Diagnosis of power transformer failures by analyzing dissolved gas samples in oil using artificial neural networks

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ABSTRACT

This work demonstrated that artificial intelligence methods could be used in predictive maintenance, obtaining valuable results to improve decision-making in scheduled maintenance plans applied to power transformers immersed in mineral oil in power generation plants.

The objective of this research is to interpret the Dissolved Gas Analysis (DGA) results in the oil of the power transformers of the generation plants using Artificial Neural Networks (ANN) to obtain a broad panorama for decision-making in the maintenance programs that are planned in the generation plants.

The bibliographic research is the primary basis for this study because it consists of the compilation of a set of results of the dissolved gas analysis performed on several power transformers from different parts of the planet. The data were previously validated and determined the state of the transformers after obtaining their respective interpretations.

The machine learning method was used by constructing an artificial neural network in Matlab and training it with the data collected and validated.

Keywords: Predictive maintenance, dissolved gas analysis, power transformers, mineral dielectric oil, artificial neural networks

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RESUMEN

El presente trabajó demostró que se puede emplear métodos de inteligencia artificial en el campo del mantenimiento predictivo, obteniendo valiosos resultados para mejorar la toma de decisiones en los planes de mantenimiento programados que se aplican a los transformadores de potencia sumergidos en aceite mineral de las centrales de generación.

Esta investigación tuvo como objetivo interpretar los resultados del Análisis de Gases Disueltos (AGD) en el aceite de los transformadores de potencia de las centrales de generación mediante Redes Neuronales Artificiales (RNA) para obtener un amplio panorama en la toma de decisiones en los programas de mantenimientos que se planifican en las centrales de generación.

La investigación de tipo bibliográfica es la que fundamentó principalmente este trabajo de investigación, porque consiste en la recopilación de un conjunto de resultados de análisis de gases disueltos realizados a varios transformadores de potencia de distintas partes del planeta. Los datos

fueron previamente validados y determinaron el estado en el que se encuentran los transformadores luego de obtener sus respectivas interpretaciones.

Se empleó el método de aprendizaje automático mediante la construcción de una red neuronal artificial en Matlab para proceder a su entrenamiento con los datos recopilados y validados.

Palabras clave: Mantenimiento predictivo, análisis de gases disueltos, transformadores de potencia, aceite dieléctrico mineral, redes neuronales artificiales.

INTRODUCTION

In the maintenance plans of power transformers of generation plants (substations and rooms), decisions must be made that always lead to the proper operation of the equipment, avoiding future damage and, therefore, long-term shutdowns to avoid significant economic losses. Actions that require the shutdown or not of the transformer will depend on its condition, which can be interpreted through visual or electrical analysis (thermography, measurement of electrical and mechanical parameters). However, it is possible to make a more accurate diagnosis through the state of its insulating paper and the active part of the equipment through physical-chemical and oil-dissolved gas (AGD) analysis.

AGD provides valuable information on the content of key fault gases, which is then entered into a computer or software using standard techniques for interpretation. Whether AGD is performed in a laboratory or via portable equipment, oil samples are taken by trained personnel. However, not all power plants have online gas monitors, another option, due to their high costs. Therefore, analyzing all these samples through online monitoring equipment or laboratories can result in different criteria that create uncertainty in the interpretation, leading to ineffective preventive or corrective maintenance decisions. Faced with this problem, the need arises to perform another analysis to interpret the results of the AGD to confirm the status of the transformer. Applying this method through artificial neural networks (ANN) is very convenient because it offers a training system based on results subjected to real verifications, thus increasing the degree of certainty in decision-making for the maintenance plans of the generating companies.

The general objective of this research was to improve decision-making for the definition of effective and efficient maintenance plans for power transformers immersed in mineral oil in power generation plants through the interpretation of the AGD using ANN. On the other hand, the specific objectives of the work were:

- To implement a database of AGD performed on power transformers of generation plants subjected to condition testing.
- Use Artificial Neural Networks for training and simulation with the implemented database to interpret the condition of power transformers in power generation plants.
- Perform analysis with AGD data from power transformers of power generation plants to establish a diagnosis based on comparisons between conventional methods and neural networks.

