Journal of Computer Science and Its Applications, December 2009, Vol. 16,

A FRAMEWORK FOR ELECTRONIC NOSE BASED CONDITION MONITORING AND DIAGNOSIS OF AUTOMOBILE ENGINE FAULTS

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ABSTRACT

A framework for condition monitoring approach that uses the sense of smell was investigated to diagnose the faults of plug-not-firing, loss of compression and carburettor faults from the exhaust fumes of gasoline fuelled automobile engine.

An electronic nose based condition monitoring hardware and software was developed using the framework to obtain smell prints that correspond to normal operating conditions and various induced abnormal operating conditions.

Fuzzy C-means and K means clustering were used as exploratory data visualization tools to ascertain if the obtained smell prints from the developed system could characterize the faults considered.

The results of exploratory cluster analysis showed that the obtained smell print could typify the faults considered.

Key words: Electronic nose, condition monitoring, automobile engine, fault diagnosis, cluster analysis.

1.0 INTRODUCTION

The efficiency of every machine, equipment or system is of great concern to both the manufacturer and the end user [5]. Condition Monitoring (CM) is defined as 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 [10]. It can be used to appraise the current state and estimate the future state of equipment, using real time measurements and calculations. Reference [3] pointed out that a contributing factor in providing condition is the use of CM techniques. Its 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 [11]. CM techniques have been applied in various fields for the purpose of fault detection and isolation. Vibration measurements were also carried out with single and multiple sensors on 35kW induction motor for the purpose of fault identification of the motors as reported by [11]. Reference [1] reported the use of

CM 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. Reference [13] developed a CM based diesel engine cooling system model. The developed model was experimented on a real life diesel engine powered electricity generator to simulate various faults such as fan fault, thermostat fault and pump fault.

Electronic noses are technology implementation of systems that are used for the automated detection and classification of odours, vapours and gases [6]. Electronic nose utilizes an instrument, which comprises two main components; an array of electronic chemical sensors with partial specificity and an appropriate pattern-recognition system, capable of recognizing simple or complex odours [6]. These two main components can be further divided into six functional blocks, as shown in Fig. 1, namely; odour handling and delivery system, sensor array chamber, signal conditioning, data acquisition, signal processing and intelligent pattern recognition.

