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ABSTRACT
The efficiency and effectiveness of every equipment or system is of paramount concern to both the manufacturers and the end users, which necessitates equipment condition monitoring schemes. Intelligent fault diagnosis system using pattern recognition tools can be developed from the result of the condition monitoring. A prototype electronic nose that uses array of broadly tuned Taguchi metal oxide sensors was used to carry out condition monitoring of automobile engine using its exhaust fumes with principal component analysis (PCA) as pattern recognition tool for diagnosing some exhaust related faults. The results showed that the following automobile engine faults; plug-not-firing faults and loss of compression faults were diagnosable from the automobile exhaust fumes very well with average classification accuracy of 91%.

Key words: Electronic nose, Condition Monitoring, Automobile, Fault, Diagnosis, PCA.

1. INTRODUCTION

The engine is one of the most critical and complex sub-systems in the automobile. It is more prone to fault because of its electromechanical nature. It has been shown that early detection of the malfunctions and faults in automobiles 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, 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 when employed with intelligent pattern recognition tools.

Condition monitoring consists of methods 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 [11]. It can be used to appraise the current state and estimate the future state using real time measurements and calculations. Reference [6] pointed out that a contributing factor in providing ongoing assurance of acceptable plant condition is the use of condition monitoring 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 [5]. Its techniques have been applied in various fields for the purpose of fault detection and isolation. Reference [17] developed a condition monitoring based diesel engine cooling system model.

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. Reference [1] used micro-acoustic viscosity sensors 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. Electronic noses are technology implementation of systems that are used for the automated detection and classification of odours, vapours and gases [3].

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 [3]. 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 [16]. Reference [7] reported the use of electronic nose for the discrimination of odours from trim plastic materials used in automobiles. Reference [9] used electronic nose to quantify the amount of carbon monoxide and methane in humid air. A method for determination of the volatile compounds present in new and used engine lubricant oils was reported by [15].

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. In [3], electronic nose-based condition monitoring scheme consisting of array of broadly tuned Taguchi metal oxide sensors (MOS) was used to acquire and characterize the exhaust fume smell prints of three gasoline-powered engines operating under induced faults. 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 (O_2) sensor. The results obtained showed that the electronic nose sensors were adequate to monitor different aspect of the engine's exhaust chemical components qualitatively.

In this present study, a prototype of an electronic nose-based condition monitoring scheme using array of ten broadly tuned Taguchi metal oxide sensors (MOS) was used to acquire the exhaust fume of a gasoline-powered engine operating with induced faults. The acquired exhaust fume data were analysed by PCA to diagnose some exhaust related faults.

2. MATERIALS AND METHOD

2.1 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. Fig. 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.

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].

