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CHARACTERIZATION OF GASOLINE ENGINE EXHAUST FUMES USING ELECTRONIC NOSE BASED CONDITION MONITORING

Strictly as per the compliance and regulations of:

Characterization of Gasoline Engine Exhaust Fumes Using Electronic Nose Based Condition Monitoring

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Abstract - An electronic nose-based condition monitoring of three automobile engines was conducted to obtain smell prints that correspond to normal operating conditions and various induced abnormal operating conditions. Fuzzy C-means clustering was used to ascertain the extent to which the smell prints can characterize faulty engine conditions. Silhouette diagrams and silhouette width figures were used to validate the clusters. Results obtained indicate that the smell prints do in general characterize the faults as most clusters have silhouette width greater than 0.5. In particular the results showed that the following automobile engine faults; plug-not-firing faults and loss of compression faults are diagnosable from the automobile exhaust fumes.

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I. Introduction

Condition monitoring is a method by which small variations in the performance of equipment can be detected and used to indicate the need for maintenance and the prediction of failure [1].Condition monitoring and performance estimation are used to appraise the current state and estimate the future state of plant by using real time measurements and calculations. Such monitoring provides ongoing assurance of acceptable plant condition [2]. Some of the condition monitoring technologies that are widely used for detecting imminent equipment failures in various industries include vibration analysis, infra-red thermal imaging, oil analysis, motor current analysis and ultra-sonic flow detection [3]. Diesel engine cooling system model based on condition monitoring was developed by Twiddle [4]. The developed model was tested on a real life diesel engine powered electricity generator to simulate detection of fan fault, thermostat fault and pump fault using temperature measurements. Agoston et al. [5], used micro-acoustic viscosity sensors to conduct on - line condition monitoring of lubricating oils in order to monitor the thermal aging of automobile engine oils and predict appropriate timing of engine oil change.

Electronic noses are technology implementation of systems that are used for the automated detection and classification of odours, vapours and gases[6]. The main motivation for the implementation of electronic noses is the need for qualitative low cost, real-time and portable methods to perform re- liable, objective and reproducible sensing of volatile compounds and odours [7]. Guadarrama et al. [8] reported the use of electronic nose for the dis- crimination of odours from trim plastic materials used in automobiles. Huyberechts et al. [9] used electronic nose to quantify the amount of carbon monoxide and methane in humid air. A method for determining the volatile compounds present in new and used engine lubricant oils was reported by Sepcic, et al. [10]. The identification of the new and used oils was based on the abundance of volatile compounds in headspace above the oils that were detectable by electronic nose. The electronic nose sensor array was able to correlate and differentiate both the new and the used oils by their increased mileages. Hunter et al., [11] applied high temperature electronic nose sensors to exhaust gases from modified automotive engine for the purpose of emission control. The array included a tin-oxide-based sensor doped for nitrogen oxide (NO_x) sensitivity, a SiC -based hydrocarbon (C_xH_y) sensor, and an oxygen sensor (O_2) [11]. The results obtained showed that the electronic nose sensors were adequate to monitor different aspect of the engine's exhaust chemical components qualitatively

In the present study, a prototype of an electronic nose-based condition monitoring scheme using array of broadly tuned Taguchi metal oxide sensors (MOS) was used to acquire the exhaust fume of three gasoline-powered engines operating under induced fault conditions. Three gasoline engines were

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used so as to compare and establish the viability or otherwise of using exhaust smell prints to diagnose the fault conditions.

II. Materials And Methods

a) The Automobiles Engine

The automobile engine is a mechanical system based on the internal combustion process and its parts vary depending on the type of engine and the manufacturer. In a gasoline fuelled engine, a mixture of gasoline and air is sprayed into a cylinder where the mixture is compressed by a piston. The ignition systemproduces a high-voltage electrical charge that is transmitted to the spark plugs via ignition wires. The hot gases in the cylinder are at a higher pressure than the air-fuel mixture and thus drive the piston down. In a perfectly operating engine with ideal combustion conditions, the following chemical reactions would take place in the presence of the of air, fuel and electrical spark:

1. Hydrocarbons (HxCy) would react with oxygen to produce water vapour(H2O) and carbon dioxide (C O2), and
2. Nitrogen (N2) would pass through the engine without being affected by the combustion process

If there is any variation in the components of basic combustion or lossof compression due to worn piston rings or high operating temperature the composition of the exhaust gases will change. Specifically, the exhaust will contain H2O , CO2, N2, NOX , CO , HxCy and O2. Measurements of exhaust gases such as C O2 , C O , N Ox, and O2 can provide information about the chemical process inside the combustion chamber and the state of other parts of the engine unit. For example, CO2 is an excellent indicator of efficient combustion; high CO2 measurement is indicative of high efficiency of the engine. High HxCy indicates poor combustion that can be caused by ignition misfire (ignition system failures) or insufficient cylinder compression.

