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Fuzzy Model for Power Transformer Condition Monitoring and Fault Detection

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Abstract. Power transformers are equipment of great importance, and their availability is crucial for the security and continuity of the electricity supply for domestic and industrial users. During their life cycle, transformers are exposed to various environmental and operational conditions that affect their performance, especially when these exceed the operational design limits. This paper describes the use of Fuzzy Logic models as supporting tools for the automatic classification of power transformer operating conditions. The proposed methodology involves a binary classification (failure or no failure), followed by a multi-classification into seven types of failures. For this purpose, a power transformer fault database was developed, compiling information from operational data curated by power transformer experts. The results show a high predictive capacity for transformer fault conditions, with 96% balanced accuracy, and acceptable effectiveness in detecting different faults. This approach may serve as useful guidance in power transformer condition monitoring, helping engineers to reduce the time required to detect and repair incipient faults.

Keywords: Power transformers, fuzzy logic, fault diagnosis, artificial intelligence.

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1 Introduction

Power transformers are primary equipment in the distribution of electricity. It is therefore of the utmost importance to provide adequate maintenance to avoid rapid deterioration or to make it irreparable, as this affects both social and economic aspects to a great extent. An electricity company will be prepared to address the challenges presented, only if it has a methodology for the optimal management of its assets, that is, if it can make the right and timely decisions. In this regard, the level of risk for each unit should be assessed. When assessing the risk, a classification by merit and condition of transformers can be established, allowing action planning for the medium and long term (Ceron, et al., 2015). Currently there are more than 100,000 power transformers operating in the United States and more than 400,000 worldwide (U.S. Department of Energy, 2014). In Mexico, the electricity company of the Federal Electricity Commission operates more than 60,000 transformers of different types and power in the National Transmission Networks and General Distribution Networks (Comision Federal de Electricidad, 2023).

The transformer is an efficient and reliable machine that, under normal operating conditions, is designed and constructed to have a service life of close to 40 years. The transformer experiences changes over time. Consequently, as it ages, the likelihood of faults increases. According to Hartffor Steam Boiler, one of the largest transformers insurers in the United States, 3 out of every 100 transformers installed in the 1960's is prone to failure, the average replacement cost of a 100 MVA transformer can reach $2 million and can take 18 to 24 months to build (U.S. Department of Energy, 2014). Various diagnostic strategies have been used using intelligent techniques to identify possible failures in power transformers. Although these methods yield positive results, their practical implementation is complicated, and they face limitations with regard to the detection of failures. This is why, with historical data obtained from standardized health tests, models based on artificial intelligence techniques can be fed and thus the condition of the transformer can be determined without affecting the continuity of service.

With that in mind, this paper proposes the development of a fuzzy model for Power Transformer Fault Detection, using a database provided by different bibliographic sources. These samples were obtained from a specialized database and technical literature: from the technical brochure of CIGRE (CIGRE, 2014), technical report of IEEE (IEEE, 2013), technical papers (Golarz, 2016), and expert curation; the which includes the concentration of five oil-dissolved gases from 741 cases of power transformers, with the purpose of determining the state of health of transformers through the diagnosis of failures and which subsequently serves as a decision support to the experts and can make relevant decisions.

2 Background

2.1 Power Transformers

A power transformer is a machine composed of several subsystems, the condition of which can be monitored and evaluated independently (Ceron, et al., 2015). They are critical elements for the transmission of electricity from power generation plants to residential and industrial end consumers (Zorrilla, 2020). Several works have successfully identified the main subsystems of a transformer, but one of the more complete is developed in IEEE C57.140 (IEEE, 2013), where the transformer is divided into eight main subsystems and twenty-five components.

2.2 Monitoring and diagnosis

Transformer failures generally have origins and are mixed with each other, i.e. several causes can create a single effect. Possible causes of failures include design or manufacturing errors, damage to the auxiliary equipment of the transformer, human error during the maintenance and operation processes of the equipment and failures in the protection circuits (Zorrilla, 2020). The eight subsystems that make up power transformers, two of them make up the active part of the unit, i.e. the core and the welds (Ceron, et al., 2015).

It is precisely these two subsystems that are most difficult to maintain as they constitute the internal part of the equipment, are immersed in the oil, are not easily replaced and an intervention involves putting the unit out of service, action of high risk and undesirable by the owners of the asset since it facilitates the entry of moisture, involves long time out of use, can produce oil losses and spills, among other consequences.

2.3 Dissolved Gas Analysis (DGA)

Overloads, partial discharges (PD) and arches inside the transformer chemically degrade the oil-paper insulation, generating various gases that dissolve in the oil according to the energy associated with the failure (Azcarraga, 2014). Accordingly, it is possible to diagnose a particular type of failure by measuring the concentration of certain gases. The time-based trend analysis of these concentrations, combined with acoustic PD detection, oil physicochemical analysis and furfural detection make the DGA a standardized, cost-effective, and low-cost diagnostic tool. The preferred analysis methods for DGA are maximum concentration criteria, the Duval triangle, and Dornenburg and Rogers methods (Azcarraga, 2014).

