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Yusuf Amrulloh, *The University of Queensland*
Udantha Abeyratne, *The University of Queensland*
Chandima Ekanayake, *The University of Queensland*

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Gas and Optical Sensing Technology for the Field Assessment of Transformer Oil

Yusuf Amrulloh, Udantha Abeyratne, and Chandima Ekanayake

Abstract

Oil testing has found widespread use in assessing the quality of the insulation system of a transformer. Techniques such as Dissolved Gas Analysis (DGA) have been proven to be reliable in this task, but are expensive, laborious and time consuming. It is also not available for field use. This paper proposes the combined use of gas and optical sensing technology for the testing of transformer oil. It provides a low-cost, portable technology capable of fast and reliable field screening of transformers. The method consists of an oil handling and unit as well as a gas and optical sensor array. Gas sensing targets moisture, hydrocarbons and other volatile compounds dissolved in transformer oil; optical measurements provide information on the absorption properties of transformer oil, within a band of frequencies made possible by the recent advances in Blue-LED technology. These measurements are then combined through a pattern recognition system producing a collective decision on the state of the transformer. The performance of the method was evaluated on a database of 26 transformer oil samples, using a leave-one-out validation technique. Our results indicated that the method was capable of categorizing transformer oil into three classes, 'acceptable,' 'marginal' and 'bad' with reasonable accuracy, based on the acidity and furfuraldehyde levels estimated from gas-optical measurements. The results need to be further validated using a larger database of transformer oil samples.

KEYWORDS: optical sensing, gas sensing, condition monitoring, aging

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1 Introduction

Power transformer is an indispensible component in an electrical power system. From large step-up transformers in a power generating facility down to small distribution transformers near the consumers, there is a wide range of transformers found in an electricity grid. The geographical locations of these transformers may be spread across thousands of kilometers. In countries such as Australia, it is not uncommon to find expensive and performance-critical transformers in remote areas, making the monitoring and servicing of these a challenging task.

In many countries in the world, a substantial percentage of power transformers currently in service are operating beyond their nominal design lifespan. Over the years this has allowed power companies to keep delivering energy with minimal new infrastructure investments. However, with many transformers entering the end of their useful life, power transformer failure has now become one of the main challenges to the reliable, uninterrupted operation of the electricity grid. There is a great need for a reliable and low-cost transformer condition-monitoring tool, which can be operated even in remote areas with minimal human intervention. Continuous online monitoring and the ability to predict potential failure will be highly desirable features of any monitoring system.

At present, there are several techniques available for the condition monitoring of transformers [1], [2] based on the estimation of the quality of its insulations. The insulation system of a power transformer consists of two main components: oil insulation and the paper based insulation. Both of these age and degrade over time due to reasons of physical (e.g.: thermal heating, partial discharge) and chemical (moisture-hydrolysis; Oxygen-oxidation) origin [2].

Power transformer insulation uses paper/pressboard, which is formed of cellulose [3]. It is an organic compound with a molecule comprising of a long glucose ring. Transformer oil, which serves as an electrical insulator as well as a liquid coolant, is a hydrocarbon. The decomposition of the insulation system produces characteristic chemicals (see Fig. 1) such as Furanic compounds (e.g.: 2-Furfural, 5-hydroxymethyl-furfural), moisture, hydrocarbons (e.g.: CH_4, C_2H_4, C_2H_6) as well as other gases such as CO and CO_2. These chemical products dissolve in transformer oil and also lead to a change in its acidity level [3]. Thus, the investigation of the actual chemical composition of oil and resulting physical, chemical and electrical properties (acidity, spectral adsorption, turbidity, conductivity etc.) paves an elegant way to monitor the state of the insulation system of a power transformer [4].

There are several techniques for the analysis of transformer oil. One of the simplest methods is the visual inspection (ASTM D-1524) of transformer oil for properties such as color and turbidity. While being simple, it is subjective and needs human interpretation. Attempts to automate and capture optical features have resulted in methods such as the Infra-red (IR) analyzer [5] and rapid spectrophotometry [6]. These techniques rely on only the optical properties of transformer oil, and the outcomes have not been considered sensitive or specific enough for the reliable condition monitoring of transformers.

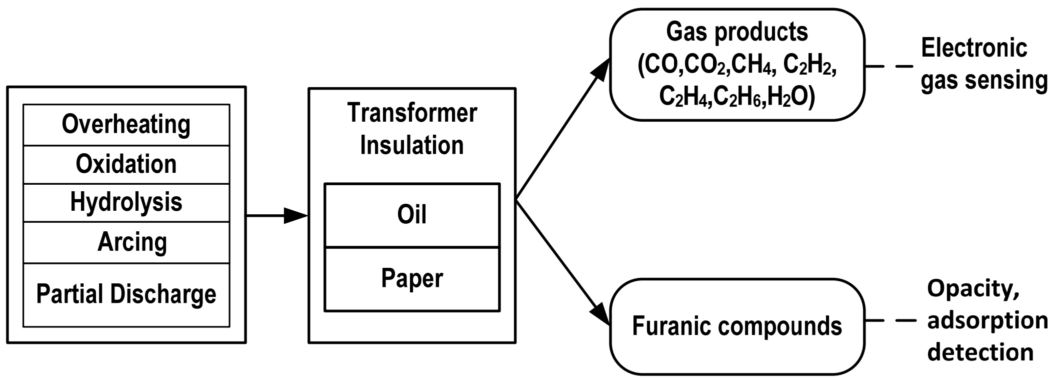

Figure 1. Physical and electrical stresses cause the insulation system to degrade and produces gas and other chemicals, which then dissolve in transformer oil, changing its properties. Oil testing provides an elegant way to monitor the condition of a transformer.

Dissolved Gas Analysis (DGA) is considered the golden standard in the condition monitoring of a transformer insulation system. It is a sophisticated technique, which depends on the extraction of dissolved gases from transformer oil followed by gas chromatography. The four key gases that usually used to determine the transformer fault are hydrogen, carbon monoxide, ethylene, and acetylene [7] (see Figure 1). DGA is capable of highly sensitive and specific measurements, but requires access to expensive laboratory equipment. Thus, it is not available as a fast, low-cost solution for field use. It is also not suited as a part of a continuous real-time condition monitoring and response system.

The level of acidity as measured from transformer oil (see Table 1) can be used as an indicator of the state of the transformer insulation system. The acidity of oil is (per ASTM D-974) the amount of potassium hydroxide (KOH) in milligrams needed to neutralize 1g of oil. This method has to be carried in a laboratory; it is expensive, time consuming, and not suitable for field use.

