

Diagnosing Potentially Abnormal Attribute of Power Transformers Method

ABSTRACT

Design Method: In this paper, the program integrates those diagnostic methods from the Big data, the ANSI/IEEE C57.104 specification, and the Key gas, Their main diagnostic element is the insulating oil dissolved gas, which is integrated through the "correlation coefficient" and "classical detection and estimation theory". To develop a novel method diagnoses the latent abnormality attribute of the power transformer. The novel method is been designed via the circulation of control gates to complete and lots of test repeated it. This method is superior to the existing traditional diagnosis method in type of latent abnormality of diagnose , and has an accuracy of 90% under the verification those actual cases obtained from Research Institute of Taiwan Electric Power Company. This method is based on the MATLAB application software. In addition to being easy to operate and displaying the test results in text, it not only improves the accuracy of the diagnosis of the latent abnormal attribute inside the power transformer, but also prevents the accident of blackout equipment and affects the power supply. It can to say, it is a powerful tool for electrical equipment maintenance technicians to detect.

Design Purpose: Based on this diagnostic method to improve the accuracy of the diagnosis of the latent abnormal properties inside the power transformer by MATLAB application software.

Design Effectiveness: The program has been tested from some actual cases to improve the accuracy of diagnosis is been risen 90% up.

Keywords: Correlation Coefficients, Power Transformers, ANSI/IEEE C57.104, the Key Gas Method.

1. INTRODUCTION

The power transformer plays an extremely important role in the power system; it must be shouldered to operate efficiently and safely for a long time, depends on regular inspection and maintenance. In terms of testing, it is necessary to regularly and accurately determine the concentration of each dissolved gas in the insulating oil every year, so as to detect whether there is a potential abnormality inside the transformer and immediately eliminate it to avoid accidents affecting the power supply. The so-called concentration value of each gas in the oil, these gases are the insulating oil decomposed at high temperature by a special detection instrument "Decomposition Chromatography" (AST D 3612), which can be measured as hydrogen (H₂), methane (CH₄), ethane (C₂H₆), ethylene (C₂H₄), acetylene (C₂H₂), oxygen (O₂), nitrogen (N₂), carbon monoxide (CO), carbon dioxide (CO₂) and other nine gas components, of which the total flammable gas (Total Combustible Gas, TCG) is composed of H₂, C₂H₄, C₂H₂, CH₄, C₂H₆, CO and other gases. There are many diagnostic methods used in the industry today, each with their own advantages and disadvantages. After reviewing each diagnostic method, this paper only summarizes three representative and high-accuracy methods into a novel diagnostic method.

2. LITERATURE REVIEW

References [1], [2] explain the gas concentration content of insulating oil in power transformers decomposed by "Decomposition chromatography" at under high temperature. According to ANSI/IEEE C57.104 standard specification, it is divided into four types: normal, abnormal, attention and danger. The grade range is used to determine the interval of oil quality. References [3], [4], [5] describe various diagnostic methods and introduce the advantages of the "the key gas" diagnostic method. it is through the combination of the concentration percentages of each gas in the six kinds of oil, the attribute of the latent faults inside the power transformer can be judged. Reference [6], [7], [8], [9], [10] describes the diagnostic techniques used by MATLAB application software. References [11], [12] describe the theory of correlation coefficients, especially introduction how to applicate in mathematical. Reference [13] describes that two sets of normal and abnormal detection data are obtained from big data information, and then a

"threshold value" is obtained by using the "classic detection and estimation theory" after comparing the correlation coefficient, which is used as a base for judging either normal or abnormal status. Reference [14] describes the comparison between the manufacturer's equipment testing data and the photos of the maintenance results. The above tedious calculations are all designed with MATLAB application software.

3. DESIGN PROGRAM

Continuing the above-mentioned references to select the best and save the quince, and then use the MATLAB software computer program to compile the Big data and ANSI/IEEE C57.104 and the Key gas method to design a high-precision diagnostic method. The development process steps are described as follows.

