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Intelligent System for the Estimation of Gases Dissolved in Insulating Mineral Oil from Physicochemical Tests

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Abstract

The objective of this work was to make the modeling through artificial neural networks of the gas concentrations dissolved in insulating mineral oil from the results of physicochemical tests. In this case, a mapping between the data of physicochemical tests and gas chromatography was obtained by means of artificial neural networks. The proposed approach proved to be efficient to identify the amount of gases, taking the following attributes as input: color degree, density, dielectric rigidity, interfacial tension, power factor of the insulating oil, neutralization index, and water level. In addition, artificial neural networks provide not only a new methodology to support decisions but also satisfactory results comparatively to actual analyses when referring to the estimation of gases.

Keywords: intelligent systems, artificial neural networks, power transformer

1. Introduction

The power transformer is an extremely important and expensive equipment consisting, in short, of two or three windings, the core, and the insulation system. The windings are arranged such that the magnetic leakage flux is dispersed as little as possible. The core is the medium by which the magnetic flux finds a path of low reluctance and preferably flows through it. Among these elements, core, windings, and the transformer tank, there is also the insulation system. The insulation system consists essentially of insulating paper and insulating mineral oil.

During its operation, various wear and aging processes may occur in the transformer insulation system. Examples can be hot spots, overheats, and overvoltages, among other phenomena that change the transformer insulation system [1]. Thus, the reduction in the lifetime of transformers is directly linked to the deterioration of the dielectric materials used in their manufacture. In this sense, there is an important motivating aspect for the development of supervision and preventive maintenance programs in order to provide an increase in the useful life of the equipment and, consequently, a better management of them under the command of the electric

utilities. In fact, the electricity market is becoming increasingly competitive, and the high costs involved in maintenance require the development of processes in order to lower its costs, increase asset performance, as well as extend its useful life [2].

Among the methodologies used to identify failures in power transformers immersed in insulating mineral oil, we highlight those based on the monitoring of their electrical parameters, acoustic monitoring, and the evaluation of dissolved gas concentrations in oil. On the other hand, the condition associated with the insulating paper present in the power transmission transformer coils is one of the main responsible for the lifetime of this equipment. Winding insulation paper can deteriorate abruptly, resulting in unpredictable failure of these transformers, particularly if in contact with oxygen, humidity, and metal contaminants. All these possible scenarios can be avoided if the degradation process is discovered in time [3].

For identifying failures from the dissolved gases in the oil, several chromatographic tests are then performed, which result in their respective concentrations. The examination of such dissolved gases is based on the premise that failures from partial discharges, high energy discharges, corona effect, overheating, etc. react with the insulating mineral oil causing alterations in their physicochemical properties, which are responsible for the release of gases that eventually react with the oil and, consequently, are dissolved within it. Therefore, the dissolved gas analysis (DGA) in insulating mineral oil is one of the main methods used to diagnose the insulation situation of the power transmission transformer windings. In addition, proper interpretation of DGA results is one of the most significant procedures for detecting fault types, as well as for identifying the process of degradation of its insulation [4, 5].

In addition to the chromatographic tests, with which it is possible to obtain the volumetric values of the main dissolved gases in the oil, there are also physicochemical tests that allow to identify several physical and chemical characteristics present in the insulating mineral oil. An important feature associated with physicochemical tests is that they can all be performed at the location where the transformers are installed, and part of them can be performed with the equipment in service, i.e., without interruption in the supply of electricity. Moreover, when power transmission transformers are in service, they may be subject to a number of environmental factors, such as heat and humidity, which must lead to an increasing aging process over time. Consequently, the electrical properties of the insulating mineral oil (resistivity, dielectric losses, relative permittivity, and breakdown strength), as well as the chemical (acidity and humidity) and mechanical properties (tensile strength and viscosity), are also modified, which directly impact its useful life [6, 7].

Therefore, it is emphasized here the motivation of a system for estimation of gases dissolved in oil from the results of physicochemical tests. Thus, the objective would then be to adapt existing methodologies based on the concentration of dissolved gases to, based on physicochemical tests, predict possible incipient failures in power transformers.

Since the estimation of these results is a complex problem, which does not have a mathematical formula capable of relating both tests, an interesting alternative is the use of computational intelligence techniques. Among these techniques, we can highlight the artificial neural networks, which do not require detailed knowledge about the relationship between the input space and the output space, as they are expert in dealing with nonlinear mappings [8].

It should be emphasized that the great novelty of this work is the precise estimation of the concentration of gases that are dissolved in insulating mineral oil, through neural networks, from the results of physicochemical tests. For the estimation of gases, we then use data from physicochemical tests performed on insulating oil taken from transformers in operation. The developed technique allowed the

estimation of these gases without the need to perform the chromatographic test. Consequently, the amount of power outages will be considerably reduced, and the associated costs in determining the gas concentration in the mineral oil will follow the same downward trend.

For this purpose, the organization of this article was divided in five sections. In Section 2, several aspects related to the main experimental tests performed on the insulating mineral oil are described. In Section 3, the intelligent system based on artificial neural networks for mapping the relationship between both physicochemical and chromatographic tests is presented. The main results produced by intelligent system in order to validate developed methodology are reported in Section 4. In Section 5, we present the conclusions about the applicability of the proposed technique.

2. Aspects related to the experimental tests in insulating mineral oil

Depending on the type of petroleum used for fractional distillation, the insulating mineral oil may have paraffinic base (paraffinic oil) or naphthenic base (naphthenic oil). Its classification is based on the results of the percentage of paraffinic (PC), naphthenic (NC), and aromatic (AC) carbons. This classification can be obtained by using infrared spectroscopy techniques by determining the amount of paraffin carbons. Oils with PC lower than 50% are considered naphthenic, while those with PC equal to or greater than 56% are classified as paraffinic; between 50 and 56% are intermediate oils.

