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Improvement of Transformer Fault Diagnosis using Fuzzy Rule and Decision Tree Based on Dissolved Gas Analysis

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***Abstract*— Early and correct diagnosis of faults in power transformers (PTs) are important aspects of electrical system maintenance. In addition to insulation and cooling functions, insulating oil contains the by-products of degradation and ageing reactions of the insulation system and related components inside the PT. In addition to sludge, water and acids, gaseous products are also generated within the transformer. Dissolved gas analysis (DGA) based on the identity and quantity of the generated gases is the most widely used technique for the early detection of faults in the active parts of PTs. In this paper, fuzzy rule (FR) and the decision tree (DT) algorithms are used for PT fault diagnosis. The ratios of Roger's four ratios and IEC 60599 methods were used as input feature vectors. The proposed methods were carried out using 168 data samples and tested on 72 data samples. The performance of the proposed diagnostic methods was evaluated and compared to the IEC 60599 and Roger's four ratios methods. From the results obtained, with a diagnostic accuracy of 95.83%, the best performance is obtained with the FR classifier using the Log of Rogers ratios as input vector.**

Keywords*— *Power transformer, Fault diagnosis, Decision tree, Fuzzy rule.

I. INTRODUCTION

The power transformer (PT) is the most valuable and important piece of equipement in electrical systems. Considered as the heart of electrical power transmission and distribution networks, its reliability is essential to the reliable delivery of electricity in the network. Indeed, the failure of a power transformer can lead to important financial lost due to the breakdown of the power grid, power outage and costly repairs or replacement [1]. Insulation systems of in-service oil-immersed PTs may be damaged due to faults caused by electrical, thermal, environmental and mechanical stresses [2]-[4]. Early detection of faults reduces the severity of damages and avoids adverse operating conditions or unplanned outages [5].

Dissolved Gas Analysis (DGA) has gained worldwide popularity for PT condition monitoring, fault diagnosis and unplanned outage prevention [6]. It is a proven method for the early-stage detection of faults in active parts of PTs [7]. Based on the identities and quantities of fault-related gases, DGA is a non-invasive monitoring technique that extracts information on the condition of the insulation system in particular and the internal parts in general from the oil as a source of information. These fault-related gases include Hydrogen (H_2), Ethane (C_2H_6), Methane (CH_4), Ethylene (C_2H_4), and Acetylene (C_2H_2) [8].

Several traditional DGA-based methods are proposed in the literature for PTs faults diagnosis. Dornenburg method in [9], Rogers ratios in [3], IEC standard symbol in [10], Duval triangle in [11], and Pentagon in [12,13] are some of these methods. Traditional DGA methods suffer from poor diagnostic accuracy. To reduce this burden, intelligent algorithms were used to detect the initial failure of the power transformer: Artificial Neural Network (ANN) [14], Support Vector Machines (SVM) [15], K-Nearest Neighbor (KNN) [16], and other algorithms such as Bayesian networks [17].

Recently, the traditional DGA-based methods are increasingly used as feature vectors in the implementation of intelligent DGA-based methods. The diagnostic methods proposed in this paper are based on this approach. They are based on the fuzzy rule and decision tree algorithms, with Roger's four ratios and IEC 60599 methods as input feature vectors.

The remaining of this paper is organized as follows: a brief description of two traditional DGA-based methods used and DGA technique are presented in section II. Section III presents the data collection and segmentation, the description of the feature vectors, and the principle and flowchart of each of the proposed classifiers. The performance of proposed methods and its comparison with traditional methods used are presented in section 4. The section 5 concludes the paper.

II. DISSOLVED GAS ANALYSIS

The DGA technique is widely used to evaluate the condition of oil-immersed PTs. Faults are detected by using the chromatography process. In this process, the amount of gases in the insulating fluid is quantifying and used [18]. The sampling process is standardized and despite the existence of many laboratories involved in this field, these analyzes

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remain very expensive. Special attention must also be given during the separation of gases by chromatography at the laboratory level. The relevance of the results strongly depends on the reliability of the data. After analysis, a diagnostic method must be used for the interpretation of the results and the transformerstate of health evaluation [19].

A. Rogers Ratio Method

The Roger's four ratios method is based on four ratios calculated from the concentrations of the five combustible gases (H_2, C_2H_2,CH_4,C_2H_6 and C_2H_4). The Table 1 below presents these ratios [20].

TABLE I. ROGER'S RATIOS

Ratio	Expression
R_1	CH_4/H_2
R_2	C_2H_2/C_2H_4
R_3	C_2H_4/C_2H_6
R_4	C_2H_6/CH_4

B. IEC Ratio Method

In this strategy, three of the four gas ratios of Roger's method are used. The C_2H_6/CH_4 gas ratio is deleted [21].