The conductivity is another important parameter [8] of the quality of transformer oil. The ageing by-products of both oil and paper mainly affect the conductivity. As conductivity is highly temperature dependent it is always important to compare the conductivities at the same temperature. Oil conductivity can be estimated by measuring current passing through oil placed between two metal electrodes due to a known voltage profile.

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Table 1: Acidity Level and Transformer state [9]

Acidity (mg KOH/g oil)	State
0 – 0.1	Good
0.05 – 0.1	Proposition A oils
0.11 – 0.15	Marginal oils
0.16 – 0.40	Bad oils
0.41 – 0.65	Very bad oils
0.66 – 1.50	Extremely bad oils

Table 2: Furfuraldehyde Level and Transformer State [3, 10]

Furfuraldehyde level (part per billion)	State
0 – 20	Good, basically new oils
21 – 100	Acceptable, normal aging
101 – 250	Questionable, probably accelerated aging
251 – 1000	Unacceptable, significant accelerated aging
>1001	Danger zone

In this paper, we propose a low-cost, portable device centered on electronic gas sensing ("electronic-nose") and optical measurements ("electronic eyes") for the condition monitoring of transformers. We also explore the conductivity as one potential parameter of oil quality. Gas sensing components target moisture, hydrocarbons and other volatile compounds dissolved in transformer oil; optical measurements provide information on the absorption properties of transformer oil, within a band of frequencies made possible by the recent advances in Blue-LED technology. Optical and gas sensing measurements are then combined through a pattern recognition system producing a collective decision.

Electronic noses have been explored in assessing the quality of transformer oil before (eg. [19], [20]). Most of these preliminary investigations relied upon extracting the gases from transformer oil before processing. Furthermore, the performance of the methods was not systematically reported.

To the best of our knowledge, the approach we describe in this paper is the first in the world using optical sensing of transformer oil at blue wavelengths and combines it with gas sensing through the Electronic Nose. The method does not require gas extraction. We also report the performance of the technique using a database of 26 oil samples and the method of leave-one-out validation. Our method has the potential to quickly evaluate the quality of transformer oil in actual field use, at a fraction of the cost of existing devices. It may also open opportunities for continuous monitoring of transformers and predicting failures.

In this paper we describe the technology developed and evaluate its performance on a database of transformer oil samples.

2 Method

The method proposed in this paper depends on the idea of combining electronic gas-sensing and optical measurements. In Section 2.1 and Section 2.2 we describe the individual gas-sensing and optical sub-systems; in Section 2.3 combined gas-optical sensor array implementation and the data acquisition protocols are illustrated.

In Section 2.4-Section 2.5 we describe the pattern recognition algorithms used in this work and details about the training, and performance evaluation procedures.

2.1 The Gas-sensing Electronic Nose (E-Nose) Sub-system

The essential component of an E-nose is a chemical sensor; electrical properties of the sensor depend on the concentration levels and the type of chemicals it is in contact with. An array of such sensors can be used to generate a 'signature' of a particular chemical and its concentration level. Signal processing and pattern recognition algorithms are used to detect such signatures. As the first step, an E-nose has to be trained using a training data set to recognize the desired signatures. Then, the performance of the E-nose with previously unseen data has to be evaluated with a test set. In order to train/test the E-nose properly, the data set has to be large and varied enough to contain samples spanning the whole spectrum of possibilities.

We designed an Electronic nose as an inexpensive and non-invasive method offering a flexible mechanism for assessing transformer oil than possible with existing technology. It comprises of an electronic sensor array with partial sensitivity, followed by a pattern classification system, which is able to generate signatures characteristic to a set of volatile chemicals in the gaseous phase (e.g.: Furanic compounds). The array also contained sensor elements that had sensitivity to gases resulting from different types of transformer insulation failures (e.g.: CH_4). Table 3 shows the gas sensors [11-13] used in this paper. We used three different elements in our sensor array. All the electronics were designed and implemented in-house, at a cost of <$1000.00.

Table 3: Gas Sensor and Its Target Odour

Sensor type	Gas
TGS2600	CO_2, C_4H_{10}, C_2H_6O, H_2
TGS2602	H_2, NH_3, C_2H_6O, H_2S, C_7H_8
TGS2620	CH_4, CO, C_4H_{10}, H_2, C_2H_6O

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2.2 The Optical Sub-system

It is well known that the optical quality of the transformer oil changes over time as the insulation system degrades. This is the basis for the visual inspection standard described in ASTM D-1524. In this paper we propose the idea of combining the optical measurements with gas-sensing, so that a given oil sample can be simultaneously assessed for a larger range of chemicals resulting from insulation failure. This is expected to lead to better classification accuracy in actual use.

2.3 The Combined Gas-optical Measurement Technique

Fig. 2 illustrates the combined gas-optical system we developed. The complete unit, except the laptop computer, measured 9cmX11cmX15cm. The design consisted of: (a) a sensor array (gas and optical sensors), (b) sensor conditioning electronics, (c) signal acquisition circuitry, (d) a central microprocessor (MSP430F2274), (e) USB interface module (eZ430RF2500) for data transfer to the computer, and (f) an oil handling system.

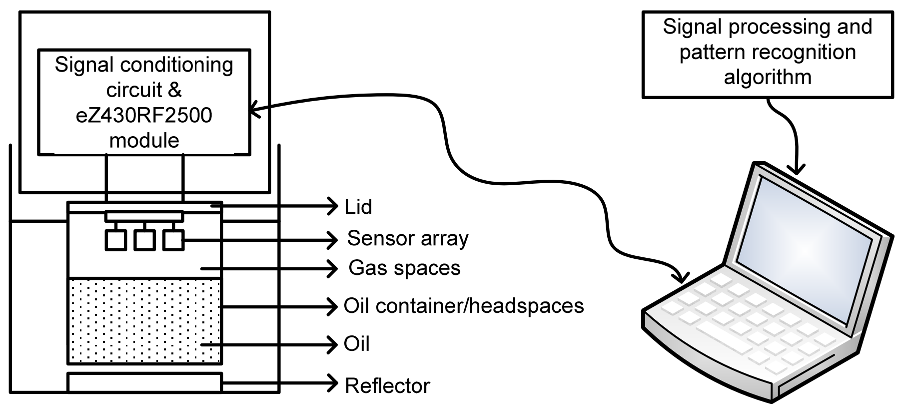

Figure 2. Block diagram of the constructed system. It comprises of three major parts: gas and light handling, data acquisition, and pattern recognition algorithm.