When different mineral oils are mixed, the properties of the resulting mixture will be an average of the properties of each of the components, since the mixed oils are of good quality. If one of these components is of poor quality, the resulting oil will be of poor quality.

Determining the physicochemical properties of insulating mineral oil is of fundamental importance to ensure the operating conditions of transformers and to maintain or extend the lifetime of these equipments [9, 10]. In order to prevent premature degradation, which can be translated into financial loss, it is therefore necessary to monitor the physicochemical properties of the insulating mineral oil. Through the analysis of physicochemical characteristics, it is then possible to evaluate the quality of both the oil and the transformer itself. These analyses are of great importance for the maintenance of electrical equipments, as they allow planned interventions to correct any defects and, in some cases, early failure diagnoses [11, 12].

To test the insulating mineral oil, it is necessary that the transformer is working, because in operation the oil goes through an aging process. This aging is due to the demand for temperature increase, to the action of oxygen, and to contact with materials present in its construction, resulting in deterioration of oil properties. This deterioration generates by-products that promote its acceleration, that is, it generates a chain reaction where the insulating mineral oil loses its insulating properties and, as a result, the cellulose degrades generating sludge. The process that governs the oxidation of hydrocarbons is the peroxidation mechanism (peroxide formation), where there is the formation of intermediate products, which may be alcohols, aldehydes, and ketones depending on the species that originated them.

In **Table 1**, it showed the main experimental tests and their respective standards, which are usually recommended to trace the transformer isolation conditions. Therefore, the various tests performed on the insulating mineral oil in use allow to diagnose some problems, such as hot spots, overheating, and leaks, as well as informing about the insulating and thermal quality of the respective oil.

Tests	Technical standards
Aniline point	ABNT-NBR-11343 [13]
Chromatography analysis	ABNT-NBR-7070 [14, 15]
Cinematic viscosity	ABNT-NBR-10441 [16]
Color	ASTM-D1500 [17]
Density	ABNT-NBR-7148 [18]
Dielectric rigidity	IEC-156 [19] and ABNT-NBR-6869 [20]
Factor of losses at 90°C	IEC-247 [21]
Index of total acidity	ASTM-D974 [22]
Interfacial tension	ABNT-NBR-6234 [23]
Oxidation stability	ABNT-NBR-10504 [24]
Point of splendor and combustion	ABNT-NBR-11341 [25]
Polymerization level related to insulating paper	ABNT-NBR-8148 [26]
Tenor of water	ABNT-NBR-5755 [27]

Table 1.
Experimental tests and technical standards applied in insulating mineral oil.

On the other hand, chromatographic tests, also known as dissolved gas analysis (DGA), are diagnostic tools for the detection and evaluation of incipient failures in insulating mineral oil. When a transformer failure occurs, the insulation system will provide chemical degradation, which will generate the production of various gases that will be present in the oil. These concentrations of gases are related to a type of transformer failure.

The main gases analyzed by DGA are listed in **Table 2**. In normal operation, the presence of these gases in the transformer is also normal, i.e., it does not indicate the existence of failures. The only exception is carbon dioxide (CO₂), whose presence indicates a failure inside the equipment.

A transformer failure can result in the variation of the standard concentration of these gases in the oil. The increase in the gas concentration in the transformer indicates the occurrence of a failure that results in the insulation oil saturation. With this saturation, gas is released from the oil by modifying the characteristics of

Dissolved gas	Chemical formula
Acetylene	C ₂ H ₂
Carbon dioxide	CO ₂
Carbon monoxide	CO
Ethane	C ₂ H ₆
Ethylene	C ₂ H ₄
Hydrogen	H ₂
Methane	CH ₄
Nitrogen	N ₂
Oxygen	O ₂

Table 2.
Gases evaluated by DGA technique.

the transformer. The amount of gas released depends on the oil temperature and the type of gas. Such gas production can be classified into three groups, namely, polarization, corona effect, and electric arc. This classification is based on the severity with which power is released during the failure. The largest and smallest amount of energy released is associated with the electric arc and corona, respectively [28].

In relation to the polarization, the gases released in the oil at low temperature are methane and ethylene, while at high temperature are methane, ethylene, ethane, and hydrogen. In cellulose, the gases generated at both high and low temperatures are carbon monoxide and dioxide. Regarding the corona effect, the gas produced in the oil is hydrogen, and the gases released by cellulose are hydrogen, monoxide, and carbon dioxide. For the electric arc, the gases released in this case are hydrogen, methane, ethane, ethylene, and acetylene.

Related to temperature, laboratory research shows that CO, CO₂, and water originate when cellulose is overheated to a temperature of 140°C. Pyrolysis, which is destruction at temperatures above 250°C, produces more CO gas than CO₂. In this case, there is also the formation of water, coal, and tar. At temperatures above 500°C, methane (CH₄), ethane (C₂H₆), ethylene (C₂H₄), CO₂, and water originate when O₂ is present.

For the extraction of gases from the insulating mineral oil to be correct, it is then necessary that there are no bubbles in the collection vessel. The sample should be slightly warmed or injected into a degassing apparatus. The sample is subjected to vacuum, and the gases are collected in a graduated burette, which is taken to the chromatograph. The chromatograph is basically an apparatus used for chemical analysis of substances, capable of separating the various components of the sample.

