

Case-based power transformer diagnose model using nonlinear mapping of oil chromatography

eISSN 2051-3305
Received on 21st August 2018
Accepted on 17th September 2018
E-First on 7th November 2018
doi: 10.1049/joe.2018.8372
www.ietdl.org

Yiming Zheng¹ ✉, Hui Yao², Jun Sheng³, Wenlin He¹, Xiang Sun¹, Wenhao Wang¹, Jiangyang Zhan¹

¹Electric Power Research Institute of State Grid Zhejiang Electric Power Corporation, Hangzhou, People's Republic of China

²State Grid Zhejiang Electric Power Corporation, Hangzhou, People's Republic of China

³State Grid Jinhua Power Supply Company, Jinhua, People's Republic of China

✉ E-mail: yiming_zheng@zj.sgcc.com.cn

Abstract: In this study, a case-based diagnostic model of a power transformer for oil chromatography is proposed. A nonlinear normalised mapping method is proposed for achieving ideal distribution characteristics of oil chromatogram gas in the case base. A similarity degree algorithm is proposed to calculate the similarity degree in the target spatial domain between the case to be diagnosed and the cases in the case base. A threshold method is proposed to determine the number of similar cases. Also, a method for calculating the weight of the diagnosis result according to the case distribution in the case base is proposed. The diagnostic method proposed is used to deploy the diagnostic system on the Internet. Defeat diagnosis conclusions of two transformers by the method and system in this paper are consistent with the disintegration results. It can be concluded that the proposed method has important practical application value in engineering.

1 Introduction

With the rapid development of power industry and ultra-high voltage AC/DC project constructions putting into operation, the development direction of a power transformer and a converter transformer turn to high voltage and large capacity. The enlargement of critical equipment increases the impact of the single device defect on the power grid safety. Therefore, timely and effective evaluation of the transformer operation status and accurate identification of equipment defects are key issues in grid operation and maintenance. With the popularisation and promotion of on-site detection and online monitoring technology, it is possible to monitor the operation status of the transformer in real time. Thus, how to apply the monitoring data on analysing the insulation condition of the equipment and judge the defect type turns out to be the crucial point in this research field.

Presently, transformer-defect diagnosis is still an empirical work. Due to the lack of effective mathematical model, defect diagnosis is mainly based on the measurement, procedural, and operational experience. It is difficult for the diagnostic efficiency and accuracy to have a breakthrough. The application of artificial intelligence and expert system [1] to assist the realisation of transformer-defect diagnosis has been gradually carried out and has become the future direction of this research field.

Transformer operation monitoring methods include dissolved gas analysis (DGA), core grounding current analysis, partial discharge analysis, winding displacement deformation measurement etc. [2–4]. Among them, DGA is the most effective means to discover the latent defects of oil-immersed transformers, of which the online monitoring has been realised and popularised. With the development of computer information technology and artificial intelligence algorithm, progressively scholars carried out research on transformer-fault diagnosis on the basis of the artificial intelligence algorithm, providing a novel method for the development of power-transformer-fault diagnosis technology. Commonly used intelligent algorithms include the back propagation neural network [5, 6], support vector machine [7, 8] and cloud theory [9].

At present, there are mainly two problems that affect the rationality and accuracy of the diagnosis model based on the DGA data. On one side, the distribution characteristics of the characteristic gases (CGs) are quite different, which makes the

construction of the signature database quite difficult. How to map the seven kinds of CGs into the target domain which can be applied directly is the key difficulty of modelling [10–12]. On the other side, how to effectively use the data from the case base to push out the diagnostic conclusion is an important part of improving the accuracy of the model. With the popularisation of online monitoring, the combination of reasonable similarity judgment criteria and case-based reasoning mechanism is more suitable for larger case base.

In consideration of the aforementioned modelling difficulties, a case-based defeat diagnosis model (CBDDM) of transformers defects was presented in this paper, including the nonlinear normalised mapping method (NNMM), case-based similarity degree algorithm (CBSDA), threshold method for determining the similar case number, and a method for calculating the weight of diagnostic results. The validity and accuracy of the model are confirmed with the help of the defect diagnosis verification of two actual transformers. It has been proved by practice that the model proposed in this paper is theoretically complete and feasible in engineering.

