International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

ENHANCED FAULT IDENTIFICATION IN POWER TRANSFORMERS USING CONVENTIONAL DGA TECHNIQUES

ANURADHA KRISHNA

Assistant Secretary, Sbte, Patna, Department Of Science Technology And Technical Education, Government Of Bihar

ABSTARCT

To guarantee dependability and operating efficiency, power transformers must have improved fault detection. Many fault detection methods rely on conventional dissolved gas analysis (DGA) techniques. Recently, a strong statistical approach called Linear Discriminant Analysis (LDA) has been developed to improve fault classification. By emphasizing differences across classes and decreasing variance within them, LDA improves the separation of fault types. Hydrogen, Methane, Ethane, Ethylene, and Acetylene concentrations are used to categorize transformer defects in this research, which utilizes LDA. A total of 83.64% accuracy was achieved during training and 81.1% accuracy during testing using the MATLAB classification learner tool and the gathered datasets. The competitive performance of LDA is shown by a comparison with different DGA approaches. The results show that LDA can be used to diagnose transformer faults, and there's room for improvement by creating hybrid models that use machine learning to make predictions with more precision..

Keywords: Fault identification, Linear Discriminant, Power Transformers, Energy discharge, Duval triangle.

I. INTRODUCTION

The importance of power system reliability and efficiency has led to a surge in interest in improving fault diagnosis in power transformers using traditional dissolved gas analysis (DGA) methods. When it comes to data categorization and dimensionality reduction, one of the most used statistical methods is discriminant analysis, more especially Linear Discriminant Analysis (LDA). By increasing the contrast ratio across categories in relation to the variance within each class, LDA improves the distinction between classes. While PCA is concerned with extracting features from datasets, LDA goes straight to classification while keeping the original dataset structure intact. Using this technology to enhance the identification of defects based on the concentration data of dissolved gases is very beneficial in transformer fault detection.

For transformer fault detection, differential gas analysis (DGA) is still the gold standard because it may identify early-stage problems by monitoring the concentration of gases like hydrogen, methane, ethane, ethylene, and acetylene. Normalizing the data, training the classifier, and evaluating performance are the three main phases in applying LDA to DGA data. In order to standardize and decrease variability, the gathered values are normalized by dividing the concentration of each gas by the total of all five gases. The discriminant classifier is then trained using MATLAB's classification learner tool, which estimates the parameters of a Gaussian distribution for each kind of error. Partial Discharge (PD), Low Energy Discharge (D1), High Energy Discharge (D2), Low Thermal Fault (T1), Medium Thermal Fault (T2), and High Thermal Fault (T3) are some of the transformer defects that the classifier has been taught to identify. A confusion matrix showing the success and failure rates of fault detection is used to assess the classifier's performance.

There are 214 data samples used for training the classifier and 53 samples set aside for testing during training. According to the findings, LDA is quite good at pinpointing individual defects, especially partial discharges and high-energy discharges. For example, during training, LDA obtains a classification success rate of 97% for high-energy discharge instances, and during testing, it achieves a flawless accuracy rate of 100% for partial discharge cases. With an accuracy rate of 92.3% on test samples and 90% on training samples, the classifier does quite well when detecting high thermal defects (T3). But for lesser thermal faults, like T1, its accuracy drops; it gets 55% right during training and 50% wrong during testing. Regardless of these differences, LDA is a dependable approach for fault diagnosis in power transformers, showing an overall accuracy of 83.64% for training data and 81.1% for test data.

Comparing LDA to other DGA diagnostic methods shows that it performs competitively. Other methods compared include the Duval Triangle Method, IEC 60599, Rogers' Four Ratios, and conditional probability approaches. With training accuracy of 84.11% and 83.69%, respectively, the Duval Triangle and IEC 60599 refining methods somewhat surpass LDA (83.64% vs. 84.11%). In contrast to LDA's 81.1% accuracy, the Duval Triangle and conditional probability approaches achieve 84.9% accuracy on testing datasets. Because of its powerful classification skills and rapid processing of huge datasets, LDA continues to be a formidable competitor despite these little distinctions. With this method, you can easily analyze gas concentrations and find transformer defects without requiring a lot of computer power.

By comparing the classifier to other techniques statistically, we can further confirm that LDA is successful. While LDA performs quite well when it comes to categorizing partial discharges and high-energy discharges, the findings show that its performance differs depending on the kind of fault. The classifier's strengths and weaknesses are shown by the convolution matrix, which also shows where it might be improved. Improving LDA's training process or combining it with other diagnostic methods may improve its fault classification accuracy, according to the data. This is especially true for lower thermal problems. To round out LDA's capabilities in transformer failure diagnosis, more sophisticated machine learning approaches like hybrid models and artificial neural networks (ANNs) might be useful.