Thus, from values obtained in physicochemical tests performed on the insulating mineral oil, we have then developed an intelligent system capable of estimating the gas values present in the insulating oil of the transformer.

3. Artificial neural network for estimating gases dissolved in insulating mineral oil

Computational models based on artificial neural networks are inspired by the knowledge we have about the nervous system of humans, which has the ability to learn from experience. They are composed of artificial neurons, which are also interconnected by artificial synapses.

Artificial neural networks can be applied to various engineering- and science-related problems. One of the areas with the greatest potential for their applicability is the universal approximation of functions, whose purpose is to represent functional relationships between inputs and outputs of typically nonlinear systems.

They can be applied to solve problems coming from various areas of knowledge, such as engineering, medicine, chemistry, and physics, where the possible solutions to the problems presented are difficult to obtain by conventional techniques.

One of the most commonly used architectures in artificial neural networks is that known as multilayer perceptron (MLP) [8], which will be also used in this application to map the relationship between results from physicochemical tests and those produced by chromatographic tests.

In addition, MLP networks are also characterized by the high possibilities of application in various types of problems related to the most different areas of knowledge, which is also considered as one of the most widely used in terms of applicability.

Figure 1 illustrates an MLP topology consisting of three neural layers, which has n signals in the input layer, with n_1 neurons (first layer), n_2 neurons (second layer), and m neurons in its output layer..

Each of the neurons of this topology illustrated in **Figure 1** can be represented according to the terminology adopted in **Figure 2**.

In purely mathematical terms, the internal processing carried out by each MLP neural network neuron can be expressed as follows:

$$y = g\left(\sum_{i=1}^n w_i \cdot x_i + b\right) \quad (1)$$

where x_i are the neuron inputs, w_i represents the synaptic weight (artificial synapse) belonging to i^{th} input value, θ refers to the activation threshold, u indicates activation potential, y represents the output response produced by the artificial neuron, and $g(\cdot)$ expresses the activation function that must be both differentiable and continuous throughout its domain, which are usually represented by the logistic activation function or by the hyperbolic tangent.

The training process of the neural network consists of applications of ordered steps that are necessary to tune the synaptic weights (w_i) and thresholds (θ) associated to its neurons, with the ultimate goal of generalizing solutions to be produced by its outputs, whose responses are representative of the physical system to which they are mapping. The learning method used here for training MLP network was

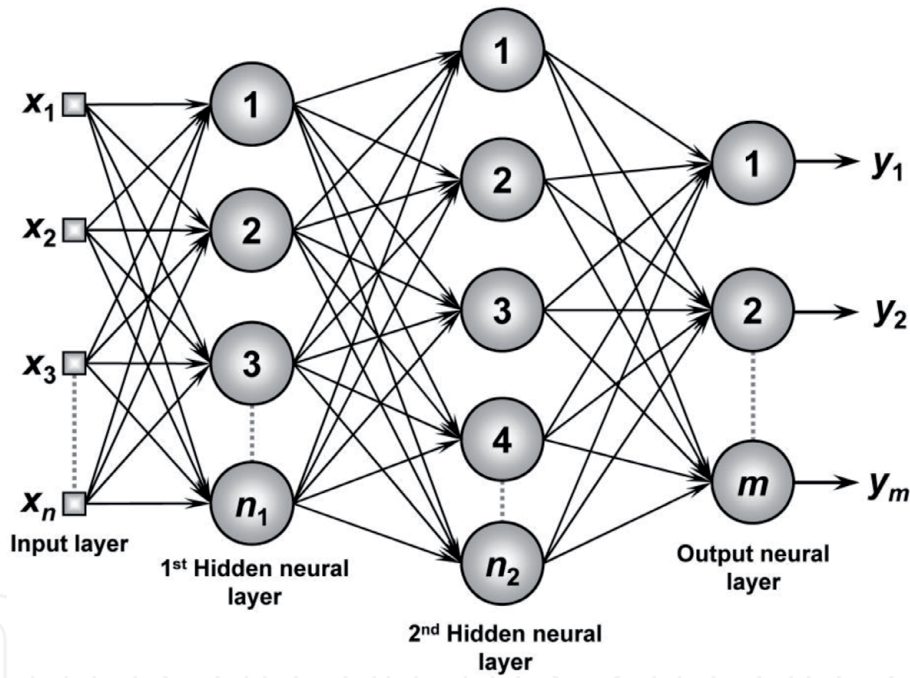


Figure 1.
Illustration of an artificial neural network with multilayer perceptron architecture.

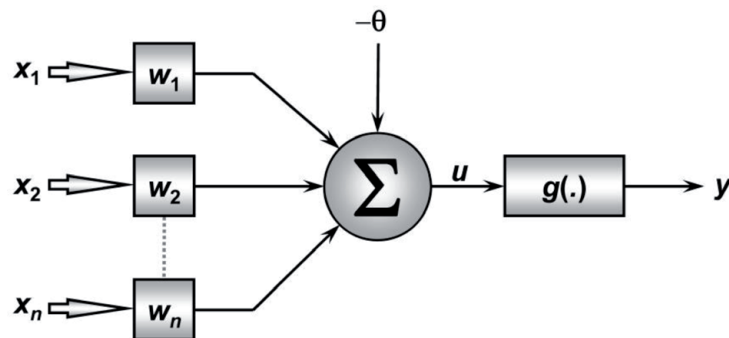


Figure 2.
Schematic diagram of artificial neuron used in MLP neural network.

that based on the Levenberg-Marquardt algorithm, whose detailed steps are presented in [29, 30].