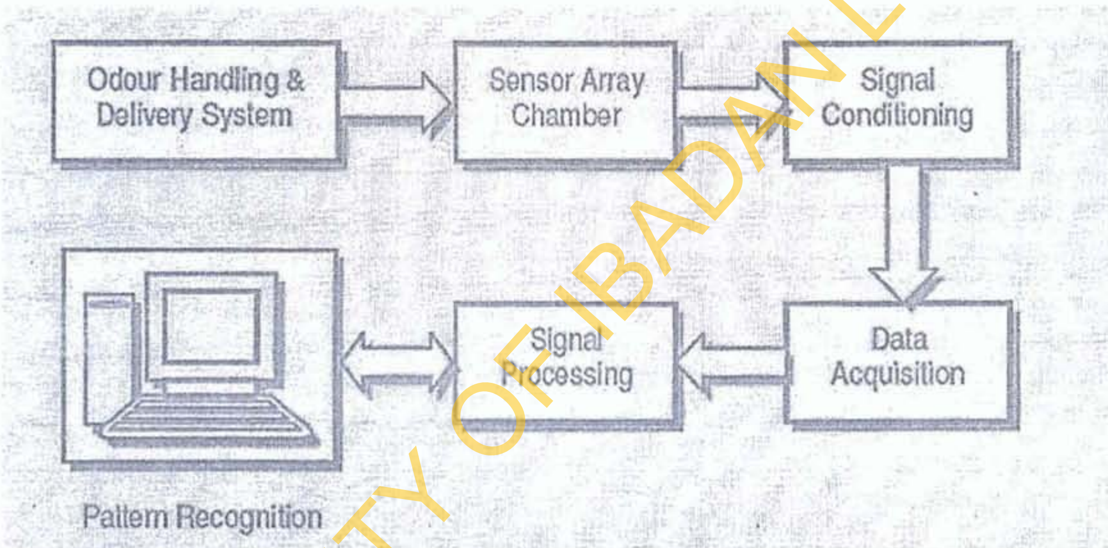


Figure 1: Functional Units of an Electronic Nose System

The first three blocks namely; odour handling and delivery system, sensor array chamber and signal conditioning provide the variations in all electronic nose implementations because of the nature of odour producing analyte that could be solid, liquid or gaseous [2]. Labels C, D and E in Fig. 1 can be called the hardware interface between the array of electronic chemical sensors and the pattern-recognition system.

Reference [7] reported the use of electronic nose for the discrimination of odours from trim plastic materials used in automobiles. Electronic nose was applied to quantify the amount of carbon monoxide and methane in humid air [9]. A method for determination of the volatile compounds present in new and used engine lubricant oils was reported by [12]. The electronic nose sensor array was able to correlate and differentiate both the new and the used oils by their increased mileages. Reference [8] 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) [8]. The results obtained showed that the electronic nose sensors were adequate to monitor different aspect of the engine's exhaust chemical components qualitatively. One of the drawbacks of non-pervasive use of the technology is the high acquisition cost.

In this study, we investigated the development of a low cost electronic nose based CM scheme that could be used to acquire the exhaust fume of gasoline powered engine for possible fault diagnosis and isolation.

2.0 METHODOLOGY

The system architecture for the development of electronic nose based CM scheme is shown in Fig. 2 consisting of both hardware and software material components. The hardware components consisting of array of chemical sensors that will sense the exhaust fumes and data acquisition system to capture exhaust characteristics (data) of automobile engine in normal operating conditions and various induced abnormal operating conditions. Software components consisting of pattern recognition algorithms were used to extract useful features from the raw data obtained from the array of sensors and data acquisition system, and to predict some induced faults.

