J. Inst. Eng. India Ser. B (August 2023) 104(4):869–876
https://doi.org/10.1007/s40031-023-00891-2

ORIGINAL CONTRIBUTION

Intelligent Approach to Interpret Incipient Faults of Power Transformer from DGA Database

Mitul M. Modi[1] · **Rakesh A. Patel**[1]

Received: 24 April 2022 / Accepted: 19 April 2023 / Published online: 25 May 2023

Abstract Power transformer is most powerful and expensive tool in power system for transmitting and distributing electrical energy to all consumers. High-voltage transformers in power system are oil-immersed type transformer. Use of oil provides much needed cooling, insulation, and reduces vibrations to power transformer. Oil of the power transformer is monitored and diagnosed on a regular basis to preserve its dependability and efficiency. Dissolved gas analysis (DGA) is effective and efficient tools to interpret incipient faults. In DGA method, dissolved gases like H_2, CH_4, C_2H_4, C_2H_6, C_2H_2 are extracted from oil. Based on the gases threshold values in oil, different faults are identified. The current article focus on three traditional fault diagnostic methods IEC, Roger ratio, and Duval triangle and one artificial neural network-based intelligent method. Result spot light that intelligent methods gives higher accuracy and consistency to identify the incipient faults of power transformer while traditional methods are proved inadequate, inaccurate and inconsistent.

Keywords DGA · Incipient faults · Transformer protection · ANN · Power transformer · Bootstrapping

Introduction

Power transformer in the power system is backbone of transmission and distribution system. Performance of the power system is depend on power transformer. So its resilience affects not only on electrical energy but also operational economy [1, 2]. As a result, timely maintenance based on observed incipient faults is necessary. Nowadays most of the power transformers used in power systems are oil immerse type. And majority of the incipient faults are caused by electrical, mechanical and chemical stress; hence, oil decomposition and few gases like "Hydrogen (H_2), methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4), acetylene (C_2H_2), carbon monoxide (CO), and carbon dioxide (CO_2)" [3] are dissolved in oil, and their threshold limits are measured in parts per million (ppm) [4, 5]. Dissolved gas analysis is the most effective method for finding early flaws (DGA) [6, 7]. Internal problems in a power transformer emit various gases that can be used to diagnose the malfunction. When many anomalies are present, the analysis is not always straightforward. Listed below are several flaws [8].

1. Partial discharge (PD)
2. Sparking discharge (SD)
3. Arcing discharge (AD)
4. Low-temperature overheating (LTO)
5. Middle-temperature overheating (MTO)
6. High-temperature overheating (HTO)
7. Thermal and electric faults (DT)

In partial discharge faults [9, 10], temperature has little bearing; the bulk of gases are H_2 and CH_4, with minor residues of C_2H_2, resulting in pinholes and carbonized tiny punctures in paper. Surface tracking of paper or the development of tiny amounts of carbon particles in oil is both caused by the Sparking Discharge (low-energy arcing) fault [11]. Production of large amount of H_2 and C_2H_2 gases is evidence of that. Further discharge may lead to arcing (high-energy discharge) type of fault which damage insulating paper. Other

✉ Mitul M. Modi
mitul.modi@ganpatuniversity.ac.in

Rakesh A. Patel
rap01@ganpatuniversity.ac.in

[1] Ganpat University, Mehsana, Gujarat, India

faults are low-, medium- and high-temperature overheating faults which may occurs at below 3000 °C, in between 3000 and 7000 °C, more than 7000 °C. As an impact of these faults, larger amount of C_2H_4 gases with small traces of CH_4, C_2H_6 are generated and decomposed in oil. In the last stage fault identification, the DGA data will be used to analyze the transformer conditions [12]. The international standards IEC 60599 and IEEE C57.104 [5] include many diagnostic approaches for DGA [13], such as the key gas method, Dornenburg, the Roger ratio method, IEC (International Electro Technical Commission) ratio method and the Duval triangle method. The current article represents three traditional methods Roger ratio method (RRM), IEC ratio method (IRM) and Duval triangle method (DTM) and one intelligent ANN-based method are implemented on MATLAB, and analysis is performed on empirical dataset [14, 15].

Methodology

This paper represents two approaches of DGA dataset interpretation methods. In traditional DGA dataset interpretation approach, three methods [16], Roger ratio (RRM), IEC ratio (IRM) and Duval triangle (DTM) are testes over different 440 empirical observations [14, 15] with six fault categories listed above. MATLAB code is developed to test methods.