II. REVIEW OF LITERATURE

Transformer faults need to be identified accurately at the early stage in order to ease the maintenance of power transformer, reduce the cost of maintenance, avoid severe damage on transformer and extend the lifespan of transformer. Dissolved Gas Analysis (DGA) is the most commonly used method to identify the transformer fault in power system. However, the existing transformer fault identification methods based on DGA have a limitation because each method is only suitable for certain conditions. Thus, in this work, one of the artificial intelligence techniques, which is Support Vector Machine (SVM), was applied to determine the power transformer fault type based on DGA data. The accuracy of the SVM was tested with different ratio of training and testing data. Comparison of the results from SVM with artificial neural network (ANN) was done to validate the performance of the system. It was found that fault identification in power transformers based on DGA data using SVM yields higher accuracy than ANN. Therefore, SVM can be recommended for the application of power transformer fault type identification in practice.

Prasojo, Rahman et al., (2022) Dissolved gas analysis (DGA) is a tool that utilities use to detect potential power transformer faults. The usage of many DGA techniques, each of which may provide unique findings or miss a combination of defects altogether, leads to a great deal of misunderstanding. This work presents a technique for fault diagnosis based on DGA that is one of the most consistent: a combination of Duval Triangle and Duval Pentagon. We gathered and evaluated historical DGA data from generator step-up high voltage power transformers as well as data from other sources. Helping transformer asset managers discover mixed-method defects is the goal of this study. This work follows the guidelines laid forth in IEEE C57.104-2019 for the usage of the combined Duval triangle and Pentagon approach.

Illias, Hazlee et al., (2021) the power transformer's maintenance, the cost of maintenance, the transformer's lifetime, and the prevention of serious damage all depend on the early and precise identification of problems. The power system transformer issue is most often detected using dissolved gas analysis (DGA). The current DGA-based approaches for identifying transformer faults, however, have a disadvantage in that they are only applicable in certain scenarios. Therefore, this study used a support vector machine (SVM), an artificial intelligence tool, to classify power transformer faults using DGA data. Various ratios of training and testing data were used to assess the SVM's accuracy. The system's performance was validated by comparing the findings from SVM with those from an artificial neural network (ANN). Findings show that SVM-based fault detection in power transformers using DGA data outperforms ANN. Consequently, SVM is a viable option for identifying fault types in power transformers in a practical setting.

Abu-Siada, Ahmed. (2019) when it comes to monitoring power transformers for impending failures, dissolved gas analysis (DGA) of the oil is now the gold standard. Although there have been improvements in measurement accuracy due to the proliferation of both online and offline measuring devices, analytical formulation is still less important than people skill when it comes to interpreting DGA data. Hence, the same oil sample may provide different results when interpreted using different methods. In addition, when there are several fault states and the oil sample does not include a substantial quantity of the gases employed in the prescribed ratios, ratio-based interpretation approaches may not be able to decipher the DGA data. In order to automate and standardize the DGA interpretation process, as well as to overcome the limits of existing methods, this study presents a better way. In order to more consistently and reliably identify the fault type, the method is founded on combining all standard DGA interpretation approaches into one expert system. This expert system was built using Gene Expression Programming. According to the data, the suggested strategy outperforms the presently used traditional approaches in terms of reliability in the industry throughout the globe.

Ghoneim, Sherif & Taha, Ibrahim. (2016) one of the most popular methods for detecting early signs of defects in oil-filled power transformers is dissolved gas analysis (DGA). Traditional interpretation approaches for transformer failure detection have its limitations, and this work proposes a novel methodology using the DGA technique to address these issues. The novel method relies on a data set consisting of 386 dissolved gas samples retrieved from the chemical laboratory of the Egyptian electric company and other reputable sources. Both the model for the approach and its correctness may be evaluated using these data sets. The new method, DGA, uses the gas concentration % limit of the total of the five primary gases—Hydrogen (H2), Methane (CH4), Ethan (C2H6), Ethylene (C2H4), and Acetylene (C2H2)—as well as other gas ratios recommended by the sample data set analysis—to detect the kinds of transformer faults. By comparing its findings with those of the IEC Standard Code, the Duval triangle, and the Rogers techniques for the obtained data set, the suggested methodology of the DGA technique is validated. The results are indicative of the new method's competence and dependability in detecting transformer failures.