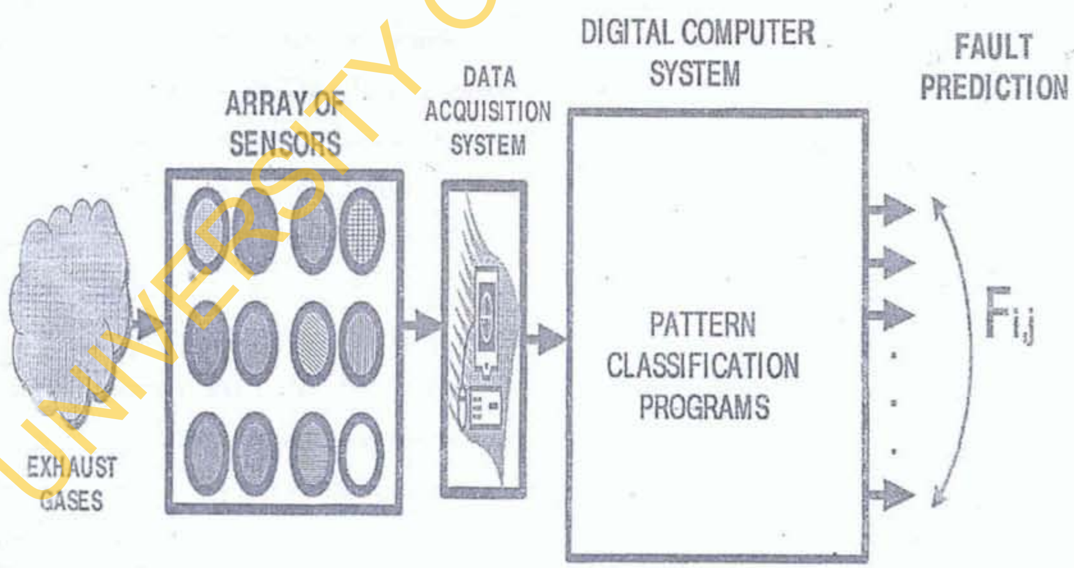


Figure 2: An Overview of the System Architecture

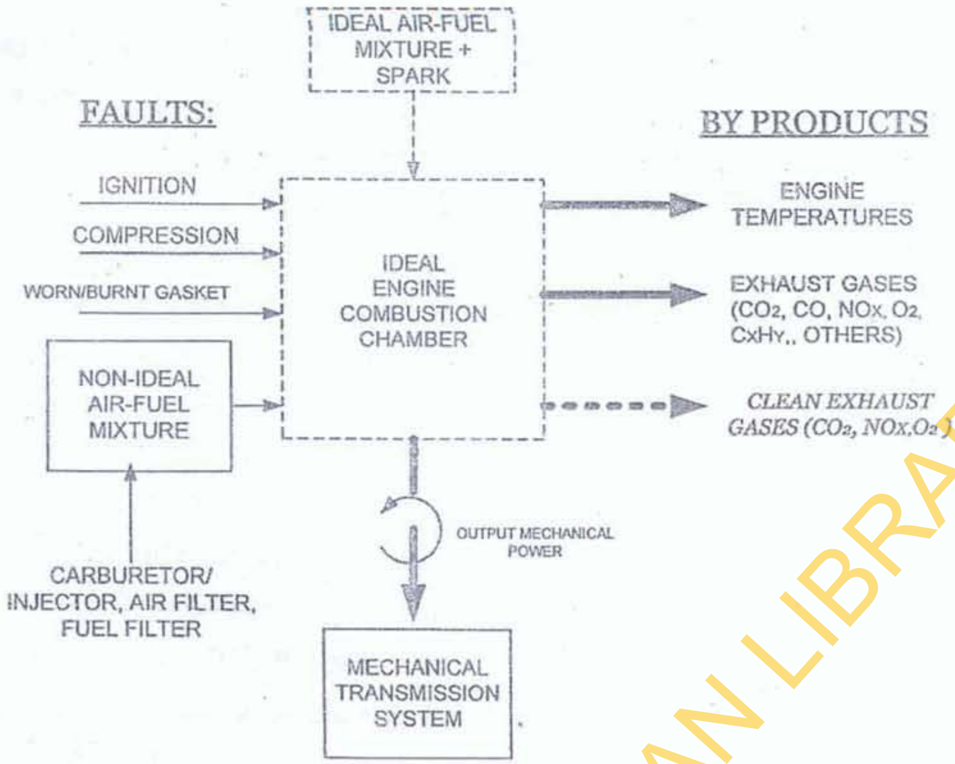


Figure 3: Automobile Engine Fault Model

An automobile gasoline powered engine fault model that takes into consideration major faults that could arise in an automobile gasoline engine with reference to the combustion chamber is proposed as shown in Fig. 3. The model consists of ideal combustion chamber; ideal air-fuel mixture and ignition spark which produce clean exhaust gases as by-product. Other non ideal situations such as plug-not-firing fault, compression faults, gasket faults, carburetor faults were included in the model. Ideal situations were represented by broken lines and solid lines represented non ideal situations. The model provided better and simplified operations of a combustion chamber of automobile engine in relation to faults.

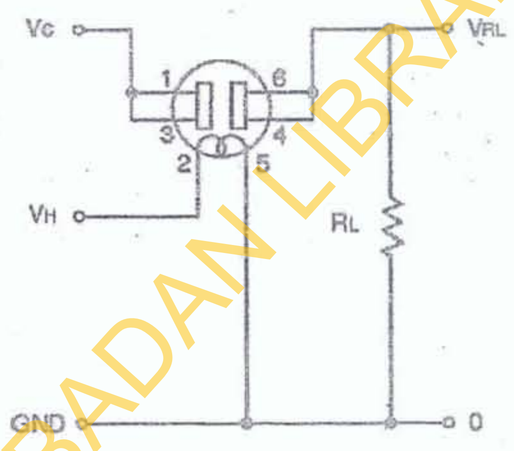
(a) The Hardware Components

The hardware materials consisted of chemical sensors, data acquisition system and some integrated and discrete electrical components. The hardware compo-nents that made up the system architecture in Fig. 2 are described as follows.