2 Power transformer-defect case base

735 power transformers' defects (faults) cases at the voltage level of 110 kV or above were collected. Based on the disintegration or internal inspection results, corresponding defect types, defeat reasons, and defeat locations of each case were presented as well. Defect types are divided into discharge defects and overheating defects. The discharge defects are classified into involving solid insulation and non-involving solid insulation, and the overheating defects are classified into electric circuits and magnetic circuits. The case number corresponding to defect types and defect locations in the case base is shown in Fig. 1. Specific defect reasons are arc discharge, multi-point grounding of iron core, oil-flow discharge, shielding layer discharge, lead overheating, and so on.

3 Case-based defeat diagnosis model (CBDDM)

The implementation process of CBDDM is shown in Fig. 2.

First, the CGs in the case base and that to be diagnosed are mapped into a normalised space domain by the same mapping

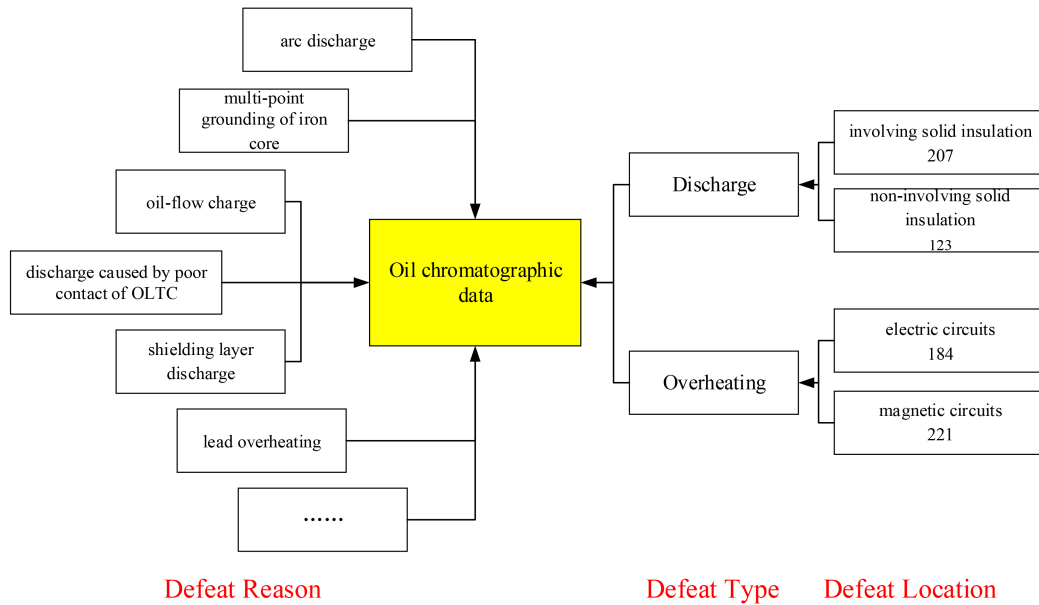


Fig. 1 Defect case base and the distribution of defect types

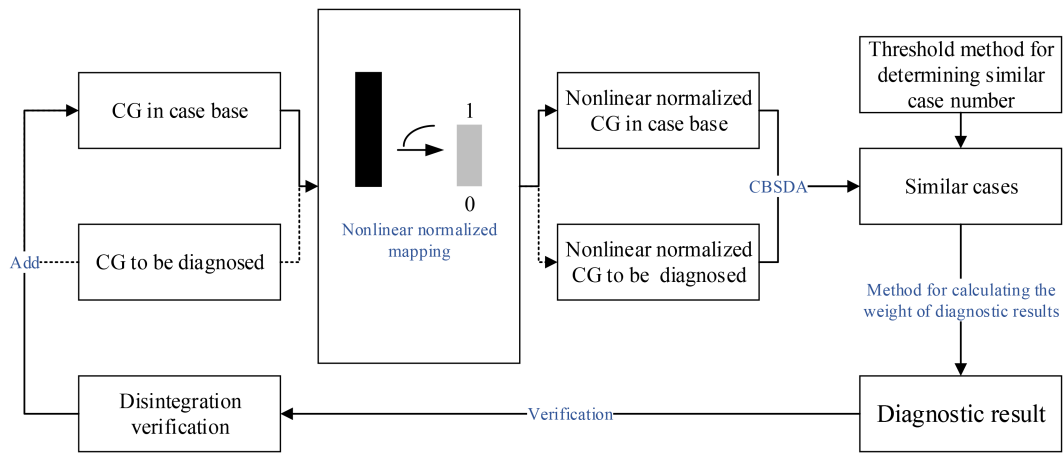


Fig. 2 Flow diagram of CBDDM

method – NNMM. Then, the case base for several cases similar to CG data to be diagnosed is searched through the similarity degree analysis and threshold algorithm. Finally, according to the defects types, defects locations and defect reasons, combined with the similarity degree of each similar case, the diagnostic conclusion is drawn. If necessary, it is better to carry out the disintegration verification of the transformer to be diagnosed and add the verified conclusion into the case base.

