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MISFIRE DETECTION IN I.C. ENGINE USING MACHINE LEARNING APPROACH

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ABSTRACT

Misfire is one of the major problem associated with the engine as it leads to power loss along with exhaust of air-pollutants like HC, CO, and NOx. Maintenance and condition monitoring of an IC engine is a very crucial activity which requires restriction of emission to the least possible levels. For misfire detection, vibration signals from engine cylinder were obtained using the piezoelectric accelerometer. As engine misfire gives specific vibration signal pattern with respect to the cylinder where misfire took place. Further, 12 statistical features like Standard Error, Sample Variance, Skewness etc. were extracted from obtained signals. Out of these, only useful features were identified using the J48 decision tree algorithm. Classification via Regression, IBk were used as classifiers for classification of these selected features. This paper deals with the comparative study of these classifiers and ensembling these classifiers using Vote classifier and from that, the better algorithm for misfire detection system is suggested.

Key words Machine learning approach, Statistical Features, Classification via Regression, IBk, Ensembling, Vote Classifier

INTRODUCTION

Misfire in the engine is nothing but one kind of abnormal combustion which leads to lower fuel economy results in wastage of fuel. According to the California Air Resources Board (CARB regulations, 1991), engine misfire means “lack of combustion in the cylinder due to the absence of spark, poor fuel metering, poor compression, or any other cause”. It is caused in a system mainly due to the faulty spark plug, cracked distributor cap, improper air-fuel mixture, inadequate compression, engine detonation due to high temperature. The study says that it leads to power loss up to 25% along with exhaust emissions of air-pollutants like HC, CO and NOx. Therefore, Maintenance and condition monitoring of an IC engine is a very crucial activity required for optimum performance and restricting emissions to least possible levels for avoiding damage to the catalytic converter.

Previously, misfire detection carried out by different methods like using parameters like acceleration signal of the engine head (Ren, 1999), crankshaft angular velocity (Lee, et al., 1995), instantaneous exhaust manifold pressure (Macián, et al., 2006) and instantaneous engine speed (Zhang, et al.,2007). Also, the technique of sliding mode observer along with cylinder deviation tor-que was used for real-time misfire detection of a four-cylinder engine (Wang, et al., 2005). The technique used involves the transformation of input estimation problem into the control tracking problem. Many methods were suggested by Klenk, et al., (1993) and they are as follows:

1. monitoring catalyst temperature at the exhaust. This method is not suitable as the temperature does not rise notably for low-frequency misfire.
2. monitoring exhaust gas using oxygen sensor. This method is also unaccepted since for the sudden rise in oxygen level we may not get a notable response from the sensor.
3. In-cylinder pressure monitoring. This method gives desired results since; mean effective pressure inside the cylinder is monitored continuously. This method becomes very costlier due to cost pressure transducers needed for each cylinder

Ye, (2009) contributed in the misfire detection field with the Matter-element model, which was built on the basis of information and knowledge gathered from practical experience. In this model, relation indices are incorporated for identifying misfire in the engine cylinder. The drawbacks observed in this technique is that the model used in training is not reliable for continuously chan-ging engine condition due to wear & tear. Bogus, et al., (2005) carried out misfire detection using vibroacoustic measurement at exhaust for misfire detection of locomotive engines. This method is encouraging but, its implementation requires mul-ti-sensor input and computational infrastructure which leads to higher setup cost. It is challenging to implement this technique with the minimum infrastructure to an onboard system for an auto-mobile. Chang, et al., (2002) reported their work by combining engine block vibration with wavelet transform for SI engines. Vong, et al., (2011) also chose wavelet packet transform for engine ignition signal diagnosis. These methods give appreciable out comes but the only disadvantage is that it requires more computational infrastructure.

Machine learning approach has been used for fault diagnosis. For misfire detection Support Vector

Machines (SVM) was implemented (Devasenapati et al., 2010). In this work, they carried out misfire detection by SVM on the basis of two features statistical and histogram features. Devasenapati, et al.,(2011) used Fuzzy logic-based classifier and decision tree classifier (Devase-napati, et al., 2010) to build this expert system for misfire detection. Bagging Classifier (Sharma, et al., 2010), kstar algorithm (Bahri, et al., 2013) are some of the classifiers used for misfire detection. Machine learning gives encouraging results and for changes in the system, conditions can be easily trained. The process flow opted in all these works was data acquisition, statistical feature extraction, feature selection followed by feature classification.

