COMPUTATIONAL RESEARCH PROGRESS IN APPLIED SCIENCE & ENGINEERING (CRPASE)

CRPASE: TRANSACTIONS OF
ELECTRICAL, ELECTRONIC AND COMPUTER ENGINEERING

Journal homepage: http://www.crpase.com

CRPASE: Transactions of Electrical, Electronic and Computer Engineering, Vol. 06(03), 127-131, September 2020 ISSN 2423-4591

Research Article

Apply the Artificial Neural Network to Diagnose Potential Fault of Power Transformer Based on Dissolved Gas-in-oil Analysis Data

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Keywords

Diagnostic system, Power transformer, Potential fault, Artificial neural network, Dissolved Gas-in-oil Analysis.

Abstract

This paper presents the development of a potential fault diagnosis system of power transformers by an artificial neural network (ANN) based on the gas components of dissolved gas-in-oil analysis (DGA) data. The input of the ANN is five components H_2, C_2H_4, CH_4, C_2H_2, C_2H_6. The outputs are 3 major conclusions about the condition of the transformer including "normal", "overheating" and "discharging". Using Multi-Layer Perception network (MLP) with a selected network structure of 5-16-3. Through testing with actual DGA data, the results show that the diagnostic system makes conclusions that are reliable.

1. Introduction

Diagnosing the potential faults of the power transformer in the electrical system is a problem of great concern to many scientists. In order to provide information on potential faults of the power transformer, in some published, diagnostic methods based on the DGA data have been presented. There are also diagnostic methods based on the power transformer frequency response, which is based on the vibration of the power transformer. Gas chromatography and oil-soluble gas analysis require specialized measuring instruments and require high accuracy. Based on these techniques, there are many modern techniques that allow for better diagnostics [1], but one common point of these methods is to rely on accurate measurement techniques. Therefore, the diagnosis results also depend heavily on the accuracy of the measurements. Another diagnostic method that can inherit expert knowledge in the form of statistical rules has been introduced [2], [3]. This method was developed based on the use of artificial neural networks. In order to get accurate diagnosis results, the method of using neural networks must have experimental data set "big enough" to train the network and choose a reasonable network structure. In fact, according to this approach, there are many network structures that can be selected with different diagnostic results. Choosing a simple network structure while still ensuring accurate diagnosis results will be advantageous. In addition, methods of using fuzzy logic and fuzzy neural are also proposed [4], [5], [6], [7], [8], [9]. The common point of these methods is to inherit expert knowledge. Research and find for new and more effective methods are always necessary for the process of scientific and technological development. Therefore, finding a simple and effective neural network structure that meets practical requirements in power transformer experiments is a problem of urgency and practicality. With this goal, in this study, the potential fault diagnosis system of the power transformer was built force using a minimal neural network based on the results of actual DGA data.

2. Diagnosis Potential Faults of Power Transformer Based on DGA

2.1. Characteristics of Generate Gas and DGA

Dissolved Gas-in-oil Analysis of the power transformer is aimed at early detection of local overheating, discharge, etc. To analyze dissolved gas in transformer oil, use an analyzer system called TOGAS (Transformer Oil Gas

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Received: 12 January 2020; Revised: 27 May 2020; Accepted: 30 May 2020

Please cite this article as: N.T. Duy, Apply the Artificial Neural Network to Diagnose Potential Fault of Power Transformer Based on Dissolved Gas-in-oil Analysis Data, Computational Research Progress in Applied Science & Engineering, CRPASE: Transactions of Electrical, Electronic and Computer Engineering 6 (2020) 127–131.

Analysis System). From the analysis of the dissolved gas in transformer oil, it is possible to diagnose the fault type of the transformer. DGA analysis without the need to disconnect the power transformer or online method. This type of analysis includes conventional DGA, which is based on periodic oil sampling and modern techniques of online gas monitoring.

Under the effect of electricity and heat, the hydrogen – carbon (H–C) element of the mineral oil can decompose into hydrogen and H–C fragments, which can combine to form gases are hydrogen (H_2), methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4), acetylene (C_2H_2), CO and CO_2. The amount of gas for each individual gas depends on the temperature at the point of impact. Many researchers have proposed methods to predict potential faults in power transformers such as Dornemberg ratio, Roger ratio, main gas method, IEC-599 standard.

2.2. Ratio Method and IEC-599 Standard

Ratio methods and IEC-599 standard using dissolved gas ratios are the main basis of fault diagnosis. Five traditional ratios are used as in Table 1. The limited concentration of the gas in the normal working state of the power transformer is given in Table 2. When the normal limit is exceeded, depending on the value, the power transformer can be at different levels of fault.

