International Journal of Engineering Science, Volume 2, Number 5, 2010

DIAGNOSIS OF GASOLINE-FUELLED ENGINE EXHAUST FUME RELATED FAULTS USING ELECTRONIC NOSE

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ABSTRACT

Fault diagnosis, isolation and restoration from failure are crucial for maintenance and reliability of equipment. In this paper, a condition monitoring approach that uses the sense of smell was investigated to diagnose ignition and loss of compression faults in gasoline-fuelled engine. An electronic nose based condition monitoring system was used to obtain smell print of the exhaust fumes of an automobile gasoline engine in different normal and faulty operating conditions. The data were analyzed with fuzzy c-means, hybrid principal component analysis and artificial neural network. Fuzzy C- means clustering was used to ascertain the extent to which the smell prints can characterize the selected engine faulty and normal conditions. Silhouette diagrams and silhouette width figures were used to validate the clusters. The faults considered were all correctly classified by hybrid principal component analysis and artificial neural network algorithm with 100% accuracy.

Key words: Fault diagnosis, Automobile, Neural Network, Principal Components Analysis, fuzzy c-means and electronic nose.

INTRODUCTION

The engine sub-system in automobile is one of the most critical and complex aspect that constitute the focus upon which the functionality of other sub-systems rely. It consists of many units such as the carburettor, radiator, ignition, crankshaft, camshaft, piston and sleeve, valves, and so on. It is prone to fault because of its electromechanical nature and as a result the overall effectiveness and efficiency of its performance reduction is noticed over a period of time. The early detection of the malfunctions and faults as well as their compensation is crucial both for maintenance and mission reliability of vehicles [2]. There are two major approaches that are employed in detecting or predicting faults in any automobile engine, namely: physical observation and electronic condition monitoring approaches. While the first approach uses human senses such as hearing, sight, and smell, while the second approach deploys electronic sensors to monitor some conditions such as thermal, vibration, acoustic emission, torque, speed, voltage, current, flow rate, power and so on. The latter approach is more desirable because it avoids human errors when properly implemented. In addition, it predicts with high level of accuracy the real status of the system to which it is deployed. Condition monitoring technologies, such as vibration analysis, infra-red thermal imaging, oil analysis, motor current analysis and ultra-sonic flow detection along with many others have been widely used for detecting imminent equipment failures in various industries [17]. Its techniques have been applied in various fields for the purpose of fault detection and isolation. In reference [15], a condition monitoring based diesel engine cooling system model was developed. The developed model was experimented on a real life diesel engine powered electricity generator to simulate detection of fan fault, thermostat fault and pump fault using temperature measurements. Micro-acoustic viscosity sensors was used to carry out on-line condition monitoring of lubricating oils in order to monitor the thermal aging of automobile engine oils so as to predict the appropriate time for engine oil change [1]. Electronic noses are technology implementation of systems that are used for the automated detection and classification of odours, vapours and gases [8]. The main motivation for the implementation of electronic noses is the development of qualitative low cost real-time and portable methods to perform reliable, objective and reproducible measures of volatile compounds and odours [14]. Reference [9] reported the use of electronic nose for the discrimination of odours from trim plastic materials used in automobiles. Electronic nose was used to quantify the amount of carbon monoxide and methane in humid air with three sensors [11]. A method for determination of the volatile compounds present in new and used engine lubricant oils was reported by [19]. 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. High temperature electronic nose sensors to exhaust gases from modified automotive engine for the purpose of emission control [10]. 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). The results obtained showed that the electronic nose sensors were adequate to monitor different aspect of the engine's exhaust chemical components qualitatively. Literature search in electronic nose applications have shown that less emphasis has been placed in the area of condition monitoring of equipment for fault diagnosis of equipment. In this 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 smell prints of a gasoline-powered engines operating with induced faults. The exhaust fume smell prints was investigated for fault diagnosis and isolation of gasoline fuel powered automobile engine with fuzzy c-means (FCM) clustering analysis and hybrid optimised principal components analysis and feed-forward multilayer perceptron neural networks trained with the back-propagation algorithm (OPCA + FBPNN).