The training of this network was performed in a supervised manner, which consists in having available, considering each sample of the input signals, the respective desired outputs, i.e., each training example is represented by input signals and their respective corresponding outputs. In this case, from a database supplied by electric utilities, the network inputs were the parameters related to the physicochemical tests (**Table 1**) performed on several isolating mineral oil samples, while the desired outputs are the respective values of those gases obtained by chromatographic tests (**Table 2**) using the DGA technique.

Therefore, the MLP network used for this purpose was composed of 10 neurons (first layer) and 20 neurons (second layer), and the activation function adopted for all artificial neurons was the hyperbolic tangent.

4. Experimental results and validation

According to the previously presented sections, several isolating mineral oil samples were also presented to the MLP network in order to select the best architecture for the problem mapping, whose results are reported in the next figures.

Figure 3 shows the estimated levels of gases dissolved in oil. Physicochemical experimental tests data were inserted in the MLP network inputs in order to produce, subsequently, the estimation of all gases dissolved in the insulating mineral oil. Network responses were compared to the values obtained from the chromatographic analyses. It is noteworthy that the MLP network responses are in accordance with the gas concentration.

Based upon **Figure 4**, it is possible to check the MLP network capacity of making adaptation and generalization about the analyzed data, whose results were compared to actual values of H_2 obtained from experimental tests.

Estimation of oxygen (O_2) obtained from 20 samples, which were not included in the training data, is shown in **Figure 5**. Considering this figure, it is possible to verify that the MLP network responses are very near to those obtained from the chromatographic tests.

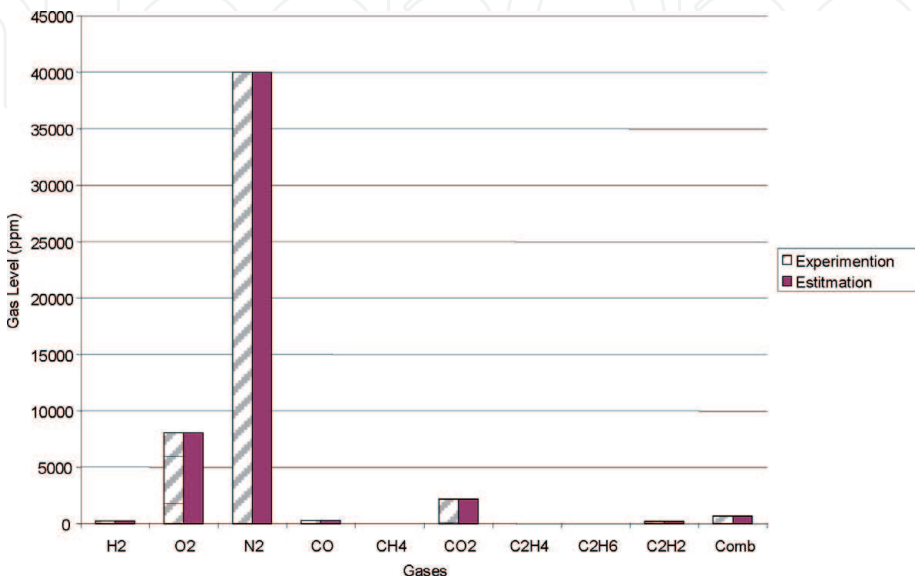


Figure 3.
Estimation of gas levels in the insulating mineral oil.

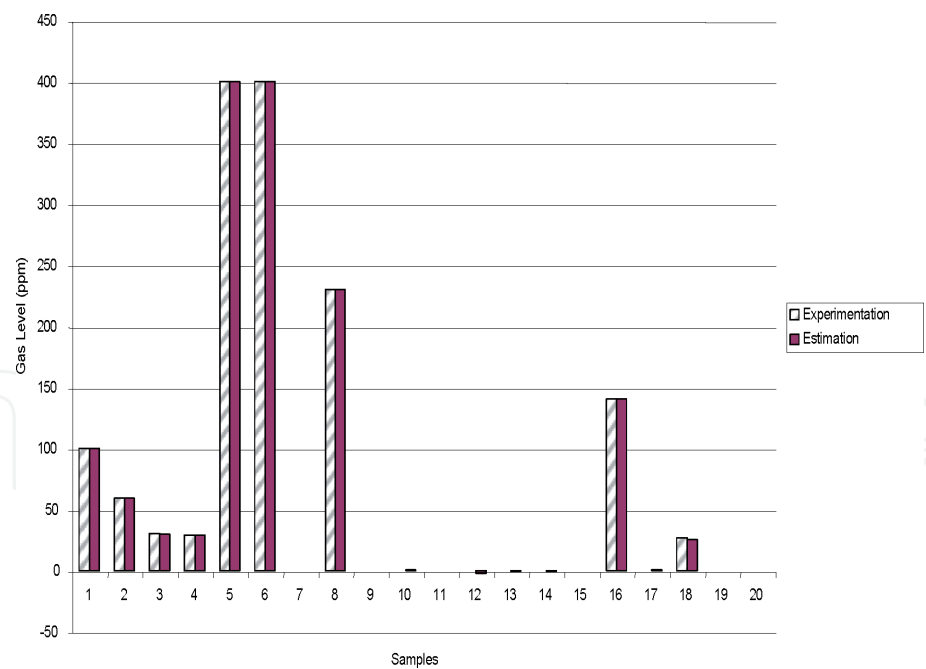


Figure 4.
Estimated levels of H₂ and comparative analysis.