(b) Chemical Sensors

This section gives brief description of the gas sensors used in this work and their specifications. Semiconductor metal oxide chemo resistive chemical sensors type were used because they are quite sensitive to combustible materials such as alcohols and combustion gases but are less efficient at detecting sulphur or nitrogen based odours. The sensitivity of this type of sensor is quite good. They are relatively resistant to humidity and to ageing, and are made of strong metals. These sensors are cheaper but relatively consume more power than other sensors. Other popular sensor types are quartz-resonator sensors and conducting polymer sensors. Figaro's chemical sensors 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 CO_2, N_2, NOx, CO, un-combusted H_xC_y, and some other gases such as H_2, methane, ethanol and benzene. TGS 813: It is a general-purpose sensor that could be used to detect a wide range of combustible gases. The major sensing element is a tin oxide semiconductor that has a low conductivity in clean air with a nylon 66 base.

The electrical specifications are summarized in the Table 1. When the sensor is connected as shown in the basic circuit in Figure 4, the output across the load resistor (V_{RL}) increases as the sensor's resistance (Rs) decreases, depending on gas concentration. The circuit diagrams for all TGS8XX are the same and similar for other series. The product information for the other chemical sensors is obtainable from the manufacturer (www.figarosensors.com).



LEGEND
PINS 1 & 3: Sensor Positive Electrodes
PINS 4 & 6: Negative Electrodes
PIN 2: Heater Positive Terminal
PIN 5: Heater Negative Terminal

Figure 4: Circuit Diagram of TGS 813 Sensor

Table 1: Electrical Specifications of TGS 813 Sensor

Item	Symbol	Rated Value	Remarks
Heater Voltage	Vh	5.0±0.2	ac or dc
Circuit Voltage	Vc	Max. 24V	dc only Ps≤ 1.5Mw
Load Resistance	Rl	0.45KΩ min	Variable
Sensor resistance	Rs	5kΩ – 15 kΩ	Methane at 1000ppm/air
Change in ratio of sensor resistance	Rs/Ro	0.60±0.05	Rs (Methane at 3000ppm/air) / Rs (Methane at 1000ppm/air)
Heater resistance	Rh	30.0±3.0Ω	At room temperature
Heater power consumption	Ph	835mW (typical)	Vh = 5.0V

(c) Data Acquisition System

A data logger is an electronic device that is used to record various measurements whether analogue or digital over time. By connecting suitable sensors, data acquisition board can be used to measure temperature, pressure, relative humidity, light, resistance, current, power, speed, vibration and so on. Pico's data acquisition system ADC-11 was used in this study *(www.picotech.com)*. It provided maximum of 11 channels of analogue input and produced digital output signals which were eventually stored into the personal computer (PC) via the universal serial bus (USB) ports for further analysis.

(d) The Computer System

A PC with Pentium IV 1.3 GHz Intel processor board was used to store digital data collected by the Pico data acquisition system.

(e) The Hardware Configuration

All the hardware components described earlier were connected to one another by soldering and where appropriate by insertion into appropriate slots to conform to the system architecture described in Fig. 2. The electrical characteristics of the interconnected hardware were fine tuned to achieve functioning hardware interface. Fig. 5 shows the picture of some hardware components interconnections. Ten Figaro chemical sensors were enclosed plastic chamber that contained the exhaust fumes: TGS 813A, TGS 816, TGS 813B, TGS 5042, TGS 2104A, TGS 2104B, TGS 2201A, TGS 2201B, TGS 822 and TGS 2602. The sensors' power supply pins were connected to the appropriate power supply units and the analog output of the ten sensors were connected to screw terminals of channels 1 to 10 on the data acquisition system. The data acquisition system was connected to the PC via the USB port. The developed hardware configuration for the electronic nose based CM scheme for fault diagnosis of automobile gasoline engine is shown in Figure 6.

