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DEVELOPMENT OF AN EMBASSYED MULTI-SENSOR SYSTEM FOR THE DETECTION OF INCIPIENT FAILURES IN ELECTRIC TRANSFORMERS

DESARROLLO DE UN SISTEMA MULTISENSORIAL EMBEBIDO PARA DETECCIÓN DE FALLAS INCIPIENTES EN TRANSFORMADORES ELECTRICOS

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Abstract: The project is based on the development of an embedded system capable of detecting incipient volatile gases in electrical transformers, in order to detect each of the gases that are located there, detailed engineering must be applied for the acquisition and acquisition of data from the multisensory system, this by means of each of the tests that must be applied to the sensors that were used for the sampling, after having done this type of engineering, an algorithm must be performed to classify the acquired data by means of the multisensory system previously proposed and this in order to know what type of gas was detected for the respective classification of them, once each of the previously formulated steps has been achieved, a wireless system capable of providing the information is going to be implemented internal that is presented in real time in the transformer in order to make a constant monitoring for prevent future damages, and with this, implement maintenance systems, whether preventive or predictive, and thus avoid costs to the company responsible for maintaining and maintaining these elements of electrical distribution.

Keywords: Electronic Nose, Neural Network, PCA analysis.

Resumen: El trabajo de investigación se basó en la elaboración de un sistema embebido capaz de detectar gases volátiles incipientes presentes en los transformadores eléctricos. Para realizar la detección de cada uno de los gases que allí se localizan, se aplicó ingeniería de detalle para la toma y adquisición de datos provenientes del sistema multisensorial, esto por medio de cada una de las pruebas que se debe aplicar a los sensores que se utilizaron para la toma de muestras, luego de haber realizado este tipo de ingeniería, se realizó un algoritmo para clasificar los datos adquiridos por medio del sistema multisensorial anteriormente planteado y esto con el fin de saber qué tipo de gas se detectó para la respectiva clasificación de los mismos, una vez logrado cada uno de los pasos anteriormente formulados se implementó un sistema inalámbrico capaz de dar la información interna que se está presentado en tiempo real en el transformador con el fin de hacer un monitoreo constante para prevenir los daños futuros, y con esto implementar sistemas de mantenimiento bien sean preventivos o predictivos y así evitarle costos a la empresa encargada de dar manteniendo y buen funcionamiento a estos elementos de distribución eléctrica.

Keywords: Nariz Electrónica, Red Neuronal, Análisis PCA.

1. INTRODUCTION

Electronic noses have become one of the primary devices used in recent times for industrial processes and medical developments, (Prieto, 2012) for this reason, the present work investigates an analysis method for assessing the oil of electrical transformers using electronic noses, aiming to detect the types of faults occurring in these systems.

Currently, such oil analysis is conducted using specialized techniques such as gas chromatography, which is a method for separating components in a mixture of volatile compounds. In most cases, this separation is performed to identify and quantify each component in the sample (Jaimes, 2019). Based on the aforementioned, the novelty of this study lies in seeking alternative strategies to replace or at least complement gas chromatography with a parallel methodology. This approach is particularly relevant for analyzing the incipient gases present in electrical transformer oils. By implementing a multisensory system called an electronic nose, it would be possible to monitor the system in real time while the transformer is in operation, thereby preventing future failures and extending its service life.

“Transformer oil analysis is a proven preventive technique that should be part of any predictive maintenance program. Thanks to an early warning system, transformer oil analysis enables companies to identify maintenance priorities, plan work allocation schedules, and order the necessary parts and materials.” Considering that “The service life of insulating oil cannot be measured in time per se, as its degradation depends on operating conditions, transformer load regime, design, insulating oil composition, and the content of natural and/or synthetic inhibitors (García y Gaspar, 2010).

Regarding the state of the art in electronic noses used in the industry for gas detection, these devices have garnered significant global attention for their application in detecting and analyzing volatile compounds in various contexts (Correa et al., 2005). For example, the implementation and evaluation of an electronic nose for detecting linear alcohols (Paredes-Doig *et al.*, 2016), is one such application.