Table 1. Definition the ratio of gas components

Ratio	$\frac{CH_4}{H_2}$	$\frac{C_2H_2}{C_2H_4}$	$\frac{C_2H_2}{CH_4}$	$\frac{C_2H_6}{C_2H_2}$	$\frac{C_2H_4}{C_2H_6}$
Abbreviation	R1	R2	R3	R4	R5

Table 2. Dornenburg's L1 limits

Gas	H_2	CH_4	CO	C_2H_2	C_2H_4	C_2H_6
L1 Limits (ppm)	100	120	350	35	50	65

In proportion methods, the number of ratios used is not the same. The Dornenburg ratio method distinguishes between thermal and electrical faults by using four scale factors as shown in Table 3.

Table 3. Dornenburg's ratio method

Fault	R1	R2	R3	R4
Thermal Decomposition	> 0.1	< 0.75	< 0.3	> 0.4
Corona (low intensity PD)	< 0.1	Not significant	< 0.3	> 0.4
Arcing (high intensity PD)	> 0.1 and < 1.0	> 0.75	> 0.3	< 0.4

The original Rogers ratio method used 5 gases and 4 ratios R1, R2, R3 as above but R4 = C_2H_6/CH_4. Recently, there is an improvement of the Rogers method is to use only 3 ratios R1, R2 and R3 (see Table 4 and Table 5).

In addition, the ratio method according to IEC-599 standard can be used when using only the 3 ratios shown in Table 6.

Table 4. Code for Roger's method

Gas ratio code	Range	Code
R1	≤ 0.1	5
	0.1 and < 1.0	0
	≥ 1.0 and < 3.0	1
	≥ 3.0	2
R2	< 5.0	0
	≥ 0.5 and < 3.0	1
	≥ 3.0	2
R3	< 1.0	0
	≥ 1.0	1
R5	< 1.0	0
	≥ 1.0 and < 3.0	1
	≥ 3.0	2

Table 5. Roger's method

R1	R2	R3	R5	Diagnosis
0	0	0	0	Normal deterioration
5	0	0	0	Partial discharge
1 or 2	0	0	0	Thermal fault lower than 150 ºC
1 or 2	0	1	0	Thermal fault (150 ºC - 200 ºC)
0	0	1	0	Thermal fault (200 ºC - 300 ºC)
0	0	0	1	Overheating in the cables
1	0	0	1	Circulating currents in the windings
1	0	0	2	Circulating currents in the tank and core, overheating in conexions
0	1	0	0	Conexions discharges
0	1/2	0	1/2	Arcing (high energy)
0	2	0	2	Low intensity continuous discharge
5	1/2	0	0	Partial discharge involving solid insulation

Table 6. IEC-60599 (2015) standard

Faults		R1	R2	R5
Normal		< 0.1	< 0.1	< 0.1
Partial discharges		< 0.1	NS (a)	< 0.2
Discharges of low energy		0.1 - 0.5	> 0.1	> 1
Discharges of high energy		0.1 - 1	0.6 - 2.5	> 2
Overheat	t < 300 ºC	> 1, NS (a)	NS (a)	< 1
	300 ºC < t < 700 ºC	> 1	< 0.1	1 - 4
	t > 700 ºC	> 1	< 0.2 (b)	> 4

Note:

(a) NS: Non-Significant whatever the value

(b) An increasing value of the amount of C_2H_2 may indicate that the hot spot t > 1000 ºC.

3. Diagnose Potential Fault of the Power Transformer by an ANN and DGA

3.1. ANN Structure

For the standard IEC-599 ratio method, each potential fault of the power transformer can correspond to different sets of values. For example, with the error "High energy discharge" corresponding value R2 > 0.6. Maybe the actual measured value R2 = 0.8 or even R2 = 2.5, etc. This shows that for each specific fault, the measured gas values can be in a sub-range value. This increases the non-linearity in the in-out relationship of the built neural network. In this study, the MLP network was selected to build the potential fault diagnosis system for the power transformer.

The power transformer fault diagnosis problem is similar to the highly complex nonlinear mapping problem because both input and output are multivariate and there is no known linear relationship. However, a 3-layer MLP network (1 hidden layer) has been shown to be able to approximate nonlinear functions that meet certain conditions. In addition, MLP networks with a propagation training algorithm with error monitoring have been successfully applied to solve various difficult problems. This shows that MLP can meet the requirements of the diagnosis problem.

