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# Vibration based Fault Diagnosis of Automobile Hydraulic Brake System using Fuzzy Logic with Best First Tree Rules

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**ABSTRACT:**

*Brakes are indispensable element of automobile. It takes significant factor to slow down or stop vehicle at an instant which will help to prevent an incident or accident in panic scenario. In appropriate braking or breakdown in braking system may direct devastating effect on automobile as well as traveller safety. To enhance potential of braking system condition monitoring is drastic demand in automotive field. This research predominantly concentrates towards fault diagnosis of a hydraulic brake system with the principle of vibration signal. Feature extraction, feature selection and feature classification are the key measures under machine learning approach. Feature extraction can certainly accomplished by acquiring vibration from the system. Statistical features were for the fault diagnosis of hydraulic brake system. Best first tree algorithm will pick most effective features that will differentiate the fault conditions of the brake through given train samples. Fuzzy logic was selected as a classifier. In the present study, fuzzy classifier with the best first tree rules was used to perform the classification accuracy*

**KEYWORDS:**

*Statistical features; Decision tree; Feature extraction; Fuzzy; Mamdani; Feature selection*

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**ACRONYMS AND NOMENCLATURE:**

AIR Air in brake fluid
BO Brake oil spill
DPWI Disc brake pad wear - inner
DPWIO Disc brake pad wear inner & outer
UDPWI Uneven disc pad wear (inner)
UDPWIO Uneven disc pad wear (inner & outer)
RL Reservoir leak
DRPW Drum brake pad wears
DRMF Drum brake mechanical brake
GOOD Brake without any fault.

## 1. Introduction

Road crashes kill more than 1.2 million people a year worldwide and injure more than 50 million, with deaths disproportionately taking place in low-to middle-income countries [1]. Brakes tend to be one of the most crucial control elements accountable for the safety along with stability of the automobile. Each and every vehicle must be loaded together with an efficient brake structure to take the automobile to rest throughout a sensible range even underneath the most undesirable circumstances. The brake system must be extremely trustworthy to encourage the maximum amount of safety on the road. It is not with such ease to sustain a brake system. We can find numerous points which should be obtained directly into consideration. The extremely important concept of servicing is safety, not alone for the individual traveling but additionally for the other individuals relocating on the street. As there are moving elements engaged, they are certain to get defective due to numerous factors, viz. wearing, air leak, fade, etc. When this kind of points takes place, the usefulness of the brake decreases producing incidents. Hence, it is necessary that they must be supervised all of the period as well as identified whenever problems appear.

Condition dependent monitoring will be the course of action of supervising a parameter associated with condition within machinery. Typically make use of condition monitoring enables servicing or another activities that will be planned, towards prevent often the implications of inability. Condition monitoring systems may basically estimate the destruction associated with the condition when breakdown takes place. Disturbance within typically beginning phases associated with deterioration will be generally a lot price efficient as well as lifesaving compared to enabling the brakes to breakdown. Machine fault diagnosis is a branch of study involved along with discovering faults arising in machine elements. A failing will reveal a few considerable alter within the actual physical framework. An earlier study reported a fault distinction model with regard to mono block centrifugal pump [2].

In order to determine faults in machine component, numerous techniques have been studied such as vibration analysis, oil particle analysis, thermal imaging, etc. Among them vibration analysis is most frequently applied one. Since, the comparison of vibration spectra of faulty signal with the fine signal circumstances provides the details required to create a choice whenever involvement is needed for maintenance. The vibration signals can be analysed using wavelet analysis, spectral evaluation as well as waveform evaluation. The actual outcomes associated with this kind of analysis are used to figure out the actual initial reason associated with the fault via root cause failure evaluation. Fault diagnosis is one of the root cause analysis of the failures. This fault diagnosis is carried out through machine learning approach. Fault diagnosis usually requires three primary methods specifically, feature extraction, feature selection as well as feature classification. Features may be primarily statistical features [3], histogram [4], etc. In this study, statistical features were chosen. The second step is feature selection.