2.4 Rogers Method

In 1978, Rogers observed that the concentration of each gas varies with the temperature of the failure and introduced a new relationship between the concentrations of the gases (Ethylene and Acetylene) that require a higher temperature to be generated (Sarria-Arias et al., 2014). He concludes that ethane and methane do not help in the identification of the malfunction, and therefore removes them from the relations used for this technique. Relationships are shown in Eq. (1-3). Table 1 shows the interpretation of the Rogers method.

$$R\ 1 = \frac{CH_4}{H_2} \quad (1)$$

$$R\ 2 = \frac{C_2H_2}{C_2H_4} \quad (2)$$

$$R\ 3 = \frac{C_2H_4}{C_2H_6} \quad (3)$$

Table 1. Rogers method failure interpretation

	Ratio range	R1 (CH_4/H_2)	R2 (C_2H_2/C_2H_4)	R3 (C_2H_4/C_2H_6)
	<0.1	1	0	0
	0.1-1.0	0	1	0
	1.0-3.0	2	1	1
	>3.0	2	2	2
Case	Failure		Code	
1	Low intensity partial discharge	1	1	0
2	High intensity partial discharges	1	1	0
3	Low energy discharge (splash)	0	1-2	1-2
4	High energy discharge (arcing)	0	1	2
5	Thermal fault below 150°C	0	0	1
6	Thermal fault between 150-300°C	2	0	0
7	Thermal fault between 300-700°C	2	0	1
8	Thermal fault above 700°C	2	0	2

2.5 Fuzzy Logic

Artificial Intelligence (AI) is a field of study that includes computational technologies to perform tasks that seem to require intelligence when carried out by humans (Tanimoto, 1990). Much of AI is related to the design and understanding of schemes that represent knowledge. Within the various techniques of AI is fuzzy logic.

Fuzzy logic (FL) was described by Zadeh in 1965 and has been applied to problems in several areas (Pérez-Gallardo et al., 2008). The fuzzy logic model allows to represent the system under consideration of the input and output variables, by means of fuzzy sets represented by linguistic terms (Purroy Vasquez, 2019). There are two types of models, the one based on the mamdani type and the other on the sugeno type (Estrada-García et al., 2023). The mamdani type is composed of three stages, the first stage is the fuzzification which is the graphical representation of the input variables by means of fuzzy sets, the second stage is an inference mechanism which consists of rules of inference of the resulting model from the fuzzy sets of the entry variables, finally the third stage is about the defuzzification, which is a graphical presentation of the output variables through fuzzy groups (Purroy Vasquez, 2019).

2.6 Literature Review

For this work, articles have been reviewed that apply conventional and Artificial Intelligence techniques such as fuzzy logic, machine learning, neural networks, among others, to facilitate decision-making and the resolution of problems related to the diagnosis of power transformer failures.

In conventional techniques such as the DGA (Huo-Ching et al., 2012) performs a real data sampling with the portable TransportX meter and performs an analysis of the dissolved gases for failure diagnosis, allowing to determine the state of the transformer and reduce failure rates. On the other hand, Perez et al. (2012) propose a real-time monitoring system for the diagnosis of the main power transformers of the company ENELBAR-CORPOELEC-Venezuela using DGA among others. Žarković Mileta and Stojković Zlatan (2017) carry out a hierarchical signal processing methodology for monitoring generator condition and failure diagnosis based on unprocessed electrical waveform data in electrical networks, which can often be measured using wave-shaped sensors strategically.

In the study conducted by Žarković Mileta and Stojković Zlatan (2017), analyze the application of the mamdani model to create a fault diagnosis system based on the current state of the power transformer. The study presents two cases, with a single controller and five independent ones; in the first case the controller inputs are the results of online and off-line transformer tests such as age, temperature, frequency, response analysis, insulation temperature, DGA and polarization index; and in the second case, in addition to the existing entries include prior measurements. The results obtained show an acceptable effectiveness in the detection of different failures and could serve as a good guidance in the monitoring of the condition of power transformers. In Fernández Blanco et al., (2021) propose a method for the diagnosis of failures in a 40 MVA transformer using FL from DGA. The proposal is simple, easy to implement and has a good accuracy of multiple failure detection. With reliable dissolved gas samples guarantees a total accuracy rate in the detection of early failures of 91.6%. Finally, Mateus et al. (2024) creates a diagnostic system for comparison with the results of standardized methods of historical data using fuzzy logic. Cheim, L. (2018) presents a work that consists of training 12 machine learning algorithms with real data from a thousand transformers that were individually analyzed by human experts. Cadena et al., (2008) presents a diagnostic tool based on artificial intelligence methodologies such as probabilistic neural networks for the detection of failures in transformers, using the results delivered by tests carried out on the oil of a transformer, through the analysis of dissolved gases (DGA).

3 Materials and Methods.

This work proposes a comprehensive model based on two fuzzy logic models for determining the health index of transformer oil, where the concentrations of the five gases dissolved in the oil of the transformer are used to provide an assessment of the same by faults. The first is a binary FL model, where the model is able to classify whether the transformer is in a normal condition or if it suffers from a failure, without specifying what type of failure it is; the second model is a multiclass output, where by means of the first model it is corroborated that the transformer presents a fault and therefore it is required to know what kind of fault it corresponds to. FL models were developed in Matlab with the Fuzzy tool under a structure of a Mamdani model.