● Correlation Coefficient

The correlation coefficient is a measure used to measure the relationship between two sets of bivariate random variables. It is generally used to measure the correlation of two random variables X and Y, and its value should be between -1 and +1. The higher the positive value, the closer the correlation of the pairing, and the less the correlation is on the contrary. When discussing correlation coefficients, it is necessary to explore the covariance between two random variables. The corresponding sequence value of the number of variables are decided the behavior of similarity.

In this paper, the Pearson correlation coefficient theory is used as the basis for the calculation. The method for calculating the correlation coefficient value is as follows (Formula 1): x and y are variables, x_i, y_i are random variable number sequences, because this paper takes the gas concentrations in 6 kinds of dissolved gas of insulating oil for corresponding comparison, so n = 6, so the variable number sequences i = 1, 2, 3, 4, 5, 6. An example is given to illustrate the correlation coefficient value obtained by the calculation of the random variable number sequence value within its variance, as shown in Table 1.

$$\gamma_{xy} = \frac{\sum x_i y_i - \frac{(\sum x_i y_i)}{n}}{\sqrt{\sum x_i^2 - \frac{(\sum x_i)^2}{n}} \sqrt{\sum y_i^2 - \frac{(\sum y_i)^2}{n}}} \quad (1)$$

Table 1. Values of X and Y with correlation coefficients

Set	H ₂	C ₂ H ₄	C ₂ H ₂	CH ₄	C ₂ H ₆	CO	γ_{xy}
X	701	101	10	401	101	571	1
Y	70	10	1	40	10	57	

● **Diagnosis of Big Data**

Based on six sets of data, represented by being divided for set A, B, C, D, E, and F respectively, all data were taken after decomposed by "Decomposition Chromatography." and all data were verified with the actual maintenance status on-site, those result of data is right, they were been divided two kinds - abnormal and normal status. The data of set C is 100 pieces of normal status and set D is 1000 pieces of normal status, and E is 100 pieces of abnormal status. The set A is made up of set C add set D; the set B is made up of set E add set D; the set F is made up of set D add the test piece. The principle of Big data diagnosis is as follows: First, use the "correlation coefficient" to identify the two sets of distribution curves of 100,000 different correlation coefficient values (distribution interval -1 to +1) generated by set A and set B, and then use the "classic detection and estimation theory" derives the boundary point for the discrimination between set A (normal) and set B (abnormal), which is called "threshold value". Next, from the test data, the data is composed of six kinds of gas concentration values, such as H₂, C₂H₄, C₂H₂, CH₄, C₂H₆, CO, etc., and the data of "set F" is totaled to 1001 pieces, and the correlation coefficient is calculated to calculate the average of 1001 pieces. The value is compared with the "threshold value." [13] If it is greater than the threshold value, it means that the detected data is abnormal (there is abnormality inside the power transformer), otherwise it is normal.

● **Diagnosis of ANSI/IEEE C57.104**

From this diagnostic method, the concentration of dissolved each gas of each set is been diagnosed that the result of diagnosis is been classified into four levels: normal, abnormal, caution and dangerous. This paper takes the gas concentration content of the six oils in the "attention level" as the diagnostic basis for this program, which is also called flammable gas. The content data for this grade are as follows: H₂ (701), C₂H₄ (101), C₂H₂ (10), CH₄ (401), C₂H₆ (101), CO (571) in parts per million (ppm).

Then compare the concentration of each gas with the data of the detection set. If the concentration of any dissolved gas in the detection set is larger than the data in the ANSI/IEEE C57.104 of attention level, the equipment in the detection set is judged to be faulty, otherwise it is normal.