In the present study, machine learning approach is taken into account for solving this problem because it doesn't need complex computation infrastructure and also cost associated is lesser than any other method. In this study Classification via Regression, IBk were used as classifiers for classification of these selected features. After optimization, these classifiers were then given for assembling using Vote classifier for misfire detection and from that the better algorithm for misfire detection system is suggested.

EXPERIMENTAL SETUP AND PROCEDURE

The experimental setup consists of IC engine test rig as shown in Fig.1 which has provision to manually create misfire in particular cylinder. The de-ailed specification of the Engine test rig used is shown in Table I. The piezoelectric accelerometer is attached to the cylinder to measure the vibration signals. This acquired signal is passed through the ADC to collect the needed data by feature extraction. The signals were recorded using the accelerometer as it has the ability to measure small as well as large signals. The sensor was placed such that vibration of all four cylinders is measured properly. The signal from the accelerometer was fed to a DACTRON FFT analyzer for conversion of the analog signal to designs digital data. Then this data was stored in the computer for further procedure.

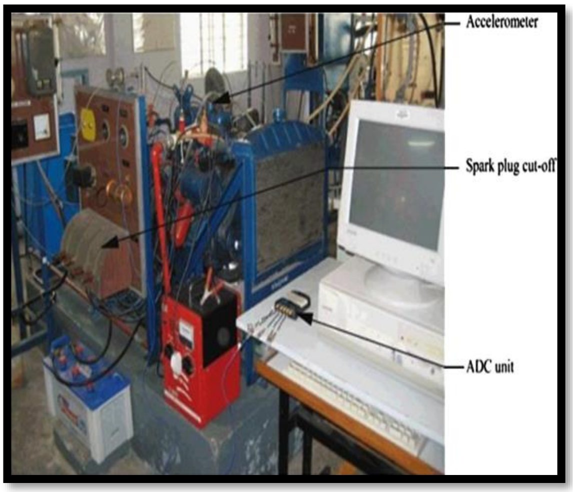

Fig. 1: Experimental Setup

TABLE I: SPECIFICATIONS OF THE ENGINE TEST RIG

Features	Specification
Make	Hindustan Motors
Number of cylinders/stroke	Four cylinders/four stroke
Fuel	Gasoline(Petrol)
Rated power	7.35 kW
Rated speed (alternator)	1500 rpm
Engine stroke length	73.02 mm
Engine bore diameter	88.9 mm
Cooling	Water cooled

Firstly, the engine was started at no load by electrical cranking and warmed for 15 minutes. Then the FFT analyzer made switched on and the data was taken only after the engine got stabilized. All the data was collected for 1500 rpm, a sampling length of 8192 and a sampling frequency of 24 kHz. For the present study, five cases are considered i.e. Good condition (no misfire), misfire in cylinder one, two, three and four. The Figure 3-7 shows sample vibration signal for each class.

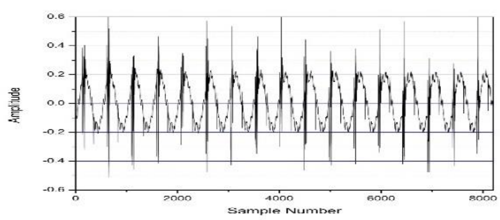

Fig. 1. Vibration signal for good Condition.

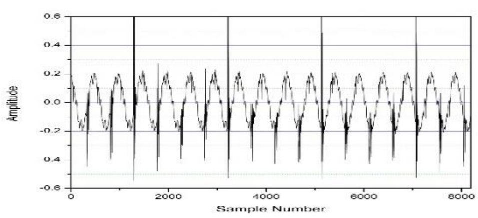

Fig. 2. Vibration signal for misfire in cylinder 1.

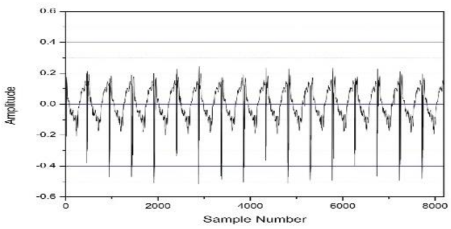

Fig. 3. Vibration signal for misfire in cylinder 2.