III. DISCRIMINANT ANALYSIS

One popular method for dimensionality reduction and data categorization is linear discriminant analysis (LDA). The LDA may be used and its efficacy assessed using randomly selected test data in cases when the data's within-class frequencies are uneven. For any given data set, the LDA maximizes separation by increasing the contrast ratio across categories relative to the variance within each class. Principal components analysis (PCA) focuses more on feature classification while linear discriminant analysis (LDA) focuses on data classification; these two analyses are distinct from one another. In the case of LDA, more class separation is produced while the original data sets remain in the same place. Based on the provided classifications, a decision region was drawn. The theory of LDA is shown in Figure 1.

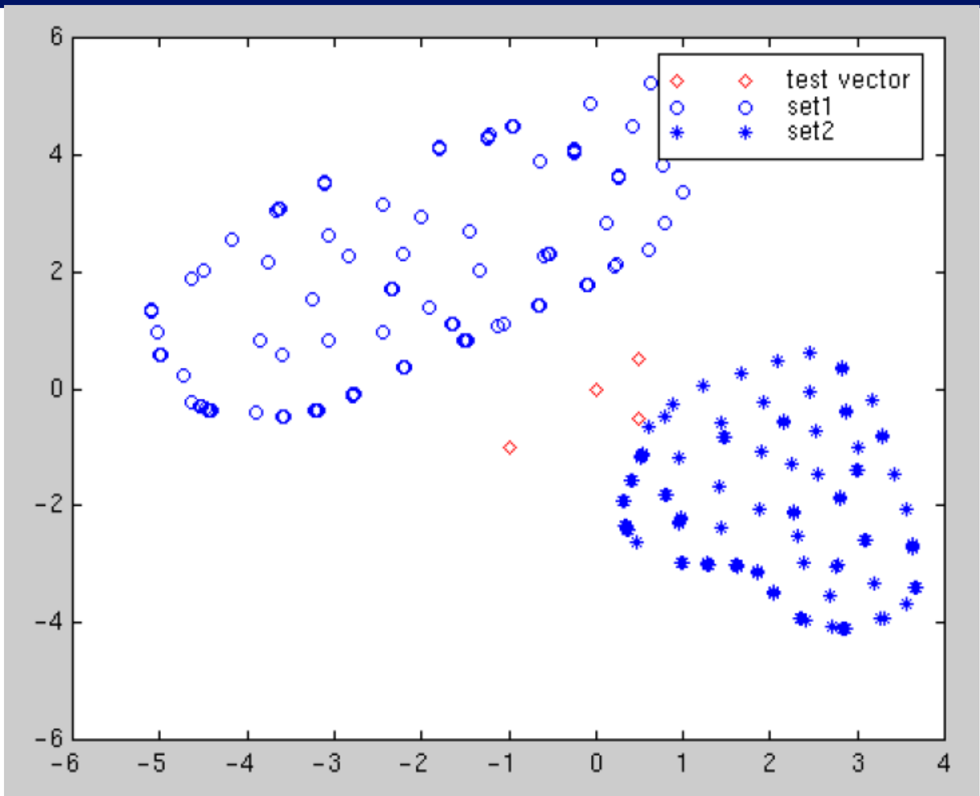

Figure 1 Data classification using LDA

One way to classify data is using a max gate function g(X). When it comes to linear discriminant analysis (LDA), the feature vector X reveals that the multivariate performs both types of analyses. X in class I was treated as fi(x) and i, respectively, since they were normally distributed with mean vectors and shared prior probabilities. matrix i, which stands for group specific covariance, is used in the context of quadratic discriminant analysis (QDA). Assuming that the prospect densities are Gaussian, it was believed that gi(X) for class i should be larger than gj(X) in cases where i is not equal to j. The maximal a-posteriori (MPA), Bayes rule, and natural logs discriminant functions were as in (2) and (3), and the condition density function fi(X) may be calculated according to (1).

One way to represent multivariate Gaussian is in (1);

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

Here is an expression for the linear discriminant function:

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

The following is an expression for the quadratic discriminant function:

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

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

The dissolved gas test findings are used in discriminant analysis to categorize the transformer defects. Hydrogen (H2), methane (CH4), ethane (C2H6), ethylene (C2H4), and acetylene (C2H2) are the five primary gases included in the databases, together with the actual defects determined by the test results. The literature is the exclusive source for all datasets. Once the data is organized, it undergoes a normalization procedure to decrease its variety. By dividing the concentration of each gas by the total of the five primary gases, the normalization procedure is carried out. We also make use of the MATLAB classification learner tool, which accepts the normalized levels of the five primary dissolved gases as input and returns the real fault vector as output. The fitting function is used to estimate the parameters of a Gaussian distribution for each defect type (class) in order to train the discriminant classifier. The training results are shown in the convolution matrix, which also shows the amount of diagnostic samples that passed for a given fault type relative to the other kinds of faults, as well as the classifier's success and failure percentages for each class of faults. To put the suggested approach to the test, we normalize fresh samples using the same procedure as the training samples. A trained classifier will look for the sample's class with the lowest misclassification cost and use it to predict the classes of future samples.