Experiments were conducted on three gasoline fuelled spark ignition automobile engines, namely, Toyota Carina II, Nissan Sunny and Mitsubishi Gallant engines. The main experimental rig is a test bed based on the Toyota Carina II engine (see Figure 1). The other two engines, Nissan Sunny engine and Mitsubishi Gallant engine, are fitted in two operational automobiles. Table 1 shows the specification of one of the three engines, the Toyota Carina II engine. Samples of the exhaust fumes from the three engines operating in normal and various induced faulty conditions were collected for analysis using an electronic nose system comprising an array of ten broadly tuned chemical sensors.

Table 1 : Toyota Carina II Engine Specification

S/N	Item	Value
1	Track (rear axle)	50.6 in
2	Kerb weight	900 Kg.
3	Engine capacity	1.61 L
4	Number of valves	8
5	Number of cylinder	4
6	Bore/Stroke ratio	1.21
7	Displacement	96.906 Cu in
8	Compression ratio	9.5:1
9	Maximum output	78.3 kW
10	Maximum rpm coolant Water	66.1 bhp/litre
11	Top gear ratio	0.86

b) Chemical Sensor

The chemical sensor is usually enclosed in an air tight chamber or con- tainer with inlet and outlet valves to allow volatile odour in and out of the chamber. The most popular sensors used to develop electronic noses are;semiconductor metal oxide chemoresistive sensors, quartz-resonator sensors and conducting polymers. Semiconductor metal oxide chemoresistive sen- sors types were used in this study because of their high sensitivity to com- bustible materials such as alcohols and poor efficiency at detecting sulphur-or nitrogen-based odours [12]. The overall sensitivity of these types of sen- sors is quite good. They are relatively resistant to humidity, ageing, and are made of particularly strong metals[13]. Taguchi metal oxide semiconductor (Figaro Sensor, Japan) TGS 813, TGS 822, TGS 816, TGS 2602, TGS 5042, TGS 2104 and TGS 2201 were used based on their broad selectivity to some exhaust gases such as C O2 , N2, N OX , C O , uncombusted HxCy , and some other gases such as H2 , methane, ethanol and benzene.

c) Induced Fault Conditions

In order to produce repeatable conditions, known faults were induced for investigation. The major fault classes under consideration in this study are plug-not-firing faults and worn piston ring (loss of compression).

Plug-not-firing faults: Any malfunctioning of the spark plugs results in a sub-optimal ignition of the air-fuel mixture; however the air-fuel mixture is still compressed by the piston thereby producing unburnt hydro-carbon with lean quantity of carbon dioxide and appreciable amount of carbon monoxide. Three different ignition faults are considered: one- plug, two-plug and the three-plug faults. The faults were induced in the engines by removing the cables connected to the spark plugs one after the other.

Worn piston ring faults: The piston ring prevents engine oil in the sump from seeping and mixing with the gasoline-air mixture in the engine combustion chamber and thus maintaining the engine compression at optimum level. When this ring is worn, the engine oil seeps and mixes with the gasoline-air mixture thereby increases the amount of unburnt hydrocarbon produced in the combustion chamber and escaping via the exhaust valve. The worn piston ring fault was induced by mixing the gasoline and engine oil in various proportional ratios as 90 : 10, 80 : 20, 70 : 30, 60 : 40, 50 : 50 and 40 : 60. The following calibration was used for the loss of compression faults: a 90 : 10 fuel mixture corresponds to a 1st degree worn ring and 80 : 20, 70 : 30, 60 : 40, 50 : 50 and 40 : 60 correspond to 2nd, 3rd, 4th, 5th and 6th degree worn ring respectively.

