1. Tural Aliyev[1], 2. Jalal Ibrahimov[2], 3. Shahla Qracova[3], 4. Zarifa Isgandarova[4]

Azerbaijan State Oil and İndustry University, Baku, Azerbaijan (1, 2, 3, 4)
ORCID: 1. 0000-0003-0751-3952, 2. 0000-0001-6435-3321, 3. 0009-0004-3878-7328, 4. 0009-0009-7268-05X

doi:10.15199/48.2024.08.38

Dissolved gas analysis based fuzzy logic feamework for power transformer asset management

***Abstract**. Dissolved Gas Analysis (DGA) is a vital tool for monitoring power transformer conditions. Despite its effectiveness, current interpretation techniques lack consistency and often rely on personnel experience, leading to varied conclusions for the same oil sample. This paper proposes a fuzzy logic approach to standardize DGA interpretation, aiming to establish a uniform method for critical transformer ranking and informed asset management decisions. The approach integrates existing DGA interpretation techniques into an expert model, enhancing reliability. The model, developed from 338 oil samples, offers a consistent and accurate basis for transformer condition assessment and asset management.*

Streszczenie. *Analiza rozpuszczonego gazu (DGA) jest niezbędnym narzędziem do monitorowania stanu transformatorów mocy. Pomimo swojej skuteczności, obecne techniki interpretacji nie są spójne i często opierają się na doświadczeniu personelu, co prowadzi do różnych wniosków dla tej samej próbki oleju. W niniejszym artykule zaproponowano podejście oparte na logice rozmytej w celu standaryzacji interpretacji DGA, mające na celu ustanowienie jednolitej metody klasyfikacji krytycznych transformatorów i świadomych decyzji dotyczących zarządzania aktywami. Podejście to integruje istniejące techniki interpretacji DGA w eksperckim modelu, zwiększając niezawodność. Model opracowany na podstawie 338 próbek oleju oferuje spójną i dokładną podstawę do oceny stanu transformatorów i zarządzania aktywami.* (***Rozmyta logika oparta na analizie gazu rozpuszczonego do zarządzania aktywami transformatorów mocy***)

Keywords: Dissolved Gas Analysis, transformer oil, Fuzzy Logic Approach, Asset Management Decision.
Słowa kluczowe: Analiza gazów rozpuszczonych, olej transformatorowy, podejście logiki rozmytej..

Introduction

Power transformers serve as crucial components within any transmission or distribution network. Ensuring the reliability of these devices and preventing catastrophic failures necessitates the adoption of effective monitoring and diagnostic techniques. The dielectric oil and paper insulation of transformers are pivotal in detecting incipient and rapidly developing faults, reflecting the overall health condition of the transformer (Abu-Siada and Islam, 2012).

Various chemical and electrical diagnostic techniques are currently employed by utilities to assess the health condition of power transformers (Arshad and Islam, 2011). Among these techniques, Dissolved Gas Analysis (DGA) is widely utilized for detecting incipient faults in power transformers. Due to the operational stresses faced by transformers, oil and paper decomposition occur, resulting in the production of gases such as hydrogen (H2), methane (CH4), acetylene (C2H2), ethylene (C2H4), ethane (C2H6), carbon monoxide (CO), and carbon dioxide (CO2) (Hydroelectric, 2003).

Different internal faults within a power transformer generate specific gases, allowing the determination of fault type and severity. However, the analysis becomes intricate when multiple faults coexist. For instance, partial discharge activity produces H2 and CH4, while arcing generates all gases, including trace amounts of C2H2. DGA aids in determining the quantity and type of gases present in transformer oil, facilitating the assessment of transformer failure rank (Liu et al., 2002).

Several DGA interpretation techniques, such as the key gas method (IEEE std, 2009), Roger ratio method (Rogers, 1978), and Duval triangle method (Duval, 2003), have been reported in the literature. However, these methods predominantly rely on personnel experience rather than rigorous mathematical formulation, and each has inherent limitations.