METHODOLOGY

The Automobile Engine

Automobile engine is a mechanical system where combustion takes place internally. The parts of an engine vary depending on the engine's type and the manufacturer. Figure 1 shows some of the basic parts of the internal combustion engine. The system is a heat engine in which combustion occurs in a confined space called a combustion chamber.

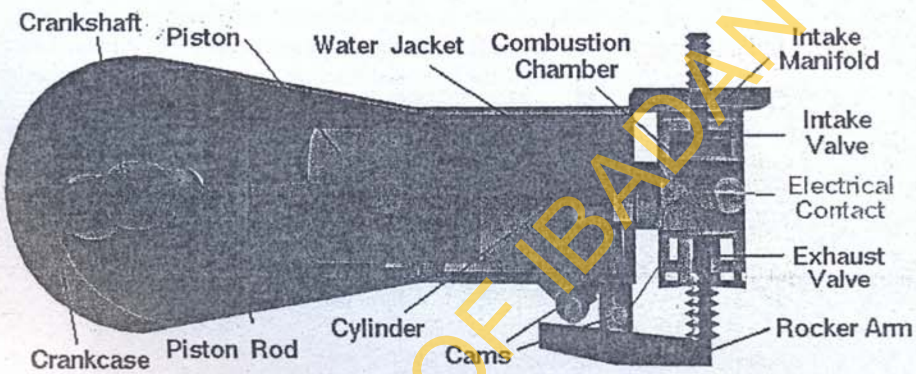

Figure 1: Basic parts of an internal combustion engine (NASA, 2007)

In a gasoline fuelled engine, a mixture of gasoline and air is sprayed into a cylinder and the mixture is compressed by a piston. The ignition system produces a high-voltage electrical charge and transmits it to the spark plugs via ignition wires. The hot gases that are contained in the cylinder possess higher pressure than the air-fuel mixture so this drives the piston down [13]. In a perfectly operating engine with ideal combustion conditions, the following chemical reaction would take place in the presence of the following components of basic combustion namely air, fuel and spark:

1. Hydrocarbons (H_xC_y) would react with oxygen to produce water vapour (H2O) and carbon dioxide (CO2) and
2. Nitrogen (N2) would pass through the engine without being affected by the combustion process.

In any case of variations in the components of basic combustion or loss of compression due to worn piston rings or high operating temperature the composition of the exhaust gases will change to H2O, CO_2, N_2, NOX, CO, H_xC_y and O2. Measurements of exhaust gases such as CO_2, CO, NOx, and O_2 can provide information on what is going on inside the combustion chamber and other things going on in the remaining engine units. For example, CO2 is an excellent indicator of efficient combustion: The higher the CO2 measurement, the higher the efficiency of the engine. High H_xC_y indicates poor combustion that can be caused by ignition misfire (ignition system failures), insufficient cylinder compression. The gasoline fuelled spark ignition automobile engine considered was the Toyota Carina II engine. The Toyota Carina II engine is a test bed automobile engine. Table 1 gives the specification of the engine, while Figure 2 shows the snapshot of the Toyota Carina II engine test bed used in this study. Samples of the exhaust fumes of the engine operating in normal and various induced faulty conditions were collected for analysis using electronic nose system that consisted of 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

Chemical sensors

The chemical sensor is usually enclosed in an air tight chamber or container 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 sensors types were used in this study because they are quite sensitive to combustible materials such as alcohols but are less efficient at detecting sulphur or nitrogen-based odours [3]. The overall sensitivity of these types of sensors is quite good. They are relatively resistant to humidity and to ageing, and are made of particularly strong metals [12].

