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Diagnosis of the Power Transformer Faults Based on DGA Using Intelligent Classifier

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Abstract

Dissolved gas analysis (DGA) is a common and important technique, which is used to detect the transformer faults by identifying the concentration of the dissolved gases. These gases are developed due to several stresses on the transformer such as electrical and thermal stresses. The traditional DGA techniques, such as IEC 60599, Rogers' ratio, and Duval triangle methods encounter some troubles to identify the transformer faults for many cases. Therefore, the intelligent classifier, such as a linear discriminant analysis, is used in the current work to enhance the diagnostic accuracy of the transformer faults. The results indicate that the diagnostic accuracy using linear discrimination classifier is increased rather than the diagnostic accuracy using the traditional DGA.

Keywords: transformer faults, dissolved gas analysis, IEC 60599, Rogers' ratio DGA method, Duval triangle method, linear discrimination classifier

INTRODUCTION

Power transformer is considered one of the most important parts in the power system network. The utilities focus on maintaining the transformer from undesired outage by identifying its status periodically [1]. Early detection of the transformer faults prevent the transformer malfunction. Therefore, DGA is used to detect the dissolved gas in transformer insulating oil. DGA is one of the common tests that operated on the insulating oil to determine the combustible and incombustibles gases due to the stresses that impacted on the transformer such as electrical and thermal stresses [2]. The combustible gases are categorized to Hydrogen (H_2), Methane (CH_4), Ethane (C_2H_6), Ethylene (C_2H_4), Acetylene (C_2H_2) and Carbon monoxide (CO). In addition, the incombustible gases are Nitrogen (N_2), Oxygen (O_2) and carbon dia-oxide (CO_2) [3].

There are several DGA techniques that used to interpret the transformer faults, such as IEC 60599, Rogers' ratio method, key gas, and Duval triangle [4]. Key gas method depends on the concentration of all the dissolved combustible gases to identify either the transformer fault type is in insulating oil or in the insulating paper [5]. IEC 60599 and Rogers' ratio interpret the transformer faults based on the ratio between the concentration of five combustible gases, such as Hydrogen (H_2), Methane (CH_4), Ethane (C_2H_6), Ethylene (C_2H_4), and Acetylene (C_2H_2) [5, 6]. Duval triangle method is developed based on the ratio between only three combustible gases, such as Methane (CH_4), Ethylene (C_2H_4), and Acetylene (C_2H_2) [7].

The traditional DGA methods have poor accuracy for transformer faults diagnose. In some cases, IEC 60599 and Rogers' ratio method are failed to interpret and specify the transformer faults, There are also interface faults in case of Duval triangle method. Therefore, these methods could be combined with artificial intelligent technique to enhance their accuracy. Many researches address the utilization of artificial intelligent with DGA techniques, such as Artificial Neural Network (ANN) [4, 8], Fuzzy Logic [1, 9], Support Vector Machine (SVM) [10, 11]. Moreover, there are many attempts to enhance the diagnostic DGA accuracy of the transformer faults identification, such as clustering method [12], conditional probability [13], Expert System [14], Hybrid System [15] and Graphical Techniques [16,17]. DGA Lab [18] is developed as a software package with different DGA techniques, which assisted the researchers to benefit from the DGA techniques and DGA data in order to make a comparison between their new proposed DGA techniques with the existence DGA techniques in DGA Lab, such as IEC 60599, Rogers' 4 ratios method, Duval Triangle, clustering, conditional probability and refining method of IEC Code and Rogers' 4 ratios.

In the current work, a linear discrimination classifier is developed to enhance the diagnostic accuracy of transformer faults based on DGA data. The results indicate that the new proposed linear discrimination classifier is able to improve the diagnostic accuracy of identifying the transformer fault types, where, the diagnostic accuracy is increased to 81.1% rather than 75.58 and 56.6 for IEC Code 60599 and Rogers' 4 ratios method, respectively.

DISCRIMINANT ANALYSIS

Linear discriminant analysis (LDA) is a commonly technique that is used for both data classification and dimensionality reduction. When the within-class frequencies of the data are unequal then the LDA can be handled and its performance can be evaluated on a randomly test data [19]. The LDA increases the contrast ratio between categories to the variation within the class in any given data set, ensuring maximum separation. The difference between the principle components analysis (PCA) and the LDA is that the first analysis does more feature classification, while the second does data classification. The location of the original data sets in case of LDA does not change but more class separation is developed. The decision region was drawn between the given classes. Figure 1 illustrates the theory of LDA.

