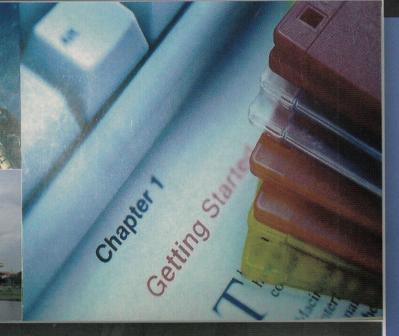
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SECTION 3

DEPARTMENT OF INFORMATICS FACULTY OF INFORMATION TECHNOLOGY INSTITUT TEKNOLOGI SEPULUH NOPEMBER











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ELECTRONIC NOSE FOR DETECTING OF PURE-GASOLINE

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ABSTRACT

Gasoline is the main fuel for all almost vehicles. The pure gasoline is important to keep vehicle operating. Unfortunately there is a bad behavior in our society that mixes gasoline with another material. Of course it will contaminate gasoline and destroy the machine. For a long time (until now) test of pure gasoline has been conduct only at laboratory, because it is not a simple procedure and the cost is so expensive. The samples are collected from everywhere, and then it is brought to the laboratory. This method is not efficient. The device that can detect pure gasoline quick and efficient is needed.

In this paper, will be proposed *Electronic* Nose that can distinguish pure gasoline from impure gassoline. This device will sense gasoline, then gives output about its status, whether pure or not. Electronic Noses are electronic device that have ability likes human nose. These device is typically array of sensors used to characterize complex samples. Arrays of sensor in these device is arrays of 4 gas sensors. The data generated by each sensor are processed by a neural network algorithm. Perceptron model is chosen, because it needs only two condition output, pure and impure gasoline. The neural network algorithm was run using PC. Asembly (microcontroller software), Matlab, and Visual Basic Language programming were used in this system.

From the experiments can be concluded that the system has been work properly with 90% accuracy. Hope that the system can give solution to ensure gasoline purity problem in our society.

Keywords: Electronic Nose, Neural Network, Array Sensor.

INTRODUCTION

Gasoline is the main fuel for all almost vehicles. The pure gasoline is important to keep vehicle operating. Unfortunately there is a bad

behavior in our society that mixes gasoline with another material. Of course it will contaminate gasoline and destroy the machine. For a long time (until now) test of pure gasoline has been conduct only at laboratory, because it is not a simple procedure and the cost is so expensive. The samples are collected from everywhere, and then it is brought to the laboratory. This method is not efficient.

The impure gasoline will harm our society. The vehicle will damage quickly. On the other hand it will increase emission of CO, finally it will destroy the environment.

On this paper will be proposed 'Electronic Nose', an electronic device that has behavior like human nose, for smelling impure gassoline. Two main component of Electronose are array of chemical sensor and artificial neural network.

2 MODEL, ANALYSIS, DESIGN, AND IMPLEMENTATION

The two main components of an electronic nose are the sensing system and the automated pattern recognition system.

The sensing system can be an array of several different sensing elements (e.g., chemical sensors), where each element measures a different property of the sensed chemical, or it can be a single sensing device (e.g., spectrometer) that produces an array of measurements for each chemical, or a combination of both. Each chemical vapor that attached to the sensor array produces a signature or pattern characteristic of the vapor. By feeding many different chemicals to the sensor array, we can built a database of signatures. This database of labeled signatures is used to train the pattern recognition system. The goal of this training process is to configure the recognition system to produce unique classifications of each chemical so an automated identification can be implemented.

The quantity and complexity of the data, that collected by sensors array, can make conventional

chemical analysis of data in an automated fashion difficult. One approach to chemical vapor identification is to build an array of sensors, where each sensor in the array is designed to respond to a specific chemical. With this approach, the number of unique sensors must be at least equal to the number of chemicals that will be monitored. It is expensive and difficult to build a highly selective chemical sensor.

2.1 Development Of Sensor

A chemical sensor is a device which give responds to a particular analyze in a selective way, that means of a reversible chemical interaction and can be used for the quantitative or qualitative determination of the analyses. All sensors are composed of two main regions: the first is where the selective chemistry occurs and the second is the transducer. The transducer allows the conversion of energy from one form to another. The chemical reaction produces a signal such as a color change, fluorescence, production of heat or a change in the oscillator frequency of a crystal (Cattrall, 1997).

Several categories of transducers are available and these include:

- Electrochemical, such as ion-selective electrodes (ISE), ion-selective field effect transistors (FET), solid electrolyte gas sensors and semiconductor based gas sensors.
- Piezoelectric, e.g. surface acoustic wave (SAW) sensors. Piezoelectric materials are sensitive to changes in mass, density or viscosity and, therefore, frequency can be used as a sensitive transduction parameter (Hall, 1990). Quartz is the most widely used piezoelectric material because it can act as a mass-to-frequency transducer.
- 3. Optical, such as optical fibers, as well as the more traditional absorbance, reflectance, luminescence and Surface Plasmon Resonance (SPR) techniques.
- 4. Thermal systems, in which the heat of a chemical reaction involving the analyze is monitored with a transducer such as a thermistor.