This study improves decision-making in planning maintenance plans for power transformers of generation plants through the analysis and subsequent interpretation of historical results of gas content in the oil.

Transformer service life

As a reference, the service life of a transformer indicated by the manufacturer can be extended for several years, depending on several factors: electrical, mechanical and environmental factors to which the machine is subjected.

Generally, transformers are reliable and robust electrical equipment, reaching a useful life of more than 35 years, with an average minimum of 20.5 years.

Insulating oil

Three types of oils are used in constructing power transformers: mineral, vegetable and synthetic. Each has different properties; only transformers immersed in mineral oil were studied for this work. The mineral oil used in transformers is a petroleum derivative resulting from a distillation process. Its structure is hydrocarbons, which can be classified into naphthenic, paraffinic and aromatic or closed-chain unsaturated hydrocarbons [1]. The main functions that mineral insulating oil performs in a transformer are: insulating, cooling and

protecting the Kraft paper. Additionally, oil is one of the means that can be used to evaluate the internal conditions of the transformer.

Degradation of the insulating oil

When the transformer operates under normal conditions and nominal temperatures, its insulating oil enters into a degradation process due to oxidation. This effect can be caused by agents such as solar radiation, overloads, transient or permanent overvoltages, temperature, humidity, deterioration of varnishes, cellulose, copper particles and metallic materials in the tank.

Electrical transformer oil is subjected to constant stress and heating. As a result, even when the transformer operates at its nominal values, its chemical, physical and electrical properties will be altered by temperature, oxygen levels, degradation in metallic parts (tank) and electrical stresses. This results in paper deterioration and sludge formation [2].

Insulating oil service life

Field maintenance experiences of oil-immersed power transformers show that the material's service life be evaluated by the standard neutralization number and color indicator test according to ASTM D-974 [3] and through the measurement of interfacial tension according to ASTM D-971 [4].

Paper degradation

The paper in the transformer windings is affected by the aging of the transformer. Therefore, there is a parameter that measures the mechanical resistance of the insulation (paper) called the degree of polymerization (GP) or (DP) which is a key indicator for making maintenance decisions.

On the other hand, the carbon dioxide to carbon monoxide ratio CO_2/CO is a helpful indicator of paper degradation. It is used as an index of cellulose decomposition, and its typical ratio ranges from 3 to 10. A value outside this range indicates problems in the insulating paper. The literature recommends an analysis of furans when the CO_2/CO ratio increases because these are the main products that degrade paper.

Dissolved gas analysis

AGD is a standard method for detecting gases in oil-immersed transformers, and its principle is chromatography prior to the extraction of gases in the oil. For this purpose, the procedures of the ASTM D 3612 standard are followed [5], where the three methods of

Dissolved gas analysis (DGA) states that in oil

The states of dissolved gas analysis in oil are categorized as follows [6] into three:

- State 1: Normal. Low gas levels; therefore, no actions are recommended.
- State 2: Possibly suspect. Intermediate gas levels indicate possible partial discharge failures and thermal failures below 300 °C. It is recommended to increase sampling frequency and monitor online.
- Condition 3: Possibly suspect. High gas levels indicate possible failure. Further monitoring and additional tests are recommended in parallel to consulting with the manufacturer for the result.

Figure 1.1 shows the relationship between different gas concentration rates in percent as a function of temperature rise determined by their fault type. The IEEE provides this graph in its 2019 guide for fault interpretation [6], based on a historical compilation of hundreds of thousands of transformers worldwide with proven diagnostics.

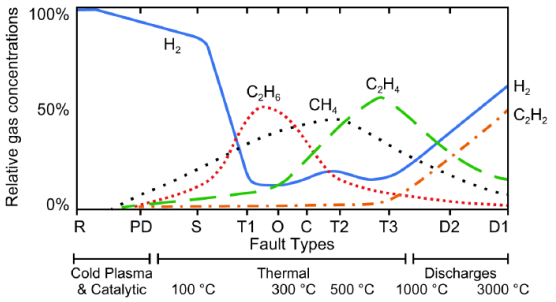

Figure 1.1: Relative percentage of dissolved gas concentrations in mineral oil as a temperature and fault type. Source: [6]