III. METHODOLOGY

A. Data collection

Data collection is the first step for a classification given to transformers. This step is necessary because of its importance. This data was obtained from the study [22], which contains 240 samples. Table 1 shows that 70% of samples represent training data and the remaining 30% of samples represent the testing data. As shown in Table 1.

TABLE II. DATABASE DISTRIBUTION

Code	*Fault Types*	*Dataset* *Training*	*Testing*
PD	Partial Discharge	19	8
D1	Discharges of low energy	29	13
D2	Discharges of high energy	39	16
T1	Thermal faults T<300 °C	49	21
T2	Thermal faults 300<T<700 °C	13	5
T3	Thermal faults T>700 °C	19	9
	Total	168	72

B. Input vectors used

The input vectors based on the DGA in this paper will be in the form of Roger's four-ratios and the IEC Ratios.

- Roger's Four-Ratios -based vector input:

$$[X]=\left[\frac{CH_4}{H_2} \quad \frac{C_2H_2}{C_2H_4} \quad \frac{C_2H_4}{C_2H_6} \quad \frac{C_2H_6}{CH_4}\right] \tag{1}$$

- IEC Ratios -based vector input:

$$[X]=\left[\frac{CH_4}{H_2} \quad \frac{C_2H_2}{C_2H_4} \quad \frac{C_2H_4}{C_2H_6}\right] \tag{2}$$

IV. ARTIFICIAL INTELLIGENCE BASSED

A. Fuzzy Rule

The basis of the Fuzzy Rule (FR) is a set of fuzzy IF-THEN rules based on the idea of a pure fuzzy logic system [23]. Uncertainty is undoubtedly always present in classification techniques. FRs have given a strong contribution to resolving and alleviating these uncertainty constraints. Consistency with the representation of human knowledge is one of the advantages of the rating system based on the FR, alongside other advantages, such as the performance of the best classification, understanding, strong ability, and the ability to explain [24]. This algorithm creates rules based on digital data, which are mysterious periods of upper dimensions. These are hyper-rectangles determined by the trapezoidal fuzzy membership functions of each dimension. The digital columns selected for the input data are used as the training input data and additional columns are used as a classification target, and either a single column containing the class information or several numeric columns with class scores between 0 and 1 can be specified [25]. Figure 1 shows the general structure of fuzzy rule.

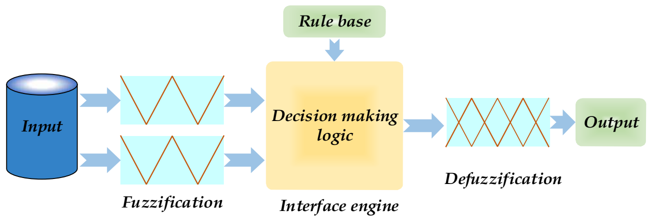

Fig. 1. FR general structure

B. Decision Tree

The decision tree is a type of supervised non-linear classification model that contains a tree-like structure [26]. The outstanding feature of the decision tree algorithm is that the tree is built without the need for domain knowledge or parameter setting, yet it performs efficiently in heuristic knowledge discovery while performing categorical data classification based on its attributes [27].Through a series of decisions, it is possible to rank the sample by using adecision FR algorithm.

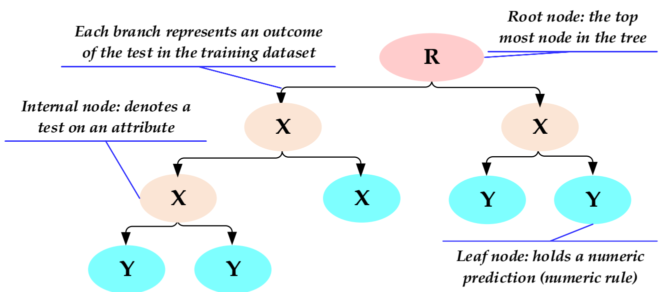

Fig. 2. Decision tree structure

tree. It is also possible to make subsequent decisions by using the present decision. The sample is categorized from the root node to the terminal node that corresponds to the decision. Each internal node is assigned sample attributes, the value of each branch corresponds to an attribute, and a category represents the final node [28]. Generally, training a decision tree classifier best division in each node as long as the full data set is not analyzed [29].Figure 2 shows the structure based on the decision tree algorithm.