Numerous methods such as principle component analysis (PCA) [5], genetic algorithm (GA) [6], and decision tree (DT) [7]. In an earlier study, decision tree was used for feature selection [8]. In order to improve the classification accuracy, the best first tree has been used for feature selection. The final step is feature classification. Many classifiers, namely decision tree [7], best first tree [8], support vector machine [9, 10, 11], clonal selection classification algorithm [12], etc., have been reported on feature classification. Within obtain towards discover a more beneficial algorithm; a comprehensive research will be required. This research especially concentrates typically the acts associated with best first tree classifier algorithms within the fault classification of vehicle hydraulic braking system with the help of fuzzy logic. Fuzzy logic was successfully applied for various fault diagnosis problem such as centrifugal pump fault diagnosis [13], bearing fault diagnosis [14], etc. Brake fault diagnosis using fuzzy logic with decision tree rules was reported in ref. [15]. In order to improve the prediction accuracy, the input rule set should be modified. Hence, the best first tree algorithm has been used to generate best first rules. In this research fuzzy classifier with best first tree rules has been selected to improve the classification accuracy.

**Fig. 1: Experimental setup**

## 2. Experimental structure

A hydraulic brake system of Maruti swift model prototype was fabricated as a brake test rig as shown in Fig. 1 [8]. The setup comprises of disc as well as drum brake paired collectively through a shaft. A variable speed DC motor (1HP) was used to drive the shaft. DC motor is composed associated with an integrated drive. Brake pedal was fixed left side of the accelerator pedal. In order to experiment with real world model, the brand new components were selected initially. Piezoelectric type accelerometer (50g range, 100mV/g sensitivity, resonant frequency 40Hz) was used to acquire the vibration signal from the test setup. The accelerometer was attached to the DAQ system where the signal is conditioned [8]. The DAQ system (NI USB 4432) was used to transfer the signal from the accelerometer. The accelerometer is connected in order to a signal conditioning unit that comprises an integrated charge amplifier as well as an analogue-to digital converter. NI - lab view was used to capture the digital version of the vibration signal.

## 3. Experimental procedure

At first, all the components are assumed to be in good condition. The vibration signals were acquired from the hydraulic brake system setup under constant brake force (Speed: 60km/h, brake force: 667N). The vibration signals were acquired under the following parameters:

1) Sample length: The sample length was chosen arbitrarily as 10000.
2) Sampling frequency: 24 kHz Using Nyquist sampling theorem.
3) No. of samples: 55 samples for each fault condition.

Often the subsequent faults had been simulated one-by-one although almost all other elements stay in good condition as well as the related vibration signals had been obtained [8]. The considered fault were, air in the brake fluid, brake oil spill on disc brake, drum brake pad wear, disc brake pad wear (even) - inner, disc brake pad wear (even) - inner and outer, disc brake pad wear (uneven) - inner, disc brake pad wear (uneven) - inner and outer, reservoir leak, good.

## 4. Feature extraction and selection

Feature extraction is the process of extracting information contained in the signal. A sufficient collection of statistical variables, namely, standard error, kurtosis, sample variance, skewness, minimum, standard deviation, maximum, count, mean, median and mode can be extracted from the vibration signal. These statistical features were extracted using feature extraction technique using excel. All the features may not be required for the classification. Hence feature selection was carried out. All the twelve features were classified using best first tree algorithm. The results were obtained as rules. Referring the generated rules, only few feature, namely, minimum, standard deviation, skewness, kurtosis were contributed for feature classification. Hence the four features were selected for feature classification.