For special purpose, Electronic nose, the following sensors have been developed:

1. Catalytic or tin oxide sensor: A commercially available Taguchi Gas Sensor (TGS) can be and widely used as the core-sensing element in array based odor detectors. This consists of an electrically heated ceramic pellet upon which a thin film of tin (II) oxide doped

with precious metals is deposited. Tin (II) oxide is an n-type semiconductor and when oxygen adsorbs on the surface, one of the negatively charged oxygen species is generated depending on the temperature. This result in the surface potential becoming increasingly negative and the electron donors within the material become positively charged. When an oxidizable material comes into contact with the sensor surfaces the adsorbed oxygen is consumed in the resulting a chemical reaction. This reduces the surface potential and increases the conductivity of the film. Several recent developments with tin oxide detectors have led to further advantages over the Taguchi sensor, which generally requires high power consumption and high temperatures. These include the fabrication of thin-film (II) oxide arrays using planar microelectronic technology leading to reduced size and lower power use, the production of thin-film sensors by chemical vapor deposition and the use of screen printing to make thick-film sensors.

- Conducting polymer sensors: Many other materials conducting are semiconducting) and show a variation in conductivity. Conducting polymers are very popular in the development of gas and liquid-phase sensors with poly pyrrole and poly aniline being the favored choices. Materials used to make conducting polymers tend to have some common features, including the ability to form them through either chemical or electrochemical polymerization and the ability to change their conductivity through oxidation or reduction. Conducting polymers are being widely used as odor-sensing devices, for several major reasons, there are:
 - a. the sensors display rapid adsorption and desorption phenomena at room temperature;
 - b. power consumption is low;
 - c. specificity can be achieved by modifying the structure of the polymer;
 - d. they are not easily inactivated by contaminants;
 - e. they are very sensitive to humidity.
- 3. Acoustic wave sensors: AT-cut quartz crystals (+35_15¢ orientation of the plate with respect to the crystal plane) are favored as piezoelectric sensors because of

their excellent temperature coefficients. The type of acoustic wave generated in piezoelectric materials is determined by the crystal cut; thickness of the material used and by the geometry and configuration of the metal electrodes employed to produce the electric field (Thompson & Stone, 1997).

MOSFET technology: In the 1970s, improvements in semiconductor technology led to the development of a FET. This is a very high impedance transistor and the most measurements of small potentials requiring very low current flows are made using this technology. In the FET, current flows along a semiconductor path called the channel, from one end that is called a source electrode. At the opposite end is the drain electrode. The effective electrical diameter of the channel can be varied by application of a voltage to a control or gate electrode. The conductivity of the FET depends on the electrical diameter of the channel. A small change in gate voltage leads to a large variation in current from the source to the drain. This allows the signal to be amplified. For the MOSFET, the thermal oxidation process used to form the silicon dioxide layer on the silicon surface of the device also forms a double layer, which can induce a conducting channel in the silicon substrate. In the MOSFET, the conducting channel is insulated from the gate terminal by a layer of oxide. Thus, there is no conduction even if a reverse voltage is applied to the gate. FET sensors can be operated both with and without a reference electrode.

2.2 Pattern Recognition System

In this research, pattern recognition will be done using an artificial neural network. Artificial neural network, like human brain, it is composed of billions of neurons and organizes them to perform certain functions. It learns through experience.

This system has a natural propensity for storing experiential knowledge and making it available for later use. It resembles the brain in two respects:

1. Knowledge is acquired by the network through a process called learning.

2. Interneuron strengths known as synaptic weights are used to store the knowledge.

The relationship between the brain and the artificial neural network can be described as figure 1 and 2 below.



Figure 1. Basic Human neuron

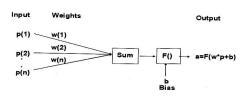


Figure 2. Basic processing unit of Artificial Neural Network

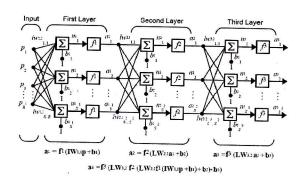


Figure 3. Multilayer Neural Network

Can be seen that the neural network neuron is very similar to the biological neuron of the brain. These neurons are usually grouped in layers, and the layers are grouped into networks.

When an Artificial neural networks (ANNs) is combined with a sensor array, the number of detectable chemicals is generally greater than the number of sensors. Also, less selective sensors which are generally less expensive can be used with this approach. Once the ANN is trained for chemical vapor recognition, operation consists of propagating the sensor data through the network. Since this is simply a series of vector-matrix multiplications, unknown chemicals can be rapidly identified in the field.