3.1 Nonlinear normalised mapping method (NNMM)

The selection of mapping methods should follow two principles:

- The mapping method and its parameters should be based on the statistical features of the CG data, so that various CGs in the target spatial domain may have the distribution characteristics as close as possible.
- One CG may be normal or abnormal in different cases, and its value varies greatly. The mapping method should balance the abnormal and the normal CGs.

The distribution of various CGs is similar. Taking CO_2 as an example, a histogram is shown in Fig. 3. It can be seen that the frequency of the gas content decreases with the increasing of the gas content. In most cases, the single-CG content is normal and very close to zero.

In order to ensure that both the normal and abnormal data are considered, the mapping function should be an increasing convex function. Since the lower limit of the CG is zero and the upper

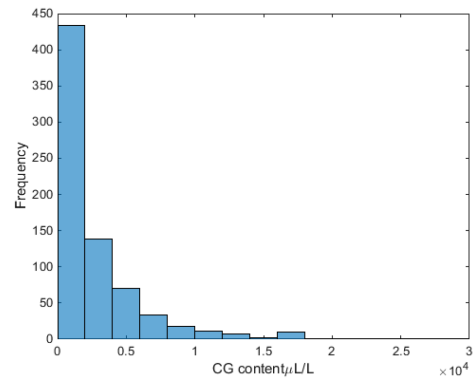


Fig. 3 Histograms of CG content in the case base (CO_2)

limit is infinite, the range of the normalised mapping function can be set as $[0,1)$.

According to the two aforementioned principles, the selected nonlinear normalised mapping function should have the characteristics as shown in Fig. 4.

Specifically, the selected mapping function can be obtained as

$$\bar{g}_i = -e^{-\alpha_i g_i} + 1 \quad (1)$$

where g_i is the i th CG content, which is also known as the source data; $\bar{g}_i$ is the i th normalised CG, which is also known as the target

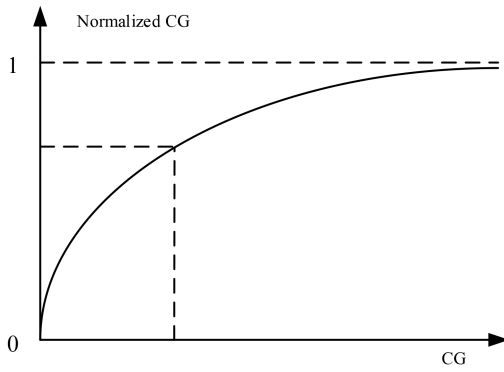


Fig. 4 Characteristics of normalised mapping function

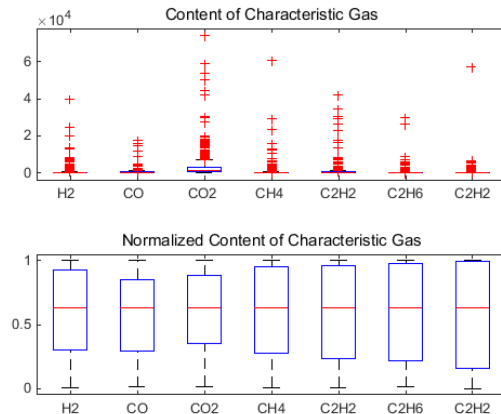


Fig. 5 Box diagrams of CG before and after normalised mapping

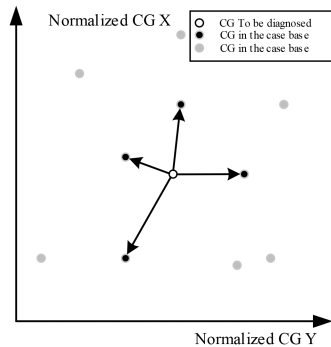


Fig. 6 Schematic of similar cases

domain data; α_i is the distribution coefficient of the i th CG, the reciprocal of the median of the gas content, which is set to make the distribution of CG in the target domain close to each other.

CG data in the case base are non-linearly normalised and mapped according to (1), and the box diagram before and after the mapping is drawn as shown in Fig. 5.

It can be seen from the distribution feature of the CG that due to the large value of the outliers, the vast majority of the CG before the mapping are only distributed in a small part of the whole range. Using the CG directly for diagnosis may exaggerate the influence of outliers and make it difficult to distinguish the CG close to zero. After the normalised mapping, all the CG are normalised into the interval of [0,1). The median and the overall distribution of each CG are similar, making it suitable for further defect diagnosis.