3.1 Fault binary classification model

The binary model is developed with the concentrations of the different gases, i.e. with the concentrations in parts per million as provided in the database. The database consists of 741 cases of power transformer curated by power transformer experts. The DGA uses the concentrations of several dissolved gases. For the binary model, the standard established by IEEEC57 is taken, where gas concentrations are divided into four ranges. The considers the standards of gas concentrations in ppm, established by the IEEE. The schematization of the binary model is presented in Figure 1. Table 2 shows the variables used for the binary model, while table 3 and 4 show the fuzzy sets established based on the above-mentioned standard. The model considers the standards of gas concentrations in ppm, established by the IEEE.

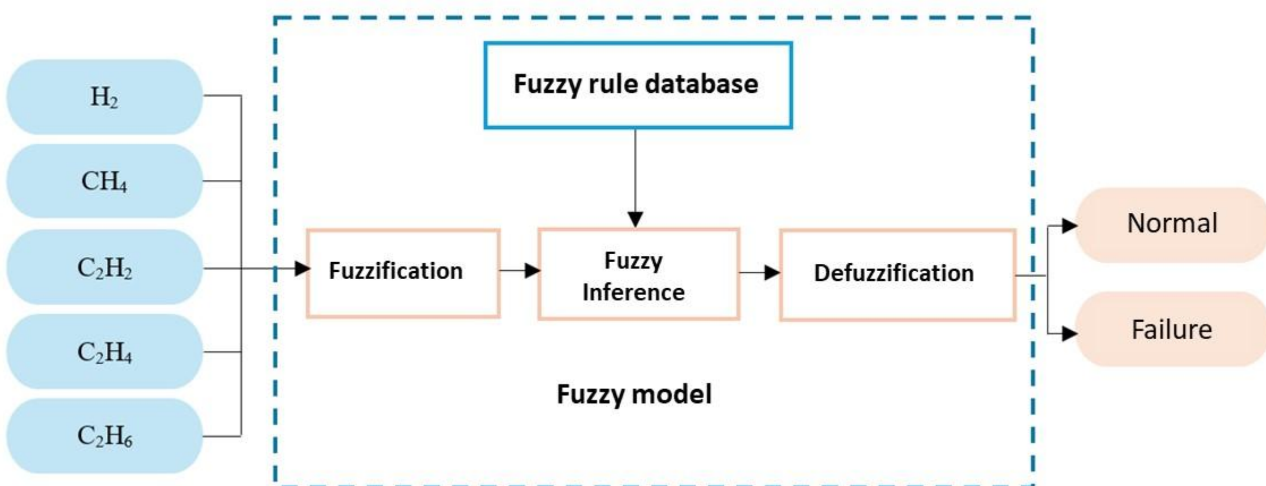

Fig. 1. Schematization of the fuzzy binary classification model.

Table 2. Input and output variables for the binary fuzzy logic model.

Variable	Definition	Unit
H_2	Dissolved hydrogen in transformer oil	ppm
CH_4	Dissolved methane in transformer oil	ppm
C_2H_2	Dissolved acetylene in transformer oil	ppm
C_2H_4	Dissolved ethylene in transformer oil	ppm
C_2H_6	Dissolved ethane in transformer oil	ppm
Normal	Normal condition of the transformer	--
Failure	Failure present in the transformer	--

Table 3. Input linguistic variables of the fuzzy sets of the binary fuzzy logic model.

Input Variable	Linguistic Variables	Membership Function	Interval
H_2	Low	Trapezoidal	[0, 0, 100, 101]
	Medium		[100, 101, 700, 701]
	High		[700, 701, 1800, 1801]
	Very high		[1800, 1801, 3000, 3000]
CH_4	Low	Trapezoidal	[0, 0, 120, 121]
	Medium		[120, 121, 400, 401]
	High		[400, 401, 1000, 1001]
	Very high		[1000, 1001, 3000, 3000]
C_2H_2	Low	Trapezoidal	[0, 0, 1, 2]
	Medium		[1, 2, 9, 10]
	High		[9, 10, 35, 36]
	Very high		[35, 36, 200, 200]
C_2H_4	Low	Trapezoidal	[0, 0, 50, 51]
	Medium		[50, 51, 100, 101]
	High		[100, 101, 200, 201]
	Very high		[199, 200, 1000, 1000]
C_2H_6	Low	Trapezoidal	[0, 0, 65, 66]
	Medium		[65, 66, 100, 101]
	High		[100, 101, 150, 151]
	Very high		[150, 151, 500, 500]

Table 4. Fuzzy sets output linguistic variables of the binary fuzzy logic model

Output Variable	Linguistic Variable	Membership Function	Interval
Diagnostic	Normal	Triangular	[1, 1, 1]
	Failure		[3, 3, 3]

For the binary model 268 inference rules were obtained, which were subsequently fed to the model in Matlab. Table 5 presents some of the established inference rules. Figure 2 shows how the inference rules are finally visualized in conjunction with the membership functions, where the case prediction is also carried out by introducing the input variables.