A high percentage of engine oil in the mixture corresponds to a high degree of wear in the piston ring and this adversely affects the efficiency of the engine.

d) Data acquisition

The required exhaust fumes of the gasoline fuelled engine operating under various induced fault conditions were obtained from the engine exhaust tail pipe in the absence of a catalytic converter. The exhaust gas specimens were collected into 1000ml Intravenous Injection Bags (IIB). Drip set was used to connect each of the IIB containing the exhaust gases to a confined chamber that contained the array of the selected Taguchi MOS sensors. Static headspace analysis odour handling and sampling method was used to expose the exhaust fume samples to the plastic chamber because the exhaust fume tends to diffuse upwards in clean air due to its lighter weight. Thus there was no need for elaborate odour handling and sampling method. Readings were taken from the sensors 60 seconds after the introduction of each ex- haust fume sample into the air tight plastic chamber so as to achieve odour saturation of the headspace. The digitized data were collected continuously for 10 minutes using Pico ADC 11/10 data acquisition system (connected to a personal computer) and stored further analysis. 1400 × 10 data samples (1 dataset) for each of the ten (10) fault classes making a total of 14000 ×10 data samples (10 data sets) were collected from the test bed engine. The sensors were purged after every measurement so they can return to their respective default states (also referred to as baseline) with the use of compressed air. These measurement procedures were repeated for the engine fitted into the two operational vehicles. The 6th degree worn ring fault measurement could not be carried out because it was difficult to start the engine. All data collection were done with the engine speed maintained at 1000 revolutions per second except for 5th degree worn ring, 6th degree worn ring and 3 plugs bad fault conditions that were collected at engine speed of 2000 revolutions per second.

e) Data analysis

Our hypothesis is that various induced fault conditions can be inferred from the odour prints of the exhaust gas. A clustering analysis of the data was conducted and the validity of the cluster generated was demonstrated. The data collected from the array of sensors represent features characteristic of each type of induced fault and form patterns in a 10-dimensional space. Data cluster analysis is an unsupervised learning technique that can be used to discover the underlying groupings in a data set, usually represented a vector of measurements, based on some measure of similarity [14]. Given a number of clusters, C, the idea is partition the data into the clusters based on some measure of similarity. Fuzzy clustering, also called fuzzy C-means (FCM), assigns each data point into clusters with some probability of belonging. This is in contrast to the popular k-means clustering where data points are assigned to exactly one cluster. Let u*ik* denote the strength of membership of the *i*-th data sample in the k-th cluster. The membership strength for each data sample behaves like probabilities with u*ik* > 0 for all *i* and *k* = 1. . . C, and $\sum_{k=1}^{c} uik$[15]. Usually, the pair wise distances of the data samples, {dij} is computed and the membership strengths are obtained iteratively by minimizing the objective function [15],

$$J = \sum_{k=1}^{k} \frac{\sum_i \sum_j u_{ik}^2 u_{jk}^2 d_{ij}}{2 \sum_i u_{ik}^2} \qquad (1)$$

subject to the non-negativity and unit sum constraints.

The quality of the clustering can be ascertained using several cluster validity techniques. In this paper, the quality of the clusters formed were validated using silhouette index proposed by Rousseeuw [16]. It has been shown to be a robust approach to predict optimal clustering partitions [17]. For a given cluster, Xk (k = 1, . . . , C), this method assigns to each sample of Xk a quality measure, s(i)(i = 1, . . . , m), (m is the number of samples in cluster Xk) known as the silhouette width.The silhouette width is a confidence indicator on the membership of the i-th sample in cluster Xk and is defined as

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}} \qquad (2)$$

where a(i) is the average distance between the i-th sample and all of thesamples included in Xk ; and b(i) is the minimum average distance between the i-th sample and all of the samples clustered in Xj (j = 1, . . . , C; j = k). From Equation 2 it follows that the −1 ≤ s(i) ≤ 1.

When s(i) is close to 1, one may infer that the I -th sample has been "well clustered", i.e. it was assigned to an appropriate cluster. When a s(i) is close to zero, it suggests that the i-th sample could also be assigned to the nearest neighbouring cluster. If s(i) is close to -1, one may argue that such a sample has been "misclassified" [16]. Thus, for a given cluster, Xk

Global Journal of Researches in Engineering (D) Volume XI Issue V Version I August 2011

(k = 1. . . C),it is possible to calculate the average silhouette width or cluster silhouette value Sk , which characterizes the heterogeneity and isolation properties of the cluster,

$$S_j = \frac{1}{m} \sum_{i=1}^{m} s(i) \tag{3}$$

where m is number of samples in Sk

III. Result and Discussion

The results of data clustering analysis on the three engine data sets are shown in Figures 2 to 7. Figure 2 shows the results of FCM clustering algorithms on the Toyota Carina II engine data sets. Figures 4 and 6 show the results of clustering datasets from the Mitsubishi Gallant engine and Nissan sunny engine respectively. The results of FCM clustering shows that most of the data fall into distinct grouping and there are clear boundaries. Silhouette diagrams for the cluster validity are shown in Figures 3, 5 and 7 with the silhouette values for each cluster. None of the silhouette values in the silhouette graph of Figure 3 is negative. Considering the case of overlap in Figure 2 (40% worn ring and 10% worn ring faults); the silhouette values for clusters 2 and 5 are 0.70 and 0.75 respectively, this indicates that the clusters are well formed with high positive values. All other FCM clusters and silhouette diagrams in Figures 4 to 7 show results similar to that of Figures 2 and 3 except the silhouette diagrams in Figures 5 and 7 with two clusters having small negative silhouette values that suggest that the clusters involved overlap adjacent clusters. The silhouette graph in Figure 5 shows that clusters 6and 9 have silhouette values close to -0.2 with cluster 9 having more data points overlapping other clusters. Similar arguments hold for Figure 7 where clusters 1 and 5 are having small negative silhouette values.

