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# CYLINDER MISFIRE DETECTION USING ENGINE SOUND QUALITY METRICS AND RANDOM FOREST CLASSIFIER

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This paper proposes a novel method to detect cylinder misfiring using the sound quality metrics of the sound waves emitted from the engine, as features in a random forest classifier. This method was tested on a four-stroke, four-cylinder SI engine run on a wide range of load torques, 20 to 50 Nm, and wide range of speeds, 1260 to 3340 rpm, where at every test condition a cylinder was misfired intermittently. Fifty-two sound signals were measured near the engine, containing 26 pairs of no misfiring condition and its corresponding one cylinder misfiring condition. Sound pressure level and the key sound quality metrics namely, Loudness, Roughness and Fluctuation Strength of the engine sounds were used as features in a random forest classifier. The model correctly classified misfiring signals and no-fault signals with 100% test accuracy. Thus, engine sound quality metrics successfully predict misfiring of an SI engine using a random forest classifier. The proposed technique is advantageous over existing misfire detection techniques, as it does not require an in-cylinder or engine-attached measurement, thus eliminating the need for costly sensors and regular maintenance. Additionally, the proposed method is robust over wider torque and speed range than most existing techniques. A classifier based on this method integrated with any affordable microphone placed underhood could be a cheap misfiring prediction device.

Keywords: cylinder, misfire, load, speed, sound quality

## 1. Introduction

Misfiring in a spark ignition (SI) engine is a leading cause of sudden power drops and increased emissions [1-2]. Over the years, many techniques have been developed to detect engine misfire. The current widely used techniques measure one or more of the following physical quantity to detect misfire: a) instantaneous crankshaft angular velocity (engine speed) [3-8], b) in-cylinder (combustion chamber) pressure [8], c) exhaust gas pressure [8], d) engine vibrations [8-9], and e) ignition signal [10-11]. All of these methods involve measurement through a direct contact with engine component(s) such as through in-cylinder sensors, spark plug sensors, flywheel-attached sensors, or engine block-attached sensors. These sensors are costly because they have to withstand very high temperatures and pressures. Further, they are subject to wear and tear due to presence of very high temperature and pressure and exhaust fumes inside the cylinder. The engine block-attached sensors get disconnected due to engine vibrations especially at high engine speeds and need to be inspected and fixed from time to time. To overcome the these limitations in the existing methodologies, the authors are the first to have proposed and tested the use of exhaust sound quality metrics to diagnose the occurrence of a fault such as a cylinder misfire ([12]). This paper extends this concept to test the sound quality metric of the sound waves emitted from the engine for detecting engine misfiring. The engine sound quality metrics can be easily extracted by measuring sound pressure waves through an acoustic sensor placed underhood, but not in direct contact with any hot engine component. Thus, this method of misfire diagnosis can be applied with any low-cost and low-maintenance acoustic sensor.

Machine learning algorithms such as support vector machines, regression, and neural networks have gained popularity in the recent years for classifying the misfiring signals [1, 2, 10, 11] because of their high misfiring prediction accuracy and less computation time. However, these machine-learning algorithms are highly condition dependent, and have been shown to work only for low load and/or low speed conditions [1, 9, 11]. Random forest is an improved, tree-based supervised machine learning classification technique. However, its use in machinery fault diagnosis has not been explored as yet. This paper is the first to test and apply this classification technique for machinery fault diagnosis.

This paper presents a novel non-contact-based technique to detect engine misfiring using the sound quality metrics of the sound waves measured from a sensor underhood to train a random forest classifier for predicting future misfires. An experiment is conducted to test this method for predicting misfires in a 4-stroke 4-cylinder SI engine.

# 2. Theory

## 2.1 Sound quality metrics for misfire detection

Human ear sensitivity to sound is strongly dependent on frequency, being more sensitive in the middle frequencies (250 to 12,500 Hz) while sounds of lower or higher frequencies are perceived much lower than their actual sound pressure level (SPL) ([13]). Sound quality metrics, also known as psychoacoustic metrics have been devised to quantify how a human ear perceives sounds, therefore these metrics correlate well with the human ear frequency-related filtering of a sound signal. Previous research shows that engine sound quality metrics correlate with the operating characteristics of an engine [14-15]. Thus, it is quite probable that the engine sound quality metrics may provide useful information about an engine fault, specifically about the occurrence of a cylinder misfire. This paper proposes that sound quality metrics of sound waves emitted from the engine are important features that classify misfiring of an engine. The most widely used metrics for automotive engine sound quality analyses are Loudness, Roughness, and Fluctuation Strength [15]