Associated material	Type of Failure	Gases present
Oil	Partial downloads	H_2
	Thermal heating at low temperatures	CH_4 C_2 H_6
	Thermal heating at high temperatures	C_2 H_4 C_2 H_6
Cellulose	Partial downloads	H_2 CO CO_2
	Thermal heating at low temperatures	CO_2 (CO)

Type of failure (Diagnosis)	Relation							
	$R1 = \frac{CH_4}{H_2}$ Oil / Gas		$R2 = \frac{C_2H_2}{C_2H_4}$ Oil / Gas		$R3 = \frac{C_2H_2}{CH_4}$ Oil / Gas		$R4 = \frac{C_2H_6}{C_2H_2}$ Oil / Gas	
1.- Thermal decomposition (hot spot)	> 1, 0	>0 ,1	< 0,7 5	<1 .0	< 0, 3	<0 .1	>0. 4	>0 .2
2.- Corona (Low partial discharge)	<0 ,1	< 0, 01	Not relevant		<0 ,3	<0 ,1	>0, 4	>0 ,2
3.- Arc (High Partial Discharge)	>0 ,1 >0 ,0 1	<1 ,0 <0 ,1	>0, 75	>0 ,1	>0 ,3	>0 ,1	<0, 4	<0 ,2
	Thermal heating at high temperatures		CO (CO_2)					
NA.	Electric Arc		H_2 C_2 H_2 (CH_4 C_2 H_6 C_2 H_4)					

Table 1.1: Fault gases present in a transformer. Source: [7]

Codes				States/diagnostics
R1	R2	R3	R4	
0	0	0	0	Normal state
5	0	0	0	Partial downloads
5	0	0	1 y 2	Partial downloads
0	0			Continuous sizzling
0	0	1 y 2	1 y 2	Arch
0	0	0	1	Disruptive discharge
1 y 2	0	0	0	Slight overheating at < 150ºC
1 y 2	1	0	0	Slight overheating at 150 - 200ºC
0	1	0	0	Slight overheating to 200 - 300ºC
0	0	1	0	General overheating of conductors
1	0	1	0	Circulating currents in the windings
1	0		0	Overheating due to current circulation in core and tank

Table 1.3: Diagnosis according to Rogers' method. Source: Own elaboration

Table 1.4: Relationships and diagnostics for key gases according to Dornenburg. Source: [6]

Methods of interpretation of the AGD

Since the 1970s, several methods have been applied and have evolved over the years. Some have been perfected based on numerical and graphical relationships. In other cases, statistical methods have been applied, and since the 21st century, with the development of artificial intelligence, some algorithms can be applied in electrical and maintenance engineering. Tables 1.2, 1.3, 1.4 and 1.5 show the history of methods developed and applied to date:

Relations	Ranges		Cases
$R1 = \frac{CH_4}{H_2}$	-	<0.1	5
	0,1<	<1	0
	1≤	<3	1
	-	≥1	2
$R2 = \frac{C_2H_6}{CH_4}$	-	<1	0
	-	≥1	1
$R3 = \frac{C_2H_4}{C_2H_6}$	-	<1	0
	1 ≤	< 3	1
	-	≥3	2
$R4 = \frac{C_2H_2}{C_2H_4}$	-	<0,5	0
	0,5≤	< 3	1
	-	≥3	2

Table 1.2: Relationships and ranges of values used in Rogers' method. Source: Own elaboration

The method developed by Duval proposes the use of three gases that represent based on their concentrations an increase in energy or temperature content such as: Methane (CH4) for low energy or temperature faults, ethylene (C2H4) for high temperature faults and acetylene (C2H2) for very high temperature / energies / electric arc faults. The relative percentages of these three gases are plotted on each side of the equilateral triangle. Equations 1.1, 1.2 and 1.3 express the gas content ratios in percent to obtain the points to be plotted in triangle 1 shown in Fig. 1.2.