## 5. Feature classification using best first tree

Best-first decision tree learning tree produces good performance models. When building models decision tree algorithms separate instances from the root node to the terminal nodes. While performing classification, the decision tree algorithms start at the root node, test the attribute, and then move down to the tree branch corresponding to the value of the attribute. This process is repeated until a terminal node is reached. The classification of the terminal node is the predicted value for the instance. The best-first decision tree learning expands the "best" node first. It generates fully expanded tree for a given set of data [8]. The splitting criterion is used to find out the maximal decrease of the impurity at each node. Like standard decision trees, best-first decision trees were constructed based on the following procedural steps:

1. To find the best attribute to split
2. To find which node is to be expanded next
3. To make the decision when to stop growing trees

Best-first decision tree learning chooses the best node to split at each step. In order to find the best node, sort all nodes in the list in descending order according to Gini gain. After sorting, the first node is to be expanded next. If the reduction of impurity of the first node is zero, then the reduction of all nodes is also zero. Thereafter further split cannot be possible. Hence the stopping criteria, stops expanding a tree the impurity of all nodes cannot be reduced by further splitting. All the selected four features were classified using the best first tree algorithm. It provides the maximum classification accuracy as 97.82% [8]. This classification accuracy was predicted using the following best first tree rules:

1) If minimum (M1) < -8.10137 & standard error (SE 1) < 35.12149 & minimum (M2) < -17.80949 then its DRPW.
2) If minimum (M1) < -8.10137 & standard error (SE 1) < 35.12149 & minimum (M3) > = -17.80949. then its AE.
3) If minimum (M1) < -8.10137 & standard error (not SE 1) < 35.12149 then its DPWIO.
4) If minimum (not M1) > = -8.10137 & standard error (SE2) < 8.72299 & skewness (SK1) < -0.01995 then its BO.
5) If minimum (not M1) > = -8.10137 & standard error (SE2) < 8.72299 & skewness (not SK1) > = -0.01995 & kurtosis (K1) < -0.30506 then its UDPWIO.
6) If Minimum (not M1) > = -8.10137 & standard error (SE2) < 8.72299 & skewness (not SK1) > = -0.01995 & kurtosis (not K1) > = -0.30506 & skewness (SK2) < 0.42699 then its DRMF.
7) If minimum (not M1) > = -8.10137 & standard error (SE2) < 8.72299 & skewness (SK2) < 0.42699 & skewness (SK3) > = 0.42699 then its RL.
8) If minimum (not M1) > = -8.10137 & standard error (not SE2) > = 8.72299 & kurtosis (K2) < -1.08945 then its GOOD.
9) If minimum (M5) > = -2.80165 & kurtosis (not K2) > = -1.08945 & standard error (not SE2) > = 8.72299 & minimum (not M1) > = -8.10137 then its UDPWI.
10) If standard error > = 9.3917 & kurtosis (not K2) > = -1.08945 & standard error (not SE2) >= 8.72299 & minimum (not M1) > = -8.10137 then its DPWI.

## 6. Feature classification using fuzzy logic

Fuzzy logic provides a precise approach for dealing with uncertainty. Fuzzy inference is a method that interprets the values in the input vector and, based on some set of rules, assigns values to the output vector. It means an input space is mapped to an output space [15]. A list of 'if-then" rules are used for mapping. In fuzzy logic rules are the inputs for building a fuzzy inference engine. All rules are evaluated in parallel, and the order of the rules is not important. Sometimes the real world data do not have sharply defined boundaries and it cannot be used in fuzzy. Fuzzy Logic provides the tools to classify information into broad, coarse categorizations or groupings [16]. The condition of the brake system (good or faulty) is basically fuzzy in nature. All the faults do not occur instantly. In that case, there is no threshold value (crisp data) based on which the decision on the condition of the brake component (whether it is in a good condition or a faulty condition) can be taken. The problems of this kind can be modelled using fuzzy logic more closely [17]. The objective of the study is to maximize the classification accuracy. Rules created from best first tree are used to form member ship functions. Four member ship functions were generated from the rules. Member ship functions are formed for minimum, standard error, skewness and kurtosis.

## 7. Results and discussion

From the experimental setup, the vibration signals under different fault conditions and good conditions were acquired. Twelve sets of statistical variables were extracted from the vibration signal using feature extraction technique. All the twelve features were classified using best first tree algorithm. By referring the best first tree rules, it was found that only four parameters, namely, minimum, standard error, skewness and kurtosis were selected for classification process. Hence the four features were selected as maximum contributor. The selected features were again classified again using best first tree algorithm. The classification accuracy using best first tree algorithm was found to be 97.8182%.