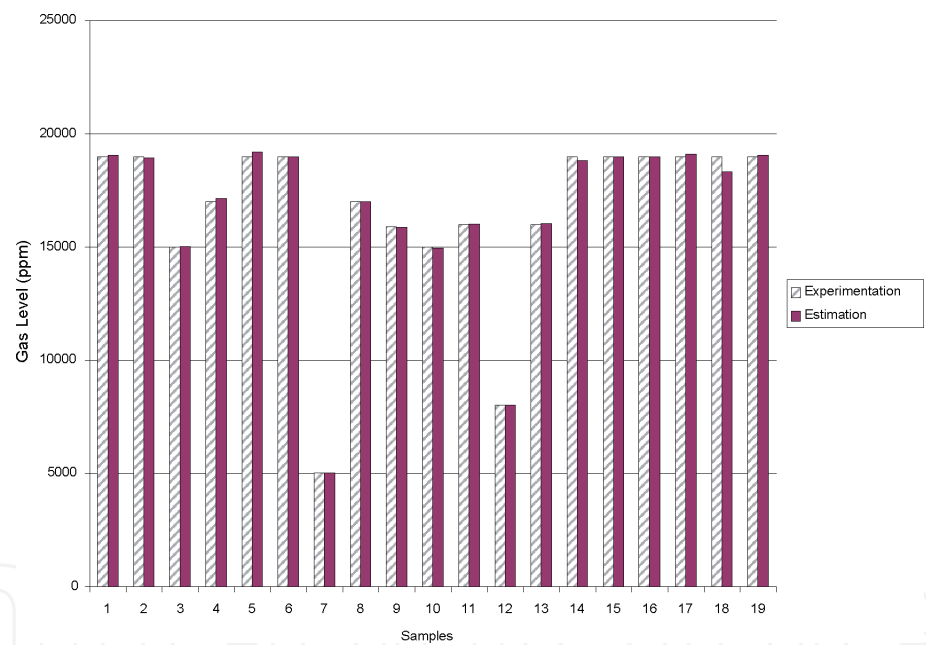


Figure 5.
Estimated levels of O₂ and comparative analysis.

Regarding oxygen (O₂), it is noticed that the MLP network generalization about physicochemical analysis is very reasonable. Therefore, it is appropriate to estimate such parameters.

Estimation of carbon monoxide (CO) obtained from 20 samples, which were not included in the training data, is shown in **Figure 6**. Considering this figure, it is possible to confirm that network computed results are very near to those obtained from the chromatographic analysis.

In addition, it is noted that generalization of CO gas values carried out by the neural network based upon physicochemical analysis is positive. Therefore, it is also appropriate to estimate such gas values.

Estimation of carbon dioxide (CO₂) obtained from 20 samples, which were not included in the training data, is shown in **Figure 7**. Considering this figure, it is

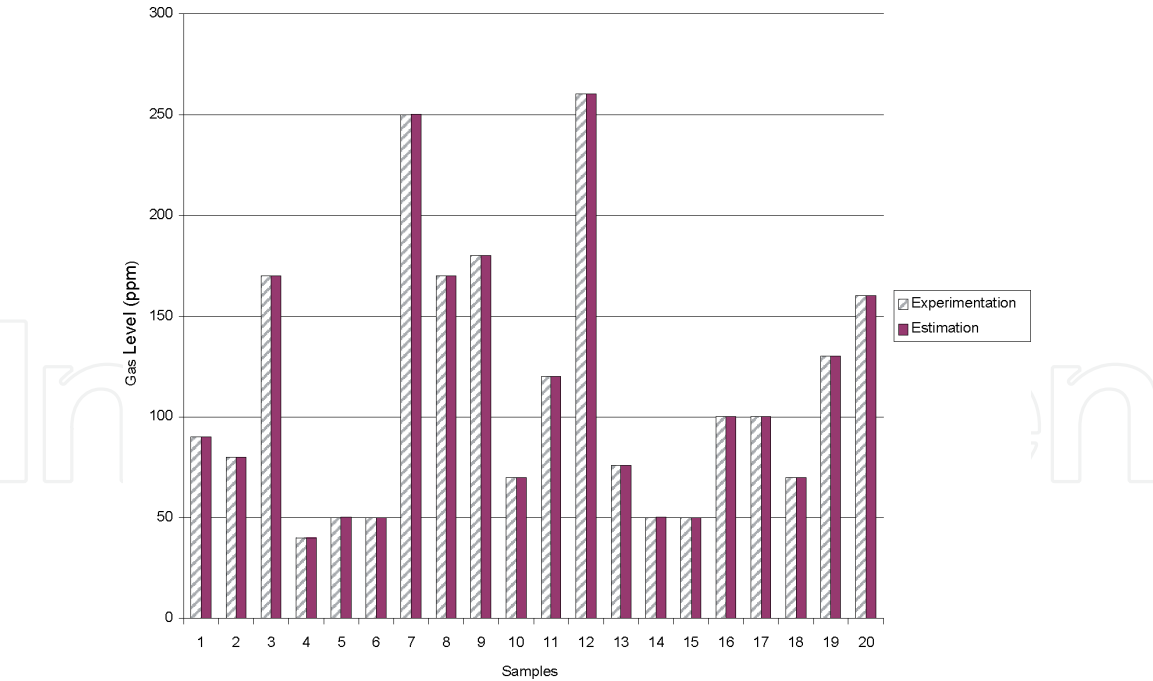


Figure 6.
Estimated levels of CO and comparative analysis.