(f) Software Components

K-Means (KM) and Fuzzy C-Means (FCM) data clustering algorithms were coded into programs using Matlab 6.5 programming environment and pattern recognition toolbox from PRTools [4] and STPRTools [14] in this work for unsupervised classification of the data samples obtained. The choice of Matlab was because of large collection of analysis toolboxes and good handling of multi-dimensional data.

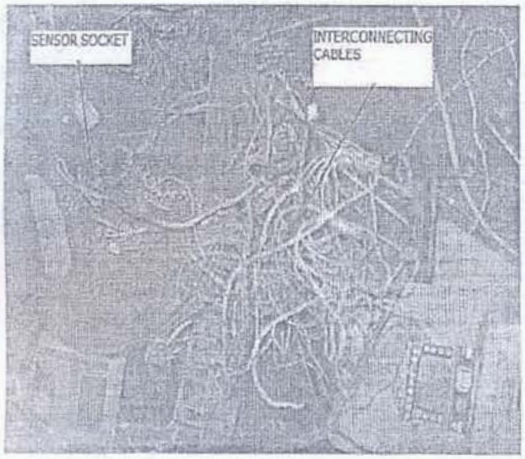


Figure 5: Picture Showing Interconnection of some Hardware Components

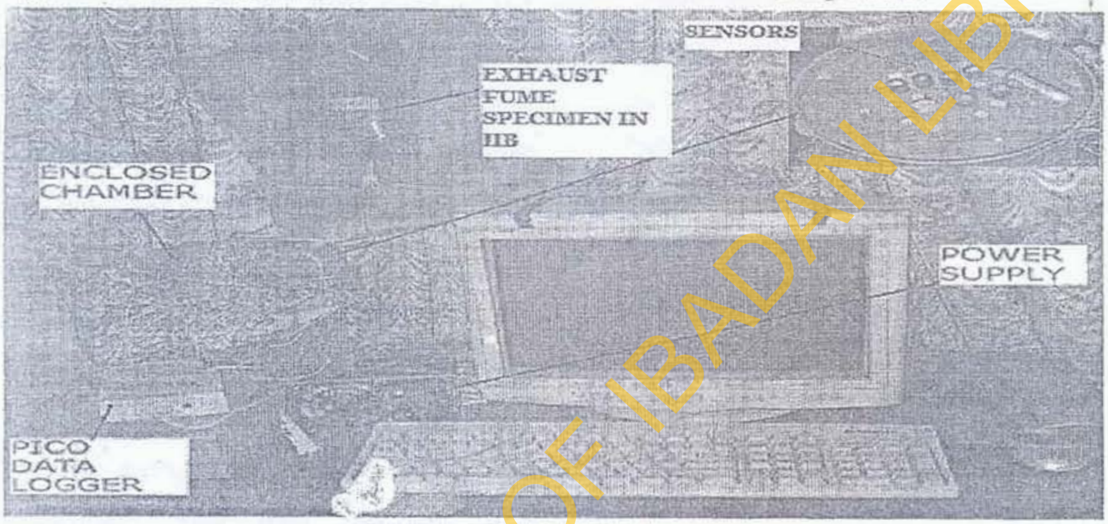


Figure 6: The Picture of the Developed Electronic Nose Based CM Scheme for Fault Diagnosis of Automobile Gasoline

3.0 DATA COLLECTION AND ANALYSIS

The developed system shown in Fig. 6 was used to collect exhaust fumes of the gasoline fuelled engine operating in various induced fault conditions. The exhaust fumes were obtained from the engine exhaust tail pipe in the absence of a catalytic converter as specimens into 1000ml Intravenous Injection Bags (IIB). Drip set was used to connect each of the IIB containing the exhaust gases to the confined chamber that contained the array of the selected Taguchi 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 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 system into the personal computer for storage and further analysis. 1400 x 10 data samples (1 dataset) for each of the ten (10) fault classes making a total of 14000 x 10 data samples (10 datasets) 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.