In intelligent approach, two ANN-based training functions, Levenberg–Marquardt and Bayesian regularization is developed in MATLAB. Initially, both functions were tested with same observation but due to the lower size the observations, accuracy is compromised. To achieve the better accuracy, samples sizes are increased using bootstrapping.

Traditional DGA Interpretation Methods

IEC, IEEE C57.104 and other many standard [17] have been highlighted for the incipient fault detection of the power transformer.

Roger's Ratio Method (RRM)

Four gas ratios (R1 = CH_4/H_2, R2 = C_2H_6/CH_4, R3 = C_2H_4/C_2H_6, R4 = C_2H_2/C_2H_4) are used in this method to predict 11 incipient faults [18]. But after revision in IEEE C57.104-1991, R2 no longer exists [19]. As a result, only six types of incipient faults (PD, AD, SD, LTO, MTO, HTO) excluding no faults (NF) condition can be identified. Faults are recognized using ratio range scheme shown in Table 1.

RRM was developed in MATLAB and tested on empirical dataset of 440 observations; results highlight that algorithm gives the moderate result with accuracy of 63.42%.

Table 1 Gas analysis by RRM [16]

Fault type	R1	R3	R4
NF	> 0.1 to < 1	>1	< 0.1
PD	< 0.1	< 1	< 0.1
AD	> 0.1 to < 1	>1 to <3	>0.1 to < 3
SD	> 0.1 to < 1	>3	> 3
LTO	> 0.1 to < 1	>0.1 to <3	< 0.1
MTO	> 1	> 0.1 to <3	< 0.1
HTO	> 1	> 3	< 0.1

Table 2 Gas analysis by IRM [20]

Fault type	R1	R3	R4
NF	> 0.1 to < 1	< 1	< 0.1
PD	< 0.1	< 0.2	NA
AD	0.6 to 2.5	0.1 to 1	> 2
SD	0.1 to 0.5	> 1	> 1
LTO	> 1	< 1	NA
MTO	> 1	1 to 4	< 0.1
HTO	> 1	> 4	< 0.2

Result also enlightens that this methods fails to identify multiple faults.

IEC Ratio Method (IRM)

This method is exactly identical to RRM. Three gas ratios (R1= CH_4/H_2, R3=C_2H_4/C_2H_6, R4=C_2H_2/C_2H_4) are taken into consideration [20]. Finding which region of fault is closest to the original ratio's data point is the final step in determining the fault type. This method is able to diagnosis various overheating faults, electrical energy discharge faults and also gives the information about the normal aging (Table 2).

MATLAB code is implemented and test on empirical dataset of 440 observations [14, 15], results spot that this method gives the reasonable accuracy 71.66% but in some cases this method fails to identify the faults accurately.

Duval Triangle Method (DTM)

DTM [21] uses the three gases, methane (CH4), ethylene (C2H4), and acetylene (C2H2) proportionate concentration to identify the different types of fault. Different fault types and its zone are specified in Fig. 1 and Table 4. Table 3 indicates that the normal limits and its normal rising rate of the gases are from 10 to 50% per month. Once the fault exists, this method uses percentages of $\%CH_4$, $\%C_2H_4$ and $\%C_2H_2$ to find the exact fault category of the fault (Table 4).

Table 3 Normal limits of oil [18]

Gas	L1 limits (PPM)
H_2	100
CH_4	75
C_2H_2	3
C_2H_4	75
C_2H_6	75
CO	700
CO_2	7000

Table 4 Fault zone identification

Fault type	% CH_4	% C_2H_4	% C_2H_2
PD	98–100	0–2	0–2
AD	0–31	23–71	29–77
	31–64	23–40	13–29
SD	0–87	0–23	13–100
LTO	76–97	1–20	1–4
MTO	46–80	20–50	0–4
HTO	0–50	50–100	0–15
DT	0–35	40–100	4–29
	47–96	0–40	4–13

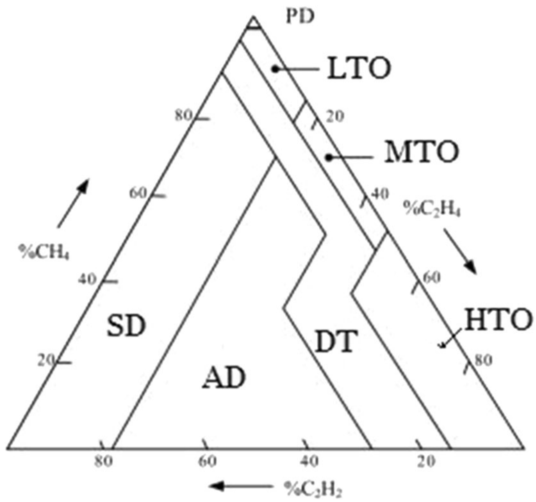


Fig. 1 Duval triangle [21]

This traditional method gives best results among all other methods with the accuracy of approximately 88%. Later stage author [22] highlights the modified version of Duval triangle in which numerical method was employed from graph.