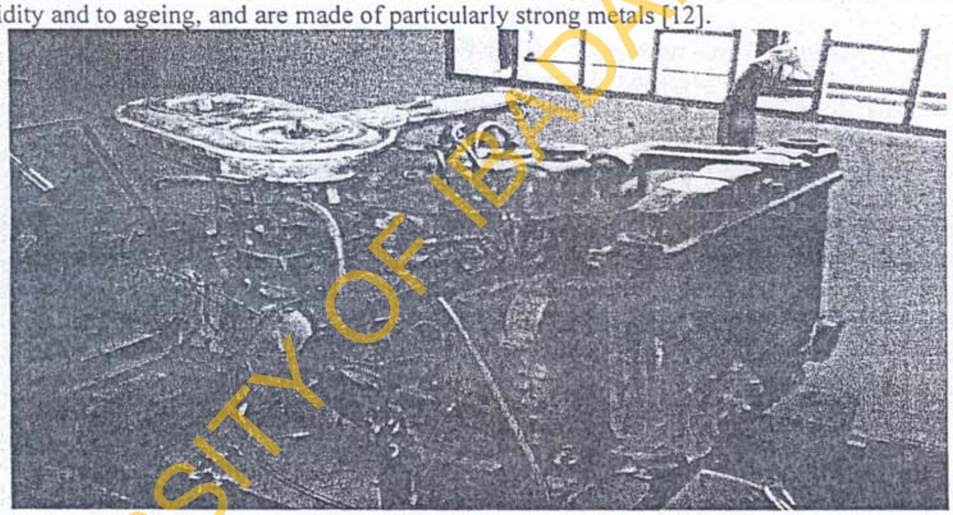

Figure 2: Snapshot of the Toyota Carina II Engine

Taguchi metal oxide semiconductor (Figaro Sensor, Japan) TGS 813, TGS 822, TGS 816, TGS 2602, TGS 5042, TGS 2104 and TGS 2201were used based on their broad selectivity to some exhaust gases such as CO2, N_2, NOX, CO, uncombusted H_xC_y, and some other gases such as H_2, methane, propane, butane, ethanol, benzene. Comprehensive sensor characteristics are available from the manufacturer (www.figarosensors.com).

Induced Fault Conditions

Faults may take time to develop in an automobile engine, hence the need to induce the faults to be investigated. The major faults classes under consideration in this work were plug-not-firing faults and worn piston ring (loss of compression).

Plug-not-firing faults:

When any of the plugs is malfunctioning, the air-fuel mixture will not be properly ignited but will only be compressed by the piston thereby producing unburnt hydrocarbon with lean quantity of carbon dioxide and more carbon monoxide. Different ignition faults considered were one plug not firing, two plugs not firing, and three plugs not firing faults. The faults were initiated into 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 from the oil sump to mix with gasoline-air mixture in the engine combustion chamber and to maintain the engine compression at optimum level. When this ring wears out, the engine oil escapes and mixes with the gasoline-air mixture thereby increases the amount of unburnt hydrocarbon that comes out of the combustion chamber 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 will correspond to a 1st degree worn ring and 80:20, 70:30, 60:40, 50:50 and 40:60 will correspond to 2nd, 3rd, 4th, 5th and 6th degree worn ring respectively. The higher the percentage of engine oil that mixes with the gasoline, the higher the (assumed) wear of the piston ring and hence the higher the reduction in the engine's efficiency.

Data acquisition
The required exhaust fumes of the gasoline fuelled engine operating in various induced fault conditions were obtained from the engine exhaust tail pipe in the absence of a catalytic converter as specimens into 1000ml Intravenous Injection Bags (IIB). Two samples were collected for each fault condition and normal condition. One sample was designated for training and the other for testing. 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 and necessary interface circuits. 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. Measurements were taken from the sensors 60 seconds after the introduction of each exhaust 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 card into the personal computer for storage and further analysis. Two 700 x 10 data samples (1 training and 1 testing data sets) for each of the ten (10) fault classes making a total of 14000 x 10 data samples (10 training and 10 testing data sets) were collected from the test bed engine. The sensors were purged after every measurement so that they can return to their respective default states known as baseline with the use of compressed air. 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 three plug not firing fault conditions that were collected at engine speed of 2000 revolutions per second because the engine was not stable at 1000 revolutions per second.