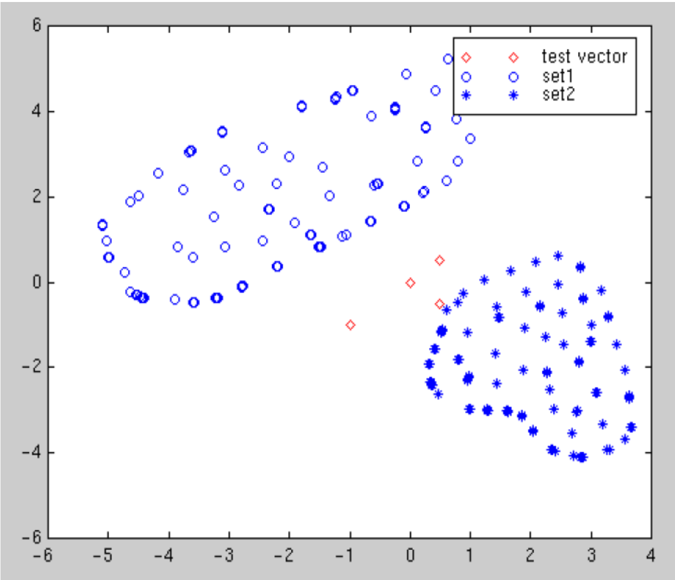

Fig. 1: Data classification using LDA [19]

A max gate function *g(X)* can be used as a classification rule to carry out both linear and quadratic discriminant analysis. The prior probability and condition density of X in class i were considered π_i and $f_i(x)$ respectively.

In case of LDA, the feature vector X indicates the multivariate normally distributed with mean vector μ_i and common covariance matrix Σ but in case of quadratic discriminant analysis (QDA), the matrix is Σ_i which refers to group specific covariance matrix. For a member X for class i, $g_i(X)$ was assumed to be greater than $g_j(X)$ where i doesn't equal j and the prospect densities are Gaussian. The condition density function $f_i(X)$ can be computed as in (1) and the maximum a-posteriori (MPA), Bayes rule and natural logs discriminant functions were as in (2) and (3) [20, 21];

Multivariate Gaussian can be expressed as in (1) [21];

$$f_i(X) = \frac{1}{(2\pi)^{P/2}|\Sigma_i|^{1/2}} exp\left[-\frac{1}{2}(X-\mu_i)^T \Sigma_i^{-1}(X-\mu_i)\right] \quad (1)$$

where, P expresses dimension factor that was 1 for LDA and 2 for QDA, and T refer to the transpose operator.

The linear discriminant function can be expressed as follows [21];

$$g_i(X) = X^T \Sigma^{-1} \mu_i - \frac{1}{2}\mu_i{}^T \Sigma^{-1} \mu_i + \log(\pi_i) \quad (2)$$

The Quadratic discriminant function can be expressed as follows [21];

$$g_i(X) = \frac{1}{2}(X-\mu_i)^T \Sigma^{-1}(X-\mu_i) - \frac{1}{2}log(|\Sigma_i|) + \log(\pi_i) \quad (3)$$

The discriminant analysis is utilized to classify the transformer faults based on the results of dissolved gases test. The datasets are arranged to include five main gases, Hydrogen (H_2), Methane (CH_4), Ethane (C_2H_6), Ethylene (C_2H_4), and Acetylene (C_2H_2), in addition to the actual faults based on the test results. All datasets are collected from literature. After arranging the data, a normalization process on the datasets is performed to reduce the diversity of the data. The normalization process is performened by dividing the concentration of each gas to the sum of the five main gases. Also the MATLAB classification learner tool is used, which took the normalized five main dissolved gases and considered them as input file and the actual fault vector as an output file. In order to train the discriminant classifier, the parameters of a Gaussian distribution of each fault type (class) is estimated using the fitting function. The results of the training process are illustrated in the convolution matrix to indicate the success and fail percentage of the classifier for each fault type (class), in addition to the number of succeeding diagnostic samples in a specified fault type according to the other fault types. New samples are normalized by the same manner of the training samples, which is utilized as a new data input to test the proposed method. in order to predict the classes of new samples, the trained classifier find the class off each sample with the smallest misclassification cost [22]. Fig. 2 explained the flowchart of the training process to get the accuracy of the model.

