# Abnormal Combustion Detection in a Compression Ignition Engine

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***Abstract*—Abnormal combustion occurrences in compression ignition engines are one of the main causes of engine failures, which severely affect the continuity of transportation operations. The detection of these occurrences may help to take measures to minimize the engine failures and increase engine life. In this work, we implement a machine learning system for abnormal combustion detection system in a single cylinder experimental compression ignition engine. The system uses k-means clustering and support vector machines to classify a combustion as normal or abnormal.**

***Keywords—combustion, engine ringing, machine learning, support vector machines, svm, k-means clustering***

## I. Introduction

Transportation has an important part in mankind's daily life, especially when we think of the transportation of raw materials and final products, or the transportation of people from one point to another. The most important constituents of transportation sector are internal combustion engines which serve as primary work sources doing the main job for facilitating mobility. Like all devices, these engines fail sometimes, and such failures interfere with the continuity of the operation. One of the main causes for these failures is abnormalities occurring in the combustion process. If we can minimize these abnormalities, then we can also expect to minimize the number of further engine failures. For this purpose, we first need to detect when abnormal combustions occur. In this project, we work on a machine learning system that can help us for detection of abnormal combustion processes.

## II. Related Work

There have been a few attempts in abnormal combustion detection.[1]–[6] One group of work uses a physical sensor system for detection by doing real time monitoring and taking advantage of sensor groups attached to internal combustion engine. Another group, Fontanesi et al., performed computational numerical analysis for predicting combustion abnormalities in direct fuel injected gasoline engines.[5] For achieving this, they have combined in-cylinder combustion and knock models with engine heat transfer simulations. However, there were no application of ML/DL methods in those works.

A ML application of failure detection was carried out by Jack et al. They performed a study on fault detection by using SVMs and ANN augmented by generic algorithms for rotary engine bearings by using vibration signals as input features in 13 different engine speeds. They observed high success rates in training with constant width SVMs.[6]

## III. Dataset and Features

We found experimental data from 135 cycles of Dimethyl-Ether (DME) combustion in a single cylinder compression ignition engine. Our data include in-cylinder pressure, injection starting time and injection duration for each experiment.

If there is an abnormal combustion, rapid increases and rapid decreases in pressure traces are observed. Moreover, high ripples in the pressure trace occur during an abnormal combustion. By looking at those traces, we can know which cycles have undergone abnormalities. Fuel injection timing and fuel injection duration are the main drivers of these ripples, which is also called engine ringing. Injection duration and timing are correlated with the in-cylinder engine pressure.

Figure 1 shows a pressure trace for each of normal and abnormal combustion processes from our data. These traces show typical behavior of each process. Crank angle is a unit which is used to measure the piston travel. In each 720º of crank angle (from -360º to 360º), a combustion cycle occurs. As can be seen, there is a rapid increase in the in-cylinder pressure in an abnormal combustion. Also, high ripples in in-cylinder pressure occur for an abnormal combustion. Because of these ripples, rapid decreases in in-cylinder pressure are also observed in an abnormal combustion.

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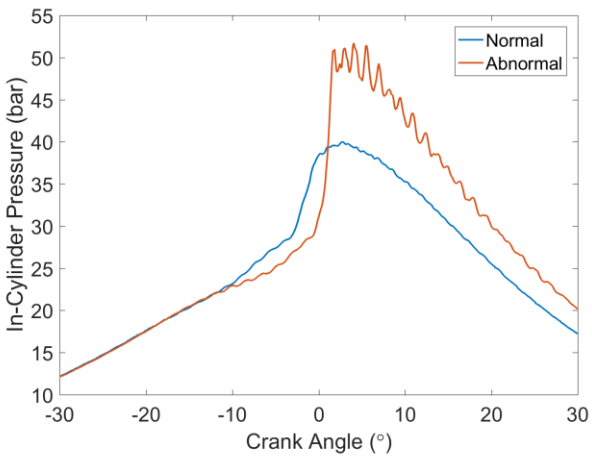


Fig. 1. A typical in-cylinder pressure trace for a normal and an abnormal combustion process

Fig. 2 shows the in-cylinder pressure traces for all our 135 combustion experiment data.