Ratio methods, including Roger, IEC, and Doerenenburg, are valid only if a significant amount of the gas used in the ratio is present; otherwise, they may yield an invalid code and fail to identify the fault type. The key gas method, while conservative, is not widely accepted for in-oil immersed transformers, as it may label a transformer with condition 4 (imminent risk) even if the gas evolution rate is not consistently increasing. Duval triangle, while effective, lacks an area for normal DGA results, restricting its use to identifying fault types in faulty transformers, with no indication of incipient faults.

Precise DGA interpretation remains a challenge in power transformer condition monitoring, with no globally accepted technique. Recent developments in DGA data history have prompted researchers to explore standardized approaches using mathematical and artificial intelligence (AI) techniques (Singh and Verma, 2008). AI applications aim to overcome the limitations of ratio methods, including the failure to identify fault types in the case of multiple fault conditions and the potential for invalid codes.

A comprehensive study on 338 oil samples with known fault conditions revealed inconsistencies in various DGA interpretation techniques, leading to different conclusions for the same oil sample (Abu Siada and Islam, 2012). To address this issue, the study's consistency analysis results were utilized to develop a fuzzy logic model. This model incorporates key features from established interpretation methods such as Roger, Doerenburg, IEC ratio methods, key gas, and Duval triangle methods. The resulting model provides a unified output corresponding to a specific fault and recommends asset management actions based on all these techniques, ensuring a reliable and consistent decision regarding the health condition of transformer oil. Users can observe the output of each individual method for enhanced transparency and understanding.

Fuzzy Logic Models

This section focuses on the development of fuzzy logic models aimed at standardizing decision-making in various Dissolved Gas Analysis (DGA) interpretation techniques. Each fuzzy logic model adheres to the fuzzy inference flow chart depicted in Figure 1. The model's input variables encompass the concentrations of the 7 key gases, measured in particles per million (ppm). The output of each model is categorized into five sets of membership functions, representing possible fault conditions observed in operating transformers. Additionally, a membership function for the normal condition (F5) is included, as outlined in Table 1. To address scenarios where ratio methods may result in an "out of code" condition for certain DGA samples, a specific membership function (F4) is introduced. The output membership functions for all models are visually presented in Figure 2.

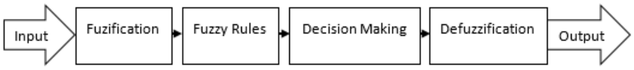

Fig1. Flow Chart of Fuzzy Logic Model

Table 1. Fault types

Method	F1 Thermal fault (Cellulose, Oil)	F2 Electrical fault (Corona)	F3 Electrical fault (Arcing)
Roger	Thermal fault 150 ºC-700 °C	Low energy electrical discharge	High energy discharge
IEC	Thermal fault 150 ºC-700 °C	Low energy electrical discharge	High energy discharge
Doeren	Thermal decomposition	Low energy electrical discharge	High energy discharge
Duval	Thermal fault 150 ºC-700 °C	Low energy electrical discharge -	High energy discharge
K. gas	Over heated cellulose/ oi	Low energy electrical discharge	High energy discharge

Table 1 has been derived from Figure 3, illustrating distinct fault types and the corresponding significant gases produced by each fault. Cellulosic thermal decomposition yields CO and CO2 at lower temperatures than those associated with oil decomposition. Trace amounts of these gases can be found under normal operating conditions. Oil thermal decomposition initiates at higher temperatures, with C2H4 production beginning around 350 ºC. At approximately 450 ºC, H2 production surpasses other gases, leading to low-intensity discharges such as partial discharge and intermittent arcing. Around 700 ºC, increased C2H2 production causes high-intensity arcing or continuous discharge, as indicated in the IEEE standard (IEEE std, 2009).

A set of fuzzy logic rules, presented in the form of (IF-AND-THEN) statements, establishes connections between the input variables and the output. These rules are developed based on interpretative techniques derived from transformer diagnostic and test data. Each fuzzy model is constructed using MATLAB's graphical user interface tool, where each input undergoes fuzzification into various sets of membership functions. The defuzzification method employs the widely used center-of-gravity approach, where the desired output z0 is calculated as follows.

$$z_0 = \frac{\int z.\mu_c(z)dz}{\int \mu_c(z)dz} \quad (1)$$

Here, μc(z) represents the membership function of the output.