V. MODEL EVALUATION

The performance of the model is evaluated using statistical measures, which are as follows: TP (*True Positive*), TN*(True Negative)*, FP *(False Positive)*, FN *(False Negative)*. Are all derived from the confusion matrix [30, 31].

$$Specificity=\frac{TN}{TN+FN} \tag{3}$$

$$Accuracy = \frac{TN + TP}{TN + TP + FN + FP} \quad (4)$$

$$Precision = \frac{TP}{TP + FP} \quad (5)$$

$$Sensitivity = \mathrm{Re}call = \frac{TP}{TP + FN} \quad (6)$$

$$F_{score} = F_{measure} = \frac{2(\mathrm{Pr}ecision \times \mathrm{Re}call)}{\mathrm{Pr}ecision + \mathrm{Re}call} \quad (7)$$

$$Cohen's\ Kappa = \frac{P_o - P_e}{1 - P_e} \quad (8)$$

P_o: the relative agreement annotators observed (i.e., accuracy).
P_e: a coincidence agreement for a hypothetical probability

VI. RESULTS AND DISCUSSIONS

To evaluate the effectiveness of each of the Decision Tree and FR algorithms based on Rogers and IEC ratios, which are according to six types of faults transformer (PD, D_1, D_2, T_1, T_2, T_3), which consist of 240 samples divided into 168 training samples and 72 test samples using the KNIME analytics platform. Figure 3 shows a simplified description of the proposed method.

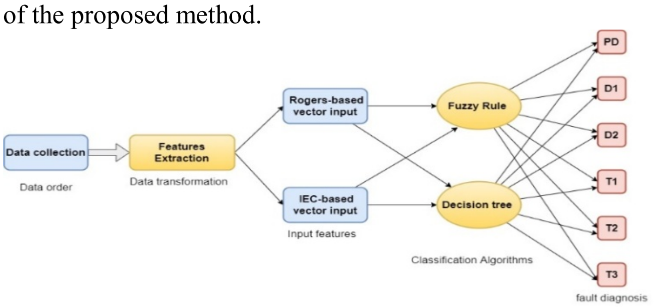

Fig. 3. Proposed methodology diagram

KNIME is used to build workflow tasks. These work tasks consist of the contract that processes data, the data is transferred through the connections between the contracts [32]. Figure 4 represents the proposed model using the KNIME analytics platform, with a brief explanation of the work steps.

- Data Processing: The data is called by the Excel reader node to identify the data and give a statistical overview of it and then process the missing values in the cells of the input table.
- Partitioning: The data is divided into 70% for the input samples for training and 30% for the input samples for testing by partitioning the node.
- Classification Algorithms Model: The model is trained by the Learner node applied to the training data and the prediction is achieved by applying the Predictor node to the test data.
- Evaluation: The efficiency of the developed model is recognized and assessed by the scorer node.

The confusion matrix is a powerful tool for visualizing the performance of a classification algorithm, Coordination between the results of fault prediction and actual (PD = 1, D_1 = 2, D_2 = 3, T_1 = 4, T_2 = 5, T_3 = 6).

In figure 5 the diagonal cells in blue indicate the number of correctly classified data and the rest of the cells refer to the incorrectly classified data by the classification algorithms. It is clear from figure 5 (A) that all the faults were classified correctly in each of (PD, D1, and T1), the D2 fault was incorrectly classified as D1, the T2 fault was classified as T3 and the T3 fault was incorrectly classified as T2. Figure 5 (B) The fault was classified as D1, as once PD FR, and once D2, D2 fault as D1, T3 fault as T2, and the rest of the other faults are correct. Figure 5 (C) shows that the D1 fault was classified as D2, the fault was D2, twice classified as D1, the fault was D3 as PD, the fault was T2 as T1, and the rest of the non-existent cases were correctly classified. In Figure 5 (D) once, the PD fault was classified as D1 and the D1 fault was classified as D2, and the D2 fault was mistakenly classified once as D1 and once as PD, and the rest of the other faults are correct. Table 2 shows varying values for Recall, Specificity, Precision , and F-measure for all faults (PD, D1, D2, T1, T2, T3), respectively. The accuracy of the FR was at input vector Rogers ratios of 95.77% and at input vector IEC ratios of 93.06% with the Cohen's Kappa constant 0.947 and 0.913, the accuracy of the decision tree algorithm at input vector Rogers ratios of 93.06% and the input vector IEC ratios of 94.44 % and Cohen's Kappa constant 0.913 and 0.931 respectively. Where the results showed the highest accuracy of the FR algorithm at input vector Rogers ratios and Decision Tree algorithms at input vector IEC ratios.