$$\%CH_4 = 100\frac{X}{X+Y+Z} \quad \text{(Eq. 1.1)}$$

$$\%C_2H_4 = 100\frac{Y}{X+Y+Z} \quad \text{(Eq. 1.2)}$$

$$\%C_2H_2 = 100\frac{Z}{X+Y+Z} \quad \text{(Eq. 1.3)}$$

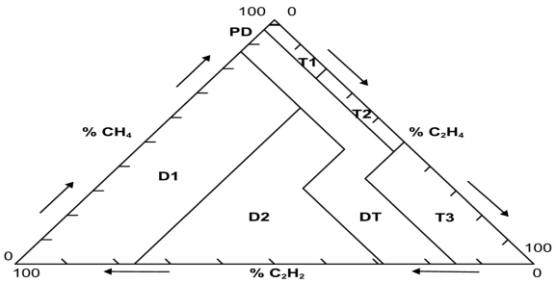

Figure 1.2: Duval's triangle 1. Source: [6]

Failure	Gas (%) / Identification	% CH_4	% C_2H_4	%C_2H_2
PS	Partial discharge	≥ 98	-	-
T1	Thermal failure <300º.	< 98	< 20	< 4
T2	Thermal failure >300º <700ºC	-	≥ 20 y < 50	< 4
T3	Thermal failure >700ºC	-	≥ 50	< 15
D1	Download BE.	-	< 23	≥ 13
D2	AE Download		≥ 23	≥ 29
			≥ 23 y < 40	≥ 13 y < 29
DT	Thermal and electrical failures	-	< 50	≥ 4 y < 13
		-	≥ 40 y < 50	≥ 13 y < 29
		-	≥ 50	≥ 15 y < 29

Table 1.5: Fault areas of Duval's triangle 1. Source: [6]

Intelligent methods for AGD interpretation:

According to Bhalla in [8], gases dissolved in mineral oils derived from petroleum can be incorporated into intelligent systems to facilitate decision-making since there is much uncertainty with the data obtained in the AGD due to the different applications of transformers, such as generation, lifting substations, reduction substations (both linked to transmission), and also the simple fact that the sample may be subject to contaminants. Therefore, a variation can be significant for the different utilities (generation, transmission, distribution and auto generators).

Due to the diverse content of dissolved gases, several artificial intelligence techniques have been presented. The techniques studied by Bhalla in [8] for their respective application in the interpretation of results obtained in the AGD are:

- Expert systems
- Fuzzy logic
- Artificial neural networks
- Genetic algorithms

In this context, studies of different artificial intelligence methods have been reviewed since 2010, applied to the diagnosis of AGD, showing good results during their application.

Use of Artificial Neural Networks for AGD interpretation:

From the practical aspects of the biological neuron, a model can be obtained where its structure is artificially detailed, as shown in Figure 1.3.

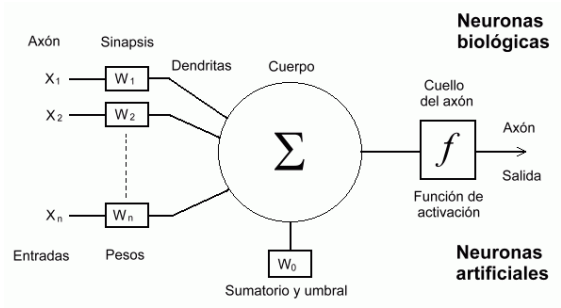

Figure 1.3. Artificial neural network model. Source: [9]

The artificial neuron model is based on the biological model; it receives stimulus inputs defined by the input vector X = {X1, X2, ... Xn}.

Radial-based neural network:

It is a unidirectional multilayer network with hybrid learning. An unsupervised algorithm is used in the first layer and supervised learning is used in the output. This type of network, due to its simplicity, this type of network is widely applied in situations requiring object recognition and pattern classification, identification and modeling of nonlinear systems.

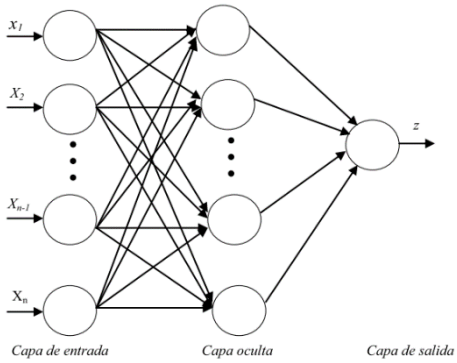

Figure 1.4 shows a radial-based artificial neural network, which contains neurons in its hidden layer that are activated by nonlinear basis functions and its output layer is activated by linear functions.