The design is comprised of two separable main structures (see Fig. 2). The first is a removable oil container, which snaps tightly to a lid physically connected to the upper box containing the electronic circuitry. The second is the darkened lower box with a circular well that accepted the oil container/sensor assembly as illustrated in Fig.2. A light reflector is installed at the bottom of the lower box, to get the maximum energy back to the optical system.

The oil container is a key element in this simplified design. It is filled partly with the particular transformer oil sample (about 10ml) to be tested. Gases and volatile compounds dissolved in transformer oil (liquid-phase) establish equilibrium with their gas-phase equivalents in the chamber above the transformer oil as described by the Henry's Law in Chemistry.

Gas sensors (together with the conditioning circuitry) produce a voltage output in response to chemical compounds found within the gas chamber. These voltage signals are then converted to a digital signal and transferred to the computer for analysis.

The optical sensor used in this device works as a reflection-type sensing device. It consists of a blue colored LED as a transmitter and a phototransistor as the receiver. The transmitter emits light within the blue spectrum (λ= 465 nm, $\Delta\lambda$= 35 nm), which passes through the gas headspace and the transformer oil. It is also reflected back by the reflector mounted below the oil container. The light returned to the receiver unit carries information on the optical absorption properties of transformer oil. Received light is then converted into an electrical signal and passed to the computer.

The operation of the electronic circuitry is carried out using an MSP430F2274 microcontroller. The overall measurement protocol involves the partial filling of the oil chamber, activation of the sensor array, waiting for the liquid-gas phase equilibriums of chemicals, and the activation of the analog-to-digital conversion circuitry and USB transfer protocols. Converted data is then sent to the computer for further processing. In the work of this paper, we allowed a two-minute time delay between the filling of transformer oil and the starting of the data acquisition process to make sure an equilibrium state is reached. This is an important consideration in maintaining the repeatability of measurements.

2.4 Estimating the Quality of Transformer Oil

In this paper, we propose to explore gas-optical data in two different roles associated with the insulation monitoring of transformers. In the first approach, we investigate if it is possible to estimate the acidity and Furfuraldehyde levels of transformer oil based on (indirect) gas-sensing and optical measurements. We use a neural network technique for the purpose. In the second approach, our target is to develop an algorithm capable of a linguistic description of the quality of transformer oil. The fuzzy logic based descriptors we propose in this paper have been chosen to comply with the existing transformer oil assessment standards.

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2.4.1 Neural Networks for the Estimation of Acidity and Furfuraldehyde Levels

Artificial neural networks (ANN) became popular in the recent past for its ability to learn arbitrary functions [14-16] to a desired level of accuracy. In this paper, we used an ANN to learn the mapping function between the input variables (gas-optical measurements) and the output variables (acidity and Furfuraldehyde levels). ANNs have been found to be highly successful in a range of other applications of electronic noses [17].

The particular ANN used for this work is a three-layer Perceptron network trained with the error back propagation algorithm (see Fig. 3). The back-propagation algorithm is a supervised learning technique; it needs a set of example input-output pairs of data ("the training set") in order to learn the association between them. Once the training is over, the trained network is assessed for its ability to produce correct outputs, when previously unseen data are shown at the input. The data set used for this purpose is called the "testing set". These data sets are made non-overlapping.

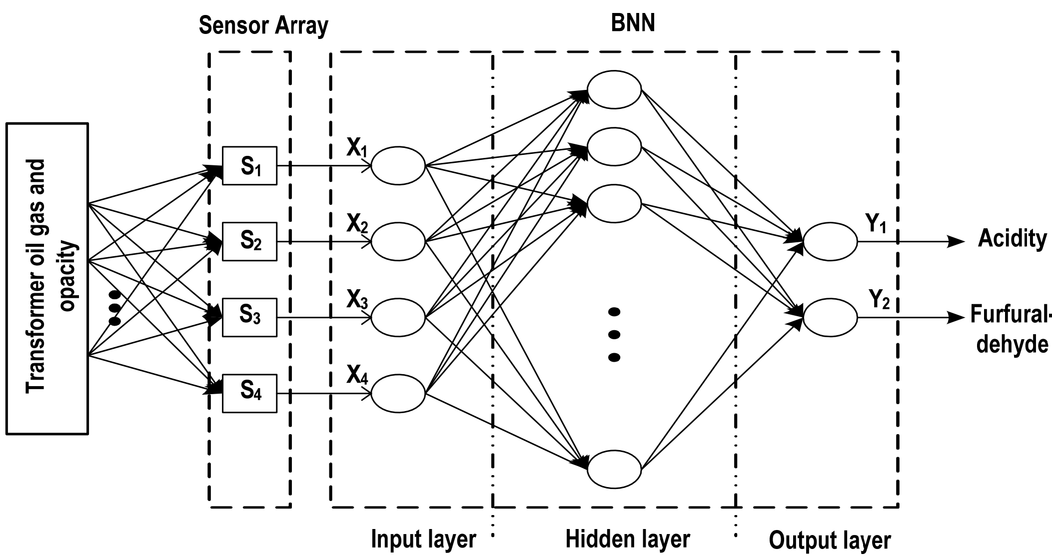

Figure 3. Back propagation neural network classifier block diagram. It consists of three layers with 2-4 neurons in input layer, 15 neurons in hidden layer, and 2 neurons in output layer.

The ANN technique requires access to a representative group of data for the training, validation and testing purposes. Also, the number of datasets has to be sufficiently large in order to discover a complex input-output relationship that may be hidden within.

The number of oil samples available to us for this work was 26. Acidity and furfuraldehyde levels were evaluated for these samples using standard laboratory measurements at PowerLink Ltd, Brisbane, Australia. A CIGRE test cell and a variable frequency voltage source with a current measuring system have been used to assess the conductivity. All the conductivity measurements were performed at room temperature (25° C).

The small size of the dataset posed a challenge in training and testing of the ANN. In order to minimize this problem, we took the following two steps as suggested in the literature:

(a) The ANN training/testing process used a leave-one-out cross-validation process. When training the ANN, 25 datasets were chosen from the available 26 sets and used as the "training set". The performance of the trained network was evaluated on the remaining dataset ("testing set"). This process was repeated 26 times until each and every dataset was used once as a "testing set".

(b) To partly overcome the problem of the small dataset, and to make the trained ANN robust to noise, we manufactured new data points as suggested in [14] using the available data using linear interpolation and the addition of noise.