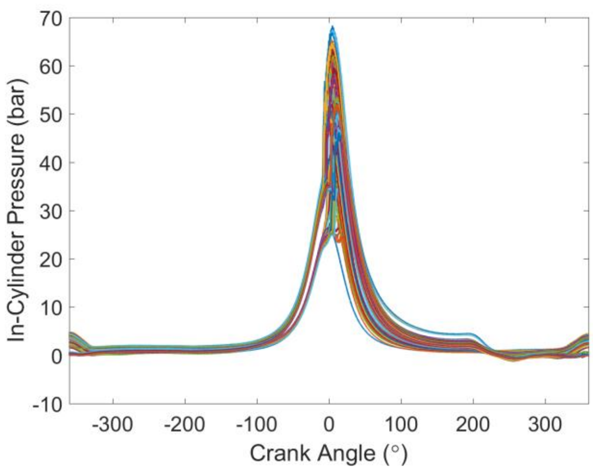


Fig. 2. In-cylinder pressure traces for 135 combustion processes

## IV. Methods

Firstly, we obtain the pressure gradients of each combustion cycle. Fig. 3 shows the rate of change in in-cylinder pressure with respect to crank angle for a sample normal and abnormal combustion process. Positive values correspond to increase whereas negative values correspond to decrease. As can be seen, the rate of change in normal combustion process is much smaller than the rate of change in abnormal combustion process. Both maximum increase rate and decrease rate are associated with the abnormal combustion process. In addition to that, large fluctuations in the rate of change occurs in abnormal combustion process.

To train our machine learning system, we use a portion of the data. The other data are used for testing. Fig. 4 shows the maximum increase and decrease rates in in-cylinder pressure for the data which is used to train our machine learning algorithm. The plot shows the values in a sorted way. Recall that the decrease rates have negative signs as seen in Fig. 3, and that's why we use absolute value to represent the maximum decrease rates in Fig. 4.

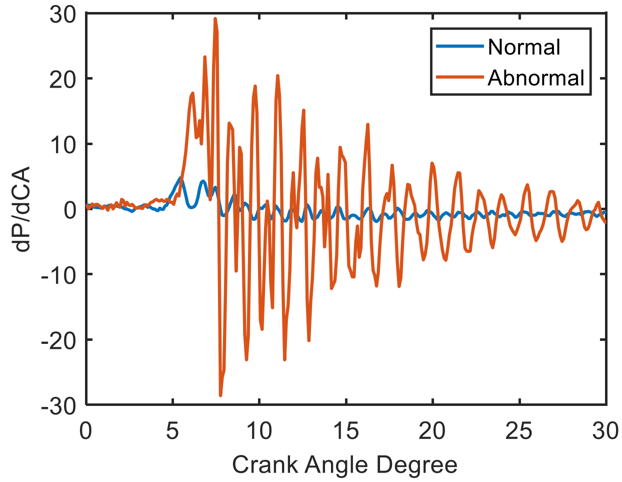


Fig. 3. A typical rate of change trace in-cylinder pressure for a normal and an abnormal combustion

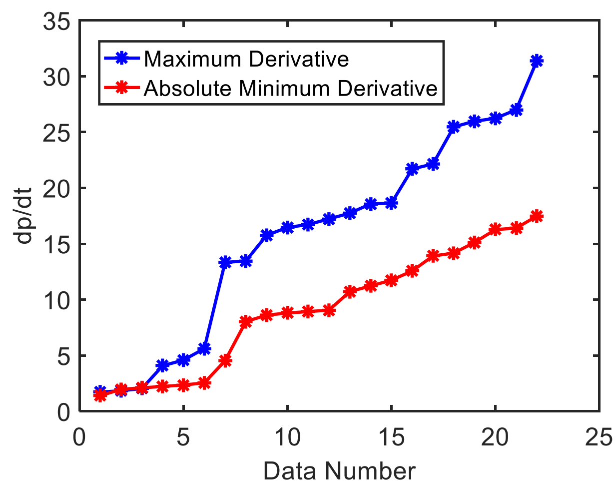


Fig. 4. Maximum observed increase and decrease rates in-cylinder pressure for a training set of our machine learning system

The core idea in our algorithm is that the abnormal combustion processes have larger maximum increase and decrease rates of change observed in the trace of in-cylinder pressure compared with the normal combustion processes. For example, in Fig. 4, the leftmost data correspond to a normal combustion process whereas the rightmost data correspond to an abnormal combustion process.