Table 5. Binary fuzzy logic model inference rules

H_2	CH_4	C_2H_2	C_2H_4	C_2H_6	Diagnóstico	
Low	Low	Low	Low	Low	1	Normal
Medium	Medium	Low	High	Very High	3	Failure
Medium	High	High	Very High	Very High	3	Failure
Low	Medium	Low	Very High	Medium	3	Failure
Low	Low	Medium	Very High	Medium	3	Failure
Low	Medium	Medium	Very High	Medium	3	Failure
Low	Low	Low	High	High	3	Failure
Medium	Very High	Low	Very High	Very High	3	Failure
Low	Low	Low	Very High	Very High	3	Failure
High	High	Very High	High	Very High	3	Failure
Very High	High	High	Very High	Very High	3	Failure
Low	Low	Very High	Very High	High	3	Failure
Low	High	High	High	Medium	3	Failure
High	Medium	Very High	Medium	Medium	3	Failure
Medium	High	Very High	Medium	High	3	Failure
Very High	Very High	Low	Low	Very High	3	Failure
Very High	Very High	Medium	Low	Very High	3	Failure
Medium	Low	Very High	Very High	Low	3	Failure
Very High	Very High	Low	Very High	Very High	3	Failure
High	Very High	High	Very High	Very High	3	Failure
Very High	Very High	Medium	Very High	Very High	3	Failure

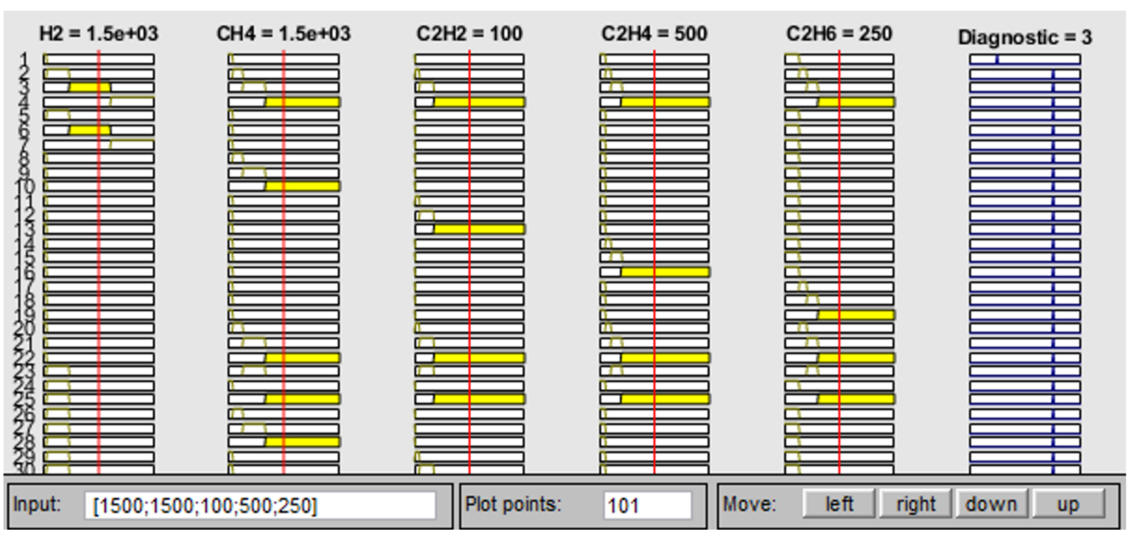

Fig. 2. Fault binary model inference rule viewer.

3.2 Fault multi-classification model

The binary classification model aims to determine whether the transformers are in a normal condition, or whether they present some kind of failure. If the model determines a normal condition the problem ends, however, if the model detects the opposite and indicates that it is a failure, a second model is tested. The schematization of the fault classification model is presented in Figure 3.

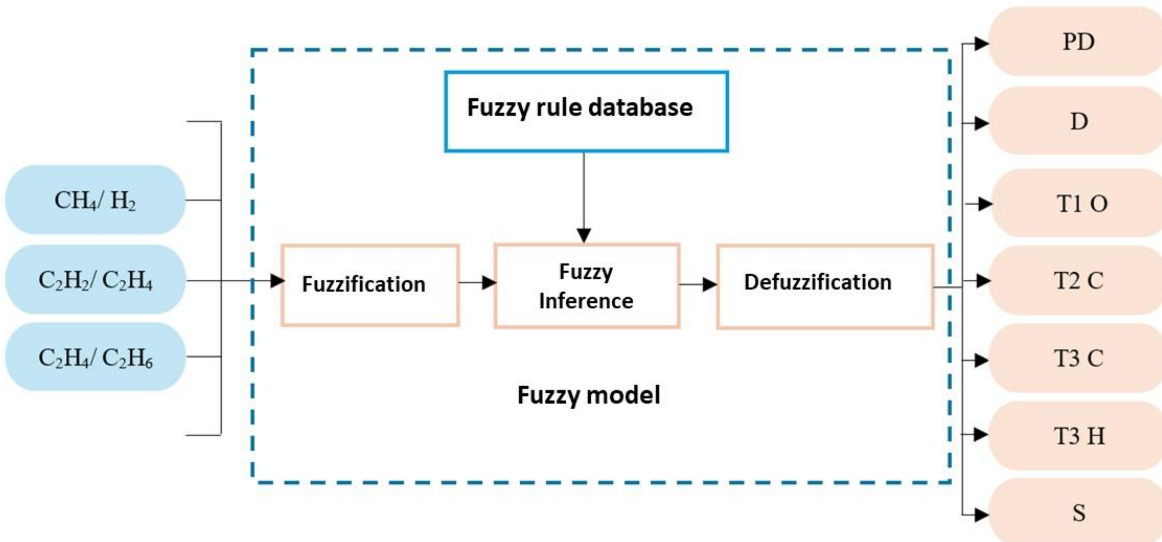

Fig. 3. Schematization of the fault multi-classification model.