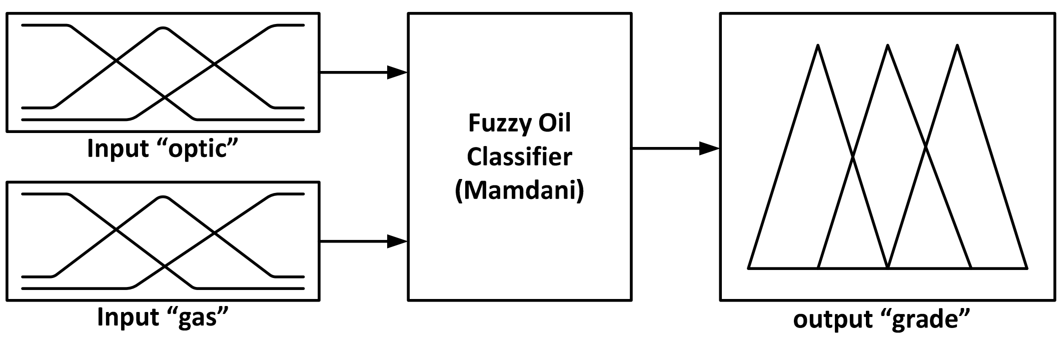

Figure 4. The block diagram of the designed fuzzy oil classifier. Two parameters (from optical and gas sensor) is utilized as the input of Mamdani fuzzy classifier to categorize it into a score which corresponding to an oil grade.

2.4.2 Fuzzy Classifiers (FC) for the Assessment of Transformer Oil Quality

A fuzzy classifier was developed to categorize oil samples according to the quality of insulation. As illustrated in Figure 4, it employed two inputs: optical and gas sensors (TGS2602). The fuzzy system we developed followed the Mamdani approach [14], which consists of three main procedures: fuzzification, inference, and de-fuzzification. Mamdani configuration is chosen for its simplicity and the ability to produce good results in practice.

In the fuzzification stage, input voltages measured are converted to a fuzzy set with memberships in the range of 0-1 (see Fig. 5). This fuzzy set is then used as the input for the inference engine, by using *if-then* rules as shown in Table 5. Max-min operator was used to determine which rules were used in a given input. The defuzzifier finally converts the output from the inference engine to a score corresponding to the state of the transformer oil. For this purpose, we used the Center of Area (COA) deffuzification technique [18] as given by (1),

$$W = \frac{\sum_{i=1}^{n} \alpha_i \cdot W_i \cdot A_i}{\sum_{i=1}^{n} \alpha_i \cdot A_i} \qquad (1)$$

where n is the number of rules, A_i is the area of membership function for rule i, W_i is the distance of fuzzy set output to the reference of rule I, and α_i is the fire strength of rule i.

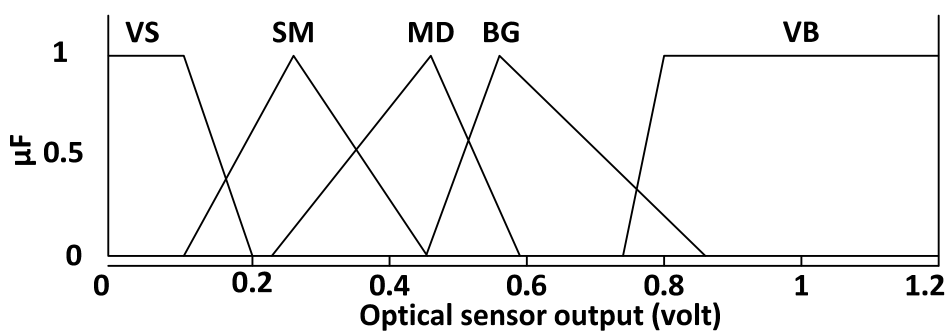

Figure 5. The membership of input variable for the optical sensor, where the x-axis is the optical sensor voltage as function of furfuraldehyde level changes and y-axis is the membership degree for each voltage level.

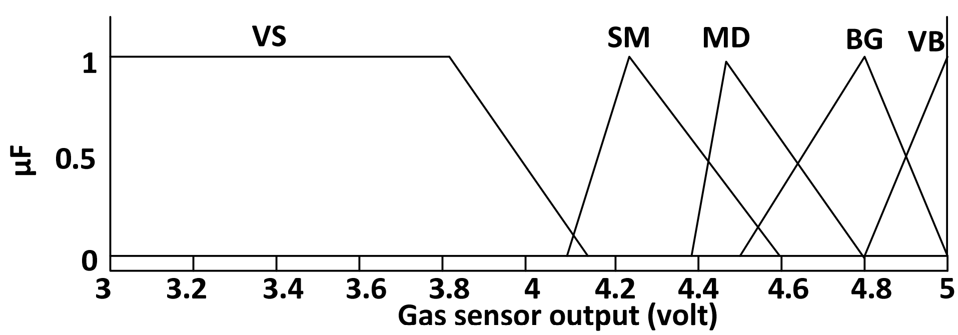

Figure 6. The membership of input variable for the gas sensor, where the x-axis is the gas sensor voltage as function of acidity level changes and y-axis is the membership degree for each voltage level.

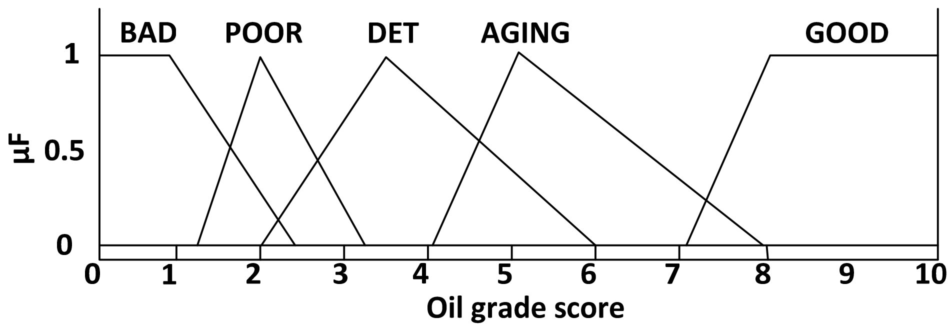

Figure 7. The membership of output variable. The x-axis is the oil grade score as a function of the true oil condition caused by the acidity and furfuraldehyde level and y-axis is the membership degree of each score.

The memberships of input and output fuzzy sets are shown in Fig. 5, Fig. 6, and Fig. 7. All of these utilize a triangular membership function. Both inputs have 5 memberships, very small (VS), small (SM), medium (MD), big (BG), and very big (VB). These labels convert the voltage outputs of sensors to membership degree (μ_F) of each membership function. The universe of discourse U of the input is the sensor voltages in response to acidity and furfuraldehyde level, U = [V_{min}, V_{max}], where Vmin/Vmax is the minimum and maximum voltage of sensors. The center of a fuzzy set is defined as the value of the input variable corresponding to the maximum value of μ_F within U. For example, as can be seen in Figure 5, the membership degree of "SM" in the optical fuzzy located in 0.268 with μ_F equal to 1.