Each data in our dataset was not prelabeled as normal or abnormal combustion. Thus, we used k-means clustering with k being equal to two to label our data. We also manually labeled data by looking at the in-cylinder pressure traces ourselves. Then, we compared the resulting labels obtained by manual labeling and k-means clustering to measure the performance of k-means clustering.

To classify each combustion as normal or abnormal, we used support vector machines (SVM). This provided us to find a threshold to make the classification.

## V. Results and Discussion

Fig. 5(a) shows the threshold line between normal and abnormal combustion processes obtained by SVM for a set of training data. Each point represents a combustion cycle from our data. Their coordinates on the figure correspond to the maximum increase and maximum decrease rate in their pressure trace. The labeled points as 'Normal' and 'Abnormal' are find by k-means clustering. We also labeled these cycles as 'Normal' and 'Abnormal' by manually checking the data. In Fig. 5(a), the result of the k-means clustering and manual labeling of the data totally matches.

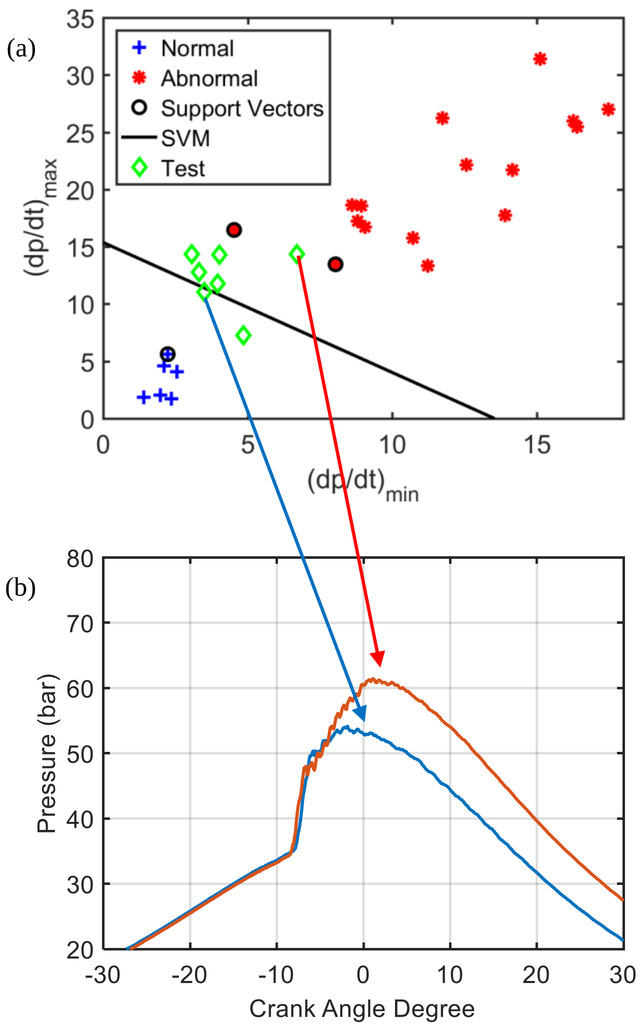


Fig. 5. (a) The threshold line between normal and abnormal combustion processes obtained by SVM. (b) In-cyclinder pressure traces corresponding to the test cycles for the test points shown by arrow.

We use these labeled points as data for our machine learning system. SVM takes the input of these training data, and gives us a threshold line, which is used to classify a combustion cycle as normal and abnormal. The data points below the threshold line correspond to normal combustion cycles whereas the ones above the threshold line correspond to abnormal combustion cycles.

After applying SVM, we tested the accuracy of our system by using test data. Fig. 5(b) shows the in-cylinder pressure traces for two test points shown in Fig. 5(a). The beginning of the arrows shows the corresponding test point for that trace. We can see that the test point above the threshold line has more ripples with larger fluctuations in its in-cylinder pressure trace compared with the test point below the threshold line. Also, the pressure reaches to a higher maximum value for the test point above the threshold line. All these are properties of an abnormal combustion process. In fact, the blue line in Fig. 5(b) correspond to an approximately normal combustion cycle whereas the red line corresponds to an abnormal combustion cycle.