● **Diagnosis of The Key Gas**

In this diagnostic method, H₂, C₂H₄, C₂H₂, CH₄, C₂H₆, and CO are taken from the gas concentrations in the above-mentioned nine gases as the basic diagnostic set, and then each gas concentrations are added up as denominator, and then the percentage of each gas is calculated out separately. Then it is divided into four different fault attributes, and the percentage of gas concentration in each of the six gases with different attributes is overheat for (H₂(1), C₂H₄(62), C₂H₂(0),CH₄(18),C₂H₆(19), CO (0)), Fig.2, Corona for (H₂ (83), C₂H₄ (2), C₂H₂ (0), CH₄ (12), C₂H₆ (3), CO (0)),Fig.3, Arc for (H₂ (62), C₂H₄ (2),C₂H₂ (32), CH₄ (3),C₂H₆(1),CO(0)),Fig.4, and paper fiber overheating for (H₂ (2), C₂H₄ (1), C₂H₂(0), CH₄ (3), C₂H₆ (2) , CO (92)), Fig.5, etc. The diagnosis method is as follows: when the data of the detection set is calculated according to the above steps, then which is been compared with "correlation coefficient" in each fault attributes construction data. If correlation coefficient reaches 0.6, it is judged that the detection set of the equipment is in faulty. Otherwise it is normal.