The ten (10) data samples corresponds to the following induced engine conditions 1st, 2nd, 3rd, 4th, 5th, 6th degree worn ring, one-plug-not firing, two-plug-not firing and three-plug-not firing faults and normal engine conditions. The data samples were normalized using fractional difference model: $\Delta R = (R - R_0) / R_0$ where R is the response of the sensor to the exhaust gas, and R_0 is the baseline reading of the sensor, the reference gas was air at room temperature. Further normalization 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 normalized data samples were used as input for the two data clustering algorithms namely FCM and KM algorithms.

4.0 RESULTS AND DISCUSSION

The results of clustering analysis carried out on the datasets are shown in Figure 7 and Figure 8. Figure 7 shows the results of KM clustering algorithms on the test bed engine. Fig. 8 shows the results of FCM clustering algorithms on the test bed engine. The results of KM clustering algorithm shows that most of the data fall into natural groupings except a few cases. Two cases of cluster center overlap were recorded, namely (*case 1*) overlap of two plugs-not firing and three plugs-not firing faults, and (*case 2*) 4th and 5th degrees worn piston ring faults. All other faults have clear cluster centers. The results of FCM clustering shows that most of the data fall into distinct grouping and there are clear boundaries. The use of two cluster algorithms was to ascertain how well represented were the data obtained from the developed system in relation to the engine conditions investigated. The obtained data was well represented by the results from the two clustering algorithm taking into consideration their membership properties. FCM assigns each data point into clusters with some probability of belonging while KM clustering assigns data points to exactly one cluster.

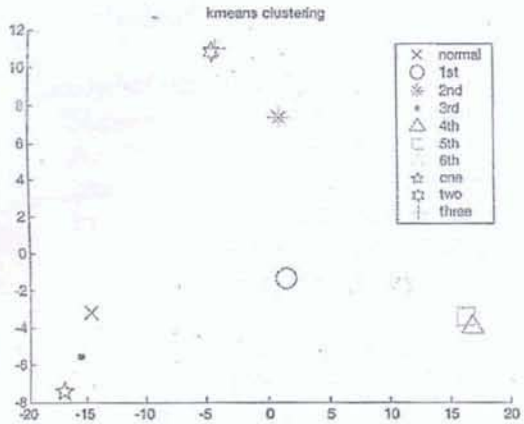


Figure 7: KM Clustering Diagram for the Engine Datasets

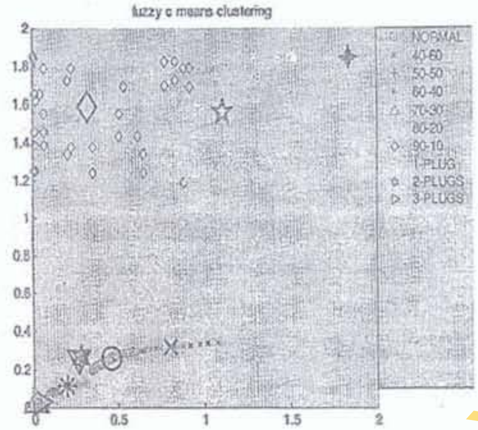


Figure 8: FCM Clustering Diagram for the Engine Datasets

5.0 CONCLUSION

A framework for the development of a low cost electronic nose based CM scheme for the acquisition of exhaust fumes of gasoline powered engine for possible fault diagnosis and isolation was investigated. The results showed that the data samples acquired with the developed system were good representations of the normal and induced faults conditions investigated. A good distance based classifier or artificial neural network model could be used on the smell prints acquired by the developed CM scheme. In conclusion, the developed system provides a framework for low cost electronic nose based system for diagnosis of exhaust related faults such as worn piston ring faults and plug-not-firing faults in gasoline fueled engine. The developed system could be extended to other odour based classification.

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