Figure 1 shows the MLP block diagram for the diagnosis potential fault of the power transformer. With MLP structure, there are 5 inputs corresponding to 5 gas components H_2, CH_4, C_2H_6, C_2H_4, and C_2H_2. In this study, the diagnosis faults were limited indicated as in Table 5. In the output layer, there may be two options: 1 output or 3 outputs. Using a network with 3 outputs, the fault diagnosis is more convenient. With 3 buttons on the output layer, they will represent "normal", "overheating" and "discharge" conditions. The number of hidden layers is 1.

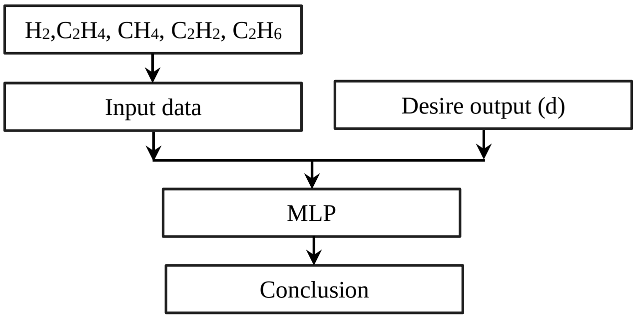

Figure 1. Blocks diagram of the diagnostic system using MLP

3.2. Training

In this study, the network was trained according to the backpropagation algorithm. The algorithm was implemented with the following options:

- Total number of neural:

$$s_j = \sum_{i=1}^{n} \omega_{ji} x_i \tag{1}$$

- Sigmoid activation functions:

$$y_j = \frac{1}{1 + e^{-sj}} \tag{2}$$

- Weight function:

$$\Delta\omega_{ji}(kT) = \Delta\omega_{ji}(k-1)T + \Delta\omega_{ji}(kT) \tag{3}$$

- Output layer:

$$\delta_j = y_j(1 - y_j)(d_j - y_j) \tag{4}$$

$$J = \frac{1}{2}\sum_{j=1}^{M}(d_j - y_j)^2 \tag{5}$$

- Other layers:

$$[\delta_j]_l = [y_j(1 - y_j)]_l \left[\sum_{i=1}^{N} \omega_{ji}\delta_i\right]_{l+1} \tag{6}$$

The training process continues until the stop condition is satisfied. The bakcpropagation algorithm is described as block diagram Figure 2.

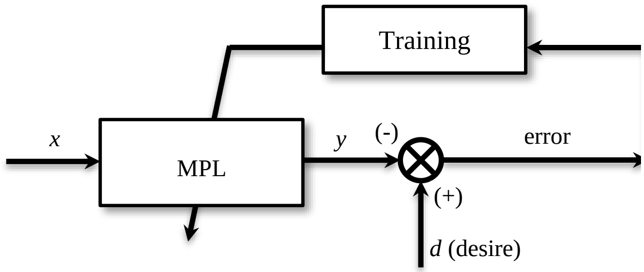

Figure 2. The diagram of backpropagation algorithm

Describe the details of the backpropagation algorithm as shown in Figure 3.

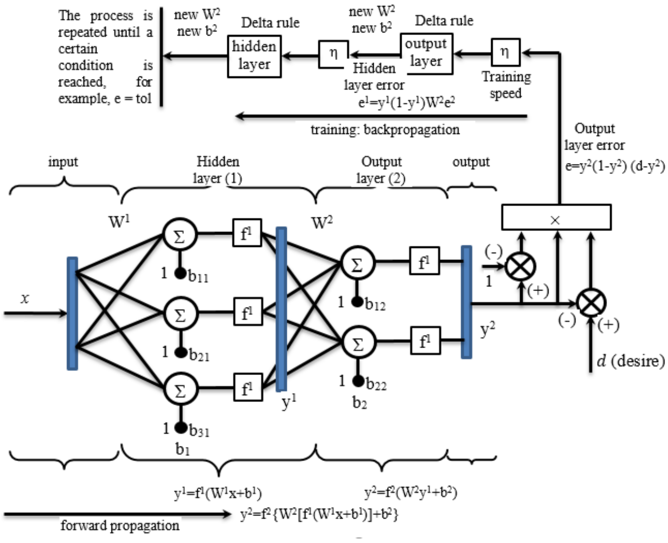

Figure 3. The backpropagation algorithm

Performing ANN training with structures 5-8-3, 5-10-3, and 5-16-3, found that the network has 5-16-3 structure for the best results. The DGA dataset used for the diagnostic process is built based on the collection of measurement and experimental sample samples and the corresponding error status of the power transformer during multiple diagnoses.