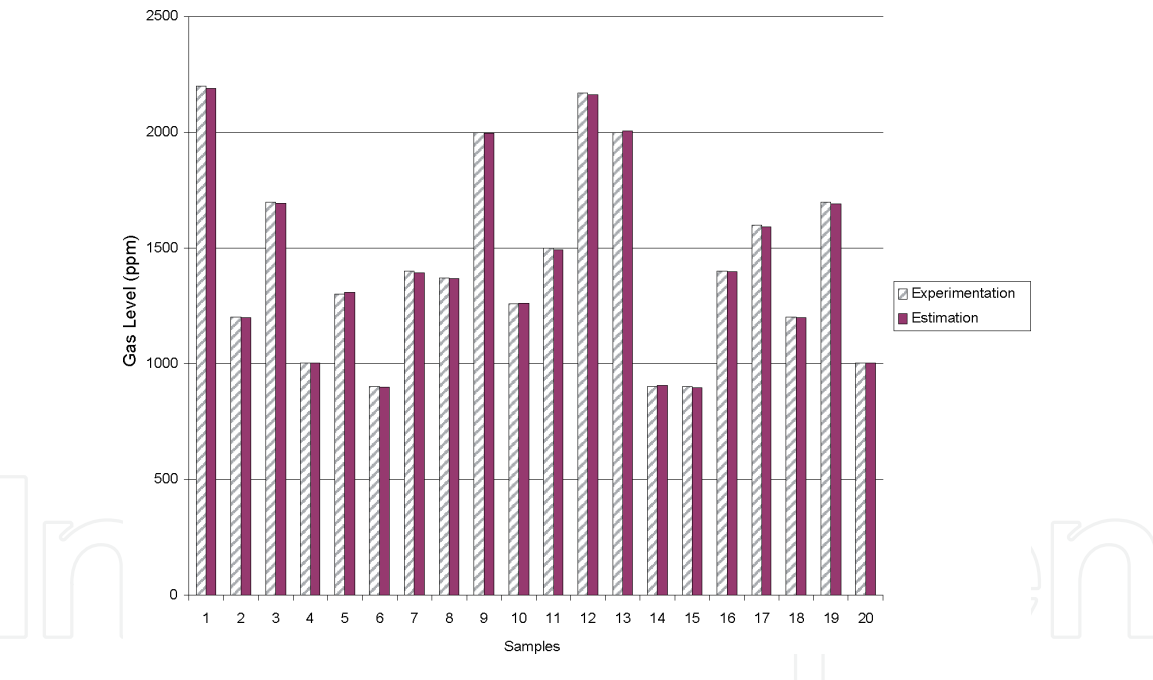


Figure 7.
Estimated levels of CO₂ and comparative analysis.

possible to check that network computed results are also very near to those obtained from the chromatographic analysis.

To summarize, it is verified that the generalization of CO₂ gas values based upon physicochemical analysis is positive. Therefore, it is also appropriate to estimate such parameters.

The following figures illustrate the results provided by the MLP neural network relating the estimated gases in relation to the physicochemical parameters.

Figure 8 illustrates the relationship between CO₂ gas levels with their colors, and these attributes are tabulated from 0.5 (for new oil) to 3.0 (for deteriorated oil). We have here checked that the relationship between CO₂ levels decreases as the color

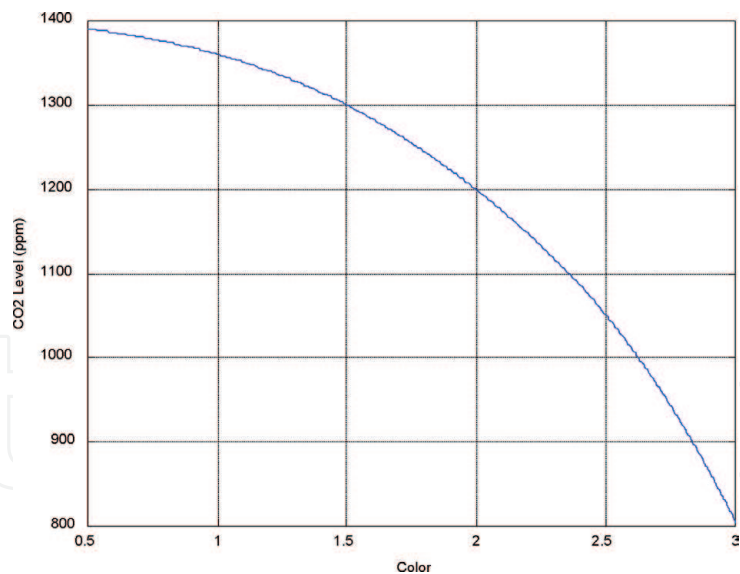


Figure 8.
Relationship between CO₂ gas levels as a function of the oil color.

level increases. This behavior is related to the heating of the insulating mineral oil, which consequently also increases its oxidation level.

On the other hand, as illustrated in **Figure 9**, it is reported that CO₂ gas levels increase linearly as the oil density value also increases. This behavior is related to abrupt changes in temperature over time.

Figure 10 shows that the relationship between CO₂ gas levels and the neutralization index of the insulating mineral oil decreases nonlinearly. This behavior may be related to oil acidity levels, since the increase of CO₂ has direct implications on its neutralization levels.

Figure 11, in contrast to **Figure 9**, has illustrated that the relationship of CO gas levels as a function of insulating mineral oil density decreases linearly, as the behavior of both gases is independent of each other.

Already in **Figure 12**, we can see that the relationship between CO gas levels with their interfacial tension values remains almost constant until tension limit of 25 dyn/cm, and from this critical point, the CO gas levels drop sharply, as the less water present in the oil also implies higher interfacial tension.