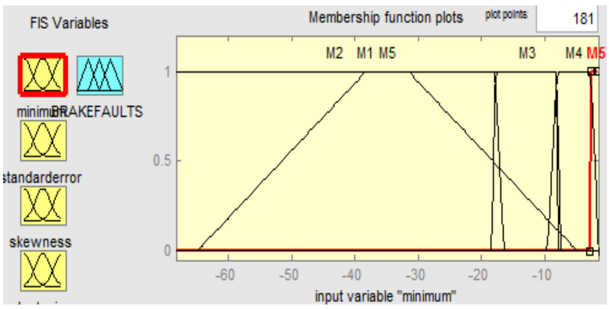


**Fig. 2: Membership functions for minimum**

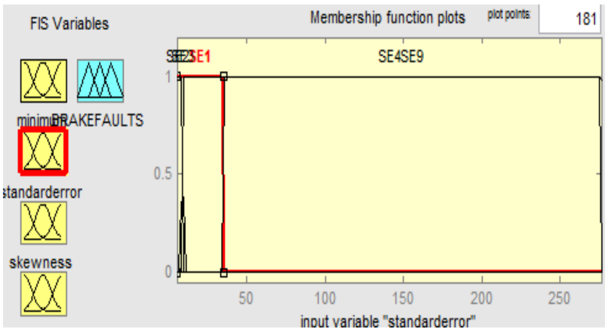


**Fig. 3: Membership functions for standard error**

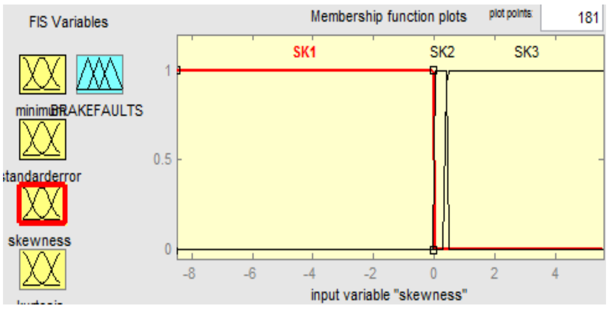


**Fig. 4: Membership functions for skewness**

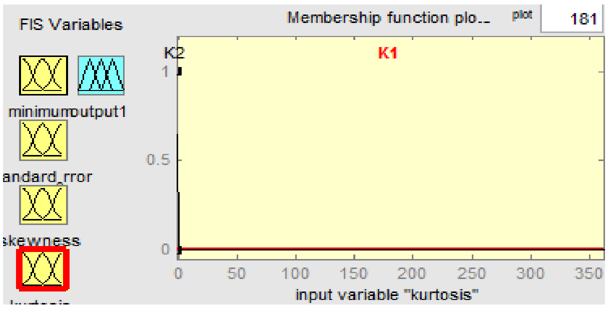


**Fig. 5: Membership functions for kurtosis**

This classification accuracy was achieved using the ten set of rules. Based on the rules, different membership functions were formed. Fig. 2 to Fig. 5 shows the input membership functions of minimum, standard error, skewness, and kurtosis respectively. Fig 6 show output membership functions of the conditions. Fig. 7 shows rule view. The generated fuzzy model was trained and tested using fuzzy tool box in MatLab. The classification accuracy was presented as a confusion matrix as shown in Table 1. The diagonal element in the confusion matrix refers the correctly classified instances. The non-diagonal elements show the misclassified instances. In confusion matrix the first row represents the total number of data points corresponding to 'Air in reservoir (AIR)' condition of the brake system.