DATA ANALYSIS

Training
The data sets (10 training and 10 testing data sets) were first normalized using fractional difference model: $\Delta R = (R - Ro) / Ro$ where R is the response of the sensor to the exhaust gas, and Ro is the baseline reading of the sensor, the reference gas was air at room temperature. Further normalisation was done by dividing each ΔR by the maximum value for each sensor, so as to set the range of each sensor to range [0, 1]. The normalised data sets were analyzed using FCM algorithm. The choice of fuzzy c-means was based on the advantage of locating the data points to clusters more accurately by assuming a soft membership degree from 0 to 1. The fuzzy c-means clustering provided insight into the data sets profile by given first hand unsupervised classification. The OPCA algorithm was used on the normalised training data sets, the output of OPCA were used as the training input for the FBPNN algorithm. Various parameters of the network such as number of hidden neurons, transfer functions were varied and the best performance was obtained with the network architecture that has ten neurons in the input layer of the ANN while twelve neurons were used in the single hidden layer and eleven neurons in the output layer (10-12-11 network structure). The architecture is shown in Figure 3. Traingdx was the training transfer function that gave the best performance. OPCA was employed because of its dimensionality reduction and feature extraction abilities while retaining the originality of the data [4] and ANN model was used to diagnose particular fault type because of its resilient to noise and random variations in patterns of interest when properly trained [16]. All algorithms were implemented with Matlab 6.5 programming environment.

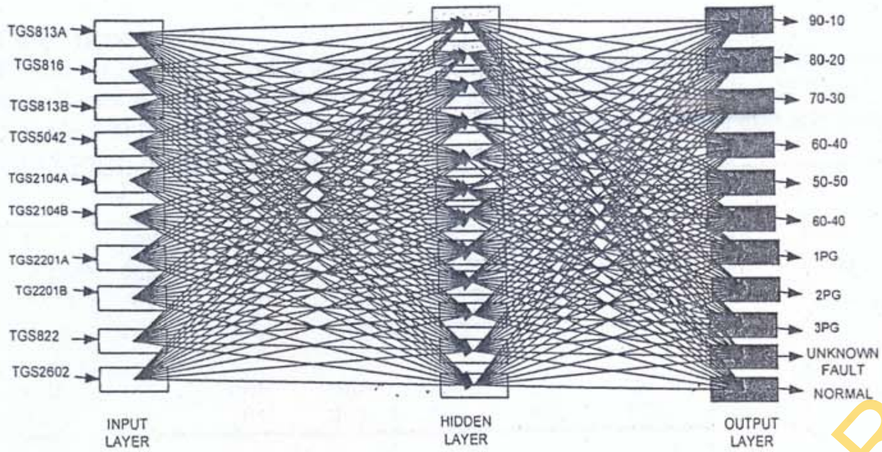

Figure 3: The Architecture of FBPNN

Testing

Each normalised testing data sets were divided into five parts of 140 x 10 sub testing data sets for all fault and normal conditions. All the sub testing data sets were fed as input to the already trained OPCA + FBPNN network one after the other to test the ability of the algorithm to classify data not seen during training. Each fault class was tested five times with the sub testing data sets. The stability of the combined classifier in the likely presence of external disturbances and sensor failure during data acquisition was evaluated using modified testing data sets. Two additional data sets called modified data sets were formed by introduction of 5% value (0.05) to the rows of the testing data sets at random interval and tail end interval. Another two data sets were formed by inserting the value 0.983 to the columns of the testing data sets. This value corresponds to the value returned by the Pico data acquisition system whenever there is sensor failure. These modifications produced four (4) additional new categories of testing data sets namely tail end interval data sets, random interval data sets, even numbered sensor failure data sets and odd numbered sensor failure data sets.

Random Interval Data sets: The 700 rows of all the fault condition data sets were divided into five regions of 140 rows each. 10% noise was introduced into the data sets by adding a value of 0.05 to the values of any 70 rows within the 1st region. 20%, 30%, 40% and 50% noise were introduced into the data sets by adding a value of 0.05 to the values of any 70 rows within the 1st and 2nd regions; within the 1st, 2nd and 3rd regions; within the 1st, 2nd, 3rd and 4th regions and within the 1st, 2nd, 3rd, 4th and 5th regions respectively.