The result of clustering all the data from the three engines is shown in Figure 8 and the silhouette diagram for same is shown in figure 9. These results show that irrespective of the automobile engine, the faults can be characterized accurately from the exhaust gases by electronic nose.

IV. Conclusion

Exhaust gas samples from three gasoline fuelled engines were collected and analyzed via electronic nose system comprising ten broadly tuned MOS sensors. The results of cluster analysis on the acquired smell prints samples from the three automobile engines using fuzzy C-means clustering algorithm showed close similarities among data items in same dataset and distant similarity among data items in different data sets with distinct fault class boundaries. The results of cluster validity showed that all the data samples were well clustered except for data sets of two induced faults in respect of Nissan Sunny engine and Mitsubishi Gallant engine that have some data points overlapping adjacent data sets. These results showed that the data samples acquired with the electronic nose based condition monitoring scheme were true representations of the normal and induced faults conditions investigated. The collected data samples could be well classified as normal and faulty states smell characteristic data for the faults investigated in this study.

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Figure 1 : Experimental rig: Toyota Carina II engine

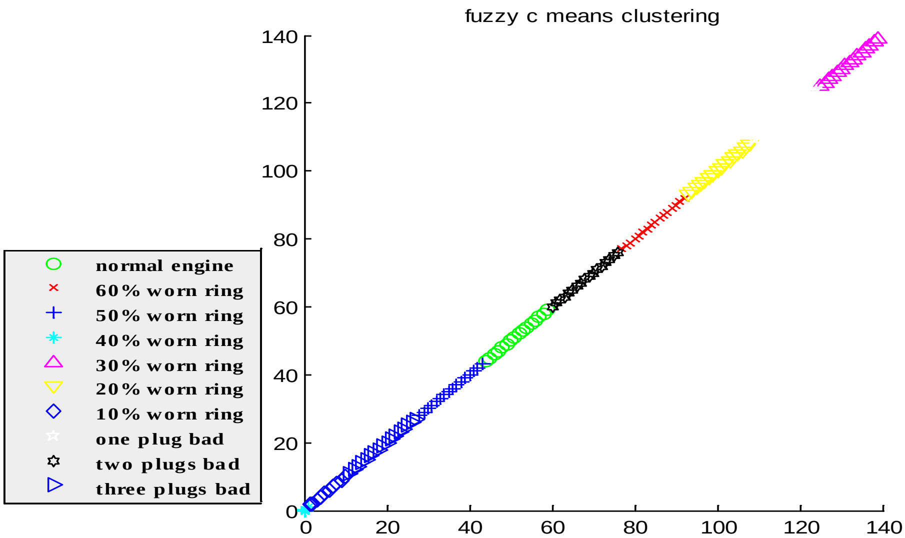

Figure 2 : FCM diagram for Toyota Carina II engine

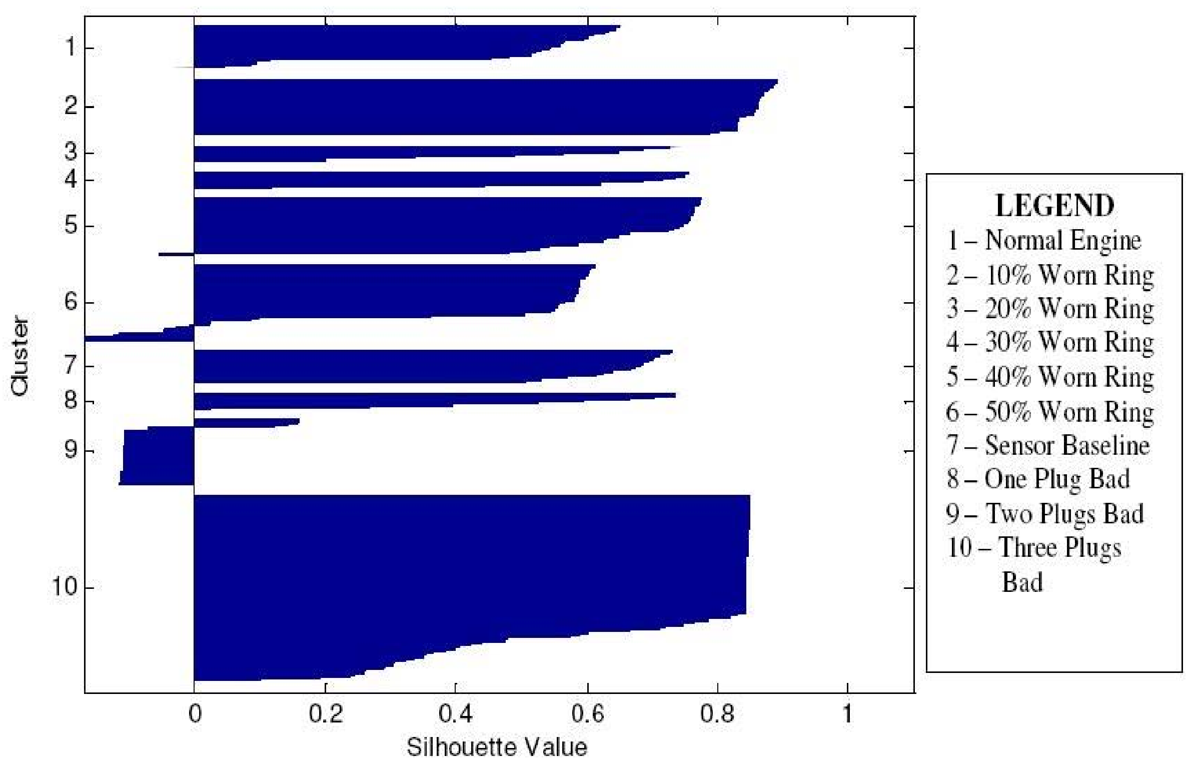

Figure 3 : FCM silhouette diagram for Toyota Carina II engine

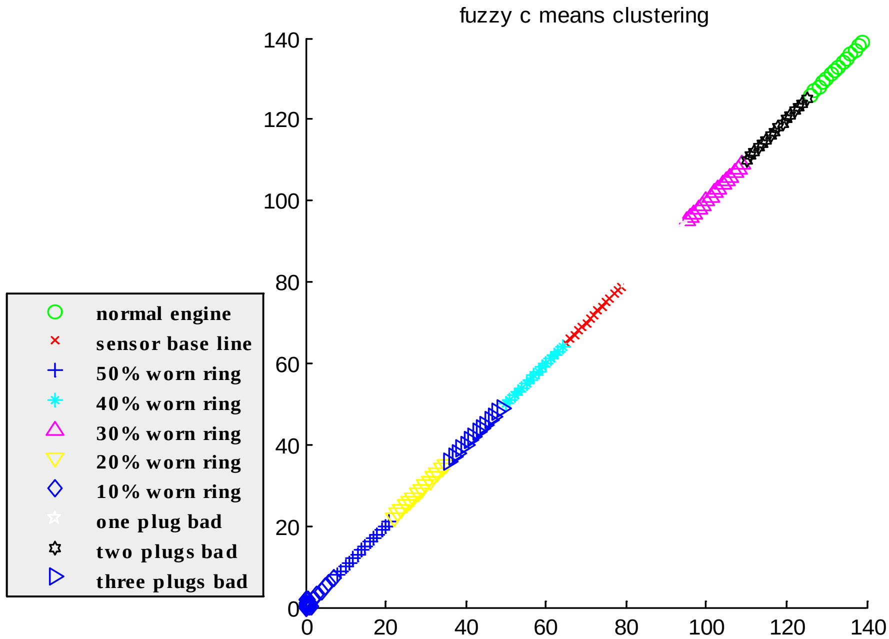

Figure 4 : FCM diagram for Mitsubishi Gallant II engine

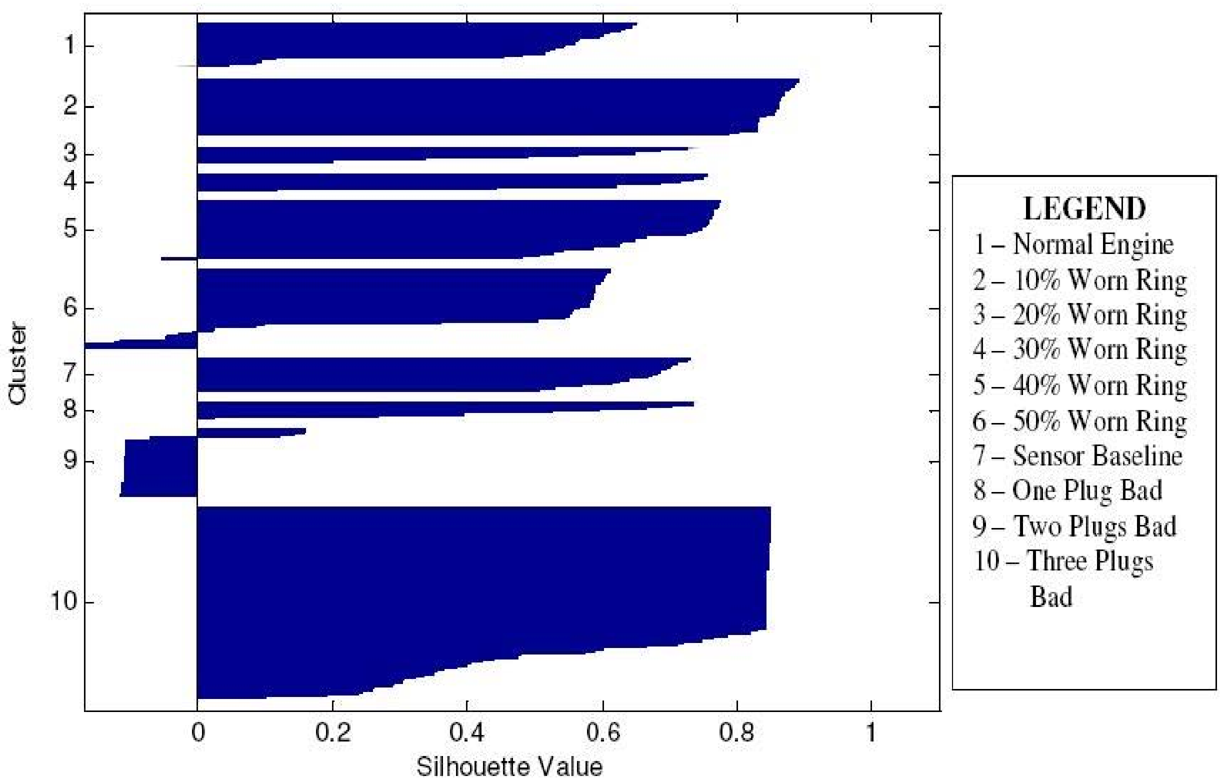

Figure 5 : FCM silhouette diagram for Mitsubishi Gallant engine

Global Journal of Researches in Engineering (D) Volume XI Issue V Version I August 2011