Another multisensory system used in this field is the electronic tongue (ET), which emulates the human tongue. Its primary objective is to operate under the same philosophy as sensory panels. These devices generate data on the global composition of the matrix through sensing. One advantage of this equipment is that it does not require highly qualified personnel, is cost-effective compared to standard equipment, is portable, and provides faster results (Durán Acevedo *et al.*, 2016).

2. MATERIALS AND METHODOLOGY

This section outlines each of the methods employed in the development of the study.

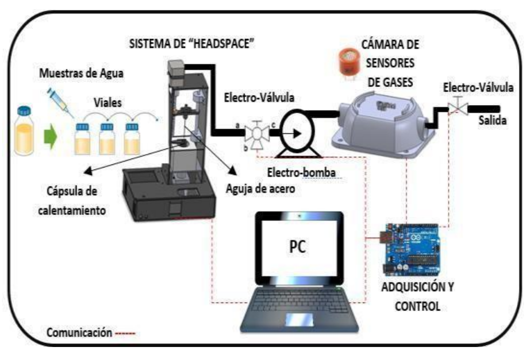

Fig. 1. General schematic of the implemented methodology. (Carrillo Gómez et al., 2019)

The aim of this research is to address the high costs associated with gas analysis using gas chromatography by employing an electronic nose. This device facilitates the application of headspace sampling as the process for extracting and analyzing the gases present. The electronic nose is capable of detecting gas concentrations and distinguishing between them through its gas chamber, using PCA (Principal Component Analysis) and the corresponding training of a neural network.

2.1 Headspace Sampling

(Muestreo de cabeza) designed and developed by young researchers at the University of Pamplona – Colombia.

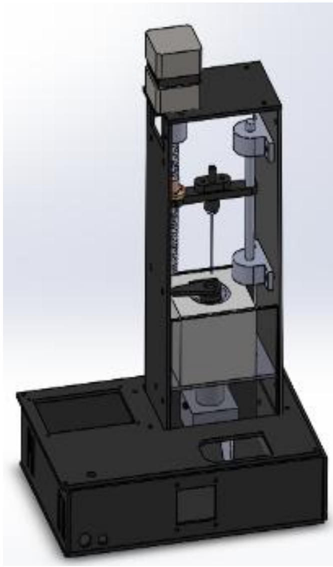

Fig. 2. Headspace Sampling Design (Own image)

Fig. 3. Headspace Sampling (own image)

The design of this stage was developed to simulate the function performed by a gas chromatograph. In the headspace sampling process, the sample to be analyzed is heated using an electric resistor. Then, through an extraction valve, the gases are sent to an electronic nose equipped with a sensor chamber. In this chamber, the gases are concentrated for a specific period, during which the sensors respond according to their characteristics or functional properties.

2.2 Procedure

For the extraction of oil from the transformers, certain conditions must be considered. The extraction should be performed using a glass syringe, as this material prevents contamination and alteration of the compound. This process was carried out in collaboration with the company CENS (Centrales Eléctricas de Norte de Santander - Colombia), the project partner.

Fig. 4. Oil extraction.

After obtaining the oil samples requested from the company CENS (the company that carried out the extraction process with the assistance of their maintenance staff), the sample was taken from a power transformer located at the company's main plant in the city of Cúcuta, this sample was taken from a transformer that was in operation at the time of extraction, in order to assess the oil's condition after prior heating, ensuring that the volatile compounds were at their highest available concentration.