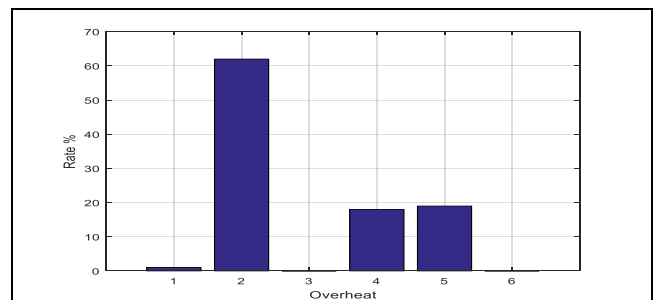


Fig.2 Overheat

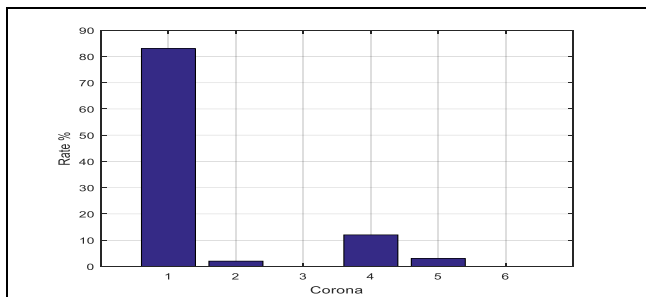


Fig.3 Corona

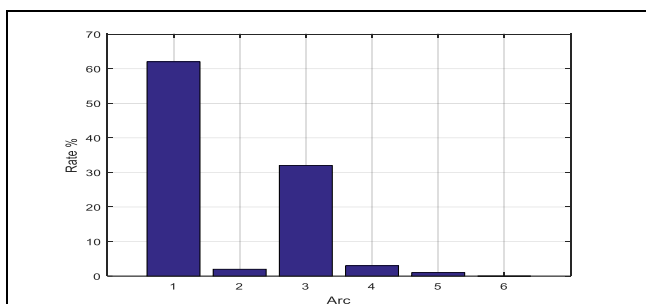


Fig.4 Arc

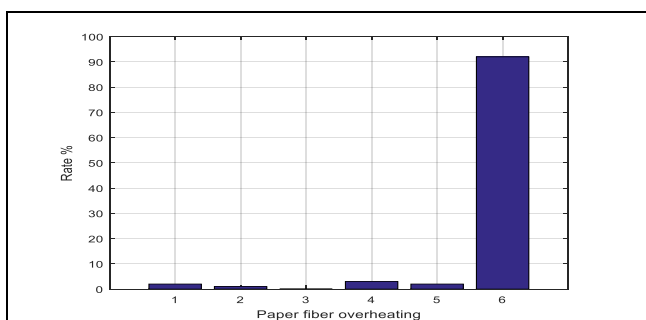


Fig.5 Paper fiber overheating

After the above three diagnostic methods have respectively diagnosed the results, the comprehensive diagnostic judgment is performed by the judgment zone to generate the diagnostic result. The operation of the judgment zone structure is to first combine the big data with the ANSI/IEEE C57.104 diagnosis results through "AND gate", and then use the "AND gate" with the Key gas diagnosis results to obtain the comprehensive fault attribute judgment result. The schematic diagram of the diagnosis structure is as follows, shown as Fig.1. For the above diagnostic methods, Big data diagnosis can only judge whether there is a latent fault inside the power transformer based on the concentration of each gas in the insulating oil, but cannot diagnose the fault attribute. The Key gas diagnosis method may produce a "false correlation coefficient." What is false is that the percentages of the corresponding gas concentrations in the two sets of data very similar, but the total gas content are very different. For an example: the data of each gas concentration in the data oil of set A are as follows: H₂ (701), C₂H₄ (101), C₂H₂ (10), CH₄ (401), C₂H₆ (101), CO (571). The total gas content is 1885; The data of each gas concentration in group B data oil are as follows: H₂ (70), C₂H₄ (10), C₂H₂ (1), CH₄ (40), C₂H₆ (10), CO (57), the total gas content is 188, the data is shown in Table 1. The corresponding percentages of the two sets of gases are almost similar, but false similarity and misjudgment occur during the Key gas diagnosis process. The sum of the gas concentration values in each set is very different, so it is necessary to pay attention. In order to improve the lack of the above two diagnostic methods, the ANSI/IEEE C57.104 diagnostic methods are included in.

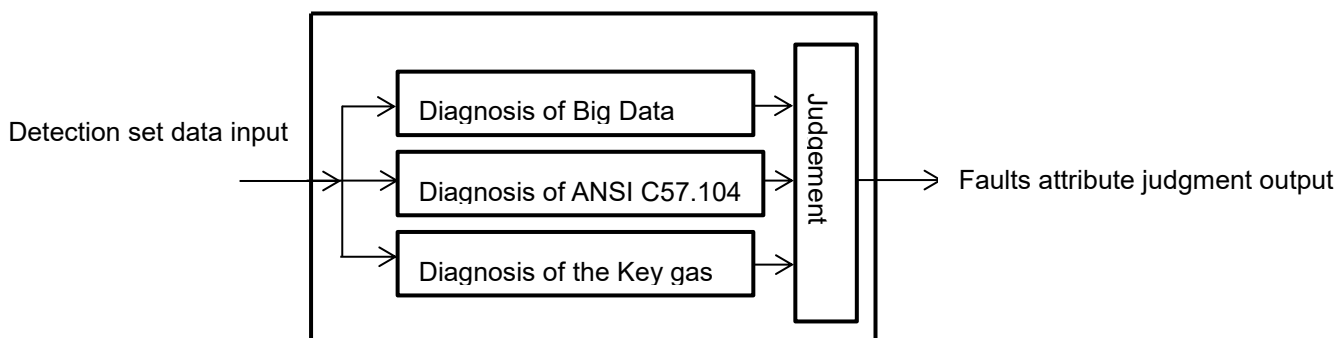


Fig. 1 Schematic diagram of the diagnosis structure

5. VERIFY

In order to verify this diagnostic program of the accuracy and feasibility, the author obtained the detection data of each dissolved gas concentration of the transformer insulating oil in the substation from 2007 to 2013 from the Taiwan Power Company through to verify the result of the maintenance equipment on - site compare with the diagnostic

results of this program are shown in Table 4 being compared with the status of each diagnosis method, the maintenance status on - site, and the result of diagnosis of this program, as shown in Table 5 from 9 out of 10 verification cases were accurately judged to be the latent fault attribute inside the transformer, thus proving that the program is feasible and the accuracy is as high as 90%.

Table 4. Comparison results from maintenance and this program in actual cases

Date	H ₂	C ₂ H ₄	C ₂ H ₂	CH ₄	C ₂ H ₆	CO	Judgment by this program	The actual condition repaired
10.5.2007	44	7	10.1	41	88	57	Normal	Normal
5.9.2010	140	21	53.8	54	79	35	Corona	Corona
3.8.2011	181	58	51.4	271	116	128	Normal	Corona
27.2.2012	113	11	36	10	2	685	Normal	Normal
9.5.2012	418	82	167	74	8	39	Corona	Corona
10.5.2012	239	787	23.7	346	78	312	Overheat	Corona
8.7.2012	48	1077	0.4	694	356	36	Overheat	Overheat
5.9.2012	1718	930	1446	884	314	199	Corona	Ace
1.10.2012	185	590	1.7	601	208	72	Overheat	Corona
23.9.2013	133	384	1.9	211	66	411	Paper fiber overheat	Overheat