The comprehensive fuzzy logic model consists of five sub-models, each representing one of the DGA interpretation techniques analyzed in this study (IEC, Roger, Doerenburg, key gas, and Duval triangle). The fuzzy model for the IEC method is elaborated upon below. A similar procedure was followed to construct the fuzzy models for the remaining interpretation methods.

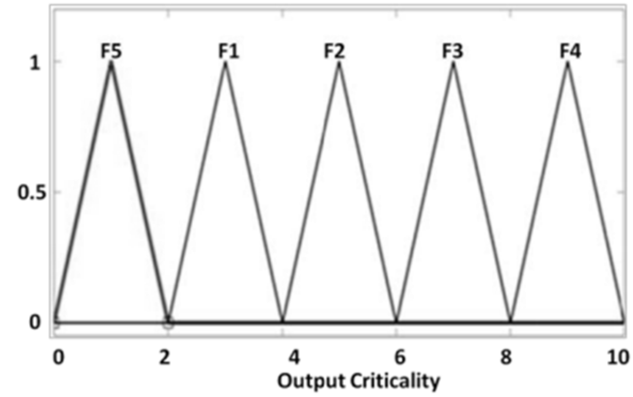

Fig2. Output Membership Functions of Fuzzy Logic Models

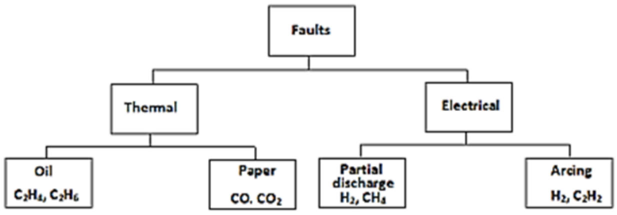

Fig3. Fault Types and Corresponding Gas Generation

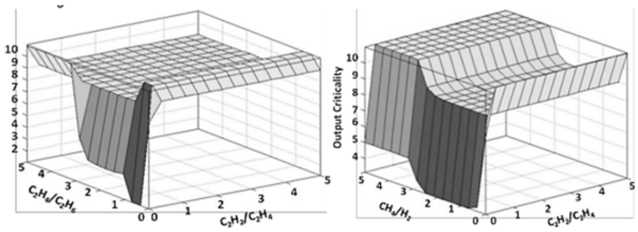

Fig4. Surface Graphs Illustrating the Developed Rules for IEC

Fuzzy Logic Applied to IEC Ratio Method

The established set of fuzzy rules that correlates the input and output variables for the IEC ratio method is illustrated in the 3D surface graphs (see Figure 4). To validate the model, specific inputs—C2H2/C2H4 (0.15), CH4/H2 (2.5), and C2H4/C2H6 (5)—were utilized, reflecting the findings from one of the transformer oil samples analyzed through Dissolved Gas Analysis (DGA). The numerical output from the fuzzy logic model is 7, as depicted in Figure 5. This result corresponds to F3 (arcing fault) in Figure 2.