The “loudness” metric quantifies the human ear perception of sound volume, or the physical strength or amplitude of the sound. The SI unit of “loudness” of a sound is ‘sones’ ([13]). The “roughness” metric is the human ear perception of roughness or unevenness (annoying quality) of a sound. More specifically, roughness quantifies the perception of rapid (15-300 Hz) amplitude modulation of a sound and is measured in the SI units of asper ([13]). The roughness of 1 asper corresponds to the roughness perception of a 60 dB, 1 kHz tone that is 100% amplitude modulated at a modulation frequency of 70 Hz. The “fluctuation strength” metric quantifies the loudness modulations at low frequencies that are discernible individually. More specifically, it quantifies slower amplitude modulation of sounds (up to 20 Hz). Fluctuation strength is expressed in units of vacil, where a fluctuation strength of 1 vacil corresponds to a 60dB, 1 kHz tone 100% amplitude modulated at 4 Hz. There are well-known standard algorithms to calculate these metrics (see details in [12-13]).

## 2.2 Random forest classifier

Decision tree algorithm is a machine learning algorithm that had been used previously for machinery fault classification [2]. Random forest, a supervised machine learning technique, is an improvement over decision trees. However, its use in machinery fault diagnosis has not been explored as yet. Decision tree algorithm involves splitting the predictor space into a number of distinct non-overlapping simple regions [16]. The most commonly occurring class in a region is used as a prediction for a given observation that falls into that region [16]. At every step of building the tree, the regions are split so that in the subsequent sub-regions the classification error rate is minimized, i.e., the fraction of the training observations in a region not belonging to the region's most common class, is minimized (see details in [16]). Decision trees provide good graphical representation and easier interpretation of a problem but they suffer from a high variance [16], i.e., they are likely to provide different predictions when trained on different training data sets from the same population. Moreover, they are not as accurate as regression-based methods [16]. Random forest combines the advantages of a decision tree and overcomes its limitations. For this purpose, in random forest classification, individual decision trees are built from many repeated samples of the training dataset, and the overall prediction is the most commonly occurring class among the predictions from the individual trees. This reduces the variance [16]. Moreover, every individual tree is built by considering a unique subset of the predictors that reduces the classification error rate [16]. A detailed description of random forest algorithm can be found in [16]. This paper applies random forest for the first time in engine misfire diagnosis using sound quality metrics as the predictors.

## 3. Experimental setup

The experimental setup was the same as used in author's previous study [12]. The test engine was a four-stroke 4-cylinder spark ignition engine. Table 1 gives the test engine specifications [12]. The engine was loaded using an eddy current absorption type dynamometer of model- E-50LC with rated power 50hp@1600 rpm. Fig. 1(a) shows the engine test rig. Sensors were placed on the engine test rig to measure the engine operating parameters such as rotational speed, torque, air flow rate and fuel flow rate. To simulate the environment of a sensor placed underhood, the engine was encapsulated using a sound absorbing jute felt enclosure. This insulated the engine sound from any reflections and reverberations inside the test cell and from other noise sources such as dynamometer noise, human noise and ventilation noise. Jute felts were used because of their good sound absorption properties. Sound signals were recorded using a B&K Type 4189 microphone placed inside the enclosure near the engine (see Fig. 1(b)). The signals were acquired at a sampling frequency of 65536 Hz using B&K PULSE Analyzer. The test engine was run at a desired load torque and speed with all cylinders firing, then keeping the torque constant, one cylinder was misfired by switching off the electric power to the cylinder spark plug. This process was repeated 26 times for the [torque, speed] conditions as listed in Table 2. Thus, 52 sound signals near the engine, containing 26 sets of correct signals and their corresponding misfiring signals were acquired.