Other traditional algorithms like Doernenburg ratio method, key gas method [23], etc. are also used to predict the various fault, but these approaches exclusively depend upon human

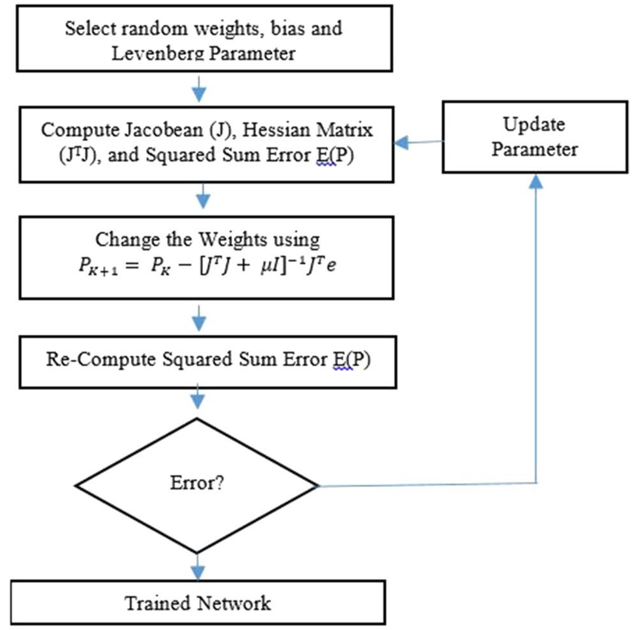


Fig. 2 Flow diagram of LMA

experience and expertise. Moreover these methods are unable to identify the multiple faults exist in the transformer oil.

ANN-Based DGA Interpretation Method

For any nonlinear input–output patterns, artificial neural network (ANN) is greatest tool to find the hidden patterns