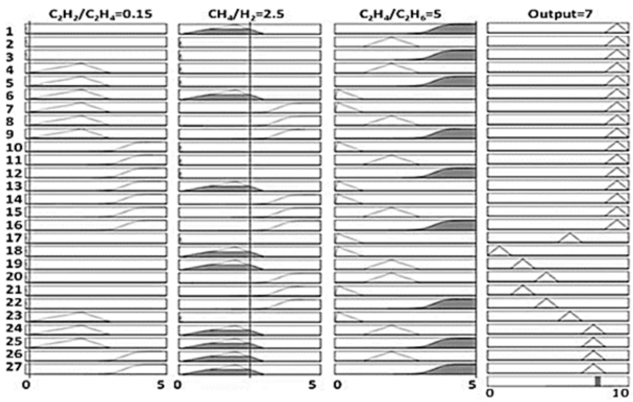

Fig 5. Fuzzy Rules for IEC Method

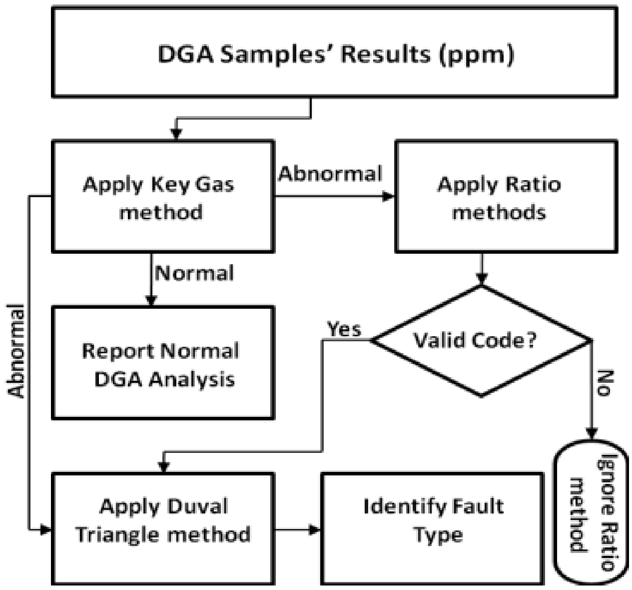

Fig6. Flowchart of the Proposed Methodology

3. Proposed Approach

The novel approach is founded on integrating various Dissolved Gas Analysis (DGA) techniques into a unified prototype software model, as depicted in the flowchart presented in Figure 6. In this model, the key gas method is initially employed to assess the health condition of the transformer oil sample based on its DGA results. If the key gas method indicates a normal condition, the model reports this finding, and no further analysis is conducted. However, if the key gas method reveals an abnormal condition, the oil sample undergoes further scrutiny using Duval triangle and ratio methods (IEC, Roger, and Doerenburg) to precisely identify the fault type.

Each individual method is utilized to identify the fault type, and the overall decision (D) is calculated based on the consistency level of each method, following the equation below:

$$D = \frac{\sum_{i=1}^{i=5} C_i D_i}{\sum_{i=1}^{i=5} C_i} \qquad (2)$$

where: D represents the overall decision, Di signifies the decision from the i-th method, Ci denotes the consistency level of the i-th method, as computed in the work of Abu-Siada and Islam (2012).

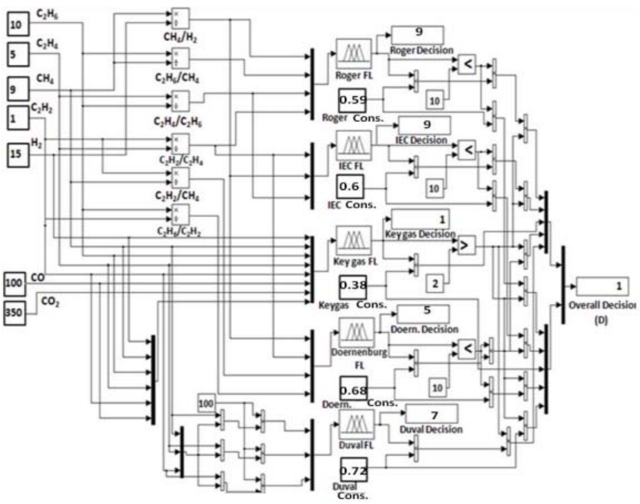

Fig7. Comprehensive Fuzzy Logic Model

In instances where any of the ratio methods yields a ratio incompatible with the diagnostic codes, the decision value corresponding to that method is set to zero. The determination of a normal condition is solely attributed to the key gas method, whereas in the presence of a faulty condition, all methods collectively specify the fault. To actualize the flowchart outlined in Figure 6, individual fuzzy logic models for various Dissolved Gas Analysis (DGA) interpretation techniques are integrated into a unified fuzzy model, as depicted in Figure 7. The inputs to the overall model include the concentrations of the 7 key gases, and the output is represented by a numerical value corresponding to the failure rank of the transformer.