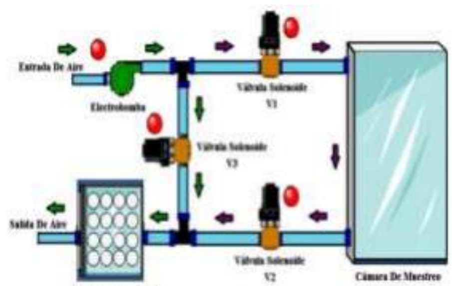

Fig. 5. Electronic Nose, E-Nose University of Pamplona

2.3 Nose electronic

A general concept of the electronic nose is that it is an instrument consisting of a set of electrochemical sensors with partial specificity and an appropriate pattern recognition system, capable of identifying simple or complex odors. In Figure 6, the electronic nose system available for the development of this project is shown, which consists of the following components (Gualdrón *et al*., 2014):

- Air pump and electric bypass valves.
- Power control circuit.
- Volatile concentration chamber.
- Gas sensor chamber
- 16-channel DAQ

Figure 6. Electronic Nose (University of Pamplona) (Gualdrón et al., 2014).

2.4 Arduino Mega

To program the headspace sampling, an Arduino Mega was used. It has 54 digital pins that function as input/output, 16 analog inputs, a 16 MHz crystal oscillator, a USB connection, a reset button, and a power input for the board.

Communication between the computer and the Arduino is established through the Serial Port. It features a USB-to-Serial converter, so the device only needs to be connected to the computer using a USB cable, similar to those used by printers.

2.5 Data acquisition and processing

Data acquisition within the electronic nose was performed using a DAQ card (National Instruments), and the processing of this data was carried out using Matlab® 2014b software. This allowed for the visualization of the response of each sensor when the sample was exposed to different temperature changes and sample types. Below, in Figures 7 and 8, the response of the sensors at 30ºC and 40ºC for the oil sample can be observed.

In Figure 7, a temperature of 30ºC is applied to the sample located in the vial to observe how the sensors react to the temperature increase, enabling the capture of the data provided by the sensors for further analysis.

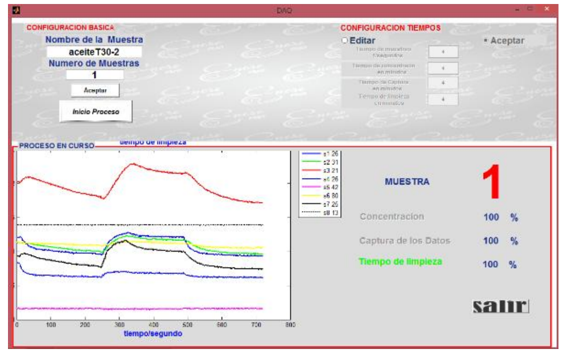

Fig. 7. Sensor Response at 30ºC

In Figure 8, a temperature of 40ºC is applied to the sample located in the vial, where the variation in the response of each line can be observed in terms of its amplitude, compared to the previously shown image. It is important to note that each sample must be taken at the same time to ensure the data size is consistent, allowing for the appropriate PCA analysis of the obtained response.

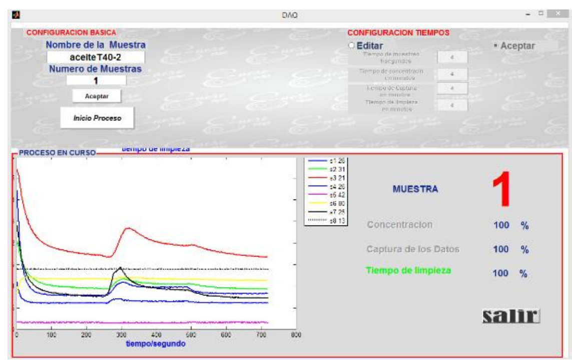

Fig. 8. Sensor Response at 40ºC

Given each of these results obtained through the software used for the proper processing of the samples, the PCA analysis is then performed on all the samples and the results obtained from them.

2.6 PCA

These techniques were initially developed by Pearson at the end of the 19th century and later studied by Hotelling in the 1930s. However, it was not until the advent of computers that they began to gain popularity. To study the relationships that occur between p correlated variables (which measure common information), the original set of variables can be transformed into another set of new uncorrelated variables (which have no repetition or redundancy in the information) called the set of principal components (Marín Díaz Araque, s.f.)