Tail End Interval Data sets: All the fault condition data sets have 700 rows each. 10%, 20%, 30%, 40% and 50% noise were introduced into the data sets respectively from the tail end by adding a value of 0.05 to the values of rows of 631-700; rows of 561-700; rows of 491-700; rows of 421-700 and rows of 351-700 respectively.

Even Numbered Sensor Failure Data sets: 10%, 20%, 30%, 40% and 50% even sensor failures were introduced by changing the entire values within the 2nd column; 2nd and 4th columns; 2nd, 4th and 6th columns; 2nd, 4th, 6th and 8th columns and 2nd, 4th, 6th, 8th and 10th columns of the testing data sets respectively, where each column represent the contributions of a sensor to each dataset.

Odd Numbered Sensor Failure Data sets: 10%, 20%, 30%, 40% and 50% even sensor failures were introduced by changing the entire values within the 1st column; 1st and 3rd columns; 1st, 3rd and 5th columns; 1st, 3rd, 5th and 7th columns and 1st, 3rd, 5th, 7th and 9th columns of the testing data sets respectively. Each modified testing data sets were divided into five parts of 140 x 10 modified sub testing data sets for all fault and normal conditions. All the modified sub testing data sets were fed as input to the already trained OPCA + FBPNN network one after the other to test the ability of the algorithm to classify modified data. Each fault class was tested twenty five times with the corresponding modified sub testing dataset in each of the four categories.

RESULTS AND DISCUSSION

For ease of result interpretation, Table 2 shows the numbers representing each fault condition investigated. Summarized in Figure 4, are the results from FCM algorithm, while Figure 5, 6 and 7 shows the results of testing of OPCA + FBPNN using the normalised data sets and the four modified data sets respectively.

Table 2: Faults Considered in the Experiments

Number	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
Fault Conditions	1st degree worn ring (90-10)	2nd degree worn ring (80-20)	3rd degree worn ring (70-30)	4th degree worn ring (60-40)	5th degree worn ring (50-50)	6th degree worn ring (60-40)	One plug bad (1-PG)	Two plugs bad (2-PG)	Three Plugs Bad (3-PG)	Normal