	1 (Predicted)	2 (Predicted)	3 (Predicted)	4 (Predicted)	5 (Predicted)	6 (Predicted)	
1 (Actual)	7	0	0	0	0	0	100.00%
2 (Actual)	0	13	0	0	0	0	100.00%
3 (Actual)	0	1	15	0	0	0	93.75%
4 (Actual)	0	0	0	21	0	0	100.00%
5 (Actual)	0	0	0	0	4	1	80.00%
6 (Actual)	0	0	0	0	1	8	88.89%
	100.00%	92.86%	100.00%	100.00%	80.00%	88.89%	

(A)

	1 (Predicted)	2 (Predicted)	3 (Predicted)	4 (Predicted)	5 (Predicted)	6 (Predicted)	
1 (Actual)	7	0	0	0	0	1	87.50%
2 (Actual)	1	11	1	0	0	0	84.62%
3 (Actual)	0	1	15	0	0	0	93.75%
4 (Actual)	0	0	0	21	0	0	100.00%
5 (Actual)	0	0	0	0	5	0	100.00%
6 (Actual)	0	0	0	0	1	8	88.89%
	87.50%	91.67%	93.75%	100.00%	83.33%	88.89%	

(B)

	1 (Predicted)	2 (Predicted)	3 (Predicted)	4 (Predicted)	5 (Predicted)	6 (Predicted)	
1 (Actual)	8	0	0	0	0	0	100.00%
2 (Actual)	0	12	1	0	0	0	92.31%
3 (Actual)	0	2	14	0	0	0	87.50%
4 (Actual)	1	0	0	20	0	0	95.24%
5 (Actual)	0	0	0	1	4	0	80.00%
6 (Actual)	0	0	0	0	0	9	100.00%
	88.89%	85.71%	93.33%	95.24%	100.00%	100.00%	

(C)

	1 (Predicted)	2 (Predicted)	3 (Predicted)	4 (Predicted)	5 (Predicted)	6 (Predicted)	
1 (Actual)	7	1	0	0	0	0	87.50%
2 (Actual)	0	12	1	0	0	0	92.31%
3 (Actual)	1	1	14	0	0	0	87.50%
4 (Actual)	0	0	0	21	0	0	100.00%
5 (Actual)	0	0	0	0	5	0	100.00%
6 (Actual)	0	0	0	0	0	9	100.00%
	87.50%	85.71%	93.33%	100.00%	100.00%	100.00%	

(D)

Fig. 4. Confusion matrix Model: (A) Confusion matrix Fuzzy Rule –Rogers, (B) Confusion matrix FR –IEC, (C) Confusion matrix Decision Tree –Rogers, (D) Confusion matrix Decision Tree –IEC

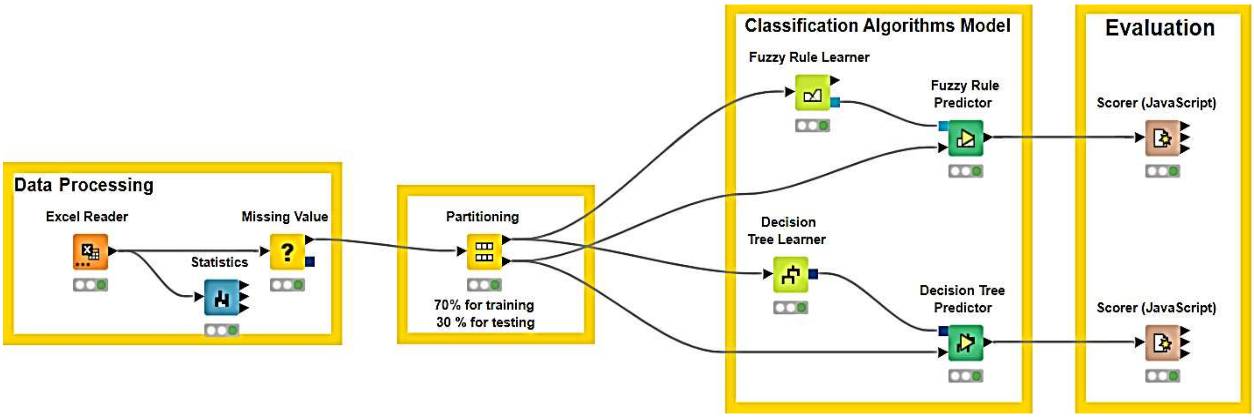

Fig. 5. Classification of the proposed model using the KNIME analytics platform.