PCA (Principal Component Analysis) In statistics, it is a technique used to describe a dataset in terms of new uncorrelated variables ("components"). The components are ordered by the amount of original variance they explain, making the technique useful for reducing the dimensionality of a dataset. Technically, PCA seeks the projection along which the data is best represented in terms of least squares. This transforms a set of observations of possibly correlated variables into a set of uncorrelated variable values called principal components. PCA is mainly used in exploratory data analysis and for building predictive models. PCA involves calculating the eigenvalue decomposition of the covariance matrix, typically after centering the data around the mean of each attribute.

Once PCA analysis was applied to all the samples taken at different temperatures through the pre-heating process performed with headspace sampling, all the results were compiled into a single file for further analysis. The following figure 9 will show the process used to select the type of analysis to be performed on the samples and then obtain the PCA analysis for two samples.

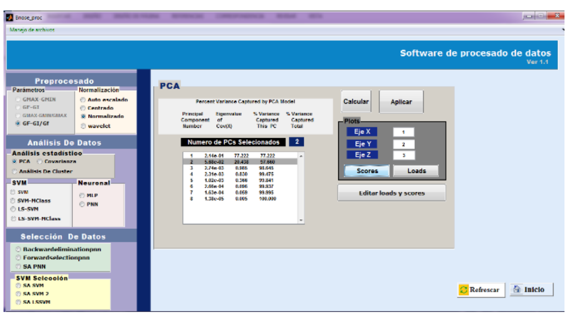

Fig. 9. PCA Analysis (own image)

When the data preprocessing has been selected and we calculate according to the sensor response for each sample, Figure 10 will show the proper classification. It should be noted that the samples were taken from two transformers in different states. The first sample was taken from a transformer in operation (samples enclosed in yellow), while the other sample is from completely new oil (samples enclosed in red).

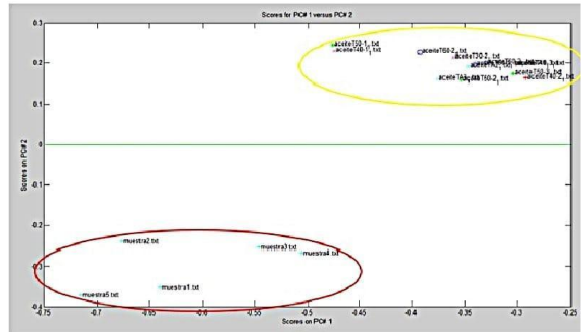

Fig. 10. Separation of Each Sample

With this result, it can be determined that the system worked 100% because when observing the condition of each sample group, the separation is clearly visible. Therefore, once the classification is done using the software, a neural network must be trained, and proper training should be carried out so that it can detect the type of fault present. This will allow the company to perform preventive maintenance on the equipment and ensure a longer lifespan for the transformer.

Table 1 will show the types of faults and the gases associated with each type of fault.

Table 1: Transformer Faults

FAULT	KEY GAS	RESULTS
Arc	Acetylene	Large amounts of acetylene and hydrogen are produced, or small amounts of methane and ethylene.
Corona	Hydrogen	Low-energy discharges produce hydrogen and methane, as well as small amounts of ethane and ethylene.
Oil overheating	Ethylene and Methane	Overheating at 150°C produces ethylene and methane, or hydrogen and methane at 600°C. Traces of acetylene may be generated if the fault is severe or if electrical contacts occur.
Cellulose overheating	Carbon Monoxide	If cellulose overheats, carbon monoxide is produced.

2.7 Arc fault

The arc fault is caused by overvoltages resulting from partial discharges, external faults, or switching maneuvers in the system, as well as the movement of windings under the action of electromagnetic forces during an external short circuit. This type of fault may occur between the windings and the core, as well as in the tank and between turns. (Brambila Tello & Gijon Olivares, 2015).

