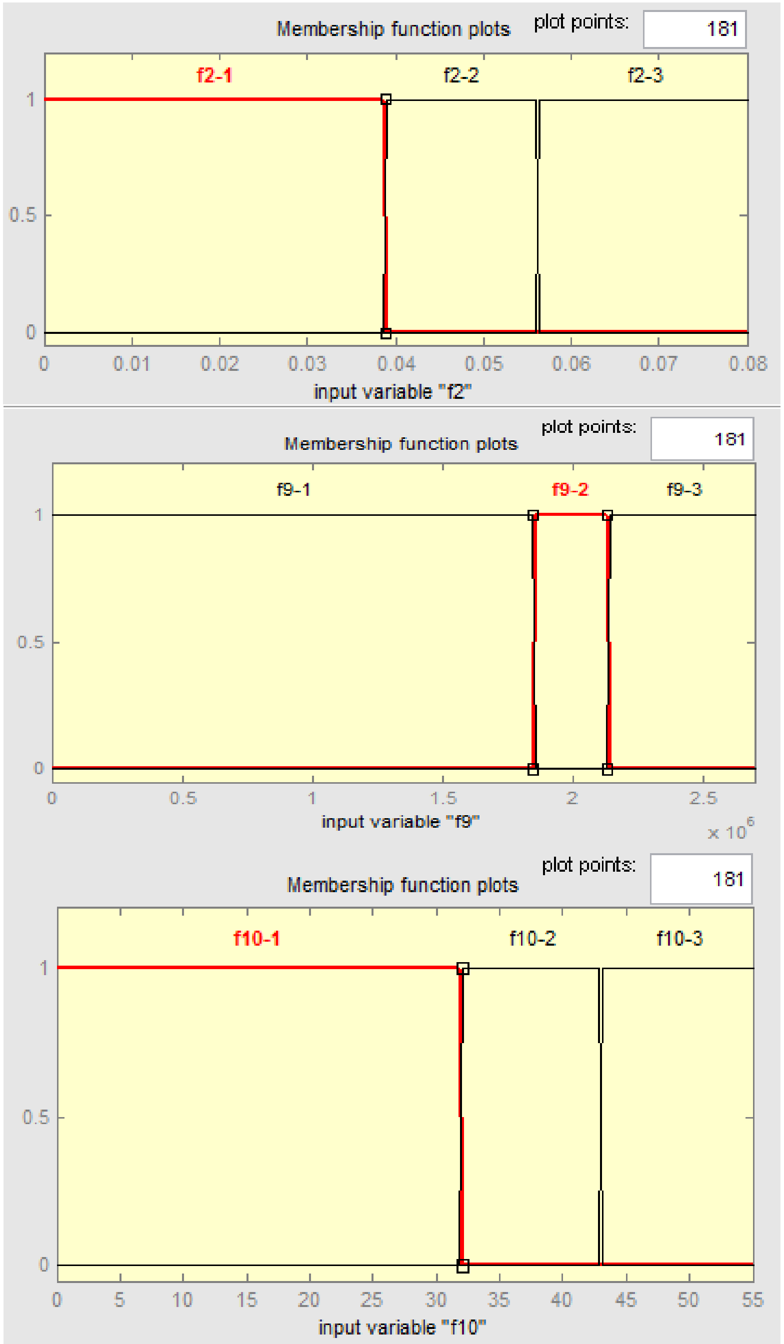

Fig.10: Membership function for ‘F2’, ‘F9’ and ‘F10’

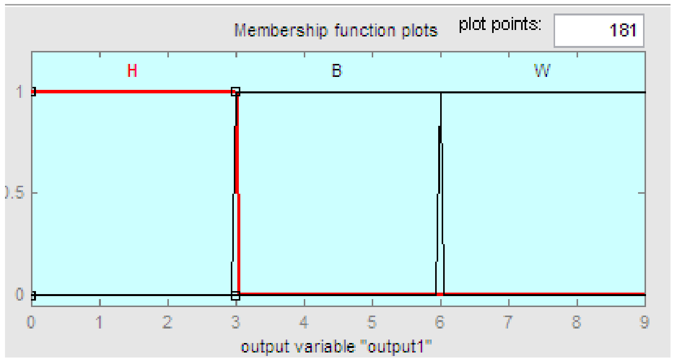

Fig.11: Membership function for output (‘STATE’)