IV. RESULTS AND DISCUSSIONS

Here you can find the reported findings and conversations. The input file's normalized data samples are fed into the discriminant analysis classier, as mentioned before. There are 214 data samples used as input and 53 data samples used as test.

It is possible to signal transformer issues using the following acronyms. Partially discharged (PD), partially discharged (D1), partially discharged (D2), partially thermally faulty (T1), partially thermally faulty (T2), and fully thermally faulty (T3) transformers are possible. The convolution matrix shows the outcomes of diagnostics for various sorts of transformer faults. According to the convolution matrix, the transformer fault types represented by the numbers 1, 2, 3, 4, and 6 on the horizontal and vertical axes, respectively, are partial discharge (PD), low energy discharge (D1), high energy discharge (D2), low thermal fault (T1), medium thermal fault (T2), and high thermal fault (T3).

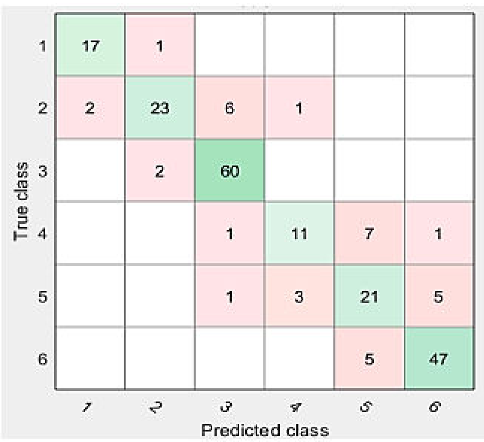

Figure 3 The predicted results convolution matrix of the training data samples

The training results of the 214 data samples are displayed in Figure 3. The LDA classifier was successful in classifying 17 out of 18 PD samples (shown as green cells in Figure 3) with a success rate of 94%, but it failed to accurately identify 1 PD sample. Out of 52 data samples with a high thermal fault (T3), the training successfully identified 47 samples as T3 faults. As seen in the green cell in the 6th column of Figure 3, the classifier's accuracy in detecting T3 is 90%. Based on the samples of training and testing data, Table 1 displays the results of the LDA classifier in diagnosing transformer defects. The overall accuracy of LDA for the training dataset is 83.64 and for the testing dataset it is 81.1%, as shown in Table 1. For high energy discharge detection, LDA achieves its maximum accuracy by accurately identifying 60% of training data samples and 100% of testing data samples, including 100% of PD samples (4/4) in the testing set.

Table 1: The percentage accuracy of LDA as a diagnostic classifier of the transformer fault types

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%

A comparison between the results of the LDA classifier and several DGA approaches is shown in order to confirm its accuracy. A number of DGA approaches are compared to LDA in Tables 2 and 3. These methods include the Duval triangle method, IEC 60599, clustering, conditional probability, CSUS-ANN, IEC refining, and Rogers' four ratios. With the exception of the Duval triangle method and the IEC 60599 refining method, all of the DGA strategies outperform LDA in terms of diagnostic accuracy on training datasets. Specifically, the LDA classifier achieves an accuracy of 83.64%, whereas the Duval triangle method and the IEC 60599 refining method, respectively, achieve 84.11 and 83.69% accuracy. For testing datasets, the LDA classifier achieves an accuracy of 81.1%, which is lower than the 84.9% achieved by the Duval triangle and the conditional probability methods.