The first model considers the standards of gas concentrations in ppm, established by the IEEE. The second fault classification model is based on the Rogers ratio method. The Rogers ratio method consists of three ratios or, three relations which considers the five gases obtained in the DGA test. Both models are divided into four trapezoidal-type membership functions, as this function allows to establish a constant belonging value equal to 1 in a defined range and not just in a point value. Table 6 shows the variables used for the fault classification model, while Table 7 and 8 show the fuzzy sets established based on the failure interpretation of the above-mentioned Rogers method.

Table 6. Input and output variables for the fault multi-classification model.

Variable	Definition
CH_4/H_2	Rogers method first ratio
C_2H_2/ C_2H_4	Rogers method second ratio
C_2H_4/ C_2H_6	Rogers method third ratio
PD	Partial discharge
D	Energy Discharge
T1 O	Thermal fault below 300°C with overheating
T2 C	Thermal fault between 300°C-700°C with carbonization
T3 C	Thermal fault above 700°C with carbonization
T3 H	Thermal fault above 700°C involving only oil
S	Stray gassing

For the fault classification model, 49 inference rules were obtained, which are subsequently fed to the Matlab model. Table 9 presents some of the established inference rules. Once established, the linguistic variables and membership functions are modeled in Matlab. Figure 4 shows how the inference rules are finally visualized in conjunction with the membership functions, where the case prediction is also carried out by introducing the input variables.

Table 7. Input linguistic variables of the fuzzy sets of the fault multi-classification model.

Input Variable	Linguistic Variables	Membership Function	Intervals
CH_4/H_2	Low	Trapezoidal	[0, 0 ,0.099, 0.1]
	Medium		[0.099, 0.1, 0.99, 1]
	High		[0.99, 1, 2.99, 3]
	Very High		[2.99, 3, 10, 10]
C_2H_2/C_2H_4	Low	Trapezoidal	[0, 0 ,0.099, 0.1]
	Medium		[0.099, 0.1, 0.99, 1]
	High		[0.99, 1, 2.99, 3]
	Very High		[2.99, 3, 10, 10]
C_2H_4/C_2H_6	Low	Trapezoidal	[0, 0 ,0.099, 0.1]
	Medium		[0.099, 0.1, 0.99, 1]
	High		[0.99, 1, 2.99, 3]
	Very High		[2.99, 3, 10, 10]

Table 8. Fuzzy sets output linguistic variables of the fault multi-classification model.

Output Variable	Linguistic Variable	Membership Function	Interval
Diagnostic	PD	Triangular	[1, 1, 1]
	D		[2, 2, 2]
	T1 O		[3, 3, 3]
	T2 C		[4, 4 ,4]
	T3 C		[5, 5, 5]
	T3 H		[6, 6, 6]
	S		[7, 7, 7]

Table 9. Fault classification fuzzy logic model inference rules

CH_4/H_2	C_2H_2/C_2H_4	C_2H_4/C_2H_6	Diagnostic	
Low	Medium	Low	1	PD
Low	High	Medium	1	PD
Low	Medium	Medium	1	PD
Medium	Medium	High	9	S
Medium	Medium	Very High	2	D1
Medium	High	High	2	D1
Medium	High	Very High	3	D2
Medium	Low	High	9	S
High	Low	Low	9	S
Very High	Low	Medium	4	T1 O
High	Low	High	6	T2 C
High	Low	Very High	8	T3 H
Very High	Low	Very High	8	T3 H
Low	Medium	High	1	PD
Low	Low	Medium	1	PD

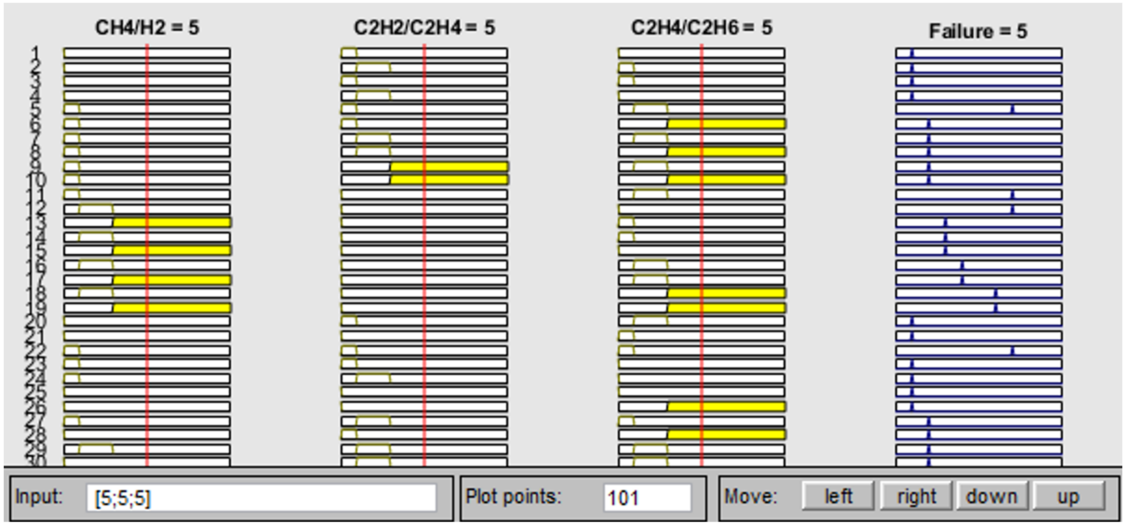

Fig. 4. Fault multi-classification model inference rule viewer.