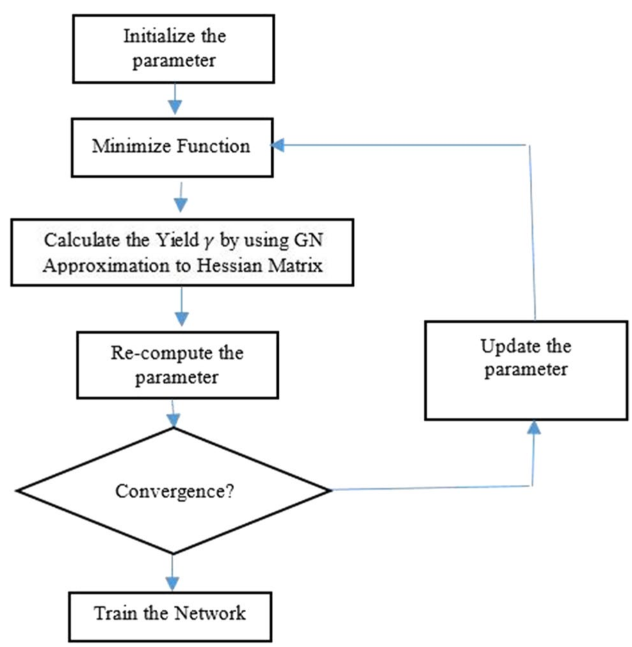


Fig. 3 Flow diagram of BR

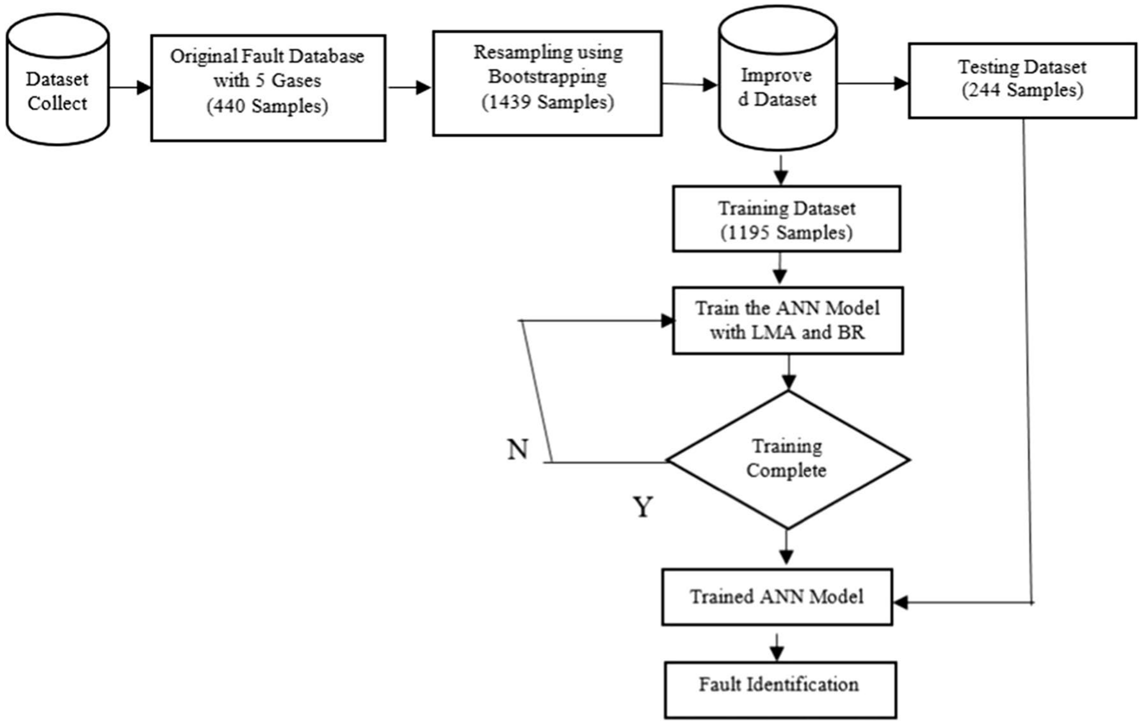


Fig. 4 Basic flow diagram of ANN-based training functions

between input–output [24]. In this article, basically two training functions (Levenberg–Marquardt and Bayesian regularization) are implemented

Levenberg–Marquardt (LM) Training Function

This approach employs statistics to reduce a nonlinear function over a set of parameters. Constraint optimization challenges include nonlinear programming and least squares curve fitting. [3]. The LMA links Gauss–Newton method with (GNA) [25] and the gradient descent (GD). LMA targets second-order training speed without computing the Hessian matrix (Fig. 2).

$$P_{k+1} = P_k - [J^T J + \mu I]^{-1} J^T e \tag{1}$$

Bayesian Regularization (BR) Training Function

Bayesian regulatory back propagation (BRP) [26] updates weight and bias variables using Levenberg–Marquardt optimization (LMO) [27]. To construct a good network, it minimizes squared errors and weights (Fig. 3).

Figure 4 shows the basic flow diagram of the ANN-based approach [28], these can be further divided into data acquisition, pre-processing, feature selection, Training and Testing with sample data.

Results and Discussion

Figure 5 shows the results of the three traditional methods. Total observation of 440 observations [14, 15] with different category of faults were taken for these diagnosis. All methods are able to identify the majority of the incipient faults with reasonable accuracy and Consistency. Out of all three conventional, RRM provides 65% accuracy, IRM gives 75% of accuracy and DTM yield best results and greater accuracy around 88%. Contrarily the results also shed a light that these methods are not able to identify multiple faults like discharge and overheating faults (DT).