In this integrated model, the individual decisions from all five methods are weighted according to the consistency level of each method and are combined as per equation (1) to yield an overall decision (\(D\)). Testing the model with DGA data, as shown in Figure 7, reveals that both Roger and IEC ratio methods provide values greater than 8, corresponding to F4 in Figure 2 (out of code). Consequently, their contributions to the overall decision are eliminated. Additionally, Duval and Doerenburg methods, even though indicating a faulty condition, have their contributions eliminated by the model since the key gas method results in a normal condition. The flowchart in Figure 6 dictates that, in such cases, the overall decision is solely determined by the key gas method.

The model's accuracy has been validated using another set of DGA data with pre-known fault conditions collected from operating transformers or referenced in research papers such as (DiGiorgio, 2005). The model demonstrated a high level of agreement with the collected data. Based on the model output, an asset management decision can be made, as proposed in Table 2.

Table 2. Asset Management Decision Derived from Model Output

Fault	Model output (D)	Fault diagnosis	Recommended decision
F5	0≤D<2	No fault	Continue normal operation
F1	2≤D<4	Cellulosic / oil decomposition Overheated cellulose and or oil	Exercise extreme caution Furan analysis is recommended Check generation rate weekly Reduce loading below 70% Plan outage
F2	4≤D<6	Corona in oil (Low intensity electrical discharge)	Exercise extreme caution Check generation rate weekly Reduce loading below 60% Plan outage
F3	6≤D<8	Arcing in oil (High intensity electrical discharge)	Exercise extreme caution Check generation rate daily Reduce loading below 50% Consider removal from service

Conclusion

This article introduces a novel approach to interpret dissolved gas analysis (DGA) results of transformer oil by integrating the strengths of existing interpretation techniques into a comprehensive expert model. Traditional methods currently lack consistency and may yield different conclusions for the same oil sample. Furthermore, a significant number of DGA results fall outside the proposed codes of ratio-based methods. The proposed approach involves amalgamating all traditional DGA interpretation techniques into a unified fuzzy logic model. The consistency-weighted decisions from individual DGA interpretation techniques are amalgamated to provide a singular overall decision for each DGA sample. This decision signifies the transformer failure ranking, and an appropriate asset management action can be recommended based on the model output.

Result

The presented article introduces a novel approach to evaluating dissolved gas analysis (DGA) results independently and consistently through the application of fuzzy logic. The conducted research successfully establishes a model that addresses unexpected result variations inherent in traditional methods employed by contemporary studies. This model amalgamates different DGA interpretations and provides consistent outcomes based on the principle of consistency. The applied fuzzy logic approach offers a more comprehensive and reliable means of assessing the health of power transformers in the energy sector and making informed decisions for optimal management.

***Authors**: Ph.D. candidate. Tural Aliyev, Azerbaijan State Oil and Industry University, E-mail: aliyev.tural@asoiu.edu.az; Ph.D. candidate. Jalal Ibrahimov, Azerbaijan State Oil and Industry University, E-mail: jalal.ibrahimov1@gmail.com; Ph.D. candidate. Shahlal Qracova, Azerbaijan State Oil and Industry University, E-mail: adnsu_e_51@mail.ru; Ph.D. candidate. Zarifa Isgandarova, Azerbaijan State Oil and Industry University, E-mail: zarifa.isgandarova@asoiu.edu.az.*