Figure 1.4. Architecture of a radial-based network. Source: [9]

The calculation involves finding the radial or so-called Euclidean distance (d) at a point in the hidden layer [10].

$$d = |x - c| = \sqrt{(x1 - c1)^2 + (x2 - c2)^2 + \cdots + (xn - cn)^2}$$

(Eq. 1.4)

The d value is the fundamental key to activating the radial function. G (•). With this value, we denote differences between MLP and backpropagation networks, which mix the result of multiplying the hidden layers with the respective weights.

MATERIALS AND METHODS

This research work is initially based on bibliographic type research, which consists of the compilation of dissolved gas analysis reports performed on several transformers from different parts of the planet, validating the state in which they are after obtaining their respective interpretations. These data were applied in the following publications: the University of Shanghai, China [11]; National Chin-Yi Institute of Technology, Taiwan [12], Taif University of Saudi Arabia [13] and Jabalpur Engineering College in India. [14]. AGD results from the College of Engineering Taif University, the Taif University of Saudi Arabia and Jabalpur Engineering College of India were used for test data [13].

The methodological development that was elaborated in this proposal to solve the problem of the interpretation of the states or early failures in the transformation equipment consisted of three main stages, as shown in Fig. 1.5, as follows:

1. Data entry stage (obtained from the AGD in the oil)
2. Training stage (according to historical data obtained from transformer fault diagnosis)
3. Testing stage.

Network No.	No. of Layers	No. of neurons	No. of training sessions	[%] of hits
1	1	5	5	63%
2	1	10	5	55%
3	2	5	5	78%
4	2	10	5	84%
5	3	5	5	45%

Table 1.6: Tests with different neural networks. Source**:** Author.

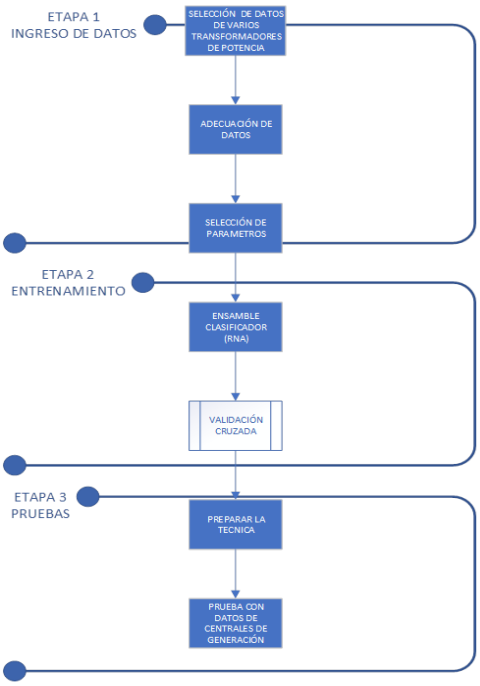

Figure 1.5. Stages of the methodology followed. Source: [15]

RESULTS

For the classifier assembly adopted by the Neural Network, several networks were designed in the Matlab nntool library to obtain the best assertiveness value. The feed-forward backpropagation type network was used. In the training stage the traingdm function was used, for the learning process the learngdm function and

the mean squared error (MSE) performance function were used.

DISCUSSION

In Ecuador, many power transformers are linked to generation, transmission company substations and distribution companies.

The total number of power transformers in public companies is 134, and in private companies is 101, resulting in 235 power transformers in Ecuador, whose maximum powers range from 1 to 173 MVA. Remembering that a power transformer equipment failure could cause significant economic losses, monitoring the transformers becomes an important task. Through this work, we offer the option of improving the monitoring interpretations for the maintenance department of the country's public and private generation plants.

Thanks to the study, it is suggested that to have greater accuracy in the diagnosis (in the case of normal state), it is necessary to have data on the type of failure and the concentration of gases that produce it that are more specific. Therefore, obtaining a complete database and introducing more classes is suggested to be more specific in each failure.

Finally, with the results obtained and due to the large number of power transformers that exist in the country (235 until 2019), generating companies can adopt the methodology presented in this research work to obtain a new perspective on the state of their transformers. In addition, this is a way to evaluate the scheduled maintenance plans for the intervention of their equipment.