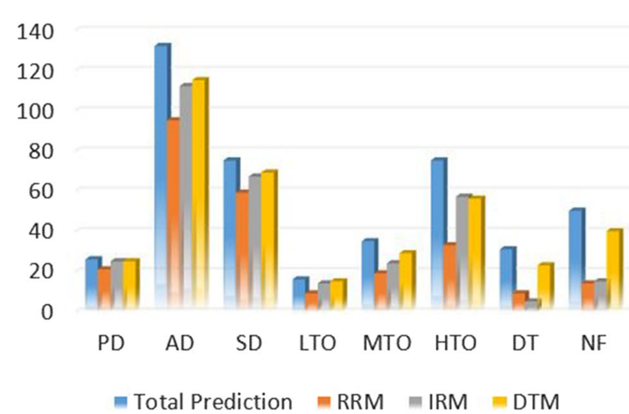


Fig. 5 Result comparison of traditional methods

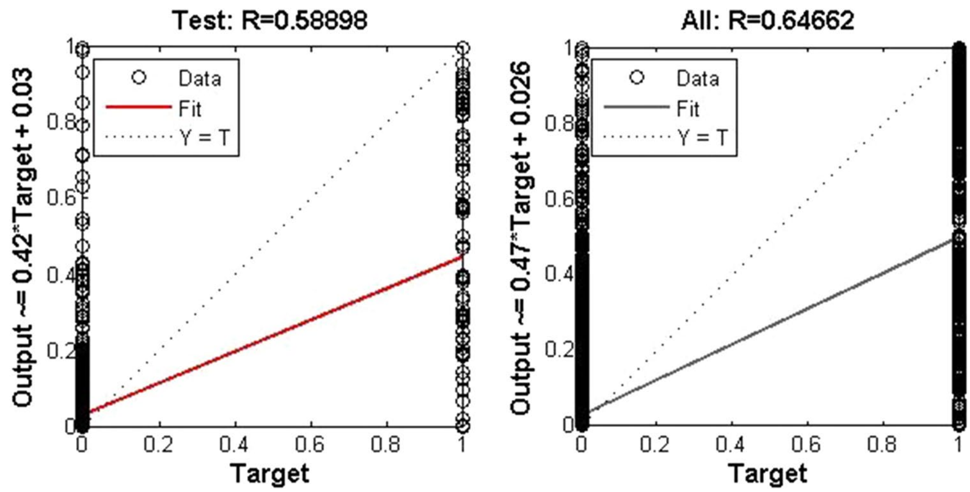


Fig. 6 Regression curve for BR training

When ANN is trained with LMA, BR and BFGS quasi-Newton training functions for same 420 observations [14] [15], accuracy during training fall in between 60 and 95% and accuracy during testing (20 observations) was 50–80%, respectively. These might be occur due to following reasons.

- Less number of observations
- Uneven faults cases
- Selection of hidden layer neurons and its activation functions

So more observation were created using bootstrapping [29].

LMA training algorithm details

- Samples for training: 1195
- Samples for testing: 244
- Inputs: 05 (H_2, CH_4, C_2H_6, C_2H_4, C_2H_2)
- Output: 08 (PD, SD, AD, HTO, MTO, LTO, DT, NF)
- Hidden layer neurons: 20
- Training algorithm: Levenberg–Marquardt
- Activation function: Hyperbolic Tangent

BR training algorithm details

- Samples for training: 1195
- Samples for testing: 244
- Inputs: 05 (H_2, CH_4, C_2H_6, C_2H_4, C_2H_2)
- Output: 08 (PD, SD, AD, HTO, MTO, LTO, DT, NF)
- Hidden layer neurons: 20
- Training algorithm: Bayesian regularization
- Activation function: hyperbolic tangent

BFGS quasi-Newton training algorithm details

- Samples for training: 1195
- Samples for testing: 244
- Inputs: 05 (H_2, CH_4, C_2H_6, C_2H_4, C_2H_2)
- Output: 08 (PD, SD, AD, HTO, MTO, LTO, DT, NF)
- Hidden layer neurons: 20
- Training algorithm: BFGS quasi-Newton
- Activation function: hyperbolic tangent

Moreover, when ANN is trained using different other training functions like one-step secant, conjugate gradient with Beale Powell series, gradient descent with momentum and resilient backpropagation, the overall accuracy which will get arround 20, 33, 47, and 59.4%, respectively (Figs. 6, 7).

Table 5 shows the results of three ANN training algorithm results and it highlights that with larger dataset of 1439 observations which was derived through bootstrapping [29] with different fault categories, accuracy of both

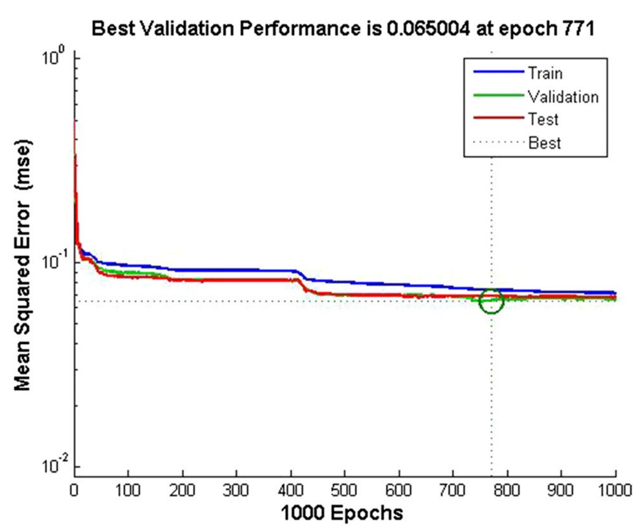


Fig. 7 Mean square error for BFGS quasi-Newton training

Table 5 Result (Accuracy) comparison between LM, BR and BFGS quasi-Newton function