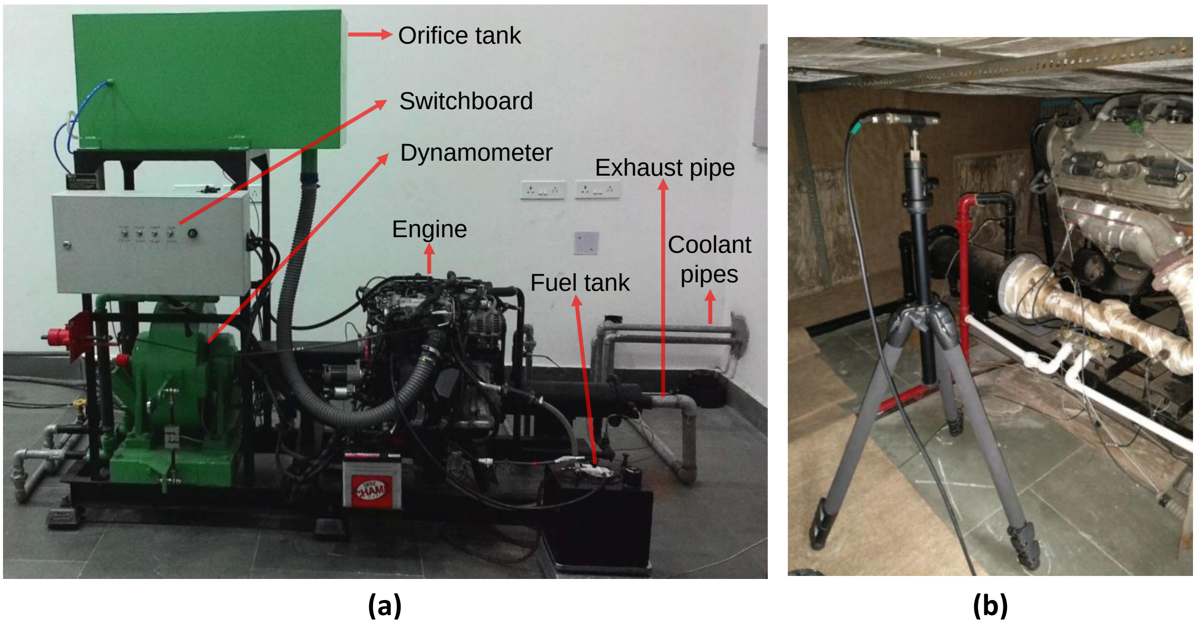


Figure 1: (a) Engine test rig. (b) Measurement of engine sound inside the acoustic enclosure

Table 1: Specifications of the test engine

| | |
|---|---|
| Make | Maruti Suzuki Eeco |
| Body | Aluminium |
| Cubic Capacity | 1196 cc |
| Fuel | Petrol |
| Fuel distribution | Multi-point Injection |
| Coolant | Water |
| No. of cylinders | 4 |
| No. of valves | 16 |
| Cylinder Bore | 0.071 m |
| Stroke | 0.0755 m |
| Connecting Rod Length | 0.12 m |
| Compression Ratio | 9.9 |
| Engine Management | 32 bit |
| Rated Power | 73 bhp @ 6000 rpm |
| Rated Torque | 101 Nm @ 3000 rpm |

Table 2: Experimental conditions

| Load Torque | Engine Speed (in rpm) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 20 Nm | 1260 | 1540 | 1800 | 2100 | 2390 | 2700 | 3060 | 3320 |
| 30 Nm | - | 1530 | 1800 | 2100 | 2390 | 2700 | 3030 | 3340 |
| 35 Nm | - | - | 1800 | 2100 | 2400 | 2700 | 3030 | - |
| 40 Nm | - | - | - | 2090 | 2390 | 2700 | 3040 | 3340 |
| 50 Nm | - | - | - | - | - | - | - | 3340 |

## 4. Classification algorithm

Fig. 2 shows the algorithm for classification of engine sound signals. Firstly, the acquired sound signals were processed in Brüel and Kjær PULSE Sound Quality to obtain Stationary, Mean and Instantaneous Loudness (in sones), Roughness (in asper), Fluctuation Strength (in vacil), and Sound Pressure Level (SPL) in (dBA and dB). These consisted of the original features for classification. The code for classifying the engine misfiring was written in Python 2.7.10. The data set was randomly split into training and test data sets in approximately 3:1 ratio. Feature selection was done to find the important subset of features that really affect the output (i.e., misfire condition). So, the extracted features were reduced by using feature importance module of random forest algorithm available in Python. The reduced feature set were input into the random forest classifier. This model has two hyperparameters, the number of trees (T) and maximum depth (D). For better classification accuracy, the best combination of these two parameters was selected using the standard 4-fold cross-validation [17] and exhaustive grid search for the best combination of (T, D) from the set of **Tree** $\epsilon$ {10, 50, 100, 200, 500, 1000} and **Depth** $\epsilon$ {3, 4, 5}. The model fitted with best (T, D) was then tested on the test set and its accuracy was noted.