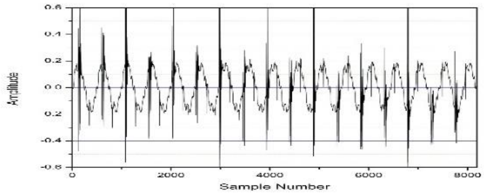

Fig. 4. Vibration signal for misfire in cylinder 3.

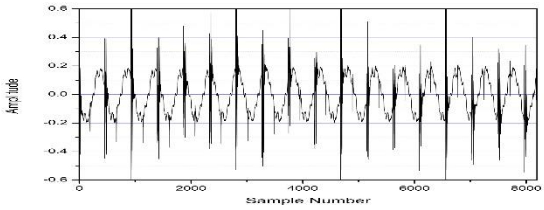

Fig. 5. Vibration signal for misfire in cylinder 4.

FEATURE EXTRACTION AND FEATURE SELECTION: The descriptive statistical features were extracted from the vibrational signals. The entire 12 features may not be useful for classification. Thus, feature selection was carried out in Weka 3.9 software. Features which contribute high classification accuracy were selected. For the current study, the J48 algorithm shown in Fig 6 is used for feature selection. Features absent in tree were not considered for further process. The feature which appears in the tree were considered from root to leaves respectively. In this case selected features were Standard Error, Sample Variance, Skewness, Minimum, Kurtosis, Range, Mean and Median. Other features were eliminated. After feature selection effect of a number of features on classification accuracy was studied as shown in Table I.

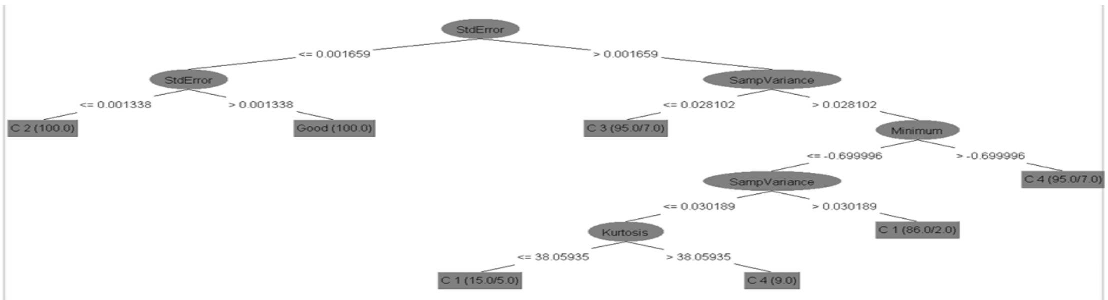

Fig. 7: J48 Decision Tree.

TABLE II: VARIATION OF CLASSIFICATION ACCURACY WITH A NUMBER OF STATISTICAL FEATURES.

No. of Feature	Classification Accuracy (%)
1	75
2	90.4
3	92.4
4	92.8
5	**93.2**
6	93.2
7	93.2
8	92.4
9	92.4
10	92.6
11	92.6
12	92.6

CLASSIFIER

Classification via regression: This classifier uses the method of regression for classification. Firstly, each class is binarized (0 or 1) and for every class value, one regression model is built. If we consider the target output (y) as a continuous variable ignoring that it is binarised then the linear regression function is given as

$f(X;W)=W_0+W_1 X_1+. . .=W_0+X^T W_1$

ing, y = f(X;W) + ε. where, ε ~ N(0,σ2) then, the objective for the parameters W reduces to least possible class fitting. In general, it is given as,

$$J_n = \frac{1}{n}\sum_{i=1}^{n}(y_i - f(Xi;W))^2 \quad (2)$$

IBk Classifier: IBk is instance-based learning with parameter ‘k’. It follows the k-nearest neighbor learning (k-NN algorithm) method of classification. In this algorithm, when an unknown sample is given, classifier searches the pattern space for the k training samples that are nearest to the unknown sample. The unknown sample is classified as the class which is most similar to all its k nearest neighbors (Vijayarani, et al., 2013).