Table 5. Comparison with each diagnostic methods and maintenance status and this program in actual cases

Date	ANSI/IEEE C57.104	Big data	The key gas	Maintenance status	This program
10.5.2007	1	0	0	0	0
5.9.2010	1	1	1	1	1
3.8.2011	1	1	0	1	0
27.2.2012	1	0	0	0	0
9.5.2012	1	1	1	1	1
10.5.2012	1	1	1	1	1
8.7.2012	1	1	1	1	1

5.9.2012	1	1	1	1	1
1.10.2012	1	1	1	1	1
23.9.2013	1	1	1	1	1
accuracy	80%	100%	90%	100%	90%
Features	Failed to identify abnormal properties	Failed to identify abnormal properties	False judgment	Actual state	Improve items on the left

Note: 1 means abnormal diagnosis, 0 means normal diagnosis

6. CONCLUSION

The diagnostic method of this program can effectively improve the discrimination accuracy rate from those dissolved gases in insulating oil. The results can be displayed on the report in text in a simple and easy way without the need for professionals. Among the three data sets A, B, and C mentioned in the Big data diagnosis, the threshold value (0.46) obtained by the set A and set B were directly extracted from the reference [12] in the design of this program. As for the data of set D, it must be loaded into the MATLAB operating system before executing the program to detect and diagnose. The verification data listed in this paper are all the gas concentration values after the transformer insulating oil is decomposed by the "Decomposition chromatography" on a regular basis every year. The above data are the results obtained from the inside of the transformer that were found to be abnormal and the transformer was shut down for maintenance. So that it is used as verification and comparison data, thus its credibility is very high, shown as Table 4 and Table 5 respectively.

The attribute of potential failures can be identified from the insulating oil, which is inspected regularly every year, and equipment maintenance can be carried out immediately. It can detect equipment with 90% accuracy, so that can prevent from black down, and avoid affecting the stable power supply of the power system and equipment safety. In fact, it is a powerful tool for internal detection of power transformers, and it is worth popularizing and adopting.

REFERENCES

1. IEEE Guide for the Interpretation of Gases Generated in Oil-Immersed Transformers—Redline, IEEE Standard C57.104-1991, Feb. 2009.
2. H. Malik, Tarkeshwar, and R. K. Jarial, "An expert system for incipient fault diagnosis and condition assessment in transformers, " in Proc. Int. Conf. Comput. Intell. Commun. Netw., Gwalior, India, Oct. 2011, pp. 138 – 142.
3. Singh, S. and Bandyopadhyay, M.N. (2010) Duval Triangle: A Noble Technique for DGA in Power Transformers. International Journal of Electrical and Power Engineering, 4, 193-197.
4. P. Rozga, T. Piotrowski, and R. Kozak, "Experiences with detection of transformer failure based on insulating oil tests, " in Proc. IEEE 19th Int. Conf. Dielectr. Liquids (ICDL), Manchester, U.K., Jun. 2017, pp. 1 – 4.
5. V. Miranda, A. R. G. Castro, and S. Lima, "Diagnosing faults in power transformers with auto associative neural networks and mean shift, " IEEE Trans. Power Del., vol. 27, no. 3, pp. 1350 – 1357, Jul. 2012.
6. J. Li, Q. Zhang, K. Wang, J. Wang, T. Zhou, and Y. Zhang, "Optimal dissolved gas ratios selected by genetic algorithm for power transformer fault diagnosis based on support vector machine, " IEEE Trans. Dielectr. Electr. Insul., vol. 23, no. 2, pp. 1198 – 1206, Apr. 2016.
7. Ming-Jong Lin, " Calculating Feeder Fault Current with MATLAB Software Program." Asian Journal of Research in Computer Science. 2021; 10(4):19-29. Article no.AJRCOS.70519
8. Ming-Jong Lin, " Design standardized program to calculate the related data from single load on single feeder." Asian Journal of Research in Computer Science. 2021; 12(4):160-176. Article no.AJRCOS.81472
9. S. K. Gill and R. Sharma, "Analysis and implementation of simple gesture recognition algorithms using MATLAB, " in Proc. 4th Int. Conf. Image Inf. Process. (ICIIP), Shimla, India, Dec. 2017, pp. 1 – 4.