Fig. 6 shows the k-means clustering result when we also use injection timing as a feature.

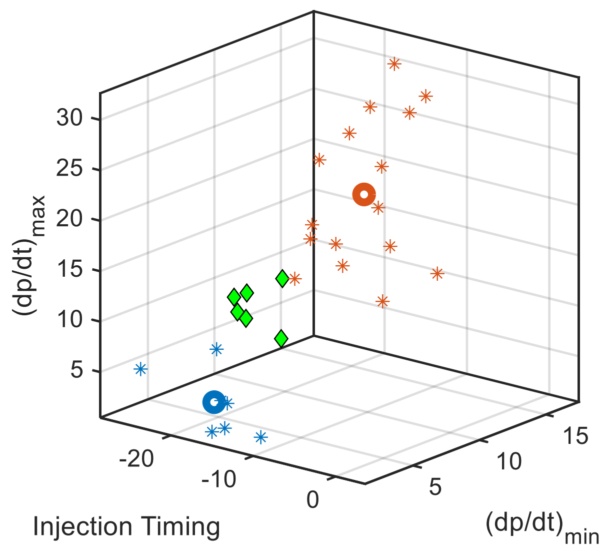


Fig. 6. Clustering of combustion cycles as normal and abnormal combustion processes

Fig. 7 shows the k-means clustering result and the threshold line between normal and abnormal combustion processes obtained by SVM when we use all the data points.

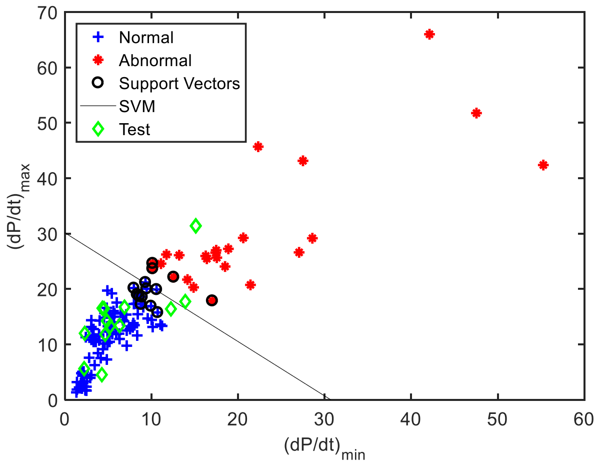


Fig. 7. Maximum observed increase and decrease rates in-cylinder pressure for a training set of our machine learning system

## VI. Conclusion

In this work, we implemented a machine learning system to detect the occurrence of an abnormal combustion. The system uses in-cylinder pressure, injection duration and injection starting time data of a combustion process occurring in a compression ignition engine, and then classify that process as normal or abnormal combustion. This detection is important since it can inform users of these engines about abnormal combustion occurrences, which helps the users to take necessary measures to prevent these occurrences to minimize the engine failures.

We notice that further improvement in this project requires to obtain larger number of data as well as to use additional features. Physical properties such as inlet air temperature and engine speed have also affect on occurrences of abnormal combustions; thus, one also needs to consider these data. Moreover, using second gradients of pressure trace might help the accuracy of the system.

The project can be extended to other types of engines. In fact, abnormal combustion detection is more crucial for gasoline engines (spark ignited engines) since abnormal combustions more frequently occur in those engines. However, since we only had the data from a compression ignition engine, we implemented our system for such engines.

One particularly beneficial add-on to this project would be to develop a system to predict abnormal combustion occurrences before they actually occur. Such a prediction might be used to perform particular adjustments to the injection properties in engines to prevent abnormal combustion occurrences, which would definitely increase the lifetime of the engines.

## VII. Acknowledgment

We would like to thank Prof. Andrew Ng, Prof. Dan Boneh and the CS 229 teaching staff for all their support thoughout the quarter. We would also like to thank Mark A. Donohue for providing us the data.

## VIII. Contributions

Both group members worked together for the all parts. They feel that it is not fair for them to give the credibility of any result or work to one of them since at each step both of them have discussed, planned and worked together.

## IX. References

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