Vote Classifier: Vote classifier is a meta-classifier used for combining classifiers by means of different combination rules like majority voting, the sum of probabilities product of probabilities etc. This method of combining two or more classifiers is known as ensembling. The main objective of using this classifier is to give better predictive performance than that of the constituent classifier alone by using various combination rules.

Results and Discussion

Classification using Classification via Regression algorithm: As shown in the above Table II the confusion matrix for Classification via Regression algorithm. All the Good signals were classified correctly. For optimizing the classifier M5P was set as a base classifier. In that further minimum number of instances made as 11.0 which gave an accuracy of 95.6% with building time of 0.03 seconds.

TABLE – III: CONFUSION MATRIX FOR USING CLASSIFICATION VIA REGRESSION ALGORITHM

Testing	Good	C1 Misfire	C2 Misfire	C3 Misfire	C4 Misfire
Good	**100**	0	0	0	0
C1 Misfire	0	**96**	0	3	1
C2 Misfire	0	0	**100**	0	0
C3 Misfire	0	4	0	**88**	8
C4 Misfire	0	3	0	3	**94**

Classification using IBK algorithm: As Table III shows the confusion matrix for IBk algorithm. According to confusion matrix, no faulty signal was classified as a normal signal. In IBK classifier highest accuracy of 95.8% was observed after setting Linear NN Search as a Nearest neighbor search algorithm. In Linear, NN Search distance function was set as Filtered distance. Time taken for building model was 0.01 seconds. Some signals were misclassified due to the similarity in two signals from a different class like 2 Signals from C1mis were classified as C3 etc. This misclassification can be reduced by increasing batch size.

Table iv: Confusion matrix for IBK algorithm

Testing	Good	C1 Misfire	C2 Misfire	C3 Misfire	C4 Misfire
Good	**100**	0	0	0	0
C1 Misfire	0	**93**	0	2	5
C2 Misfire	0	0	**100**	0	0
C3 Misfire	0	2	0	**93**	5
C4 Misfire	0	2	0	3	**95**

TABLE V: CONFUSION MATRIX FOR VOTE ALGORITHM

Testing	Good	C1 Misfire	C2 Misfire	C3 Misfire	C4 Misfire
Good	**100**	0	0	0	0
C1 Misfire	0	**91**	0	4	5
C2 Misfire	0	0	**100**	0	0
C3 Misfire	0	2	0	**93**	5
C4 Misfire	0	2	0	3	**95**

Classification using Vote classifier: For ensemling, the previously used classifiers Vote classifier was used. In this IBk and Classification via regression classifiers were set as the fold classifiers. As shown in table V the combination rule was set as the product of probabilities where highest classification accuracy of 96.2% was noted. The time taken to build the model was 0.04 seconds. The ensemble of the two classifiers resulted in accuracy increase of 0.4%. This increase in accuracy was due to classification held using majority voting of both classifiers in Vote classifier. Table IV shows the confusion matrix for this classification using Vote classifier and Table V shows the Combination rule vs. Classification accuracy characteristics

TABLE VI: COMBINATION RULE VS CLASSIFICATION ACCURACY

Combination Rule	Classification Accuracy (%)
Average of Probabilities	96.00
Product of Probabilities	**96.20**
Majority Voting	96.00
Minimum Probability	95.80
Maximum Probability	96.00

Table VI shows detailed accuracy. TP Rate means a True Positive rate which is a measure of positive proportion that is correctly classified. It should be close to 1 for higher accuracy. FP Rate denotes False Positive rate or False Alarm rate which shows the probability of getting negative results with positive prediction. Generally, FP Rate should be close to 0. Here TP Rate is 0.962 and FP Rate is 0.01. As these values are closer to the ideal values so, this method can be used for practical applications.