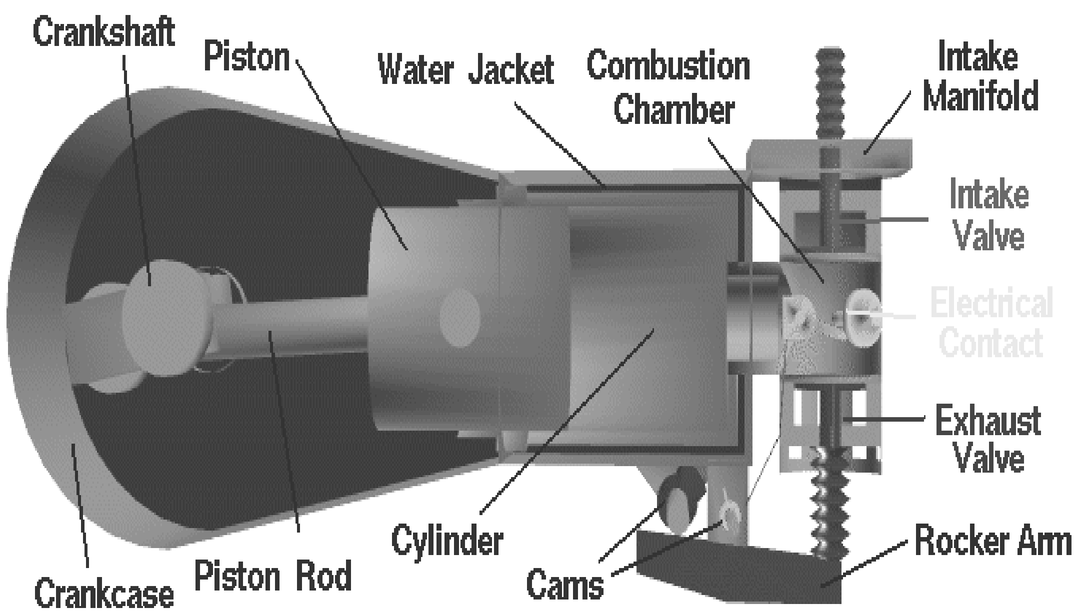

Fig. 1: Basic parts of an internal combustion engine [13]

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
3.

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, CO2, 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, CO_2 is an excellent indicator of efficient combustion: The higher the CO_2 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 a test bed automobile engine. Table 1 gives the specification of the engine, while Fig. 2 shows the snapshot of the test bed engine 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.

Fig. 2: Snapshot of the Gasoline Fuelled Engine

Table 1: The 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

2.2 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 chemo resistive sensors, quartz-resonator sensors and conducting polymers. Semiconductor metal oxide chemo resistive 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 [4]**.** 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].

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 CO2, N_2, NOX, CO, uncombusted H_xC_y, and some other gases such as H_2, methane, ethanol, benzene.

2.3 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 are plug-not-firing faults and worn piston ring (loss of compression).

(a) 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 the one-plug-firing, two-plug-firing and the three-plug-firing faults. The faults were inducted into the engines by removing the cables connected to the spark plugs one after the other.

(b) 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 degree of wearing of the piston ring which adversely affect the efficiency of the engine.

2.3 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). 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 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 in the first instance and were designated as training datasets.

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 baseline reading was taken as the unknown fault data. These measurement procedures were repeated five more times to have five samples for each fault class as testing datasets. 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.

2.4 Data Analysis

Principal Components Analysis (PCA) is a technique of linear statistical predictors that has been applied in various fields of sciences especially in process applications [18]. The primary objectives of PCA are data summarization, classification of variables, outlier detection and early indication of abnormality in data structure. PCA has been successfully applied to reduce the dimensionality of a problem by forming a new set of variables. PCA seeks to find a series of new variables in the data with a minimal loss of information [5].

Let X = x_1, x_2, x_3 …………, x_m be an m-dimensional observation vector describing the process or machine variables under consideration. A number of observation vectors (obtained or measured at different times) constitute data matrix X. The PCA decomposes the data matrix, X, as

$$X = TP^T = t_1 p_1^T + t_2 p_2^T \,.......+ t_m p_m^T = \sum_{i=1}^{m} t_i p_i^T \qquad (1)$$

Where P_i is an eigenvector of the covariance matrix of X. P is defined as the Principal Components (PC) loading matrix and T is defined to be the matrix of PC scores. The loading provides information as to which variables contribute the most to individual PCs. That is, they are the coefficients in the PC model, whilst information on the clustering of the samples and the identification of transition between different operating conditions is obtained from the score. PCA transforms correlated original variables into a new set of uncorrelated variables using the covariance matrix or correlation matrix [18].

The expectation from conducting PCA is that the correlation among the original variables is large enough that the first few new variables or PCs account for most of the variance [5]. If this holds, no essential insight is lost by applying the first few PCs for further analysis and decision making. If the original variables are collinear, k PCs (k ≤ m) will explain the majority of the variability [5]. In general, k will normally be much smaller than the number of variables in the original data. Consequently, it is desirable to exclude higher-order PCs and retain a small number of PCs.