10. M.-T. Puth, M. Neuhäuser, and G. D. Ruxton, "Effective use of Spearman's and Kendall's correlation coefficients for association between two measured traits," *Animal Behav.*, vol. 102, pp. 77 – 84, Apr. 2015.
11. Wikipedia. Pearson Correlation Coefficient. Accessed: Jun. 18, 2020.
12. S. Li, Z. Ge, A. Abu-Siada, L. Yang, S. Li, and K. Wakimoto, "A new technique to estimate the degree of polymerization of insulation paper using multiple aging parameters of transformer oil," *IEEE Access*, vol. 7, pp. 157471 – 157479, 2019.
13. Ming-Jong Lin , Liang-Bi Chen , and Chao-Tang Yu, " A Methodology for Diagnosing Faults in Oil-Immersed Power Transformers Based on Minimizing the Maintenance Cost, " *IEEE Access* , date of publication November 17, 2020.
14. Atanasova - Höhle, I. (2014) DGA-Method in the Past and for the Future. Siemens Company.

APPENDIX

Executive Program

```

clear;
fprintf('*****\n')
fprintf (' Diagnosing Potentially Abnormal Attribute of Power Transformers Method')
n= 6 ;% number of gass types
m= 2022 ;% number of data sets
data = importdata('3BO.txt');
format short
fprintf (' : Each gas concentration data of dissolved in insulating oil T=[H2|C2H4|C2H2|CH4|C2H6|CO]; \n T= ')
T=input (' ');
for i=2:m;y=data(i, :);R = corrcoef(T,y);w(i)=R(1,2); w(i)>=1011;
end
T1=sum(w);avg=mean(w);r=(avg);
fprintf (' If S6 shows 1, it means an abnormality inside for being diagnosis of the big data')
S6= r< 0.46
S=[701 101 10 401 101 571];
A=[1 62 0 18 19 0];
B=[83 2 0 12 3 0];
C=[62 2 32 3 1 0];
D=[2 1 0 3 2 92];
fprintf (' If S4 shows 1, it means an abnormality inside for diagnosis of ANSI/IEEE C57.104')
S4=T(1)>=S(1) | T(2)>=S(2) | T(3)>=S(3) | T(4)>=S(4) | T(5)>=S(5) | T(6)>=S(6);
S8=S4 & S6
T1=(T/sum(T))*100;
T2=round(T1);
fprintf (' If A6 shows 1 represent the diagnosis of the Key gas, judged for overheated')
A1=corrcoef(A,T2);
A2= min(A1);
A3=min(A2);
A4=abs(A3);
A5=A4>0.6;
A6=S8 & A5
fprintf (' If B6 shows 1 represent the diagnosis of the Key gas, judged for corona')

```

```
B1=corrcoef(B,T2);
B2=min(B1);
B3=min(B2);
B4=abs(B3);
B5=B4>0.6;
B6=S8 & B5
fprintf (' If C6 shows 1 represent the diagnosis of the Key gas, judged for arc')
C1=corrcoef(C,T2);
C2=min(C1);
C3=min(C2);
C4=abs(C3);
C5=C4>0.6;
C6= S8 & C5
fprintf (' If D6 shows 1 represent the diagnosis of the Key gas, judged for paper fiber overheating\n ')
D1=corrcoef(D,T2);
D2=min(D1);
D3=min(D2);
D4=abs(D3);
D5=D4>0.6;
D6= S8 & D5
fprintf ('If S10 show 1, the transformer needs to be repaired \n ')
S9= A6|B6|C6|D6;
S10=S4 & S6 & S9
fprintf('*****\n')
```