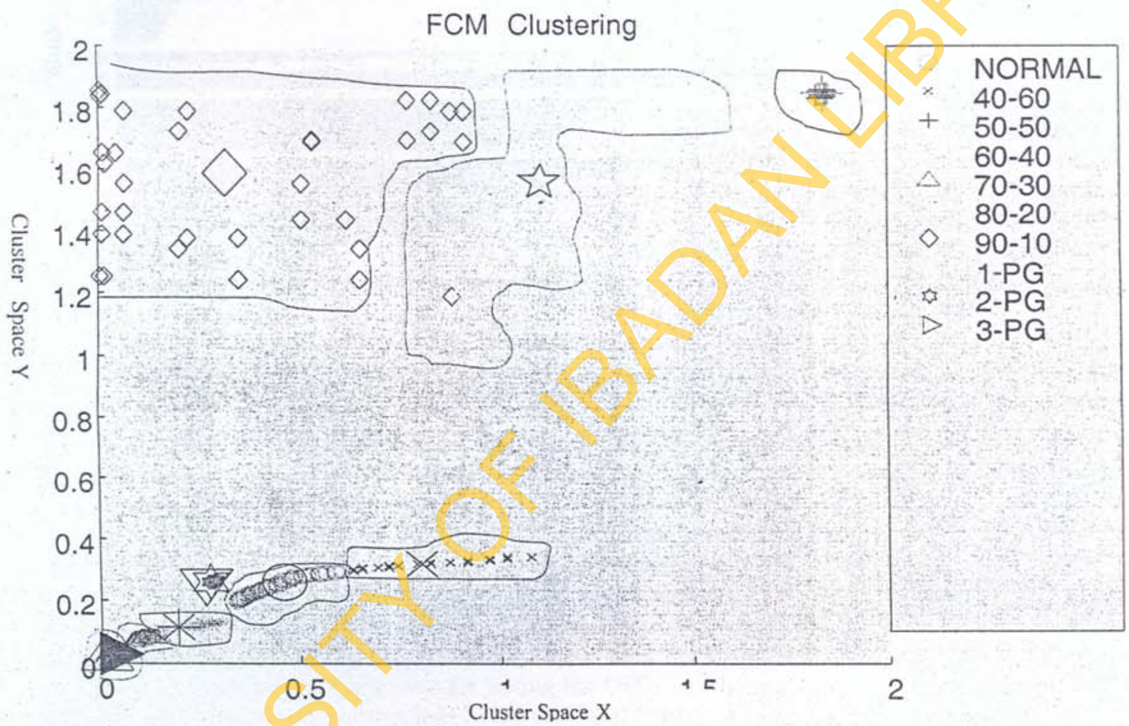

Figure 4: FCM Cluster Diagram for the Engine Data sets

The result of FCM clustering algorithm (Figure 4) showed each cluster centres with its data points distribution round it. This provides better data clustering profile visualization that shows how wide and far apart clusters are to one another. Two cases of cluster centres overlap were observable in the Figure, namely (*case 1*) overlap of 2nd degree worn ring (80-20) and two plugs bad (2-PG); (*case 2*) 3rd degree worn ring (70-30) and three plugs bad (3-Plugs), all other faults have clear cluster centres. The quality of the clusters formed were validated using Silhouette index $s(i)$ proposed by [18], which has shown to be a robust strategies for the prediction of optimal clustering partitions [5]. When a $s(i)$ is close to 1, one may infer that the ith 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" [18]. For a given cluster, X_j (j = 1… c), it is possible to calculate a cluster Silhouette value S_j, which characterizes the heterogeneity and isolation properties of such a cluster:

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

where m is number of samples in Sj.

The results of the of cluster validation using Silhouette index method is shown in Figure 5. None of the silhouette values in the silhouette graph of Figure 5 was negative. Considering the first case of overlap observed in Figure 4 (2^{nd} degree worn ring and two plugs bad faults); the silhouette values for clusters 2 and 8 were 0.70 and 0.75 respectively, this showed the clusters were well formed with high positive values. The second case of overlap (3^{rd} degree worn ring and three plugs bad faults), the silhouette values for clusters 3 and 9 were 0.55 and 0.75 respectively.