3.2 Similar cases determine method

After non-linear normalised mapping, the CG content can form a high-dimensional hypercube space, with each case corresponding to a point in this space. The proximity of two points in this space typifies the similarity degree of the two CGs. As shown in Fig. 6 (taking the two-dimensional space as an example), a number of case points closest to the case point to be diagnosed in the

normalised space are regarded as the similar cases. The CBSDA is calculated as

$$r_{ij} = 1 - \frac{d_{ij}}{\sqrt{n}} \quad (2)$$

where r_{ij} is the similarity degree, d_{ij} is the Euclidean distance between point i corresponding to the case to be diagnosed and point j corresponding to one case in the case base, n is the number of CGs, 7, if taking all CGs into consideration, with the value of similarity degree in the range of 0–1.

Calculate the Minkowski distance between the case to be diagnosed and cases in the case base. The principle for selecting similar cases is that the Minkowski distance is no greater than 20%. That is, each normalised CG in the similar cases should not deviate to that to be diagnosed by 20%.

3.3 Method for calculating the weight of diagnostic results

The weight calculation method of conclusion A, which can be a defect type, defect reason, or defect location, is

$$W_A = \frac{\sum_{R_k \Rightarrow A} 1/d_k^2}{\sqrt{N_A}} \quad (3)$$

where W_A is the weight of conclusion A, N_A is the number of cases concluded as A in the case base, d_k is the Euclidean distance between the k th similar case and the case to be diagnosed, and R_k is the conclusion of the k th case.

The method for calculating the weights of diagnostic results combines the influence of the similarity degree of each case and the number of cases corresponding to various diagnosis results. It can reflect the diagnosis results of each similar case more accurately and directly.

4 Case-based diagnosis system and model verification

By applying the model method proposed in this paper, a case-based diagnosis system of power transformer defect is deployed on the Internet platform. Two oil-immersed devices with abnormal oil chromatography are diagnosed by the proposed diagnosis model.

4.1 Case study: A 1000 kV reactor

Abnormal oil chromatographic data of a 1000 kV reactor is shown in Table 1. The acetylene and ethylene contents are abnormal. The three-ratios-method code is '102', indicating that the defeat belongs to the arc discharge. The similar cases and diagnosis result by the proposed model are also shown in Table 1.

Diagnostic results show that the defect in this reactor is non-solid-involved discharge. The cause of defects is 20.68% floating potential discharge, 41.50% oil-flow discharge, 37.82% core-ground discharge (see Fig. 7). Disintegration result shows that there are obvious discharge traces on the shielded copper strips in one of the pillars. Some of the copper strips are fractured. The defect does not involve solid insulation and is caused by the floating potential discharge due to the copper strips fracture (Fig. 8). Therefore, the diagnostic results of this model are basically correct.

4.2 Case study: A 220 kV power transformer

Abnormal oil chromatographic data of a 220 kV power transformer is shown in Table 2. The acetylene contents are abnormal. The three-ratios-method code is '022', indicating that the defeat belongs to the high temperature overheating. The similar cases and diagnosis result by the proposed model are also shown in Table 2.

There are three similar cases in the case base, and their diagnostic conclusions are the same: overheating in magnetic circuits caused by multi-point grounding of the iron core. The disintegration result shows that there are multi-point grounding

Table 1 Oil chromatography and diagnosis conclusions of a 1000 kV reactor

CG	Case to be diagnosed	Case 1	Case 2	Case 3	Case 4	Case 5
H ₂	84.85	68	100	66	168.17	145.28
CO	88.59	129	110	160	54.2	49.9
CO ₂	598.17	594	690	673	456.7	426.5
CH ₄	11.32	8	22	12	10.76	9.22
C ₂ H ₄	19.89	8	26	11	9.95	5.06
C ₂ H ₆	5.47	3	1.6	14	4.89	12.64
C ₂ H ₂	15.89	11	33	16	24.38	21.25
similarity	–	0.923	0.907	0.899	0.882	0.869
defeat reason ^a	–	OFD	CGD	OFD	FPD	FPD
defeat type	–	discharge				
defeat location	–	non-involving solid insulation				

^aOFD: oil-flow charge; CGD: Core-ground discharge; FPD: Floating potential discharge.