1500 rpm condition:

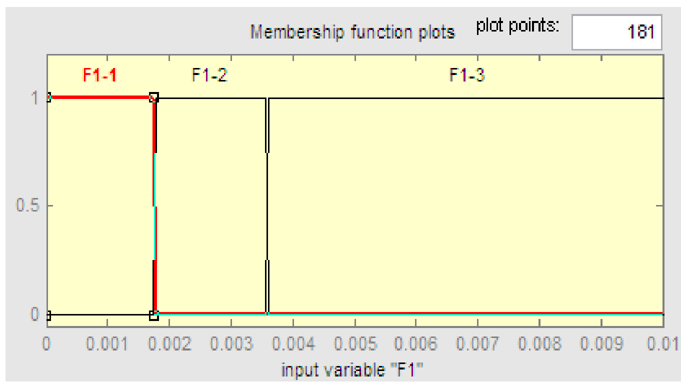

Fig.12: Membership function for ‘F1’

1800 rpm condition:

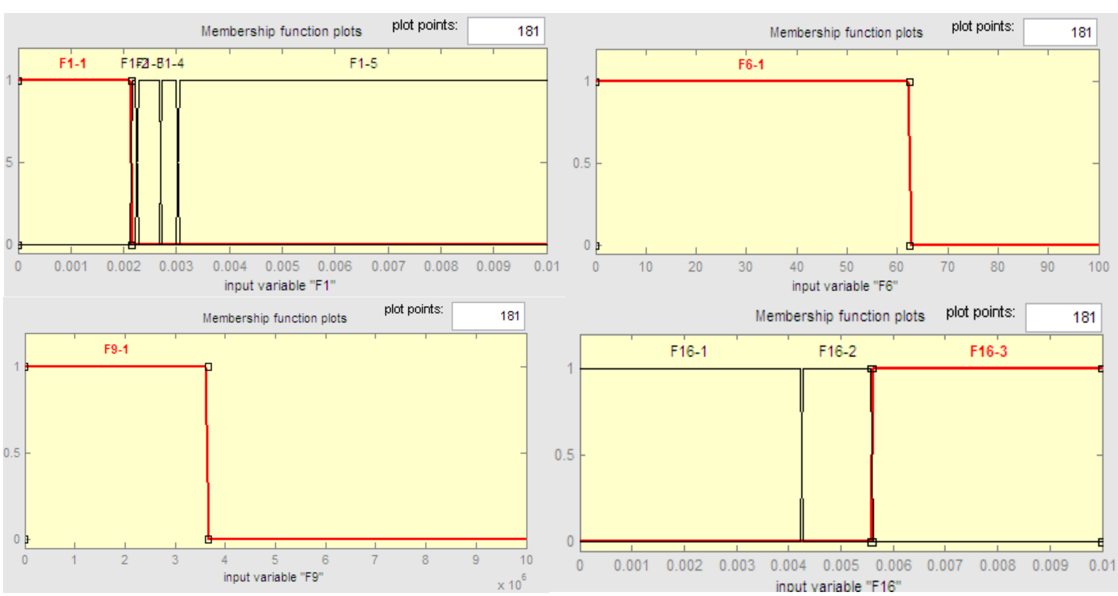

Fig.13: Membership function for ‘f1’; ‘f6’; ‘f9’ and ‘f16’

3.5 Fuzzy rules

Using Figures 7, 8 and 9, fuzzy rules were designed with ‘if-then’ statements. All rules are evaluated in parallel, and the order of the rules is unimportant.

3.5.1 Rules designed for 700 rpm condition:

1. If (f9 is f9-3) then (output1 is H) (1)
2. If (f9 is not f9-3) and (f10 is f10-1) then (output1 is B) (1)
3. If (f2 is f2-3) and (f9 is f9-1) and (f10 is not f10-1) then (output1 is B) (1)
4. If (f2 is not f2-3) and (f9 is f9-1) and (f10 is not f10-1) then (output1 is W) (1)
5. If (f2 is not f2-3) and (f9 is f9-2) and (f10 is f10-2) then (output1 is H) (1)
6. If (f2 is f2-1) and (f9 is f9-2) and (f10 is f10-3) then (output1 is B) (1)
7. If (f2 is f2-2) and (f9 is f9-2) and (f10 is f10-3) then (output1 is W) (1)

Fig. 14 illustrates the application of the rules designed. Here each row corresponds to each rule as discussed in this section. The first three blocks in rows represent the MFs of f2, f9 and f10, respectively. The fourth block corresponds to the MFs for state as shown in Fig. 11. With the help of sample inputs for f2, f9 and f10, the rules are tested as follows, for a sample input of f2 as 0.04, f9 as 1350000 and f10 as 27.5, which satisfies the second rule completely and the corresponding output condition is Broken (B), which is shown in the output block of the third row in the rule viewer shown in Fig. 14.