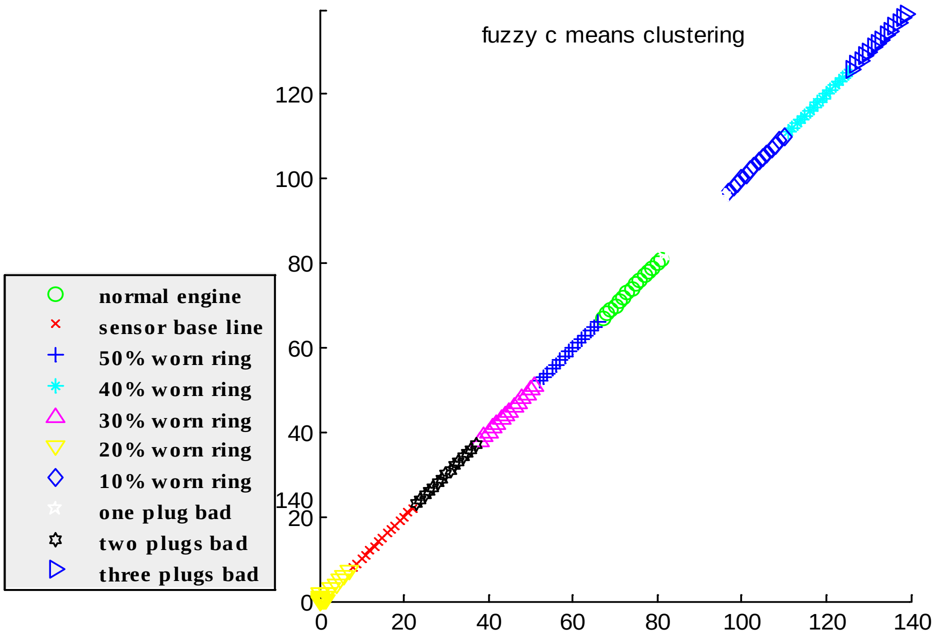

Figure 6 : FCM diagram for Nissan Sunny engine

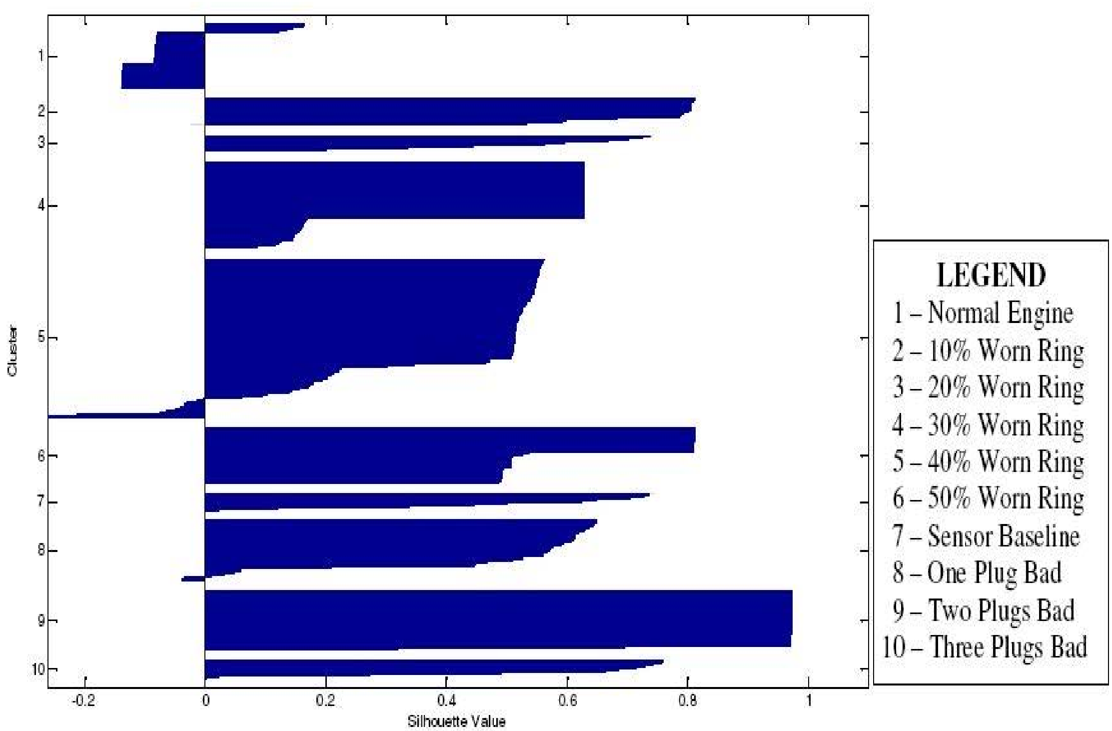