Similar to the input, the output also has 5 different memberships: good, aging, deteriorate (DET), poor, and bad. The universe of discourse of the output is the score of oil samples, which is measured on a scale from 0-10. A low score characterizes low quality oil whereas a score close to 10 represents high quality oil.

The memberships between categories of all fuzzy set are overlapping. As can be seen in Figure 5 – Figure 7, the overlap can be found between two memberships or three memberships. That overlap is designed to give a smooth transition between memberships as in human perception based on the existing transformer database. For example, in optical fuzzy set, output voltage 0.3 has two memberships which are 0.25 in medium (MD) and 0.76 in small (SM). It means that that value tends to categorize as rather small. However, both of values will be used in the calculation.

The function between input and output of fuzzy oil classifier is governed by Mamdani inference technique. To construct rules for inference system, output voltages from the sensors are mapped using knowledge of transformer acidity and furfuraldehyde in Table 1 and Table 2. The created rule for the inference system is given Table 4.

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Table 4: Fuzzy classifier rules

		Optical				
		VS	**SM**	**MD**	**BG**	**VB**
	VS	POOR	DET	DET	AGING	GOOD
	SM	DET	DET	DET	AGING	AGING
GAS	**MD**	POOR	DET	DET	DET	DET
	BG	BAD	POOR	DET	POOR	POOR
	VB	BAD	BAD	BAD	BAD	POOR

3 Results and Discussion

3.1 Sensor responses

Three different gas sensors and a blue-LED were utilized to detect the furfuraldehyde and acidity in 26 samples of the transformer oil.

In Figure 8, we illustrate the variation of the sensor outputs with acidity and the furfuraldehyde level. The output voltages of all gas sensors increased with increasing acidity and furfuraldehyde levels.

The optical sensor showed the opposite characteristic. The correlation coefficients computed between the output of the light sensor and acidity/ furfuraldehyde/conductivity are computed to be -0.68/-0.47/-0.52 respectively. These numbers indicate that the optical signal indeed carries information on the condition of the transformer oil.

Similarly, we computed the correlation coefficients between different gas sensor (TGS2600, TGS2602, and TGS2620) outputs and the properties of transformer oil (conductivity, acidity, furfuraldehyde). Conductivity was correlated with TGS2600/TGS2602/TGS2620 outputs at the values 0.41/0.46/0.40 respectively. Similar figures for acidity and furfuraldehyde are given by 0.83/0.86/0.87 and 0.57/0.54/0.58 respectively. Of particular interest is the very high correlation between gas sensor outputs and the acidity; light sensors too had the highest correlation with the acidity. These numbers indicate that gas-optical sensing carry information on the condition of transformer oil. Conductivity has the smallest correlation with gas-optical measurements; more investigations are needed to determine if conductivity and gas-optical measurements provide largely complementary information, which can be exploited in a combined device.

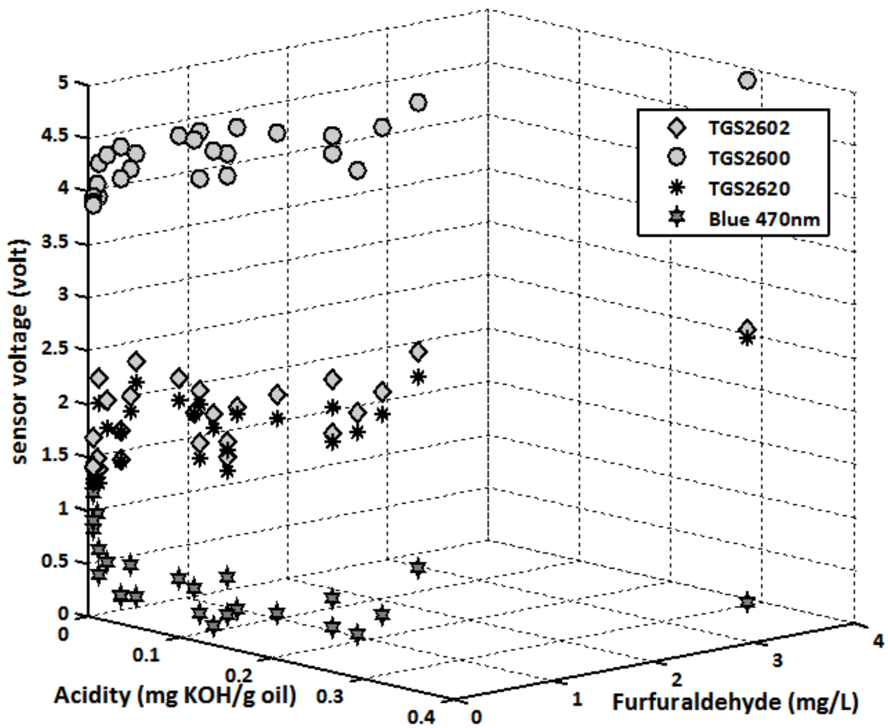

Figure 8. Sensor array response to the change of acidity and furfuraldehyde

Correlation values, however, are based on individual sensor pairs and depend on a linear curve fitting; they are of limited used in real-world interpretations. Our target is to find characteristic signatures of transformer oil, using multiple sensor outcomes, and without limiting ourselves to linear relationships. In Section 3.2, we describe the ANN technique we developed for the purpose.

3.2 Neural Network Classifier

The ANN training was done in two different ways: (i) Net-A: an ANN was trained to estimate furfuraldehyde and acidity levels using gas (TGS2602) sensing and optical data; (ii) Net-B: a second ANN was trained using gas, optical as well as conductivity data. Conductivity adds another dimension to the assessment of transformer oil, and can be easily incorporated within the neural network model. Conductivity has the advantage that it can be measured on-line, automatically and continuously, if needed.

In the training of the ANNs, the following two stopping criteria were used: (i) training is stopped when the validation error starts to increases (validation-stop); (ii) training is stopped when the error/gradient reaches a pre-set value (error-stop). Back propagation training was carried out using the Levenberg-

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Marquardt training algorithm. Table 5 summarizes the ANN parameters used in this paper.

Table 5: ANN training parameters.