3.5.2 Rules designed for 1500 rpm condition:

1. If (F1 is F1-1) then (output1 is W) (1)
2. If (F1 is F1-2) then (output1 is H) (1)
3. If (F1 is F1-3) then (output1 is B) (1)

Fig. 15 is the rule viewer for the following test data. If f1 = 0.005, then the output is 4.5, *ie* the condition is Broken.

3.5.3 Rules designed for 1800 rpm condition:

1. If (F1 is F1-5) then (output1 is B) (1)
2. If (F1 is not F1-5) and (F16 is F16-1) then (output1 is W) (1)
3. If (F1 is F1-3) and (F16 is not F16-1) then (output1 is H) (1)
4. If (F1 is F1-2) and (F16 is not F16-1) then (output1 is W) (1)
5. If (F1 is F1-1) and (F16 is not F16-1) then (output1 is H) (1)
6. If (F1 is F1-4) and (F16 is F16-2) then (output1 is W) (1)
7. If (F1 is F1-4) and (F9 is not F9-1) and (F16 is F16-3) then (output1 is H) (1)
8. If (F1 is F1-4) and (F6 is not F6-1) and (F9 is F9-1) and (F16 is F16-3) then (output1 is W) (1)
9. If (F1 is F1-4) and (F6 is F6-1) and (F9 is F9-1) and (F16 is F16-3) then (output1 is B) (1)

In each condition, 18 samples were used for testing the final model. The confusion matrix for each condition is given in Table 4. Results show that the total classification accuracy for 700, 1500 and 1800 rpm conditions are 79.63%, 100% and 96.3%, respectively.

4 Conclusions

A combined classification tree (J48 algorithm) and fuzzy inference system (FIS) have been presented to perform fault diagnosis of a gearbox. The implementation of J48-FIS based classifier requires two consecutive steps. Firstly, method Correlation-based Feature Selection (CFS) and the J48 algorithm are utilized to select the relevant features in the data set obtained from feature extraction part. The output of the J48 algorithm is a decision tree that is employed to produce the crisp if-then rule and membership function sets. Secondly, the structure of the FIS classifier is defined based on the obtained rules, which were fuzzified in order to avoid classification surface discontinuity. The classification results and statistical measures are then used for evaluating the J48-FIS model. The total classification accuracy for 700, 1500 and 1800 rpm conditions were 79.63%, 100% and 96.3% respectively. Therefore, fault diagnosis is more reliable in higher speeds of gearbox using this technique. The results indicate that the proposed J48-FIS model can be used in diagnosing gearbox faults and developing an online condition monitoring test. Work in this direction is in progress.