2.3 Analyze Contents Of Gasoline, Oil Of Diesel Engine And Kerosene

Recently, bad behavior of making impure gasoline was done by mixing pure gasoline with kerosene or mixing pure gasoline with oil of diesel engine. Therefore it is important to know from what contents of the impure gassoline is made.

In this research, Gasoline, oil of diesel engine, and kerosene are analyzed by chromatography analyzer.

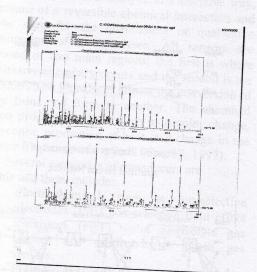


Figure 4, Chromatography analyzing of gasoline

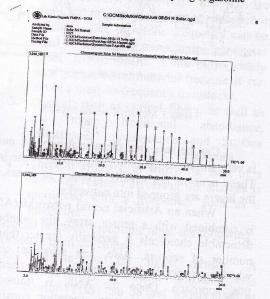


Figure 5, Chromatography analyzing of oil of diesel Engine

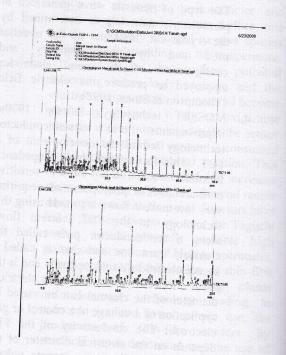


Figure 6, Chromatography analyzing of kerosene

2.4 Implementation

The basic schematic of an electronic nose for detecting impure gasoline can be viewed as follow:

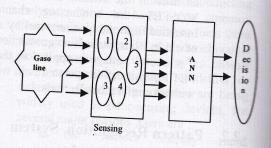


Figure 7. Schematic of an electronic Nose

The Sensors array will detect vapor of gasoline. Each chemical vapor that presented to the sensor array will produces a signature or pattern characteristic of the vapor. Array sensors used in this research are TGS 2620, TGS 2201, and TGS 2442. All of them are Figaro gas sensor. By presenting many different chemicals to the sensor array, a database of signatures is build. This database of labeled signatures is used to train the Artificial Neural Network. The goal of this training process is to configure the recognition system to

produce unique classifications of pure gasoline or impure gasoline.

In this research, An Electronic Nose are implemented to the PC. Output of the sensor array could not send to the PC directly, it is need an interfacing system.

The Model of artificial neural network in this system is multilayer feed forward. System has 3 layer, they are input layer (32 input), hidden layer (10 neuron), and output layer (1 neuron).

3 TESTING AND RESULT

Firstly the system must be trained. By presenting many different chemicals to the sensor array, a database of signatures is build. This database of labeled signatures is used to train the Artificial Neural Network. The goal of this training process is to configure the recognition system to produce unique classifications of pure gasoline or impure gasoline.

Graph of training process, until reach error smaller than 0,1 can be viewed in Figure 11.

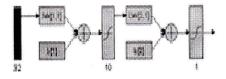


Figure 9. Design of Artificial Neural Network

From the figure can be seen that until 98 epochs, system could reach the goal (maximum error is 0,1). The next step, Electronic nose system was tested by giving variation of inputs to the system. According to the testing result, it can be concluded that system was running well. Validity of the system reach 98.2%.

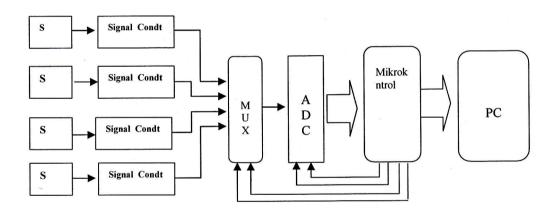


Figure.8 Interfacing PC of the electronic Nose

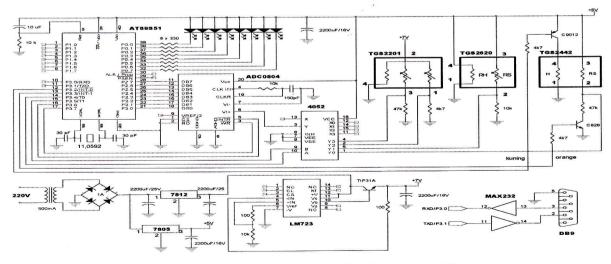


Figure 10, Electronic circuit of Electronic Nose Interfacing to the PC

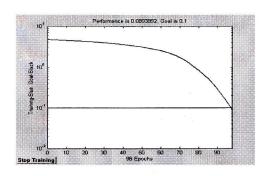


Figure 11. Training process

4 CONCLUSION

According to the testing result, It can be concluded that:

- 1. Electronic Nose is consisted of gas sensor array. Intelligent nerve of the system was implemented by artificial neural network algorithm.
- 2. Electronic Nose has knowledge, so it could classify variation of vapor/gas correctly.
- 3. Validity of the system reaches 98.2%.

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