Equation (1) can then be expressed as

$$X = TP^T + E = \sum_{I=1}^{K} t_i p_i^T + E \qquad (2)$$

Where E represents residual error matrix [19]. For instance, if the first three PCs represent a large part of the total variance, the residual error matrix will be:

$$E = X - \left[t_1 p_1^T + t_2 p_2^T + t_3 p_3^T \right] \qquad (3)$$

Typically, in the literature, it is emphasized that the first few PCs contain all the important information [5]. In this study, the singular value decomposition (SVD) technique was used to implement the PCA. In SVD, data matrix X is decomposed into three products by the following equation

$$X = U \lambda P^T \qquad (4)$$

where U are Eigenvectors, λ are Eigen values and P^T is the loading matrix. The main virtue of SVD is that all three matrices are obtained in one operation without having to obtain a covariance matrix as in conventional PCA method [5].

Loading matrices obtained in this method were used to establish the initial PCA models of the system which were based on normal condition and faulty condition data. New observations (measurements) PCA models were projected onto the initial PCA models. Discrepancy or residual between the initial PCA models and new measurement PCA models were detected by calculating the Euclidean distances of the new observations PCA models to initial PCA models.

The new measurement was classified as any of the existing PCA models with the minimum Euclidean distance or as unknown fault. Eleven initial PCA models were created from the training datasets collected. These PCA models corresponded to the following engine conditions 1st , 2nd, 3rd, 4th, 5thand 6th degree worn ring, one-plug, two-plug, three-plug, and unknown faults, normal conditions.

Five different PCA models were developed for each engine condition from the testing datasets.

3. RESULTS AND DISCUSSION

This study was conducted with various numbers of faulty conditions and normal datasets with each condition having its own developed PCA model. The first ten PCs were used for the purpose of fault classification using euclidean distance metric for to discrimination between PCA models obtained from the training datasets and the testing datasets.

Table 2 shows the summary of results of testing the new PCA models against initial PCA models. In Table 2, the number in the squared brackets represents the fault number while the number of times classification was done is shown in bold typeface. Testing of each fault class was done five times.

Results of testing of the PCA models with new data samples Compression fault with 1st degree worn ring was classified correctly four out of five times and was incorrectly classified once as compression fault with 3rd degree worn ring. One plug bad fault and compression faults with 4th and 6th degree worn ring were also not classified correctly during the testing.

Compression faults with 2nd, 3rd, 5th degree worn ring, one-plug-not-firing fault, two-plugs-not-firing fault, unknown fault and normal condition were correctly classified five out five times. Out of 55 testing samples, 5 were inaccurately classified while 50 were correctly classified.

The average classification accuracy of 91% was achieved from the testing. Out of the five inaccurately classified classifications, three were classified as a subset of the same fault class while the other two were truly misclassified to wrong classes as shown in Table 2

Table 2: Results of testing of the PCA models with new data samples

Data sample	Classification [1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]
Compression fault With 1st degree worn ring [1]	4	0	1	0	0	0	0	0	0	0	0
Compression fault With2nd degree worn ring [2]	0	5	0	0	0	0	0	0	0	0	0
Compression fault With 3rd degree worn ring [3]	0	0	5	0	0	0	0	0	0	0	0
Compression fault With 4th degree worn ring [4]	1	0	0	3	0	0	0	0	0	1	0
Compression fault With 5th degree worn ring [5]	0	0	0	0	5	0	0	0	0	0	0
Compression fault With 6th degree worn ring [6]	0	0	0	0	0	4	0	0	0	1	0
One-plug-not-firing fault [7]	0	0	0	0	0	0	5	0	0	0	0
Two-plug-not-firing fault [8]	0	0	0	0	0	0	0	5	0	0	0
Three-plug-not-firing fault [9]	0	0	0	0	0	0	0	1	4	0	0
Unknown engine fault [10]	0	0	0	0	0	0	0	0	0	5	0
Normal engine [11]	0	0	0	0	0	0	0	0	0	0	5

4. CONCLUSION

An electronic nose-based condition monitoring scheme prototype comprising of ten broadly tuned Taguchi metal oxide sensors (MOS) was used to acquire the exhaust fume of a gasoline-powered engine operating with induced faults. The acquired exhaust fume data were analysed by PCA to diagnose the exhaust related faults.

The testing of the PCA algorithm on the exhaust fume data showed a good performance with regards to automobile engine fault diagnosis. The developed system is capable of classifying the plug-not-firing faults and worn piston ring faults from the exhaust fumes very well

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