4 Results and Discussions

The first fuzzy logic model was tested with the full database, that is, 741 cases were tested. For the second model, cases with output equal to normal condition are excluded, as well as cases where no values are obtained in the Rogers ratio method, leaving a total of 467 cases to test the model.

Once the models are tested, the prediction data is counted, as are the actual labels. These data are evaluated with performance metrics to measure and evaluate the performance of models. Phyton programming was used to evaluate metrics, most used for multiclass classification models with accuracy score, balanced accuracy and confusion matrix. However, other performance metrics for the models such as the Matthews Correlation Coefficient, Cohen Kappa and Jaccard Coefficient were evaluated.

4.1 Binary Model

For binary model 741 cases were predicted, and their performance evaluated against actual labels or outputs, with an accuracy of 0.96 representing the proportion of correct predictions to the total. Meanwhile, that the Balanced Accuracy metric considers the distribution of the classes, that is, provides a more equitable measure of the performance of the model, which obtained a result of 0.97. The results obtained from the different metric tests are shown in Table 10.

Figure 5 shows the confusion matrix obtained by the metric matrix. The model correctly predicted 714 cases out of 741: where class 1 represents the normal condition and classified all cases correctly, while class 3 represents failure, and it can be observed that 3 cases classified them as class 1, and 24 cases could not classify them correctly. The latter means that the model did not find any inference rule by which it could classify that instance and therefore classifies it as the average value of the established range, in this case 2 being the average of the range 0-4.

Table 10. Results obtained from binary model performance metrics

Model	Accuracy score	Balanced Accuracy	Matthews CC	Cohen Kappa	Jaccard C
Binary	0.96	0.97	0.92	0.92	0.92

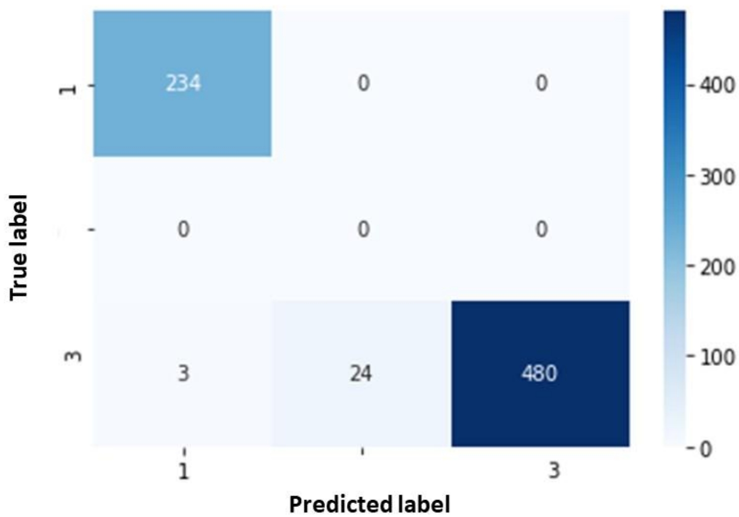

Fig. 5. Confusion matrix of true label vs predicted label of binary fuzzy logic model

4.2 Fault Multi-Classification Model

Following the same logic as the previous model, the prediction of the 463 cases of the multiclass FL model was carried out and its performance was evaluated against the actual labels, where an accuracy score of 0.80 was obtained, while the balanced accuracy metric obtaining 0.67. The results obtained by the different metrics tested in this model are shown in Table 11.

Table 11. Results obtained from fault classification model performance metrics

Model	Accuracy score	Balanced Accuracy	Matthews CC	Cohen Kappa	Jaccard C
Fault C.	0.80	0.68	0.74	0.74	0.66

Figure 6 shows the confusion matrix for the fault classification model. It can be observed that the model correctly predicted 371 cases out of 463, where classes 2,3 and 6 are the best performers. Class 7 is classified 12 times as Class 3, 9 as Class 1 and 8 as Class 2. Meanwhile, Class 3 is classified 10 times as Class 7.

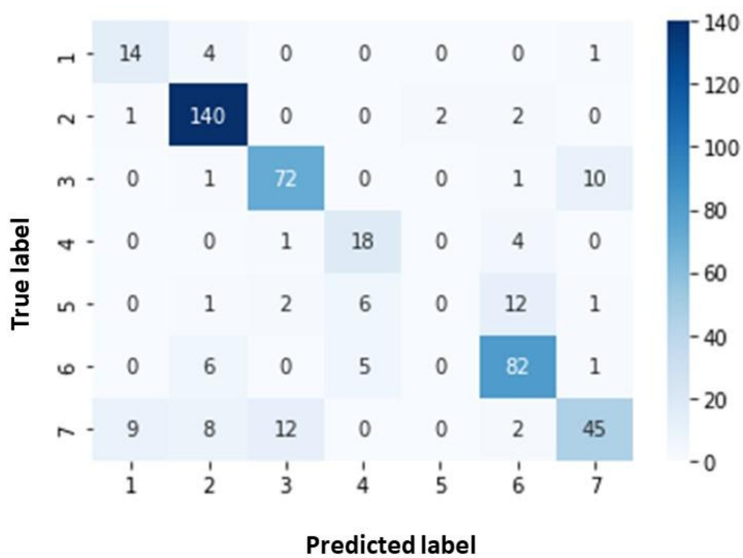

Fig. 6. Confusion matrix of true label vs predicted label of fault classification fuzzy logic model.