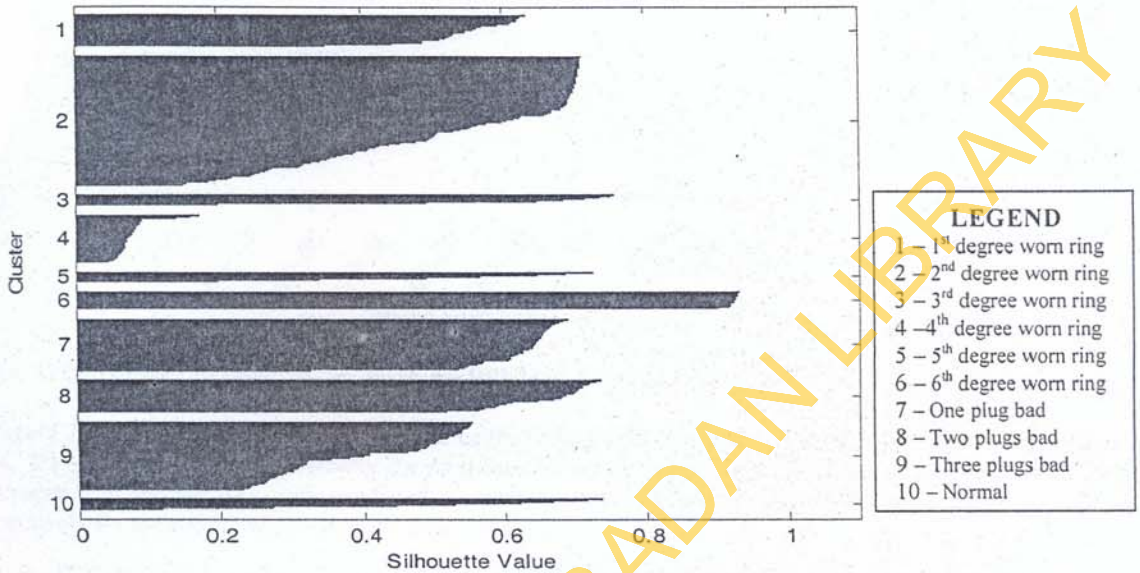

Figure 5: Cluster validation using silhouette index method

The results from FCM algorithm showed close similarities among data items in same dataset and distant similarity among data items in different data sets with distinct fault classes' boundaries. Figure 6 shows the classification accuracy achieved by using OPCA + FBPNN on the normalised data sets. All the faults were correctly identified. The results showed that the classifier was able to classify with 100% accuracy all the fault conditions. This was due to the dimensionality reduction capabilities of PCA algorithm on the data sets and the classification and predictive abilities of neural network. This result is in order with some results obtained in the literature [6], [16] and [7] using electronic nose with neural network. In addition, the deployment of PCA drastically reduced the time it took the FBPNN in convergence for both training and testing. The modified data sets used for testing the OPCA + FBPNN showed varying degrees of accuracies with the various level of modifications of the data sets, these are shown in Figures 7 and 8.

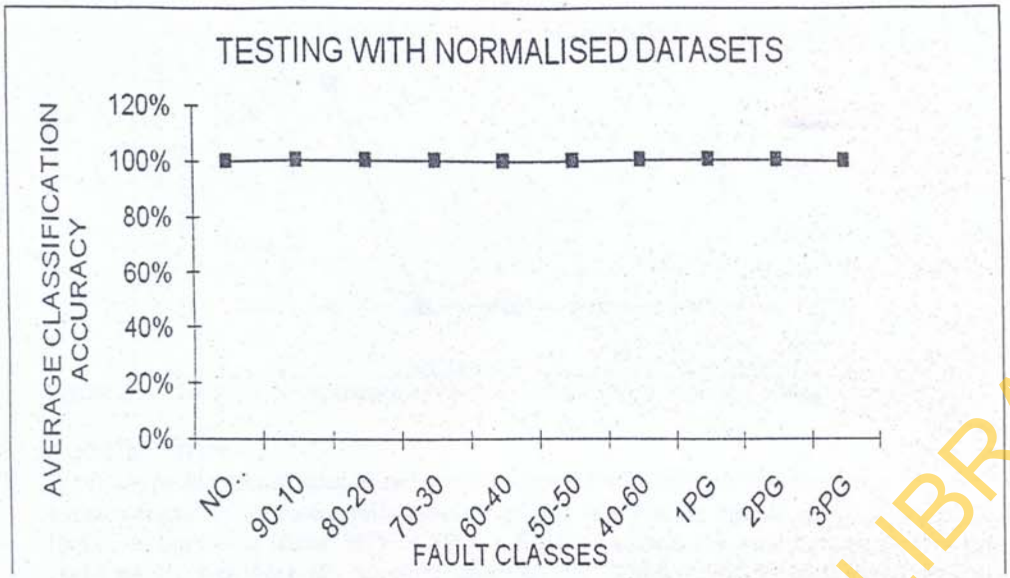

Figure 6: Classification Accuracy of OPCA + FBPNN on Original Engine Data Sets

In Figure 7, the average classification accuracies for testing data sets modified at tail end interval were 80%, 80%, 70%, 40% and 40% respectively for modification levels from 10% - 50%. The average classification accuracies for testing data sets modified at random intervals were 60%, 60%, 60%, 30% and 30% respectively for modification levels from 10% - 50%.