Types of faults	Actual cases	Levenberg–Marquardt		Bayesian regularization		BFGS quasi-Newton	
		Training	Testing	Training	Testing	Training	Testing
PD	154	100%	100%	98.5%	96%	70%	64%
AD	191	98.74%	96.87%	98.74%	93.75%	69%	58%
SD	221	92.39%	98%	93.56%	98%	67%	60%
LTO	195	95.23%	100%	96.87%	85.18%	64%	59%
MTO	99	98.70%	75%	96.10%	58.18%	63%	58%
HTO	242	99.46%	96.29%	96.25%	98.14%	64%	55%
DT	138	85.93%	90%	80.46%	60%	50%	40%
NF	209	97.71%	82.35%	95.42%	88.23%	61%	54%
Total	1439	96.06%	94.26%	93.97%	90.98%	63.4%	56%

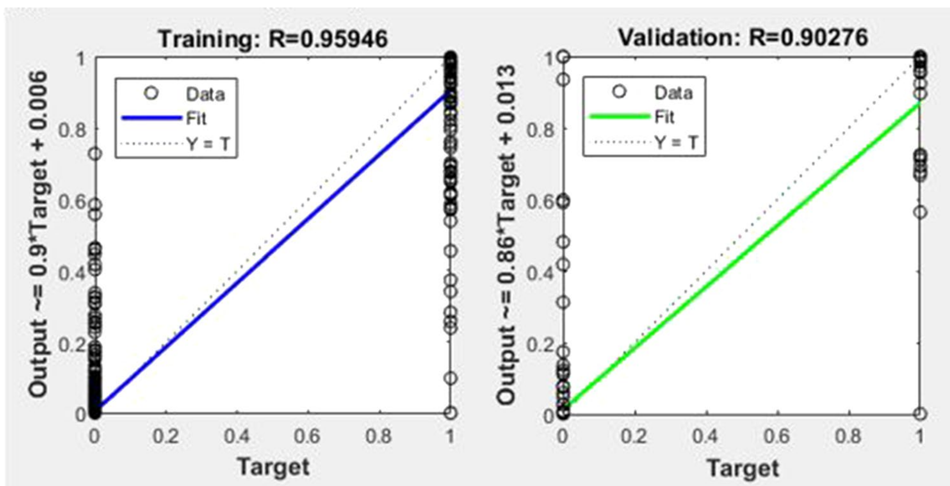


Fig. 8 Regression curve for LMA training

training function (LM and BR) are more than 90% during training and testing phases (Figs. 8, 9 and 10). But accuracy using BFGS quasi-Newton training algorithm is poor or closer to tradtional methods. Moreover, LM and BR training functions provide best results to interpret multiple faults at same time due to overheating and discharge (DT).

Conclusion

In current paper, three traditional methods, i.e., Roger ratio method, IEC ratio method and Duval triangle method, were developed and tested with empirical dataset of 440 observations. Result revealed that among three methods, Duval triangle gives best fault diagnosis with considerably higher accuracy and consistency. Ratio approaches have a flaw in that they don't cover all data regions, and occasionally ratios aren't fit for tables. When it comes to dissolved-gas measurements, there is always some level of error. Gas concentrations and other analytical computations are all affected by this inconsistency. Furthermore, an