Class 5 is classified incorrectly in all instances, being classified mostly as Class 6. These errors are because there are inference rules that match more than one tag, that is, that within the established ranges of inference rule there are cases where the same combination of inferential rules has as its output 2 different errors. However, this is due to the nature of the database and the Rogers interpretation method on which this study was based.

In Table 12. The results obtained from each FL model evaluated with the different metrics are shown. As can be seen, the binary model obtained the best ratings from the tested metrics, exceeding 90% accuracy even in the balanced accuracy, which indicates the ease for the model to classify with high accurateness between normal condition and a failure present in power transformers. The values obtained for the fault classification model presented some limitations as seen above, however, in most metrics their accuracy is above 70%, and being the overall accurateness, the best performance achieved being 80%.

Table 12. Results obtained from FL models performance metrics.

Model	Accuracy score	Balanced Accuracy	Matthews CC	Cohen Kappa	Jaccard C
Binary	0.96	0.97	0.92	0.92	0.92
Fault C	0.80	0.68	0.74	0.74	0.66

The fuzzy logic model of binary classification stands out in obtaining outstanding results with a general and balanced accuracy of more than 95%, meaning that it is very likely that the model will correctly classify the normal state of a transformer or whether it is suffering some type of failure. On the other hand, the fault classification model obtained an overall accuracy of 80% and balanced of 68%, that is, that in general, the model correctly classifies around 80% of the data 6 of the 7 faults established of a power transformer.

This study was carried out only with the gases obtained by the DGA test, it shows very good results when determining whether a transformer is in good condition for its operation or whether it has some kind of failure. This, as a first instance, is crucial for failure monitoring and diagnosis. However, this equipment is important for the distribution of electricity, so it is important to avoid rapid deterioration. The fault classification with FL model was able to classify with very good accuracy six out of seven failures. Since FL models are knowledge-based and experience-based, they have an advantage in terms of the explicability of their development and behavior, otherwise it happens with ML models, which are practically encoded to train the labelled data entered and create behavioral patterns that determine the classification of new labelling data. Therefore, this work took the knowledge and experience provided by technicians and interpreters such as the DGA and the Rogers method for the development of two FL models that together determine in the first instance whether the power transformer is in good condition to continue operating or otherwise whether it requires rigorous monitoring after having presented some type of fault, therefore the second model determine the type of failure that the transformer may be presenting and therefore carry out the relevant measures of evaluation.

5 Conclusions

Fault diagnosis and asset maintenance are a suitable area for the application of AI techniques, as demonstrated by the accuracy in predicting faults in power transformers. The development of an model for fault diagnosis in power transformers, supported by artificial intelligence techniques, has proven effective in identifying faults in these assets. This approach confirms that the application of AI can provide decisive support for transformer management, reducing the risks and damage associated with undetected faults.

Fuzzy logic emerges as a valuable technique in the diagnosis of failures in power transformers, especially in the classification and evaluation of the health of this equipment. FL-based models offer a more transparent and understandable interpretation of results, allowing more informed decision-making by power transformer experts. The inclusion of FL models together with some other AI model can improve the robustness and versatility of the diagnostic system.

The comparison between traditional fault diagnosis models and AI-based models highlights the superiority of the AI models in terms of accuracy and efficiency. While traditional methods such as the analysis of dissolved gases in oil have been useful, AI models make the most of the vast amount of data available and are able to identify subtle patterns that may go unnoticed for conventional approaches. The integration of AI models into electrical asset management promises to significantly improve the reliability and efficiency of electrical systems.

The focus of this study is to obtain solid results using only DGA data, suggesting an effective and simplified methodology for fault diagnosis. By combining the knowledge and experience provided by techniques such as the DGA and the Rogers Method, in the development of Fuzzy Logic models, it has been possible to effectively determine whether a transformer is in optimal operating conditions or if it has any failure, as well as identify the specific type of failure it may be experiencing. This comprehensive approach, which integrates both expert expertise and advanced data analysis methods, represents a significant contribution to the state of the art in power transformer failure diagnosis.

As future work, we propose to enrich the database to create a more comprehensive learning database for the development of AI models, considering offline parameters such as transformer operation characteristics (age, temperature, operating hours, frequency, and response analysis); the physical characteristics of the insulating oil (acidity, humidity, corrosion, power factor), among others.

References

Azcárraga Ramos, C., Liñán García, R., Nava Guzmán, J., & Ramírez Niño, J. (2014). Procedimientos de evaluación de la condición de transformadores de potencia y subestaciones aisladas en gas. *Informe Técnico INEEL*.