Parameter	Value
Learning rate	0.001
Number of epoch	300
Error target	1.10^{-5}
Training method	Levernberg-Marquardt
Number of layers	3
Number of neuron per layer	Input layer : 4 , Hidden layer : 15 Output layer : 2

The size of a neural network has a relationship to its generalization ability. We explored the size of the network and the number of gas-sensors needed for the best outcome, and through a trial-and-error process decided to use the number of neurons indicated in Table 5. As seen from results in Section 3.1, different gas sensors carried similar information, and thus we decided to use TGS2602 alone for the rest of the paper.

The results of the ANN estimations of the acidity/furfuraldehyde are shown in Fig. 9 and Fig.10. Note that both figures indicate the results from the 26 cross-validation trials (leave-one-out); i.e., each point in the graph represent the ANN estimated acidity of the dataset previously unseen by the ANN (the response to the "test set"). The actual acidity/furfuraldehyde and the ANN estimated acidity is both displayed for comparison.

While the number of datasets used in this study is not sufficient to form strong conclusions, it is quite clear that the ANN technique can estimate the acidity levels of an oil sample, given the gas/optical sensing measurements. When the conductivity information is included (i.e. Net-B), the accuracy in the acidity estimation is increased by about 3%, whereas the furfuraldehyde estimation is relatively unaffected.

In order to explore the utility of the methods in classifying transformer oil into different operational categories, we used the following procedure. Standard transformer oil scoring scales shown in Table 1 and Table 2 were simplified[1] by combining the acidity levels of 'good' and 'Proposition A' in to a single band of 'acceptable' oil. Acidity levels >0.16 were merged to a single category 'bad oil', and the 'marginal' category was kept unchanged. The new 3-category

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[1] One reason for merging these categories was that the number of oil samples available for this study was limited to 26, and this did not warrant keeping finer sub-categories indicated in Table 1 and Table 2. Furthermore, we believe that the intended application domain of the proposed technology would be reasonably well served (as described in the last three paragraphs of Section 3.2) even with the merged categorization we propose here.

classification is then used to obtain the contingency table (Table 6) for our ANN based estimations. A similar process is used to simplify the categorization based on furfuraldehyde levels (Table 7).

Table 6 and Table 7 succinctly summarize the performance of our method. The overall accuracy of acidity-based 3-category classification is (13+2+4)/26 = 73%; the corresponding figure for furfuraldehyde is 69.2%. A closer inspection of Table 6 reveals that the out of the 5 oil samples in the 'bad' category (actual acidity-based) 4 are correctly classified as such; similarly, out of the 10 oil samples in the 'bad' category (actual furfuraldehyde –based) 8 are correctly classified by the proposed method. If the 'bad' and 'marginal' classes are combined based on operational considerations, the classification sensitivity improves to 100% (acidity-based) and 83% (furfuraldehyde –based).

The method proposed in this paper is not considered a substitute for laboratory DGA procedures. We believe its main application will be as a low-cost, fast oil screening-tool appropriate for field use. It should also be available as a continuous transformer monitoring-device. In these contexts, the ability to maintain a high sensitivity of detection of 'marginal' to 'very bad' transformer oil grades will be extremely useful in an overall management scheme. The results we obtained indicate that the technology we propose has the potential to meet this requirement.

The acidity-based categorization has a remarkable property as seen from Table 6. The proposed method yields a specificity of detection of 100% in the 'acceptable' category (at a sensitivity of 76%). That is, all the oil samples that the proposed method categorized as 'acceptable' truly belong in the 'acceptable' category. This has the potential to make the method useful in ruling-out any (unnecessary) intervention in a large group of transformers.

Table 6: ANN Acidity Estimation (Net-A). Entries indicate the number of samples.

		Acidity estimated by the proposed method			
		0 – 0.1 (acceptable)	0.11 – 0.15 (marginal)	>0.16 (bad)	TOTAL
Actual Acidity	0 – 0.1 (acceptable)	13	1	3	17
	0.11 – 0.15 (marginal)	0	2	2	4
	>0.16 (bad)	0	1	4	5
	TOTAL	13	4	9	26

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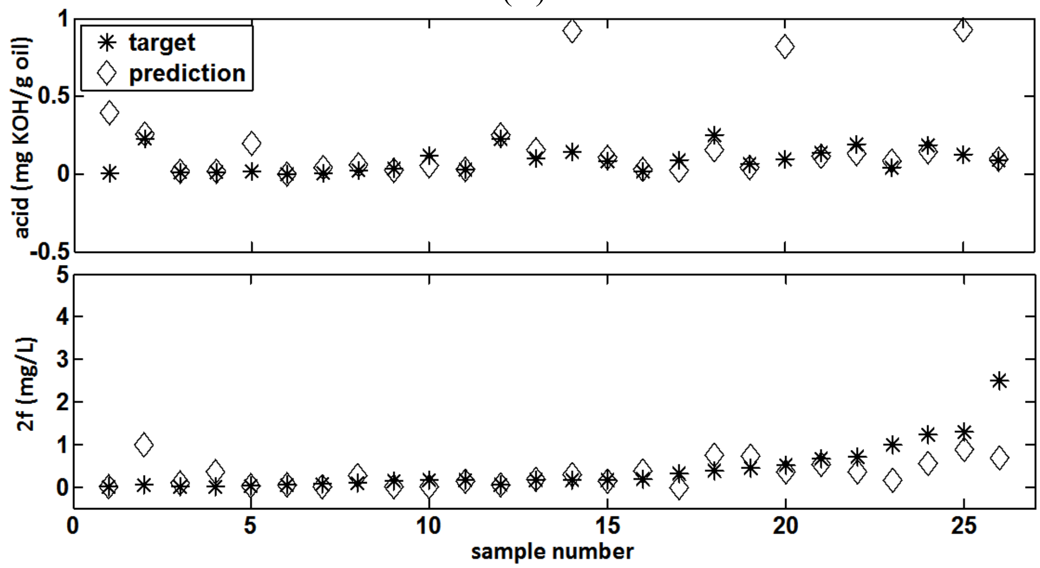
(A)



(B)