Table 7. Some samples in the DGA dataset for ANN training

Gas components (ppm)				
H_2	C_2H_4	CH_4	C_2H_2	C_2H_6
2	4	40	3	10
12	6	20	6	16
12	60	20	26	10
24	70	69	103	27
34	40	69	203	30
30	10	49	13	10

From the input data set in Table 7, the ratios R1, R2, and R5 are calculated according to Table 6, which is the diagnostic rule according to IEC-60599 (2015). The result is shown in Table 8. These ratios are the desired output value (d, Figure 2, and Figure 3). This value is used to calculate the output layer error during ANN training according to the backpropagation algorithm.

Table 8. Training data and corresponding faults

Gas components (ppm)					Ratio			Faults
H_2	C_2H_4	CH_4	C_2H_2	C_2H_6	$R1 = \frac{CH_4}{H_2}$	$R2 = \frac{C_2H_2}{C_2H_4}$	$R5 = \frac{C_2H_4}{C_2H_6}$	
2	4	40	3	10	2.00	0.75	0.40	Overheating
12	6	20	6	16	0.50	1.00	0.38	Low energy discharge
12	60	20	26	10	5.00	0.43	6.00	High energy discharge
24	70	69	103	27	2.92	1.47	2.59	Overheating
34	40	69	203	30	1.18	5.08	1.33	Overheating
30	10	49	13	10	0.33	1.30	1.00	Low energy discharge

4. Ressults

In this study, the Neural Network Toolbox in Matlab was used to train the ANN. Experiment with 5-8-3, 5-10-3, and 5-16-3 network structures. The results find that the structure 5-16-3 gives the most accurate diagnostic conclusion.

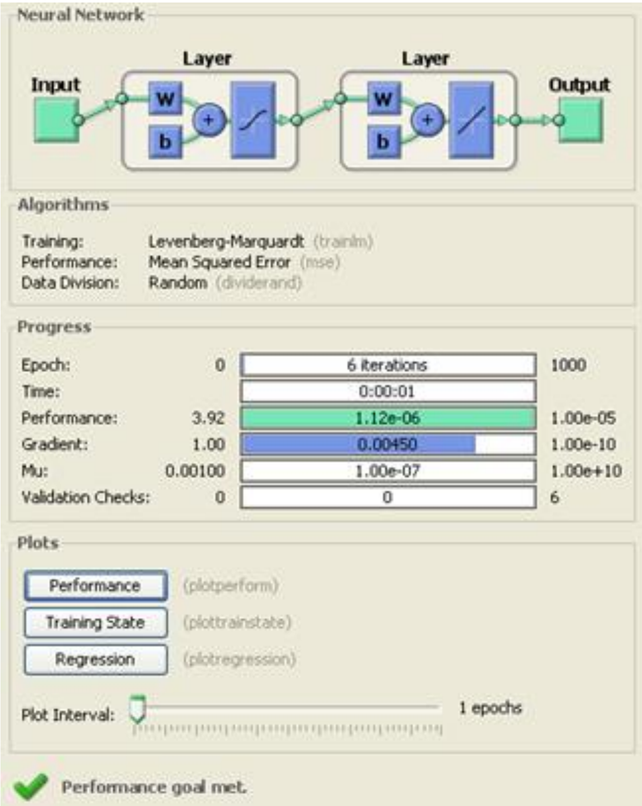

Figure 4. Training process

Figure 4 is a diagram of the training process for the MPL ANN model.

Where:

"Input" is the input vector of five gas components.
"Output" is conclusions about the state of the transformer.
W: weight
b: displacement
Activation functions input is 'tansig', and activation functions output 'purelin'
Desire error value $\varepsilon = 10^{-5}$

The training results for network structure 5-16-3 are shown in Figure 5. The training process is done after 6 epochs, mean squared error (MSE) reaches 10^{-6}. This is the network structure for the smallest MSE. In this test, 80% of the data samples in the DGA dataset are used for the training phase and 20% is used for the test phase. The observation in Figure 5 can be seen that the blue training line and the red test line are almost identical. This shows that the MPL ANN network with structure 5-16-3 as above is a good diagnosis with the classification of 3 basic errors as "normal", "overheating" or "electrical discharge".