Cadena, J. A., Cadena, J. M., & Pérez Londoño, S. (2008). Aplicación de redes neuronales probabilísticas en la detección de fallas incipientes en transformadores. *Scientia Et Technica*, 14(39), 48–53. Universidad Tecnológica de Pereira, Colombia.

Castro Vivar, I., Aguilar Lasserre, A. A., & Pérez Salazar, M. (2019). Sistema de apoyo a la decisión para la localización de puntos de abastecimiento en la cadena de suministro humanitaria. *Orizaba*.

Ceron, A. F., Orduña, I. F., Aponte, G., & Romero, A. A. (2015). Panorama de la gestión de activos para transformadores de potencia. *Información Tecnológica*, 26(3), 99–110. https://doi.org/10.4067/S0718-07642015000300014

Cheim, L. (2018). Machine learning tools in support of transformer diagnostics. *CIGRE Paris Session Papers & Proceedings 2018, SC A2 Power Transformers and Reactors* (Paper A2-206).

Comisión Federal de Electricidad (CFE). (2023). *Programa de ampliación y modernización de las redes generales de distribución 2023–2037*. México. https://www.cfe.gob.mx/distribucion/cumplimiento/Documents/PAM%20RGD%202023-2037%20VFinal%2005292023.pdf

Estrada-García, J., Romero-Mota, D., Huerta-Pérez, G. A., Aguilar Lasserre, A. A., & Méndez-Contreras, J. M. (2023). Predicting the production of probiotic biomass and lactic acid via fuzzy logic during the anaerobic treatment of swine waste with *Lactobacillus acidophilus*. *Journal of Environmental Engineering*, 150(1). https://doi.org/10.1061/JOEEDU.EEENG-7497

Fernández Blanco, J. C., Hernández González, F. H., & Corrales Barrios, L. B. (2021). Método de lógica difusa para el diagnóstico de fallos incipientes en un transformador de 40 MVA. *Ingeniería Electrónica, Automática y Comunicaciones*, 42(2), 76–88.

Golarz, J. (2016). Understanding dissolved gas analysis (DGA) techniques and interpretations. In *Proceedings of the IEEE Power Engineering Society Transmission and Distribution Conference* (pp. xx–xx). IEEE. Dallas, TX, USA.

Huo-Ching, S., Yann-Chang, H., & Chao-Ming, H. (2012). A review of dissolved gas analysis in power transformers. *Energy Procedia*, 14, 1220–1225. https://doi.org/10.1016/j.egypro.2011.12.1079

Institute of Electrical and Electronics Engineers (IEEE). (2013). *IEEE C57.152: Guides for diagnostic field testing of fluid-filled power transformers regulators and reactors*. New York, NY, United States.

International Council on Large Electric Systems (CIGRE). (2015). *Transformer reliability surveys* (Technical Brochure 642; WG A2).

Mateus, B. C., Farinha, J. T., & Mendes, M. (2024). Fault detection and prediction for power transformers using fuzzy logic and neural networks. *Energies, 17*(2), 296. https://doi.org/10.3390/en17020296

Pérez-Gallardo, J. R., Hernández-Vera, B., Aguilar-Lasserre, A. A., & Posada-Gómez, R. (2008). Interpretation of mammographic using fuzzy logic for early diagnosis of breast cancer. In *2008 Seventh Mexican International Conference on Artificial Intelligence* (pp. 278–283). IEEE. https://doi.org/10.1109/MICAI.2008.58

Pérez, R., Torrez, H., Fernández, E., & Fernández, S. (2012). Sistema de monitoreo en tiempo real para el diagnóstico de transformadores de potencia en una empresa de energía eléctrica. In *10th Latin American and Caribbean Conference for Engineering and Technology*. Panama City, Panama.

Purroy Vázquez, R., Aguilar-Lasserre, A. A., López-Segura, M. V., Cruz Rivero, L., Rodríguez-Durán, A. A., & Rojas-Luna, M. A. (2019). Expert system based on a fuzzy logic model for the analysis of the sustainable livestock production dynamic system. *Computers and Electronics in Agriculture*, 161, 104–120. https://doi.org/10.1016/j.compag.2018.05.015

Sarria-Arias, J. T., Guerrero-Bello, N. A., & Rivas-Trujillo, E. (2014). Estado del arte del análisis de gases disueltos en transformadores de potencia. *Revista Facultad de Ingeniería*, 23(36), 105–122.

Tanimoto, S. L. (1990). *The elements of artificial intelligence: An introduction using Lisp*. Computer Science Press.

U.S. Department of Energy, Office of Electricity Delivery and Energy Reliability, Infrastructure Security and Energy Restoration. (2014). *Large power transformers and the U.S. electric grid*. United States. https://www.energy.gov/sites/prod/files/2014/04/f15/LPTStudyUpdate-040914.pdf

Žarković, M., & Stojković, Z. (2017). Analysis of artificial intelligence expert systems for power transformer condition monitoring and diagnostics. *Electric Power Systems Research*, 149, 125–136. https://doi.org/10.1016/j.epsr.2017.04.025

Zorrilla Henao, J. D., Céspedes Fernández, A., & García Gómez, D. F. (2020). Técnicas para el diagnóstico de transformadores de potencia: Una revisión crítica. *Ingeniare. Revista Chilena de Ingeniería*, 28(2), 184–203. https://doi.org/10.4067/S0718-33052020000200184