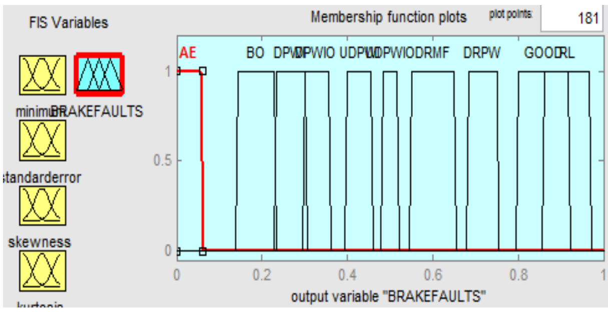


**Fig. 6: Membership function for output conditions**

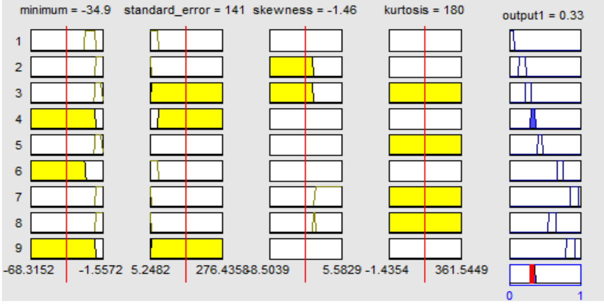


**Fig. 7: Rule view**

**Table 1: Confusion matrix for fuzzy**

| Category | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 53 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 54 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | 0 | 0 | 54 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4 | 0 | 0 | 0 | 55 | 0 | 0 | 0 | 0 | 0 | 0 |
| 5 | 0 | 0 | 0 | 0 | 54 | 1 | 0 | 0 | 0 | 0 |
| 6 | 0 | 0 | 0 | 0 | 0 | 55 | 0 | 0 | 0 | 0 |
| 7 | 0 | 0 | 0 | 0 | 0 | 0 | 55 | 0 | 0 | 0 |
| 8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 55 | 0 | 0 |
| 9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 55 | 0 |
| 10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 55 |

The first column in first row represents how many is correctly classified as 'AE' condition. The total in the first row is 55 out of that 53 is correctly classified and one is misclassified as 'brake oil spill (BO)' condition and one data set is misclassified as 'disc brake pad wear (DPWI)'.Similarly, the other elements in the first row are zero. It means no other data sets in 'AIR' condition are misclassified as other faulty conditions. The second row in the confusion matrix represents the total number of data points related to ''brake oil spill'' condition; the first column represents misclassification of those data points as 'AIR' condition. In second row, only one data point among 55 data set was misclassified as 'disc brake pad wear (DPWI)'. Second row second column in the confusion matrix represents how many of ''brake oil spill (BO)'' data points have been correctly classified as ''brake oil spill'' condition. In a 'GOOD' condition, out of 55 data points all are correctly classified and there is no misclassification. Using the confusion matrix the classification accuracy using fuzzy logic with best first tree rules was found to be 99.09%. When comparing to best first tree, fuzzy gives 99.09% accuracy which is greater than best first tree classification (97.82%) and decision tree classification (97.45%) (Refer Table 2) [8].

**Table 2: Overall classification accuracy**

| Name of the classifier | Classification accuracy (%) |
|---|---|
| J 48 decision tree | 97.45 |
| Best first tree | 97.82 |
| Fuzzy logic (best first tree rules) | 99.09 |

## 8. Conclusion

In this research, vibration based condition monitoring through fuzzy logic has been carried out. Statistical features were extracted from the vibration signals acquired from the experimental setup under various fault conditions of the brake system. Contributing features alone were selected from the extracted features. The selected features were classified using the best first tree algorithm and the classification accuracy was obtained as 97.82%. In order to improve the classification accuracy, the best first tree rules were used to generate 'If-then' rules and membership functions. The fuzzy rule set was trained and tested with the original data set. The fuzzy model produced the classification accuracy as 99.09%. Therefore, fuzzy improved classification accuracy by 1.27%. Hence, fuzzy classification is more suitable for brake fault diagnosis. This research takes significant role in atomization of condition monitoring of hydraulic brakes, which give fault scenario to traveller leads to prevention of accidents.

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