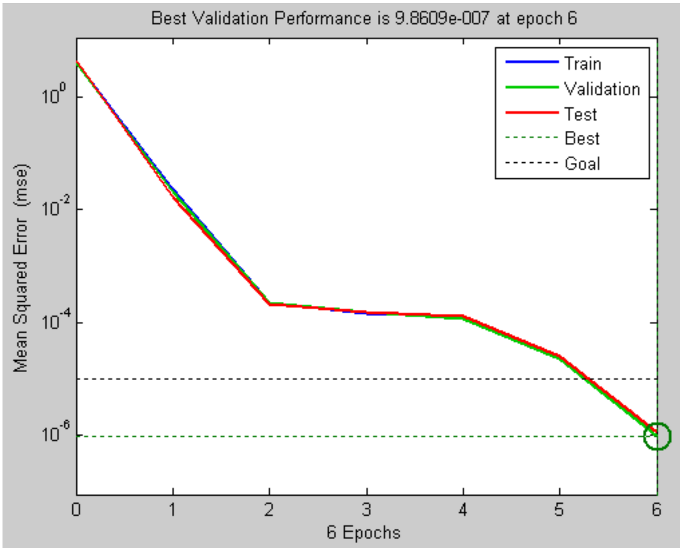

Figure 5. Results with a structure of 5-16-3

For ANN application problems, the important thing is always the data for training. In this study, DGA dataset was used from sources [10], [11]. The number of samples reached about 200 samples. Some examples and corresponding errors are as shown in Table 8. Because of the number of data samples is not big, the diagnostic faults at the output are not detailed. In order to draw the detailed conclusions shown in Table 5 or Table 6, it is necessary to have a sufficiently big number of data samples. This is a challenge that the faults diagnostic systems based on ANN always encountered. To solve this problem, it is proposed to keep the new data samples up to date during the diagnostic process and to repeat the network training process as the data size increases. It is also possible to redesign the network structure to be able to classify many faults in the output layer.

5. Conclusions

In this paper, the ANN was applied in diagnosing potential faults in the power transformer based on DGA data, the result is an MLP ANN model, which deviates after the network training process gives results pretty good within the allowed range. From the results of experimenting with MLP

ANN with hidden layers 5-8-3, 5-10-3, and 5-16-3, we found that the network 5-16-3 has the network training epoch and the smallest error.

Through experimental results, ANN have been able to diagnose basic faults in power transformer such as “normal”, “overheating” or “electrical discharge”, etc. and give good results for any of the 5 gas inputs. From this result, the ANN can be applied in fault diagnosis of power transformer with many power levels.

Acknowledgements

This paper was implemented by the “Knowledge technologies and soft computing – Thai Nguyen University of Technology (TNUT)” research group. Thank the science and technology fund of the TNUT funded for this research.

References

[1] Tapan K. Saha, Review of modern diagnostic techniques for assessing insulation condition in aged transformers, IEEE transactions on dielectrics and electrical insulation 10 (5) (2003) 903-917.
[2] Zhenyaun Wang, Artificial intelligence applications in the diagnostic of power transformer incipicent, Virginia, 2000.
[3] Fathiah Zakaria, Dalina Johari, Ismail Musirin, Artificial Neural Network (ANN) Application in Dissolved Gas Analysis (DGA) Methods for the Detection of Incipient Faults in Oil-Filled Power Transformer, IEEE International Conference on Control System, Computing and Engineering (2012) 23–25, Penang, Malaysia.
[4] N. K. Dhote, J. B. Helonde, Diagnosis of Power Transformer Faults based on Five Fuzzy Ratio Method, WSEAS Transactions on Power Systems 7 (2012) 114–125.
[5] Er. Niti Sharma, Power Transformer Diagnosis Using Fuzzy Logic, International Journal of Latest Research in Science and Technology 1 (2012) 149–151.
[6] R. Naresh, Veena Sharma, and Manisha Vashisth, An Integrated Neural Fuzzy Approach for Fault Diagnosis of Transformers, IEEE Transactions on Power Delivery 23 (4) (2008) 2017–2024.
[7] N. A. Golilarz, H. Demirel, Thresholding neural network (TNN) based noise reduction with a new improved thresholding function, Computational Research Progress in Applied Science & Engineering 3 (2017) 81–84.
[8] A. Addeh, A. Khormali, N. A. Golilarz, Control chart pattern recognition using RBF neural network with new training algorithm and pracrical features, ISA Transactions 79 (2018) 202–216.
[9] N. A. Golilarz, A. Addeh, H. Gao, L. Ali, A. M. Roshandeh, H. M. Munir, R. Khan, A new automatic method for control chart patterns recognition based on ConvNet and harris hawks meta heuristic optimization algorithm, IEEE Access 7 (2019) 149398–149405.
[10] Hongzhong Ma, Zheng Li, P. Ju, Jingdong Han, Limin Zhang, Diagnosis of power transformer faults on fuzzy three-ratio method, International Power Engineering Conference (2005) 1-456 Singapore, doi: 10.1109/IPEC.2005.206897.
[11] https://github.com/Saleh860/DGA/tree/master/datasets