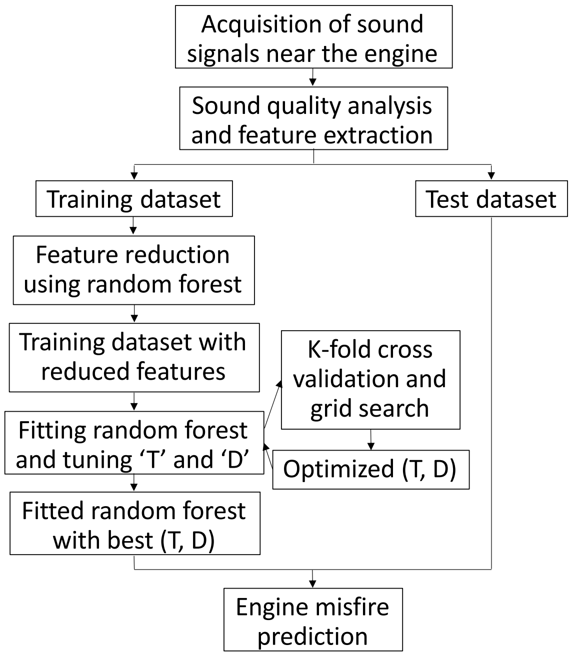


Figure 2: Model for engine misfire classification

# 5. Results and discussions

## 5.1 Classification based on engine sound quality

The data sets were randomly split into 42 training data sets (21 correct, 21 misfiring signals) and 10 test data sets (5 correct, 5 misfiring signals) so that the test data covered the full torque and speed range. The test data contained correct and misfiring signals corresponding to [35 Nm, 1800 rpm], [30 Nm, 2100 rpm], [40 Nm, 2390 rpm], [50 Nm, 3340 rpm], and [20 Nm, 2700 rpm]. A sample random forest model was fitted on the training data and using feature importance module of the model it was found that sound quality metrics namely, loudness, roughness, and fluctuation strength, as well as time domain metrics namely, rms and A-weighted level were important in classifying misfiring. These metrics were entered as features into the final random forest classifier. Table 3 shows the result of classification. The developed method correctly classified the test engine sound signals with 100% training accuracy and 100 % test accuracy in 120 s. Thus, the engine sound quality metrics also successfully predict a cylinder misfiring using random forest with very high accuracy. However, the random forest algorithm is computationally slower than the support vector machine (SVM) algorithm [see 12].

Table 3: Result of random forest-based classification

| Features used | Training Accuracy | Testing accuracy | Computation time |
|---|---|---|---|
| RMS<br>A weighted level<br>Stationary loudness<br>Fluctuation<br>Strength Roughness | 100 % | 100 % | 120s |

## 5.2 General discussions and future recommendations

It is found that the stationary loudness, fluctuation strength, and roughness of engine sounds are highly sensitive to cylinder misfiring. These features input into a random forest classifier predict misfiring with 100% accuracy. Existing misfire techniques are system-dependent and have been usually shown to perform well only under low load and low torque conditions [1, 9, 11]. Our proposed method has been tested to be robust over a wide range of load torques, from 20 Nm to 50 Nm, and wide range of engine speeds, from 1260 rpm to 3340 rpm. The method is condition independent, for example, it correctly predicted misfiring at 50 Nm torque without being trained on any signal recorded at 50 Nm. A comparison of these results with the previous result of authors' [see 12] indicates that random forest may give a higher accuracy than SVM classifier but is computationally much slower. Results validates that engine sound quality metrics are important features for classifying misfiring of an SI engine. The proposed technique has high potential in engine fault diagnosis. Future experiments will be done to test if this method can classify both the presence of a misfire and the location of misfire, i.e. which cylinder misfired.

## 6. Conclusions

This paper proposes a novel non-contact based approach to detect engine misfiring using sound quality metrics of the sound waves emitted from the engine to train a random forest classifier. This method was tested on a four-stroke, four-cylinder SI engine over a wide range of load torques (20 to 50 Nm) and wide range of speeds (1230 to 3340 rpm). Results show that the sound quality metrics namely, stationary, loudness, fluctuation strength, and roughness, along with rms and A-weighted level are highly sensitive to cylinder misfire. These metrics input as features in a random forest classifier correctly predicted misfiring with 100% accuracy in 120s computation time over the entire load torque and speed range. Random forest was found to be more accurate but computationally slower than support vector machine. The proposed method is a drastic improvement over existing misfiring methodologies as it does not require an in-cylinder or engine-attached contact-based measurement; thus eliminating the need for costly, difficult to maintain, and less durable sensors. Moreover, the proposed method is load torque and engine speed independent. A classifier build based on this method integrated with any affordable microphone placed underhood in a vehicle could be a cheap misfiring prediction device.

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