**Fig. 7** Defeats in the 1000 kV reactor**Fig. 8** Defeats in the 220 kV power transformer**Table 2** Oil chromatography and diagnosis conclusions of a 220 kV power transformer

CG	To be diagnosed	Case 1	Case 2	Case 3
H ₂	104.88	90	131.68	120.1
CO	608.08	416	633.48	782.99
CO ₂	2.11×10 ³	2765	3.68×10 ³	4008.01
CH ₄	156.52	124	210.37	192.74
C ₂ H ₄	208.75	259	195.11	205.41
C ₂ H ₆	27.89	26	25.27	29.29
C ₂ H ₂	9.11	5.9	13.99	16.68
similarity	–	0.908	0.902	0.887
defeat reason	–	multi-point grounding of iron core		
defeat type	–	overheating		
defeat location	–	magnetic circuits		

phenomena in the iron core caused by the partial discharge. There are obvious carbonisation traces on the contact site of the upper press plate, clamps, and upper beam pad on the low voltage side.

The diagnostic results of this model coincides with those of disintegration conclusions.

5 Conclusions

(i) The NNMM proposed in this paper can normalise the CG content into the range of [0,1) in the target space domain. Normalised CGs have similar median and distribution, which can be used for further defect diagnosis.

(ii) By applying the similarity degree algorithm and threshold algorithm proposed in this paper, the cases which are closest to the case to be diagnosed (Euclidean distance and distance to the nearest neighbour) can be searched in the target domain. The weight calculation method combines the influence of the similarity of each case and the number of cases corresponding to various diagnosis results, so as to obtain reliable conclusions.

(iii) Disintegration results of two oil-immersed transformer devices verify the correctness of the defect diagnosis model in this paper. Diagnostic systems deployed on Internet platforms can effectively improve on-site diagnostic efficiency.

6 References

- [1] Matsuda, S., Akimoto, Y.: 'The representation of large numbers in neural networks and its application to economical load dispatching of electric power'. IEEE Int. Joint Conf. on Neural Networks, Washington, DC, USA, 1989, vol. 1, pp. 587–592
- [2] Wang, M., Vandermaar, A.J., Srivastava, K.D.: 'Review of condition assessment of power transformers in service', *IEEE Electr. Insul. Mag.*, 2002, **18**, (6), pp. 12–25
- [3] Jiao, L., Bo, L., Wang, L.: 'Fast sparse approximation for least squares support vector machine', *IEEE Trans. Neural Netw.*, 2007, **18**, (3), pp. 685–697
- [4] Markalous, S.M., Tenbohlen, S., Feser, K.: 'Detection and location of partial discharges in power transformers using acoustic and electromagnetic signals', *IEEE Trans. Dielectr. Electr. Insul.*, 2008, **15**, (6), pp. 1576–1583
- [5] Bhalla, D., Bansal, R.K., Gupta, H.O.: 'Integrating AI based DGA fault diagnosis using Dempster–Shafer theory', *Int. J. Electr. Power Energy Syst.*, 2013, **48**, (1), pp. 31–38
- [6] Guardado, J.L., Naredo, J.L., Moreno, P., *et al.*: 'A comparative study of neural network efficiency in power transformers diagnosis using dissolved gas analysis', *IEEE Trans. Power Deliv.*, 2001, **16**, (7), p. 71
- [7] Souahlia, S., Bacha, K., Chaari, A.: 'MLP neural network-based decision for power transformers fault diagnosis using an improved combination of Rogers and Doernenburg ratios DGA', *Int. J. Electr. Power Energy Syst.*, 2012, **43**, (1), pp. 1346–1353
- [8] Huang, J., Pan, H., Rui, L., *et al.*: 'Independent component analysis algorithm and application based on quantum computation', *J. Vib. Meas. Diagn.*, 2014, **34**, (1)
- [9] Zhao, W., Zhang, Y., Zhu, Y.: 'Diagnosis for transformer faults based on combinatorial Bayes network'. IEEE Int. Congress on Image and Signal Processing, Tianjin, China, 2009, pp. 1–3
- [10] Bacha, K., Souahlia, S., Gossa, M.: 'Power transformer fault diagnosis based on dissolved gas analysis by support vector machine', *Electr. Power Syst. Res.*, 2012, **83**, (1), pp. 73–79
- [11] Duval, M.: 'Dissolved gas analysis: it can save your transformer', *IEEE Electr. Insul. Mag.*, 1989, **5**, (6), pp. 22–27
- [12] Wang, X., Li, Q., Li, C., *et al.*: 'Reliability assessment of the fault diagnosis methodologies for transformers and a new diagnostic scheme based on fault info integration', *IEEE Trans. Dielectr. Electr. Insul.*, 2013, **20**, (6), pp. 2292–2298