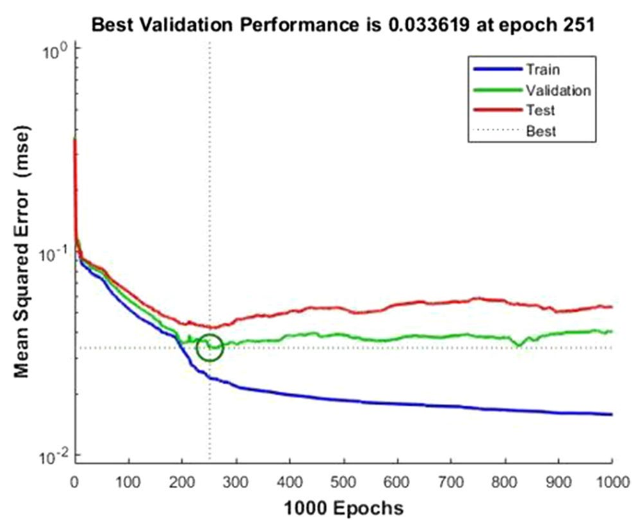
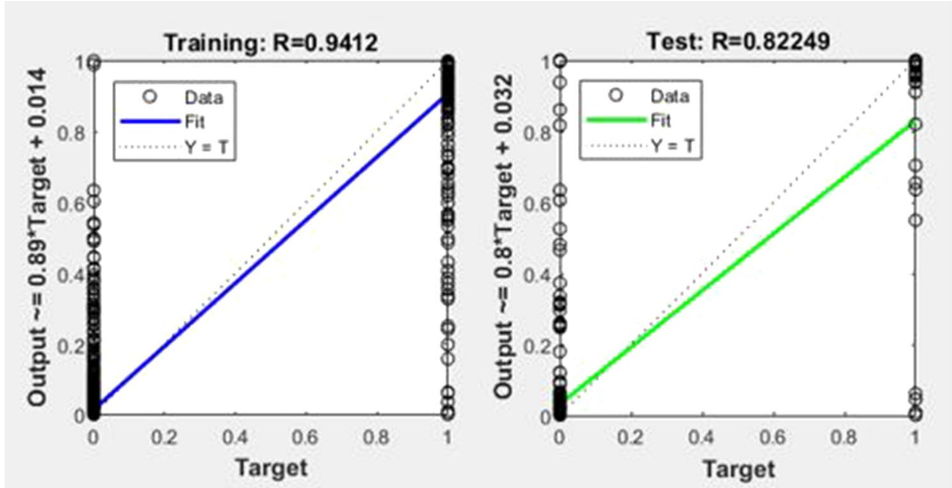


Fig. 9 Mean square error for LMA training

Fig. 10 Regression curve for BR training



ANN-based strategy was constructed, tested, and assessed using two distinct training functions: Levenberg–Marquardt and Bayesian regularization. Result of both training functions revealed that highest accuracy and consistency were achieved during training and testing phases, results also pined that ANN-based method easily identifies the multiple incipient faults presents in transformer. Moreover in future, the accuracy and consistency may increase by applying fusion of AI and ML techniques like (ANN + SVM), (ANFIS + SVM), (ANN + DT), etc.

Author Contributions MMM contributed to conceptualization, methodology, data curation, writing—original and final draft preparation, visualization, investigation, simulation, and result validation. RAP contributed to supervision and reviewing.

Funding Not applicable.

Data Availability All data generated or analyzed during this study are included in this article.

Declarations

Conflict of interest The author declares that they have no competing interests.