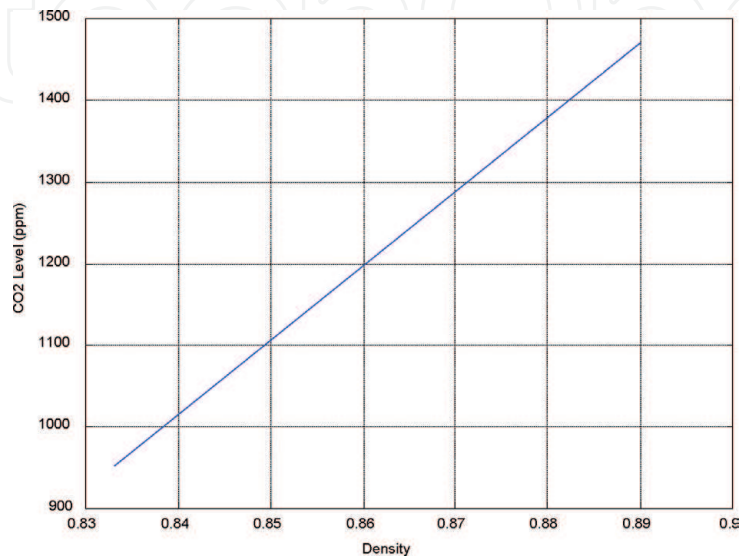


Figure 9.
Relationship between CO₂ gas levels as a function of the oil density.

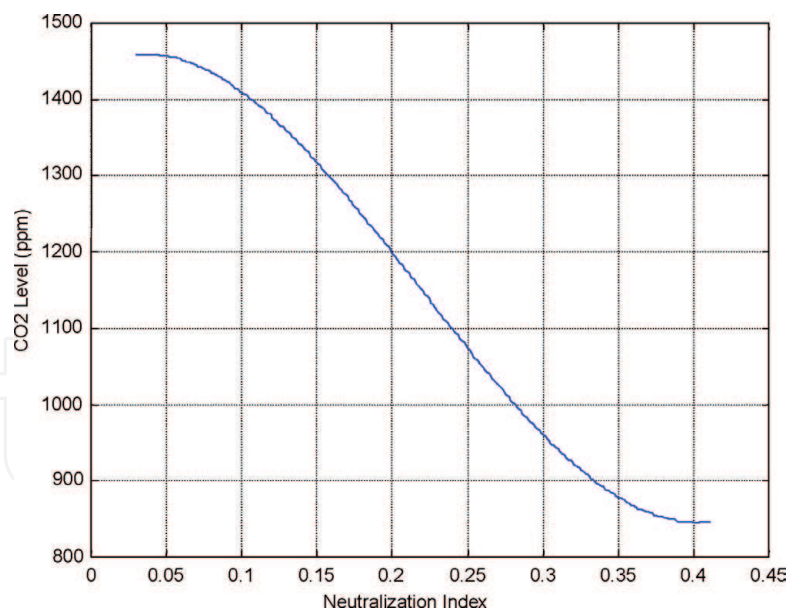


Figure 10.
Relationship between CO₂ gas levels as a function of the oil neutralization index.

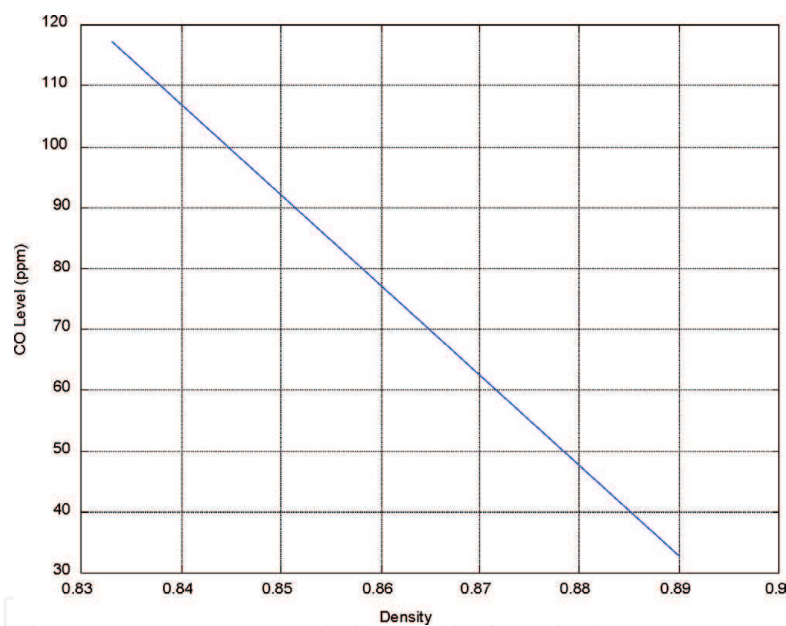


Figure 11.
Relationship between CO gas levels as a function of the oil density.

Figure 13 now shows that CO gas levels as a function of water quantity are also inversely proportional. This behavioral profile is probably associated with temperature, as its decrease also implies a reduction in water evaporation and, consequently, increases its concentration in the insulating mineral oil.

Finally, as shown in **Figure 14**, it is reported that the relationship of O₂ gas levels as a function of oil density has a decreasing profile. Such behavior may be due to changes in acidity levels of insulating oil as density increases.

From the results presented in this section, we demonstrate the possibility of mapping, by means of artificial neural networks, concentration values of gases dissolved in insulating mineral oil from the results of physicochemical tests. To estimate the gases, data from physicochemical tests performed on insulating mineral oil taken from operating transformers were used.