CONCLUSIONS

According to the comparative study carried out, it was confirmed that the neural network methodology is more than 42% more effective than the conventional methods evaluated. This is because conventional methods use a gas ratio that cannot always be satisfied because indeterminate results are sometimes obtained. However, unlike the intelligent methods, which learn based on the examples introduced, they will always obtain a result, not numerical indeterminacy.

With all the results obtained, it is finally concluded that the technique presented in this work is of great help for planning the maintenance that is implemented to the power transformers in the generation plants. On the other hand, if a standard policy is adopted regarding the reduction in the sampling intervals (frequency) of gas levels in power transformers by the generating companies to create more numerous databases, the results when applying neural networks for their interpretation would increase their effectiveness.

REFERENCES

[1] C. Jara y D. M. , «Análisis del estado y la vida remanente de un transformador elevador de 275 MVA, 18KV/550KV,» *X SEMINARIO DEL SECTOR ELECTRICO PARAGUAYO - CIGRÉ,* pp. 1-10, 2012.

[2] E. Gallo Martínez , Diagnóstico y mantenimiento a transformadores en campo, Bogotá : Transequipos, 2010.

[3] ASTM, «Standard Test Method for Acid and Base Number by Color Indicator Titration». Patente ASTM D974 - 21, 2021.

[4] ASTM, «Standart Test Method for Interfacial Tension of Insulating Liquids Against Water by the Ring Method». Patente ASTM D971 - 20, 2020.

[5] ASTM, «Standard Test Method for Analysis of Gases Dissolved in Electrical Insulating Oil by Gas Chromatography». Patente ASTM D3612 - 02 (2017), 2017.

[6] IEEE, «IEEE Guide for the Interpretaion of Gases Generated in Mineral Oil-Immersed Transformers». Patente IEEE Std C57.104-2019, 1 11 2019.

[7] A. Carrera Gómez, Análisis de gases disueltos en el aceite para el mantenimiento preventivo a transformadores de potencia mediante la implementación de software, México D.F., 2013.

[8] D. Bhalla, R. Kumar Bansal y H. Om Gupta, «Application of artificial Intelligence Techniques for Dissolved Gas Analysis of Transformers - A review,» *World Academy of Sience and technology,* vol. 4, nº 2, p. 9, 2010.

[9] E. F. Caicedo y J. A. López, «La neurona artificial,» de *Una aproximación práctica a las redes neuronales artificiales*, Cali, Programa editorial unibersidad del valle, 2017, p. 219.

[10] C. G, *Curso de Redes Neuronales,* Merida: Universidad de los Andes, 2008.

[11] L. Ganyun , C. Haozhong, Z. Haibao y D. Lixin, «Fault diagnosis of power transformer based on multilayer SVM classifier,» *Electric power systems research* , vol. DXXV, pp. 9-15, 2005.

[12] H. Chin-Pao y W. Mang-Hui, «Diagnosis of incipient faults in power transformers using CMAC neural network approach,» *Electric power systems research* , vol. DXXI, pp. 235-244, 2004.

[13] S. Ghoneim y I. Taha, «Artificial neural networks for power transformers fault diagnosis based on IEC code using dissolved gas analysis,» *International journal of control automation and systems,* vol. IV, nº 2, pp. 18-21, 2015.

[14] K. Shrivastava y A. Choubey, «A novel association rule mining with IEC ratio based dissolved gas analysis for fault diagnosis of power transformers,» *International journal of advanced computer research,* vol. II, nº 2, pp. 34-44, 2012.

[15] J. M. Cadena Zapata y J. A. Cadena Zapata, «Aplicación de redes neuronales probabilísticas en la detección de fallas incipientes en transformadores,» *Scientia et Technica* , vol. XIV, nº 39, pp. 48-53, 2008.

[16] P. VIEGO y J. GOMEZ, «RECOMENDACIONES SOBRE EL USO DE ARRANCADORES SUAVES PARA AHORRAR ENERGÍA EN MOTORES ASINCRONOS CON CARGAS PARCIALES,» *ESPACIOS,* vol. 38, nº 51, p. 22, 2017.