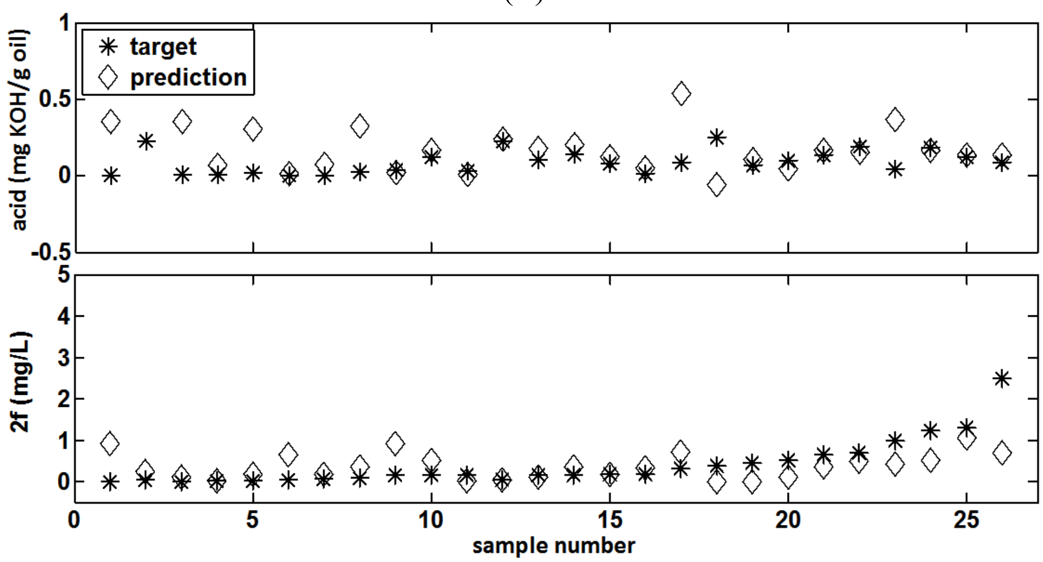


Figure 9. *Net-A*: Neural network classifier output which uses leaves one out cross validation technique. Both of outputs (A) with error stop mechanism (B) with validation stop mechanism shows the similarity in its results, but the later has less accuracy.

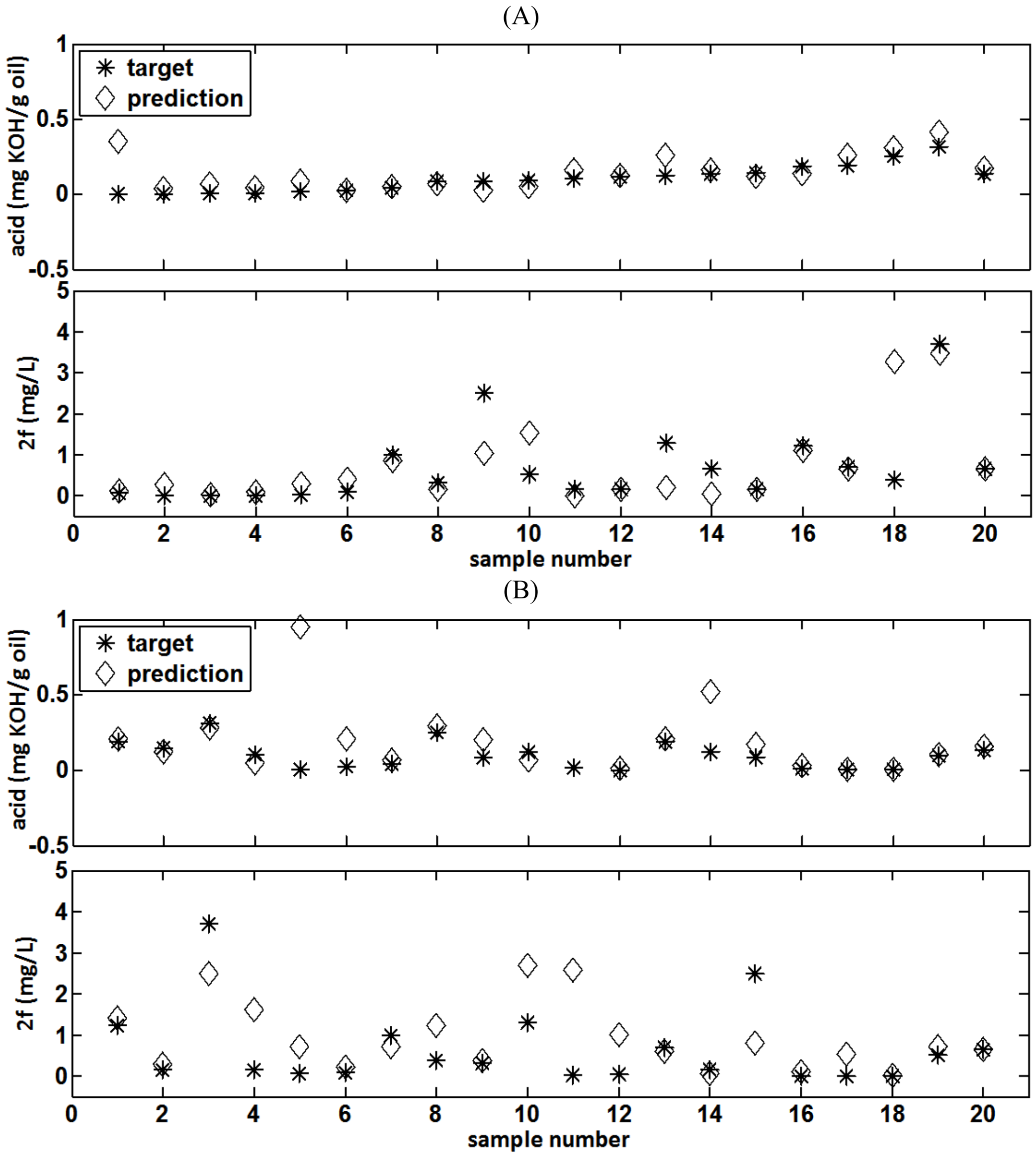


Figure 10. ANN output. (A) using net-A, and (B) by using Net-B. Conductivity input improves the prediction in the acidity but not furfuraldehyde.

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Table 7: ANN Furfuraldehyde Estimation (Net-A). Entries indicate the number of samples.

		Furfuraldehyde estimated by the proposed method			
		0 – 100 (acceptable)	101 – 250 (marginal)	>251 (bad)	TOTAL
Actual Furfuraldehyde	0 – 100 (acceptable)	7	0	1	8
	101 – 250 (marginal)	2	3	3	8
	>251 (bad)	1	1	8	10
	TOTAL	10	4	12	26

Note that it is possible to combine (using several techniques), different acidity, furfuraldehyde and conductivity based categorizations (e.g. Tables 6 and Table 7) of oil into a single classification system. The ANN method itself can be used to map multiple measurements such as gas/optical/conductivity directly to descriptive oil categories.

3.3 Fuzzy Classifier

Fuzzy algorithm is used to classify the transformer in to its grades. As explained before, Fuzzy algorithm only used two inputs, one gas sensor and one optical sensor based on facts that the gas sensors have similar responses. The input-output mapping of the fuzzy classifier is shown in Fig. 11. The x and y axis represents the input from gas and optical sensor while the z axis is the output score which categorizes the transformer oil into a state. There are 5 categories representing a score from 0 to 10, which are “bad”, “poor”, “deteriorating”, “aging”, and “good”. The membership range and center of each category is shown in Table 8.