Figure 7 : FCM silhouette diagram for Nissan Sunny engine

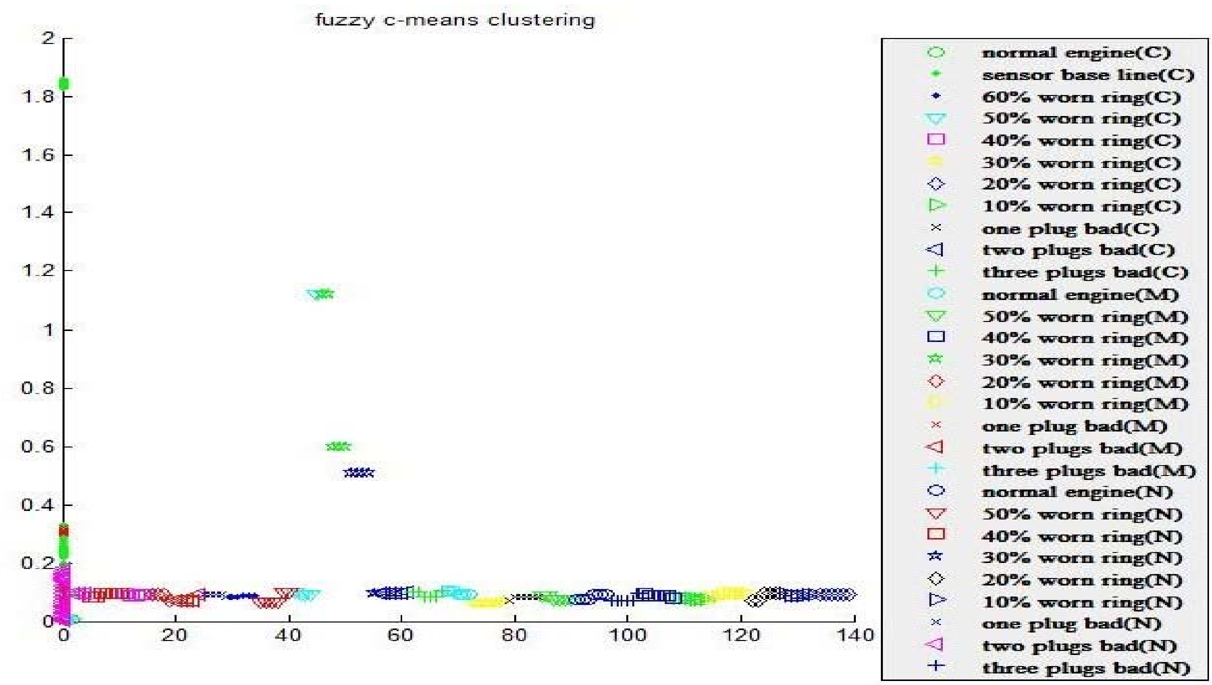