REFERENCES

1. Deng, C., Zhang, Y., Wang, Y., & Li, J. (2020). A Comprehensive Review of Dissolved Gas Analysis Methods for Power Transformers: Challenges and Opportunities. Energies, 13*(19), 5043. [DOI: 10.3390/en13195043]
2. Li, J., Sun, C., Wei, Y., & Liu, G. (2021). A Novel Transformer Fault Diagnosis Model Based on Dissolved Gas Analysis and Deep Learning. Energies, 14*(6), 1501. [DOI: 10.3390/en14061501]
3. Morais, A. M., Faria, J. A., Morais, T., & Martins, P. (2021). Artificial Intelligence-Based Techniques for Fault Diagnosis in Power Transformers: A Review. Energies, 14*(12), 3670. [DOI: 10.3390/en14123670]
4. Gao, J., Li, J., Zhao, Y., & Lin, C. (2020). A Novel Fault Diagnosis Method for Power Transformer Based on an Improved Wasserstein Generative Adversarial Network. Energies, 13*(8), 1857. [DOI: 10.3390/en13081857]
5. Zhou, B., Liu, Y., Zhang, Y., & Li, Y. (2021). Power Transformer Fault Diagnosis Based on Dissolved Gas Analysis and Grey Relational Analysis. Energies, 14*(5), 1341. [DOI: 10.3390/en14051341]
6. Rios, M. A., Sandoval, J. C., & Valencia, J. F. (2021). Fault Diagnosis in Power Transformers Using Dissolved Gas Analysis and Machine Learning: A Review. Energies, 14*(5), 1222. [DOI: 10.3390/en14051222]
7. Cai, Y., Gu, C., Yang, F., & Zhang, J. (2020). Power Transformer Fault Diagnosis Based on Weighted k-Nearest Neighbor Algorithm Using Dissolved Gas Analysis. Energies, 13*(18), 4822. [DOI: 10.3390/en13184822]
8. Zhang, Y., & Tan, J. (2019). Power Transformer Fault Diagnosis Based on Dissolved Gas Analysis Using a Feature Fusion Network. Energies, 12*(23), 4492. [DOI: 10.3390/en12234492]
9. Zhang, J., & Han, X. (2018). Dissolved Gas Analysis of Transformer Oil by Gas Chromatography-Mass Spectrometry: A Critical Review. Energies, 11*(9), 2341. [DOI: 10.3390/en11092341]
10. Wang, Y., Wang, W., Li, C., & Han, J. (2018). Dissolved Gas Analysis of Transformer Oil Based on DGA-MF-ANN Integrated Technique. Energies, 11*(5), 1120. [DOI: 10.3390/en11051120]
11. Li, J., Ma, Y., Li, Y., & Li, H. (2018). A Novel Fault Diagnosis Method for Power Transformers Based on a Deep Convolutional Neural Network. Energies, 11*(11), 3030. [DOI: 10.3390/en11113030]
12. Liu, H., & Yu, D. (2017). A Novel Fault Diagnosis Model for Power Transformers Based on Dissolved Gas Analysis and Particle Swarm Optimization Algorithm. Energies, 10*(12), 1985. [DOI: 10.3390/en10121985]
13. Li, W., Guo, M., Yuan, Y., & Wang, J. (2017). Dissolved Gas Analysis in Transformer Oil Using Multiscale Weighted Permutation Entropy and Support Vector Machine. Energies, 10*(9), 1298. [DOI: 10.3390/en10091298]
14. Zhang, C., & Song, Y. (2016). A Novel Method for Fault Diagnosis of Power Transformers Based on Dissolved Gas Analysis and Ensemble Learning Algorithms. Energies, 9*(8), 623. [DOI: 10.3390/en9080623]
15. Wang, Y., & Wang, W. (2015). A Novel Fault Diagnosis Model for Power Transformers Based on Dissolved Gas Analysis and Decision Tree. Energies, 8*(10), 11712. [DOI
13. Электрооборудование и электроустановки. Методы измерения характеристик частичных разрядов. - ГОСТ20074-83.
14. Аксенов, Ю.П. Использование усовершенствованных методов электромагнитной локации разрядных явлений для определения объема ремонта трансформаторов / Ю.П. Аксенов, В.И. Завидей, И.В. Ярошенко // Электро. - 2004. - №5. - С. 19-24.
15. Forsthoffer, M. Forsthoffer's Component Condition Monitoring. 1st ed. Oxford, Butterworth-Heinemann, 2018, 204 p. ISBN