The developed technique allowed the gas estimations in insulating mineral oil and without need to perform the chromatographic tests. Thus, the amount

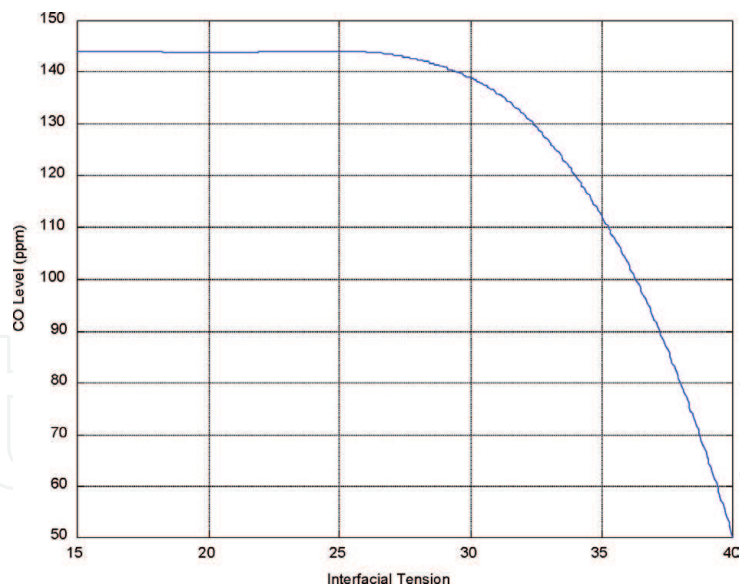


Figure 12.
Relationship between CO gas levels as a function of the oil interfacial tension.

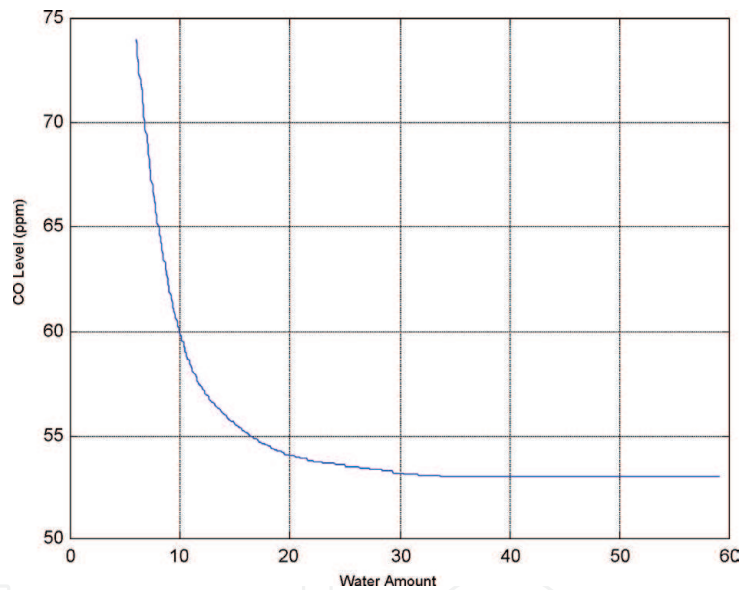


Figure 13.
Relationship between CO gas levels as a function of the water concentration in the insulating mineral oil.

of power supply interruptions can be considerably reduced, and the associated costs in determining the concentration of gases in the mineral oil follow this same downward trend.

5. Conclusion

An approach based on artificial neural networks was presented in this article, and its target was to estimate gas levels dissolved in insulating oil. Based upon data obtained from physicochemical analyses, decisions for transformer maintenance may be supported by the network; it can even indicate whether chromatographic analyses are necessary.

The artificial neural network approach proved to be efficient for estimating the gas levels dissolved in insulating oil. Based upon input data provided by

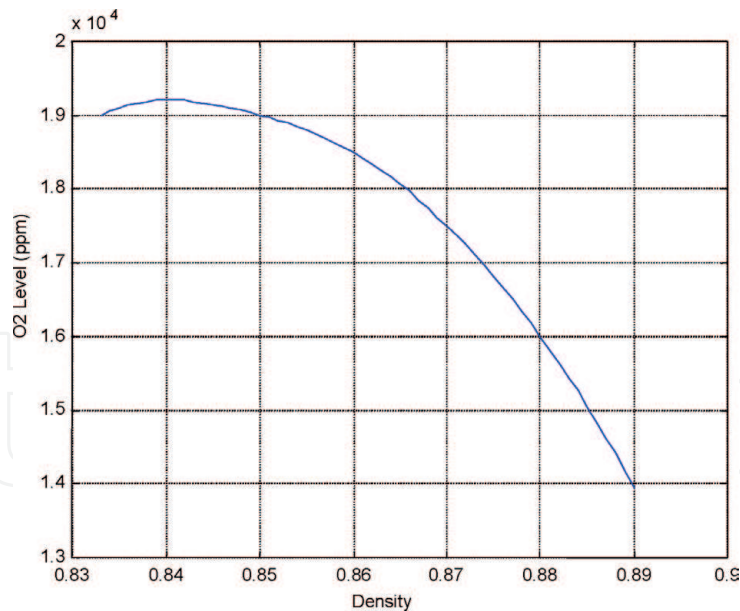


Figure 14.
Relationship between O₂ gas levels as a function of the oil density.

physicochemical analyses, estimation of any gas obtained from chromatographic analyses becomes possible (without physicochemical analysis). Furthermore, artificial neural network approach was developed in order to set up the relationship between attributes which did not have any apparent relationship.

Finally, the developed neural approach is innovative, and it is also the first one that performs the estimation of dissolved gases in insulating mineral oil from the results of physicochemical tests. Therefore, in order to authenticate the developed methodology, the results provided by the artificial neural network were compared with those actual values obtained by chromatographic tests.

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