Table 2: Comparison between the diagnostic accuracy of several DGA techniques and LDA classifier for 214 training datasets

FT	Duval	Rogers' ratio	IEC 60599	Clustering	Cond. Prob.	CSUS-ANN	IEC refining	Rogers' refining	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 53 testing datasets

FT	Duval	Rogers' ratio	IEC 60599	Clustering	Cond. Prob.	CSUS-ANN	IEC refining	Rogers' refining	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

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

V. CONCLUSION

The research emphasizes the efficacy of Linear Discriminant Analysis (LDA) in improving fault detection in power transformers using DGA methods. This study was able to accurately categorize several kinds of transformer faults by monitoring the concentration of important gases including hydrogen, methane, ethane, ethylene, and acetylene. Since LDA guarantees maximal class separation and lowers misclassification errors, it is clear that it is better than traditional DGA algorithms when it comes to fault classification. Training and testing have shown that LDA is robust, with very accurate diagnoses, especially for partial discharge and high-energy discharge defects. In addition, when compared to other diagnostic approaches, LDA shows competitive performance, reaching or surpassing accuracy levels seen in traditional DGA-based models. In order to improve the reliability of classification findings, the research also highlights the need of data pretreatment and standardization. According to the findings, current transformer monitoring systems may benefit from incorporating LDA into their fault diagnostic processes for a more automated and accurate method, which in turn improves maintenance efficiency and decreases the likelihood of human mistake. To further improve the predicted accuracy and reliability of transformer failure detection, future research might investigate hybrid models that combine LDA with machine learning approaches.

REFERENCES

1. Prasojo, Rahman & Putra, Muhammad & ., Neelmani. (2022). Mixture of Faults Identification on Power Transformers Using Multi-Method Dissolved Gas Analysis. International Journal of Frontier Technology and Engineering. 1. 1-12. 10.33795/ijfte.v1i01.221.

2. Abu-Siada, Ahmed. (2019). Improved Consistent Interpretation Approach of Fault Type within Power Transformers Using Dissolved Gas Analysis and Gene Expression Programming. Energies. 12. 730. 10.3390/en12040730.

3. Ghoneim, Sherif & Taha, Ibrahim. (2016). A new approach of DGA interpretation technique for transformer fault diagnosis. International Journal of Electrical Power & Energy Systems. 81. 265-274. 10.1016/j.ijepes.2016.02.018.

4. Illias, Hazlee & Choon, Chan & Liang, Wee & Mokhlis, Hazlie & Ariffin, Azrul & Yousof, Fairouz. (2021). Fault Identification in Power Transformers Using Dissolve Gas Analysis and Support Vector Machine. 33-36. 10.1109/ICPADM49635.2021.9493970.

5. H. R. Zhang, J. X. Sun, K. N. Hou, Q. Q. Li and H. S. Liu, "Improved information entropy weighted vaguesupport vector machine method for transformer fault diagnosis," High Voltage, vol. 7, no. 3, pp. 510–522,2022.

6. Y. L. Liang, Z. Y. Zhang, K. J. Li and Y. C. Li, "New correlation features for

dissolved gas analysis basedtransformer fault diagnosis based on the maximal information coefficient," High Voltage, vol. 7, no. 3, pp.302–313, 2022

7. Y. X. Liu, B. Song, L. N. Wang, J. C. Gao and R. H. Xu, "Power transformer fault diagnosis based ondissolved gas analysis by correlation coefficient-DBSCAN," Applied Sciences, vol. 10, no. 13, pp. 4440,2020.

8. M. M. Islam, G. Lee and S. N. Hettiwatte, "Application of Parzen Window estimation for incipient faultdiagnosis in power transformers," High Voltage, vol. 3, no. 4, pp. 303–319, 2018.

9. T. Kari, W. S. Gao, A. Tuluhong, Y. YILihamu and Z. W. Zhang, "Mixed kernel function support vectorregression with genetic algorithm for forecasting dissolved gas content in power transformers," Energies,vol. 11, no. 9, pp. 2437, 2018.

10. T. Kari, W. S. Gao, D. B. Zhao, Z. W. Zhang, W. X. Mo et al., "An integrated method of ANFIS andDempster-Shafer theory for fault diagnosis of power transformer," IEEE Transactions on Dielectrics andElectrical Insulation, vol. 25, no. 1, pp. 360–371, 2018.

11. X. H. Yang, W. K. Chen, A. Y. Li, C. S. Yang, Z. H. Xie et al., "BA-PNN-based methods for powertransformer fault diagnosis," Advanced Engineering Informatics, vol. 39, pp. 178–185, 2019.

12. Malik, R. Sharma and S. Mishra, "Fuzzy reinforcement learning based intelligent classifier for powertransformer faults," ISA Transactions, vol. 101, pp. 390–398, 2020.

13. L. C. Hong, Z. H. Chen, Y. F. Wang, M. Shahidehpour and M. H. Wu, "A novel SVM-based decisionframework considering feature distribution for power transformer fault diagnosis," Energy Reports, vol. 8,no. 11, pp. 9392–9401, 2022.