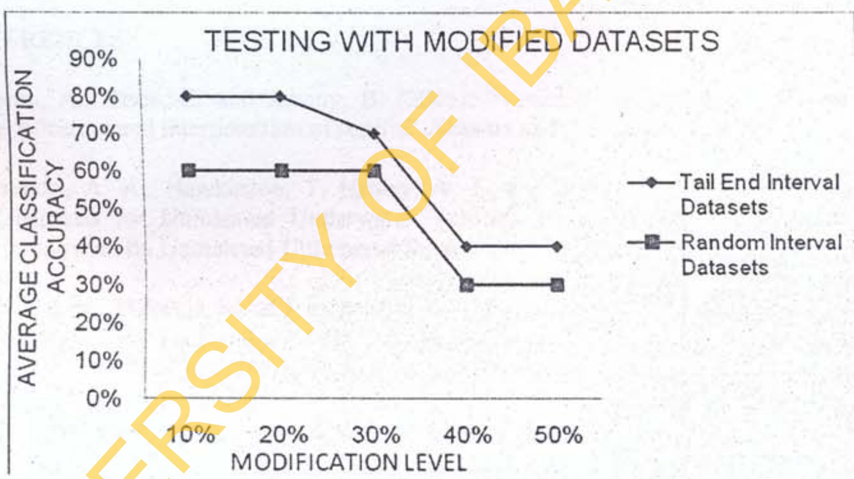

Figure 7: Average Classification Accuracy of OPCA + FBPNN on Modified Data Sets

Figure 8 shows the average classification accuracy of OPCA + FBPNN algorithm in the presence of odd and even numbered sensor failure. The total number of sensor used was ten and were numbered serially from 1 to 10. The arrangement of the sensors is as follows: TGS813a, TGS816, TGS813b, TGS5042, TGS2104a, TGS2104b, TGS2201a, TGS2201a, TGS822 and TGS2602. The results obtained from odd numbered sensors failure showed that when 10% failure level in sensors occurred (TGS813a was assumed to be faulty), the average classification accuracy was 70%. When the failure level in odd numbered sensors was increased to 20% to 50%, none of the fault conditions was identified correctly. Testing with even numbered sensors failure showed average classification accuracies of 0% for all modification levels. The import of these results is that all the sensors were contributing to the data sets and a failure of one sensor will greatly affect the performance of the algorithm. All the sensors used were fully or partly sensitive to the exhaust gases components.

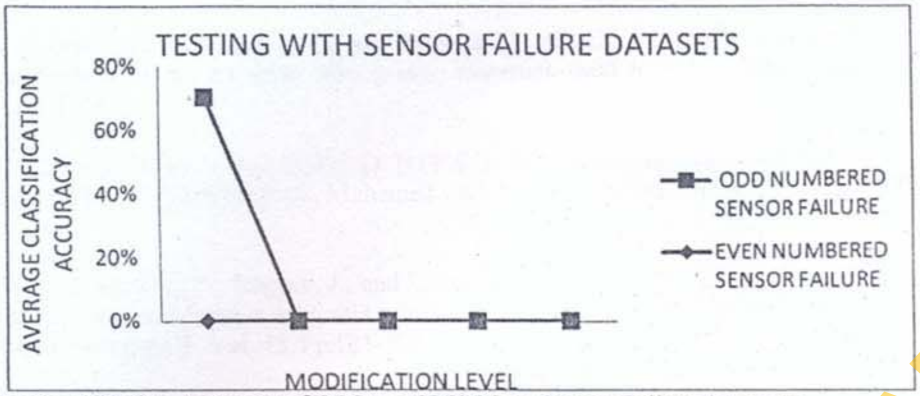

Figure 8: Classification Accuracy of OPCA + FBPNN on Sensor Failure Data sets

CONCLUSION

A prototype electronic nose based condition monitoring system was employed to obtain smell prints of the exhaust fumes of an automobile gasoline engine in different operating conditions to diagnose ignition and loss of compression faults. FCM, OPCA + FBPNN algorithms were used to analyse the collected data. The faults considered were all classified correctly by OPCA + FBPNN algorithm with 100% accuracy. The results from FCM algorithm showed that the data sets acquired from the prototype electronic nose based condition monitoring and diagnosis scheme were true representations of the fault conditions investigated. The performances of OPCA + FBPNN algorithm based on random variations of the data sets gave 80% and 60% average classification accuracy on modification level of 10%-20% of the tail end interval and random interval data sets respectively. The failure of more than one sensor will drastically affect the performance of the algorithm. It is concluded that, these results show the possibilities of using electronic nose in fault diagnosis of the selected automobile engine faults.

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