References

1. O.E. Gouda, S.M. Saleh, S.H. El-Hoshy, Power transformer incipient faults diagnosis based on dissolved gas analysis. Indones. J. Electr. Eng. Comput. Sci. **1**(1), 10–16 (2016)
2. N. Lelekakis, D. Martin, W. Guo, J. Wijaya, Comparison of dissolved gas-in-oil analysis methods using a dissolved gas-in-oil standard. IEEE Electr. Insul. Mag. **27**(5), 29–35 (2011)
3. A. Lakehal, F. Tachi, Bayesian Duval triangle method for fault prediction and assessment of oil immersed transformers. Meas. Control **50**(4), 103–109 (2017)
4. M. Duval, A review of faults detectable by gas-in-oil analysis in transformers. IEEE Electr. Insul. Mag. **18**(3), 8–17 (2002)
5. IEEE guide for the interpretation of gases generated in oil-immersed transformers, IEEE Std C57.104-2008 (Revision of IEEE Std C57.104-1991), (2009), pp. 1–36
6. Mineral oil-impregnated electrical equipment in service-guide to the interpretation of dissolved and free gases analysis. Second edition. IEC Standards 60599 (1999)
7. A. D3612-02, Standard test method for analysis of gases dissolved in electrical insulating oil by Gas Chromatography (2017)
8. J.J. Zhang, Y.X. Song, Y. Qu, in *A time series analysis and neural network based scheme for fault diagnosis of transformers in Sensors, Mechatronics and Automation II*, Applied Mechanics and Materials, vol 742 (Trans Tech Publications, 2015), pp. 412–418
9. G. Cleary, M. Judd, Uhf and current pulse measurements of partial discharge activity in mineral oil. Sci. Meas. Technol. **153**, 47–54 (2006)
10. Y.P. Nerkar, R.S. Nema, Characterisation of partial discharges in oil impregnated pressboard insulation systems. In 11th International Symposium on High Voltage Engineering, vol 3 (1999), pp. 364–367
11. Z. Wang, S. Hettiwatte, P. Crossley, A measurements-based discharge location algorithm for plain disc winding power transformers. IEEE Trans. Dielectr. Electr. Insul. **12**(3), 416–422 (2005)
12. R. Patsch, J. Menzel, D. Benzerouk, The use of the pulse sequence analysis to monitor the condition of oil. In: IEEE Conference on Electrical Insulation and Dielectric Phenomena, (2006), pp. 660–663
13. R. Green, Dissolved gas analysis plays key role. Transform. Oper. **40**(06), 54–56 (2008)
14. M. Duval, A. dePabla, Interpretation of gas-in-oil analysis using new IEC publication 60599 and IEC tc 10 databases. IEEE Electr. Insul. Mag. **17**(2), 31–41 (2001)
15. E. Li, Dissolved gas data in transformer oil–fault diagnosis of power transformers with membership degree. IEEE Access **7**, 28791–28798 (2019)
16. N.A. Bakar, A. Abu-Siada, H. Cui, and S. Li, Improvement of DGA interpretation using scoring index method. In: 2017 1st International Conference on Electrical Materials and Power Equipment (ICEMPE) (2017), pp. 502–506
17. M. Duval, J. Dukarm, Improving the reliability of transformer gas-in-oil diagnosis. IEEE Electr. Insul. Mag. **21**(4), 21–27 (2005)

18. N.A. Bakar, A. Abu-Siada, S. Islam, A review of dissolved gas analysis measurement and interpretation techniques. IEEE Electr. Insul. Mag. **30**(3), 39–49 (2014)
19. Y. Cui, Investigation of data centric diagnostic techniques for transformer condition assessment, Ph.D. dissertation, The University of Queensland, Australia (2016)
20. I.B.M. Taha, S.S.M. Ghoneim, A.S.A. Duaywah, Refining dga methods of IEC code and rogers four ratios for transformer fault diagnosis. In: IEEE Power and Energy Society General Meeting (PESGM) (2016), pp. 1–5
21. S. Permana, S. Sumarto, W.S. Saputra, Analysis of transformer conditions using triangle Duval method. IOP Conf. Ser. Mater. Sci. Eng. **384**(1), 012065 (2018). https://doi.org/10.1088/1757-899x/384/1/012065
22. S. S. Desouky, A.E. Kalas, R.A.A. El-Aal, A.M.M. Hassan, Modification of Duval triangle for diagnostic transformer fault through a procedure of dissolved gases analysis. In: 2016 IEEE 16th International Conference on Environment and Electrical Engineering (EEEIC) (2016), pp. 1–5
23. H.-C. Sun, Y.-C. Huang, C.-M. Huang, A review of dissolved gas analysis in power transformers. Energy Procedia **14**, 1220–1225 (2012)
24. Y. Brar, T. Nagpal, Artificial neural network approaches for fault classification: comparison and performance. Neural Comput. Appl. **25**, 1863–1870 (2014)
25. Ujjwal, S. Kukrety, L. Kakinada, and Shalini, Wind Power Forecasting Using Artificial Neural Networks (ANN) and Artificial Neuro-fuzzy Inference System (ANFIS). In: Proceedings of 6th International Conference on Recent Trends in Computing: ICRTC 2020, (Springer, 2021), pp. 535–541
26. Y.J. Sun, S. Zhang, C.X. Miao, J.M. Li, Improved BP neural network for transformer fault diagnosis. J. China Univ. Min. Technol. **17**(1), 138–142 (2007)
27. M. Kayri, Predictive abilities of Bayesian regularization and Levenberg–Marquardt algorithms in artificial neural networks: a comparative empirical study on social data. Math. Comput. Appl. **21**(2), 20 (2016)
28. D. Siva Sarma, G. Kalyani, Ann approach for condition monitoring of power transformers using DGA. In: 2004 IEEE Region 10 Conference TENCON 2004, vol C, pp. 444–447, (2004)
29. Y. Zhao, R. Duangsoithong, Empirical analysis using feature selection and bootstrap data for small sample size problems. In: 2019 16th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON) (2019), pp. 814–817