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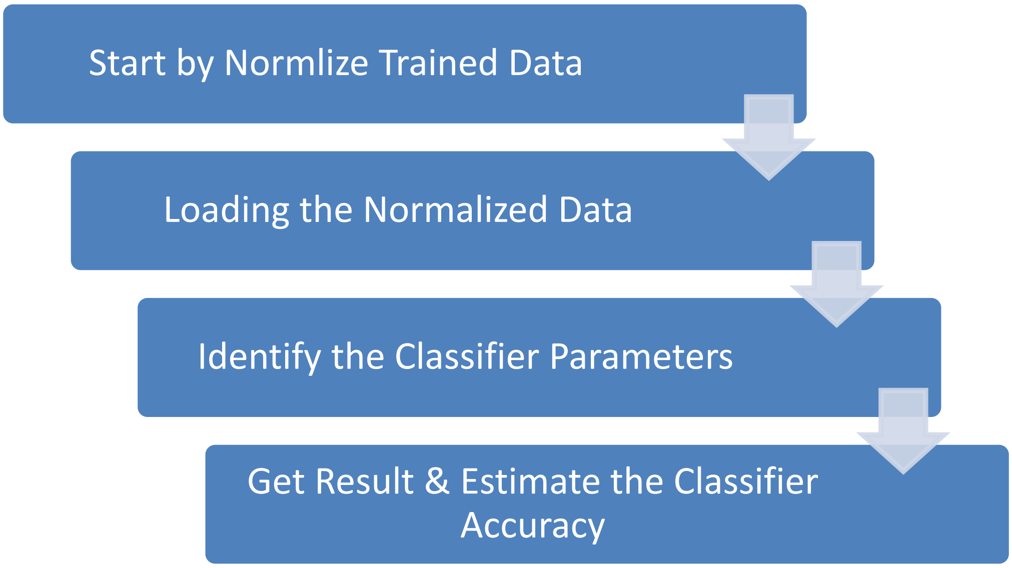

Fig. 2: Flowchart of the data classifier

RESULTS AND DISCUSSIONS

In this section, the results and discussions are reported. As explained in the previous section, the discriminant analysis classier is applied on the normalized data samples of the input file. 214 data samples are taken as an input data samples, and 53 data samples are used as test data samples. Table 1 illustrates the number and distribution of transformer faults for training and testing data samples. The following abbreviations could be utilized to indicate the transformer faults. The transformer faults could be categorized as Partial discharge (PD), low energy discharge (D1), high energy discharge (D2), low thermal fault (T1), medium thermal fault (T2), and high thermal fault (T3). The convolution matrix illustrates the results of diagnostic of different transformer fault types. In the convolution matrix, 1, 2, 3, 4, 5, and 6 on the horizontal and vertical axes refer to the transformer fault types Partial discharge (PD), low energy discharge (D1), high energy discharge (D2), low thermal fault (T1), medium thermal fault (T2), and high thermal fault (T3), respectively. Figure 3a and b illustrates the training process results of the 214 data samples and as shown in Fig. 3 a, the LDA classifier succeed to classify 17 PD sample from 18 sample with 94 % that are shown in Fig. 3b as a green cell and failed to detect 1PD sample correctly. For High thermal fault (T3), the training succeed to detect 47 T3 samples correctly from 52 data sample with T3 fault. Thus, the accuracy of the classifier to detect T3 is 90% as in green cell in the 6th column in Fig. 3b. Table 2 shows that results of LDA classifier to diagnose the transformer faults based on the training and testing data samples. As in Table 2, the overall accuracy of LDA for training and testing datasets is 83.64 and 81.1%, respectively. The max accuracy of LDA is for detecting the high energy discharge, where it succeeded to detect correctly 60/64 data samples of the training data samples with the percentage of 97% and for testing data samples, the LDA succeeded to detect correctly all PD data samples (4/4) with 100% accuracy.

Fault types	No. of data samples	
	training	testing
PD	18	4
D1	32	8
D2	62	15
T1	20	6
T2	30	7
T3	52	13
Total	214	53

Table 1: The number of data samples according to the transformer fault types

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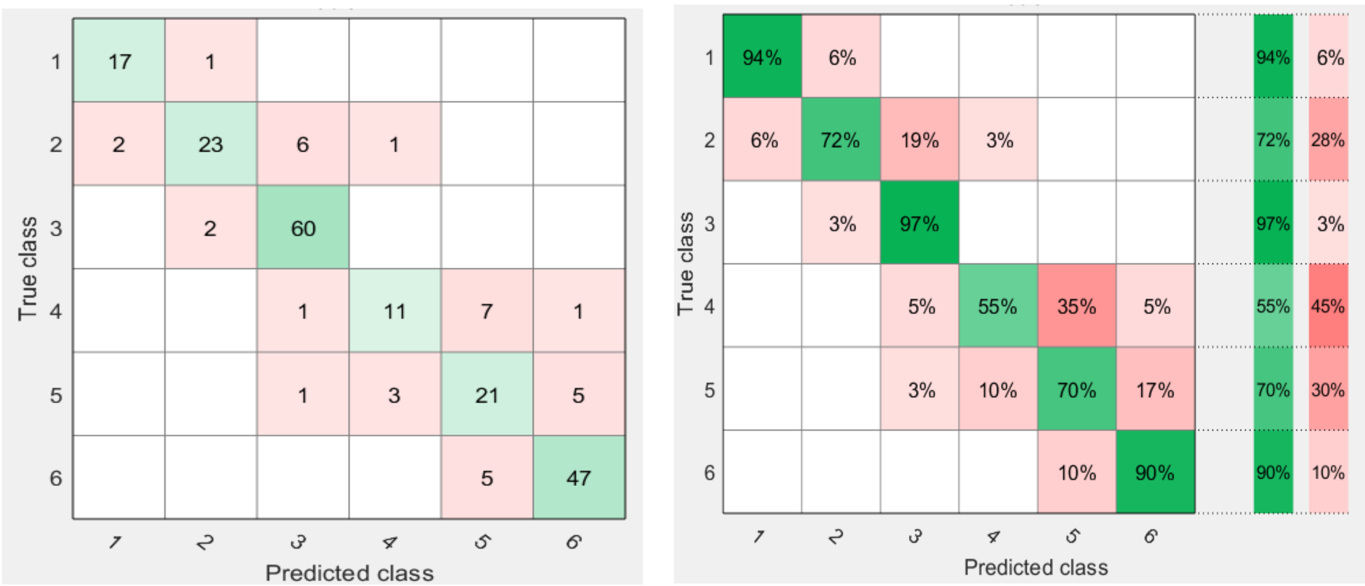