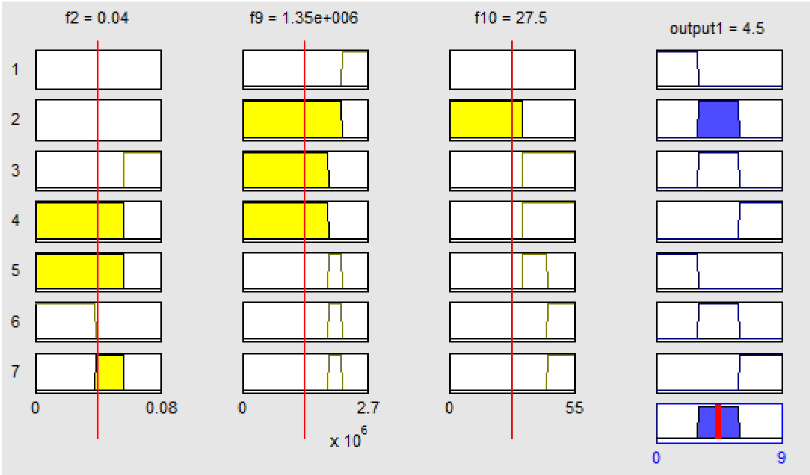

Fig.14: Rule viewer for one of the test data of 700 rpm condition

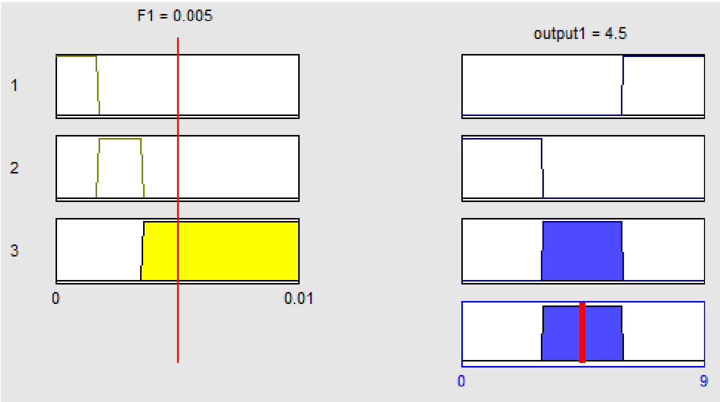

Fig.15: Rule viewer for one of the test data of 1500 rpm condition

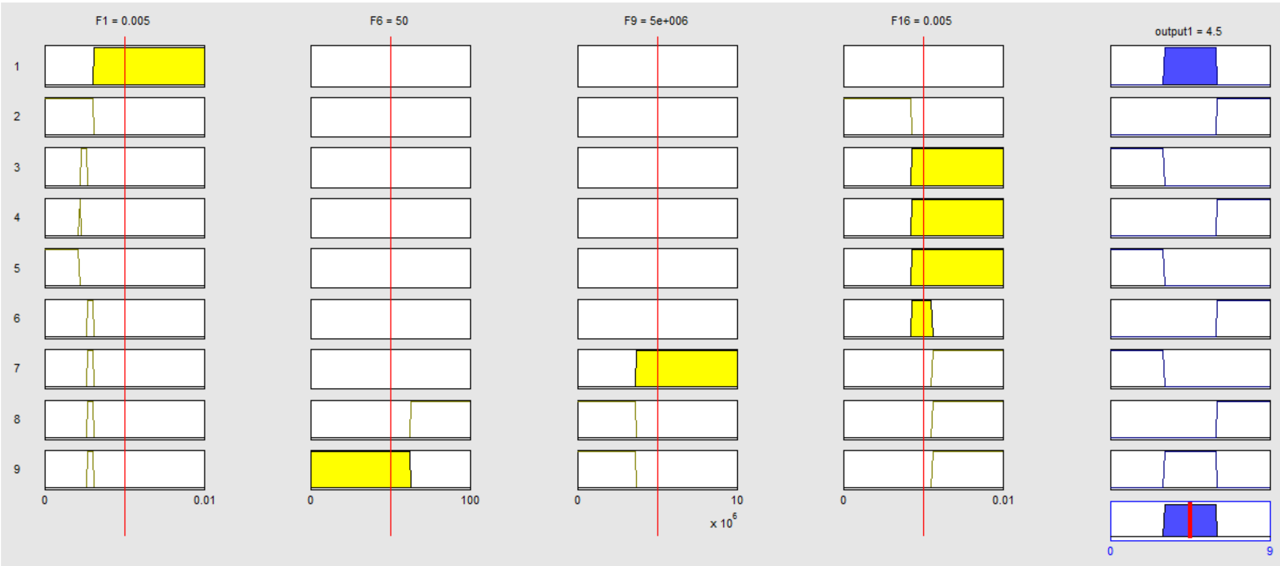

Fig.16: Rule viewer for one of the test data of 1800 rpm condition

Table 4: Confusion matrices of decision trees for three working speeds of gearbox

Condition	700 rpm			1500 rpm			1800 rpm		
	Healthy	Worn	Broken	Healthy	Worn	Broken	Healthy	Worn	Broken
Healthy(H)	16	2	0	18	0	0	17	1	0
Worn(W)	3	14	1	0	18	0	0	17	1
Broken(B)	1	4	13	0	0	18	0	0	18

Acknowledgement
The authors are very grateful to the Kurdistan Tractor Manufacturing co. and University of Tehran for their help and their assistance during the experiments.

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