2.8 Corona faults

Corona faults are internal failures that occur within the transformer windings. This happens when the dielectric insulation, whether liquid or gaseous, loses its properties, leading to ionization. The fault manifests as a luminous effect around the windings, hence its name, corona effect. (Brambila Tello & Gijon Olivares, 2015)

2.9 Oil Overheating

This type of fault can be distinguished into two stages: high and low temperature, depending on the relative amount of energy being dissipated. At low temperatures, carbon-carbon bonds within the oil molecule can break, forming Methane and Ethane. (Gutiérrez & Montes, 2021)

2.10 Cellulose Overheating

The thermal energy supplied by an abnormal situation, such as a hotspot, will cause oil decomposition with a notable increase in gases, accompanied by the presence of Ethylene (C_2H_4) in higher concentrations than Ethane (C_2H_6). Decomposition products include Ethylene (C_2H_4) and Methane (CH_4), along with smaller amounts of Hydrogen (H_2) and Ethane (C_2H_6). In severe faults or those involving electrical contacts, traces of Acetylene (C_2H_2) may form. (Rodríguez Díaz et al., 2020)

3. NEURAL ALGORITHM IMPLEMENTATION

The human brain is the most complex computational system known to mankind. Computers and humans excel at different types of tasks; for instance, recognizing a person's face is relatively simple for humans but challenging for computers, while managing the accounting of a company is a costly task for an expert accountant but a straightforward routine for a basic computer. This definition gives us an idea of the immense information-processing capacity of humans. Innovative studies in recent years have been inspired by human composition to create new technologies. (UPV-EHU, 2008)

Neural networks are more than just another way to emulate certain human characteristics, such as the ability to memorize and associate facts. If we closely examine problems that cannot be expressed through an algorithm, we will notice they all share a common feature: experience. Humans can resolve such situations by relying on accumulated experience. Thus, it seems evident that one way to approach these problems is by constructing systems capable of reproducing this human trait. (Matich, 2001)

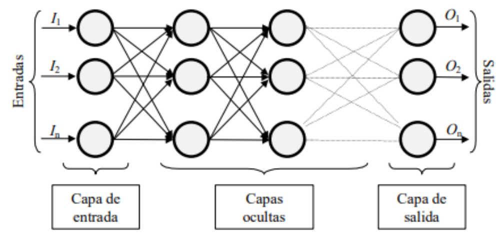

Fig. 11. Connected Neural Network

Within the project, a neural network was developed to train the data obtained from the sampling conducted on the transformer oil, achieving a 100% classification accuracy. This is reflected in Figure 12. All of this was made possible within the same interface designed using the Matlab mathematical tool, with the following results provided by the software (Custodio, 2019)

The training of an MLP neural network is established as a classifier for the data obtained from the sensor responses in the system, which differ from those used in the PCA. The training method for the neural network will be partitioned, where it is trained with one dataset and validated with another completely distinct dataset to test the robustness of the obtained algorithm. The first item defines 5 neurons in the hidden layer and 1 neuron in the output layer, with Tansig activation functions in the hidden layer and Purelin in the output layer. The number of iterations scheduled before running the algorithm again without finding good parameters is set to 100. All these parameters can be found in Figure 25. Once defined by the user, the command to begin calculating the MLP is given. After training is completed, the following results are obtained. (TANCO, 2021)

Fig. 12 Training of the Neural Network

4. RECOMMENDATIONS

This project remains in a very open field in terms of research. The next step will be to implement wireless communication between the device and a central control station, enabling real-time data monitoring of the transformer's performance during operation. Additionally, considering the vast potential of electronic noses in industrial applications today, further exploration into their integration for continuous monitoring will enhance the system's capabilities.

5. CONCLUSIONS

The most productive outcome of this work is the extensive knowledge gained through the researchers who accompanied and advised us during its development. It allowed us to expand our research capacity as an academic method. Despite facing many complications at the beginning, each one was successfully resolved, allowing us to achieve the general objective.

The use of each of the methods that enabled us to meet the goal proved to be the most effective. Moreover, the application of an electronic nose in electrical transformers is an innovation, where technology is used to perform real-time functions and prevent major damage. As we know, this is the very purpose of engineering: to provide solutions and efficiency to everyday products and systems.

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