TABLE VII: DETAILED ACCURACY BY CLASS

Class	TP Rate	FP Rate	Precision	Recall	F-Measure
Good	1.000	0.000	1.000	1.000	1.000
C1	0.930	0.010	0.959	0.930	0.944
C2	1.000	0.000	1.000	1.000	1.000
C3	0930	0.013	0.949	0.930	0.939
C4	0.950	0.025	0.905	0.950	0.927
Weighted Avg.	0.962	0.010	0.963	0.962	0.962

CONCLUSION

All three-studied algorithm showed higher accuracy and 100% accuracy to distinguish between Normal condition signal & faulty signal so, all the three algorithms can be employed for the primary purpose of misfire detection. For condition monitoring of engine to maintain optimum performance & to reduce emissions, IBk algorithms can be employed as they showed the higher accuracy of 95.8% with least model building time of 0.01 seconds. Also, combining IBk algorithm with Classification via regression algorithm in Vote classifier gave a higher accuracy of 96.2% with model building time of 0.04 seconds. Hence, this ensemble Vote is the proposed classifier which can be used practically in the industrial application for misfire detection.

REFERENCES

Bahri, Anish, V. Sugumaran, and S. Babu Devasenapati, Misfire Detection in IC Engine using Kstar Algorithm. *arXiv preprint arXiv 1310. 3717* (2013).

Boguś, Piotr and Jerzy Merkisz, Misfire detection of locomotive diesel engine by non-linear analysis. *Mechanical Systems and Signal Processing* 19(4): 881-899 (2005).

California Air Resources Board. Technical status Update and Proposed Revisions to Malfunction and Diagnostic System Requirements Applicable to 1994 and Subsequent California Passenger Cars, Light-Duty Trucks and Medium-Duty Vehicles – (OBDII). CARB staff report (1991).

Chang, Jinseok, M. Kim and K. Min, Detection of misfire and knock in spark ignition engines by wavelet transform of engine block vibration signals. *Measurement Science and Technology* 13.7 (2002): 1108.

Devasenapati, S. Babu and K. I. Ramachandran, Hybrid fuzzy model based expert system for misfire detection in automobile engines. *International Journal of Artificial Intelligence e* 7A (11): 47-62 (2011).

Devasenapati, S. Babu, V. Sugumaran and K.I. Ramachandran, Misfire identification in a four-stroke four-cylinder petrol engine using decision tree. *Expert Systems with Applications* 37 (3): 2150-2160 (2010).

Klenk, Martin, W. Moser, W. Mueller and W. Wimmer, *Misfire detection by evaluating crankshaft speed-A means to comply with OBDII*. No. 930399. SAE Technical Paper (1993).

Lee, Donghyeon and Giorgio Rizzoni, *Detection of partial misfire in IC engines using a measurement of crankshaft angular velocity*. No. 951070. SAE Technical Paper (1995).

Macián, V., J. M. Luján, C. Guardiola and A. Perles, A comparison of different methods for fuel delivery unevenness detection in Diesel engines. Mechanical systems and signal processing 20(8): 2219-2231 (2006).

Ren, Yaping, Detection of knocking combustion in diesel engines by inverse filtering of structural vibration signals. PhD diss., University of New South Wales (1999).

Sharma, A., V. Sugumaran and S. Babu Devasenapati, Misfire Detection in an IC Engine Using Vibration Signal and Bagging Classifier *IJEIR* 2(4): 386-390 (2013).

Vijayarani, S., and M. Muthulakshmi, Comparative analysis of bayes and lazy classification algorithms. International Journal of Advanced Research in Computer and Communication Engineering 2(8): 3118-3124 (2013).

Vong, Chi-Man and Pak-Kin Wong, Engine ignition signal diagnosis with wavelet packet transform and multi-class least squares support vector machines. *Expert Systems with Applications* 38(7): 8563-8570 (2011).

Sugumaran, V.K.I. Ramachandrana, S. Babu Devasenapatia, Misfire detection in a spark ignition engine using support vector machines. Int. J. Comput. Appl. 5(6): 0975–8887 (2010)

Wang, Yunsong and Fulei Chu, Real-time misfire detection via sliding mode observer. Mechanical *Systems and Signal Processing* 19(4): 900-912 (2005).

Ye, Jun, Application of extension theory in misfire fault diagnosis of gasoline engines. *Expert Systems with Applications* 36(2): 1217-1221 (2009).

Zhang, Yongxiang and R.B. Randall, The in-cylinder pressure reconstruction and indicated torque estimation based on instantaneous engine speed and one measured in-cylinder press-ure, *Comadem Conference, Faro, Portugal* (2007).