(a) (b)

Fig. 3 The results convolution matrix of the training data samples

In order to validate the accuracy of LDA classifier, a comparison between LDA classifier results and different DGA techniques is reported. Tables 3 and 4 illustrat the comparison results of LDA and different DGA techniques, such as Duval triangle method, IEC 60599, Rogers' four ratios, clustering, conditional probability, CSUS-ANN, IEC refining and Rogers' 4 ratios refining methods. For training datasets, the diagnostic accuracy of LDA is greater than all DGA techniques except the Duval triangle method and IEC 60599 refining method, where the accuracy of LDA classifier is 83.64%, compared to 84.11 and 83.69 % for Duval triangle and IEC 60599 refining methods respectively. in case of testing datasets, the accuracy of LDA classifier is 81.1% compared with 84.9 % for both Duval triangle and conditional probability techniques.

Fault types	Accuracy of LDA	
	training	testing
PD	94%	100%
D1	72%	87.5%
D2	97%	86.7%
T1	55%	50%
T2	70%	57.1%
T3	90%	92.3%
Overall accuracy	83.64%	81.1%

Table 2: The percentage accuracy of LDA as a diagnostic classifier of the transformer fault types

FT	Duval [7]	Rogers' ratio [5, 6]	IEC 60599 [5]	Clustering [12]	Cond. Prob. [13]	CSUS-ANN [4]	IEC refining [3-23]	Rogers' refining [3-23]	LDA classifier
PD	61.1	77.77	77.77	94.44	94.44	72.22	88.88	77.77	94
D1	96.87	0	68.75	59.37	50	43.75	43.75	6.25	72
D2	100	87.09	82.25	79.03	88.7	95.16	93.54	75.8	97
T1	45	60	70	90	55	100	86	60	55
T2	60	53.33	80	30	83.33	33.33	83.33	76.66	70
T3	94.23	71.15	82.69	78.84	80.76	73.07	92.3	94.23	90
Overall	84.11	62.14	78.5	71.49	77.57	71.96	83.17	68.69	83.64

Table 3: Comparison between the diagnostic accuracy of several DGA techniques and LDA classifier for 214 training datasets

FT	Duval [7]	Rogers' ratio [5, 6]	IEC 60599 [5]	Clustering [12]	Cond. Prob. [13]	CSUS-ANN [4]	IEC refining [3-23]	Rogers' refining [3-23]	LDA classifier
PD	50	50	50	75	100	75	75	50	100
D1	100	0	62.5	62.5	50	75	25	0	87.5
D2	93.33	86.66	73.33	73.33	100	60	93.33	86.66	86.7
T1	50	66.66	50	100	50	83.33	50	66.66	50
T2	71	57.14	100	28.57	100	28.57	100	100	57.1
T3	100	53.83	84.61	92.3	92.3	76.92	84.61	100	92.3
Overall	84.9	56.6	73.58	73.58	84.9	66.03	75.47	75.58	81.1

Table 4: Comparison between the diagnostic accuracy of several DGA techniques and LDA classifier for 53 testing datasets

CONCLUSIONS

In this work, LDA classifier is used as a diagnostic tool for transformer faults. Poor accuracy of several DGA techniques is an inspiration to seek about a new technique to enhance the diagnostic accuracy of transformer faults. The results indicated that the LDA classifier has an efficient ability to use as a diagnostic tool for transformer fault based on dissolved gas concentrations. Duval triangle DGA method is only gave a higher accuracy than LDA for both training and testing datasets. The accuracy results of LDA for training and testing datasets are 83.64 and 81.1 % compared to 84.11 and 84.9% for Duval triangle method.

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