Figure 8 : FCM diagram for the three engines

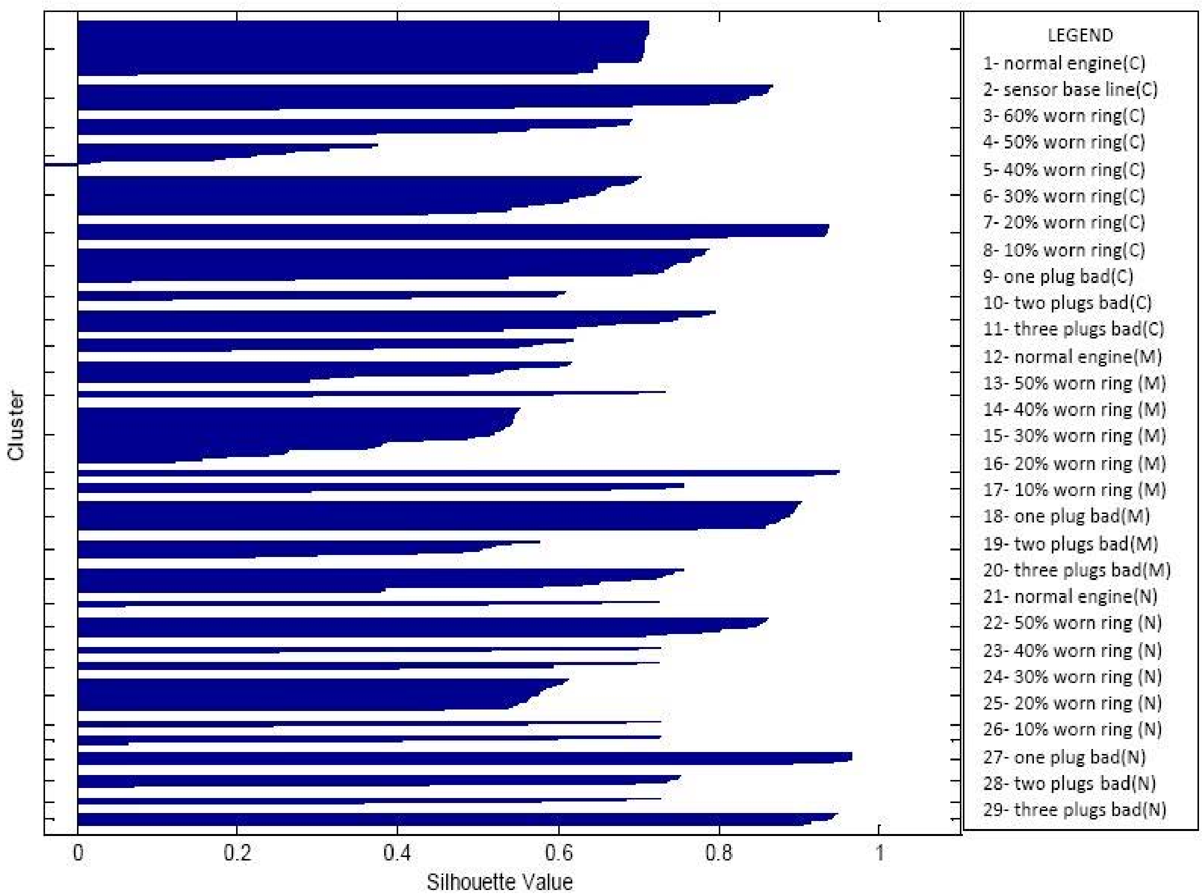

Figure 9 : FCM silhouette diagram for the three engines