A. Comparison results

Comparing the results obtained for the FR algorithm input vector Rogers ratios with the traditional Rogers' four ratios method, and also comparing the Decision Tree algorithm input vector IEC ratios with the traditional IEC 60599 ratios method. The results of the traditional methods were obtained by entering the test data consisting of 73 samples into the DGA Lab software included in the study (Ibrahim, Sherif S, & Ibrahim B, 2018). The results of Table 3 showed the superiority of both the FR algorithm and the Decision Tree algorithm over the traditional methods in terms of diagnostic accuracy.

TABLE III. CLASSIFICATION PERFORMANCE OF THE DIFFERENT MODELS

Model	Class	TP	FP	TN	FN	Recall (%)	Precision (%)	Specificity (%)	F-measure %)	Cohen's Kappa	Accuracy Overall (%)
FR input vector Rogers	PD	7	0	64	0	100.00	100.00	100.00	100.00	0.947	95.77
	D1	13	1	57	0	100	92.86	98.28	96.30		
	D2	15	0	55	1	93.75	100.00	100.00	96.77		
	T1	21	0	50	0	100.00	100.00	100.00	100.00		
	T2	4	1	65	1	80.00	80.00	98.39	80.00		
	T3	8	1	61	1	88.89	88.89	98.39	88.89		
FR input vector IEC	PD	7	1	63	1	87.50	87.50	98.44	87.50	0.913	93.06
	D1	11	1	58	2	84.62	91.67	98.31	88.00		
	D2	15	1	55	1	93.75	93.75	98.51	90.91		
	T1	21	0	51	0	100.00	100.00	100.00	100.00		
	T2	5	1	66	0	100.00	83.33	98.51	90.91		
	T3	8	1	62	1	88.89	88.89	98.41	88.89		
Decision Tree input vector IEC	PD	8	1	63	0	100.00	88.89	98.44	94.12	0.913	93.06
	D1	12	2	57	1	92.31	85.71	96.61	88.89		
	D2	14	1	56	2	87.50	93.33	98.21	90.31		
	T1	20	1	50	1	95.24	95.24	98.04	95.24		
	T2	4	0	67	1	80.00	100.00	100.00	88.89		
	T3	9	0	63	0	100.00	100.00	100.00	100.00		
Decision Tree input vector Rogers	PD	7	1	63	1	87.50	87.50	98.44	87.50	0.931	94.44
	D1	12	2	57	1	92.31	85.71	96.61	88.89		
	D2	14	1	55	2	87.50	93.33	98.21	90.32		
	T1	21	0	51	0	100.00	100.00	100.00	100.00		
	T2	5	0	67	0	100.00	100.00	100.00	100.00		
	T3	9	0	63	0	100.00	100.00	100.00	100.00		

B. Evaluate the effectiveness of algorithms

The format of the input vector data has been changed from [X] to Log[X] to the effectiveness of the developed algorithms in this paper and how to deal with any change in the data. The suggested results in Table 4 showed high performance and efficiency regarding the fuzzy base algorithms.The accuracy improved at the input vector Log[X], and it became at the input vector Log[Roger] 95.83% and the Log [IEC] input vector 94.37%, while the accuracy did not change at the Decision Tree algorithm to be fixed at 93.06% and 94.44% for both the Log [Roger] and Log [IEC] input vectors, respectively.

TABLE IV. COMPARISON BETWEEN AI TECHNIQUES AND THE TRADITIONAL METHOD

Model	Accuracy [%]
Fuzzy Rule –Rogers	95.77
Rogers' four ratios	66.67
DecisionTree – IEC	94.44
IEC 60599	62.50

TABLE V. COMPARISON OF DATA INPUT VECTORS FOR EACH ALGORITHM

FR				DT			
Input vectors				Input vectors			
Rogers	Log [Rogers]	IEC	Log [IEC]	Rogers	Log [Rogers]	IEC	Log [IEC]
Accuracy [%]							
95.77	**95.83**	**93.06**	**94.37**	**93.06**	**93.06**	**94.44**	**94.44**

VII. CONCLUSION

This paper deals with diagnosing power transformers using classification algorithms for both the FR algorithm and the Decision Tree. Diagnostic accuracy of 95.77% was achieved for the FR algorithm when using the input vector Rogers ratios and 94.44% if the Decision Tree algorithm used the IEC ratios input vector. These proposed algorithms have proven to be effective when compared to the traditional DGA methods for both Rogers' four ratios and IEC 60599 ratios. When changing the format of the input vector data from [X] to Log[X], the results showed the efficiency of the proposed algorithms, as the accuracy improved in the FR algorithm, to get the highest accuracy of 95.83% when the input vector is Log[Rogers] and the accuracy did not change in the Decision Tree algorithm, and this confirms the high capabilities of the proposed models to diagnose types of power transformer faults.

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