Table 8: Output membership range and the center

Category	**Range**	**Center**
Bad	0 – 2.42	1
Poor	1.24 – 3.3	2
Deteriorate	2 – 6	3.5
Aging	4 – 8	5
Good	7 – 10	8

Since the memberships of classification in the de-fuzzification are overlapping, a number of classification result might has two memberships. For example, the fuzzy oil classifier yields output with value 2.5, which is located between ‘poor’ and ‘deteriorating’ membership. The degree of ‘poor’ membership is higher than that for ‘deteriorating’; thus we can say that the oil tends to be ‘poor’.

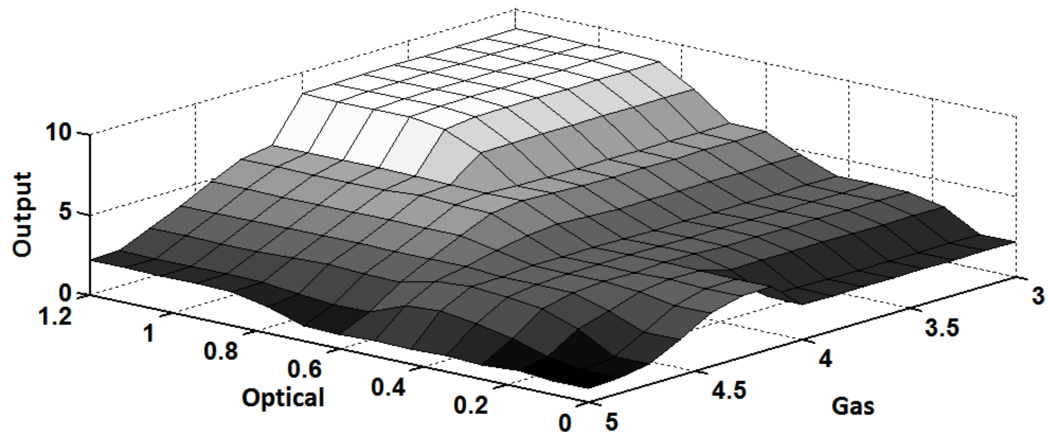

Figure 11: The inference rules which illustrate interaction between gas and optical input to the score output and give score that equivalent to the oil the real oil condition.

The output of the fuzzy classifier is shown in Fig. 12. Twenty six samples are used for the testing in four different measurements. The consistency of the output in the testing is represented by the number of output, which is pointing to a similar value between measurements. It has 98.17% precision as characterized by the small value of variance and deviation (0.062 and 0.059 respectively).

The accuracy of classification is calculated by a comparison between the fuzzy classifier output and the actual oil category. To get the same language perception, the real category is derived from Table 1 and Table 2 which is connected with the operator “and”. It means that if both the acidity and furfuraldehyde values are available, then the lowest grading of those values represents the overall oil grading.

Although the accuracy (65.3%) is not too high, fuzzy classifier provides a clear description the oil condition by giving a single score, which represents the overall oil condition. For example, transformer oil with a score below four needs further investigation while a score higher than 5 represent normal aging of the oil. However, this classification is heavily affected by the transformer oil database used for developing all fuzzy set and decision rules. A larger database should improve the classification accuracy in future work.

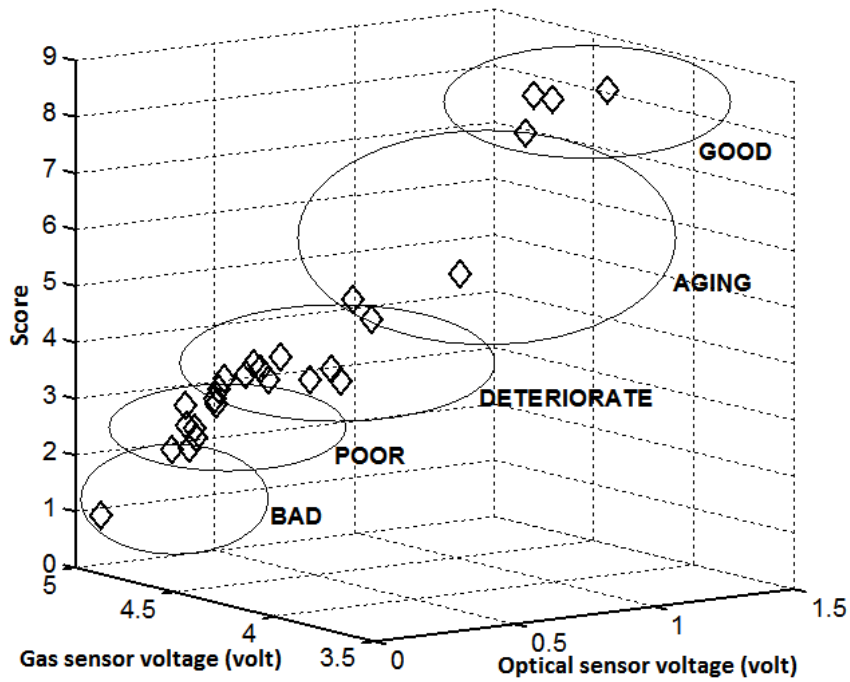

Figure 12: Fuzzy classifier outputs, which classify transformer oil samples into different grades. High level of acidity and furfuraldehyde from the sensor reading will be classified into a bad grade and vice versa.

4 Conclusion

In this paper, we address the issue of condition monitoring of a transformer based on the assessment of its oil. We propose a novel approach where the electronic gas sensing (electronic-nose) is combined with optical sensing (at blue wavelengths) to derive characteristic signatures of oil. We developed two signal-processing approaches to estimate important parameters such the acidity and furfuraldehyde levels of transformer oil, and to classify the condition of the transformer into a group of states. We also explored conductivity as one of the potential parameters to augment gas-optical measurements in further improving the accuracy of our method.

The gas-optical methods proposed by us show potential as a non-invasive technique for assessing transformer oil quality, without the need for expensive gas extraction techniques. The method is suitable for implementation on low-cost ($<1000.00/unit) portable units suitable for field use. It is also expected to be amenable for continuous automated measurements in actual use.

The electronic circuitry and the gas handling system can be further improved via miniaturization and automation. The sensor array can also be improved and optimized for better performance. While the results illustrated here point to the potential usefulness of the proposed technology in real-life, further development of the technique is needed (with a larger dataset) before a strong conclusion is reached.

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