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Statistical approach for Dissolved Gas Analysis on power Transformer

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ABSTRACT

Determining transformer condition is useful in itself for making short term decisions regarding operation and maintenance. Dissolved gas analysis is the most important tool in determining the condition of a transformer. Transformer generates gases while subject to Electrical and Thermal stresses in operation Dissolved Gas Analysis used to diagnosis the fault based on this gases. In this paper Interpretation of Dissolved Gas analysis is discussed and A statistical approach is explained using support vector machine to diagnosis the Transformer fault.

Keywords : Power Transformer, Dissolved Gas Analysis, Support Vector Machine.

1 INTRODUCTION

Transformer oil sample analysis is a useful predictive, maintenance tool for determining transformer health. Along with the oil sample quality test, performing a Dissolved Gas Analysis of the insulating oil is useful in evaluating transformer health. Insulating mineral oils for transformer are mixture of many hydrocarbons. These hydrocarbons are decomposed when thermal or electrical faults occur. [1] – [2] The fundamental chemical reactions involves the breaking of carbon hydrogen and carbon – carbon bonds and produce the following gases : Hydrogen (H_2) , Methane (CH_4) , Acetylene (C_2H_2),Ethylene (C_2H_4) and Ethane (C_2H_6). The gases listed above are generally referred to as key gases. The total of all key gases may indicate the existence of anyone or combination of thermal, electrical or corona fault. Therefore the concentrations of the individual dissolved gases found in transformer insulating oil may be used directly to suggest any fault within the transformer. The standards associated with sampling, testing and analyzing the results are ASTM D3613, ASTM D3612 and ANSI/IEEE C57.104 respectively. From these we know ,If there is no appereciable rise in concentration of various gases then transformer [4] is healthy(table.1) and if the rise in concentration is too rapid that is of the order of hundreds or thousands of ppm every weak or at lesser intervals then transformer needs immediate breakdown maintenance.but some situation demands continous monitoring table.1 further simplified as table.2 and made applicable to those cases of condition monitoring.

2 Frequency of DGA monitoring

Depending on the concentration of individual gas components it is possible to fix or alter the period of DGA monitoring of transformers in service from once in a month to once in a year.

Case .1 : Results are normal and transformer needs DGA monitoring once in a year or Results have shown a small increase in gas concentration other than C_2H_2 and subsequently the values are steady or showing decreasing trends in such case the frequency of DGA monitoring for transformer will be once in a year.

Case.2: Results have indicated the presence of C_2H_2 and there is no rise in concentration or there is fluctuating of gas concentration the frequency of monitoring will be increased to two to four times in a year.

Case.3 : Results had indicated a steady and sustained rise in gas concentration of C_2H_2 and / or C_2H_4 and afterwards gas values are remaining constant or increasing at a rapid manner then the frequency of monitoring will have to be increased from once in a year to twelve times in a year.

Case.4 : Initial result shows a substential concentration of one or more gases and one of the gases shows rapid increase then the transformer will have to be immediately opened and fault will have to be looked into.

The following table shows various interpretation methods of DGA and their results.

Table.1

Rise in gas concentration	Key gas method	Rogers Method	IS:10593 standard
Nil	Normal aging	Normal aging	Normal aging
CH_4	-----	Thermal Fault below 150^0C	Thermal Fault from150^0C to300^0C

C_2H_4	Over heating	Conductor overheating	Thermal fault of low temperature upto 150_0C
CH_4 & C_2H_6	------	Thermal Fault from150^0C to300^0C	--------
CH_4 & C_2H_4	------	Circulating currents and over heated joints	Thermal Fault of 300_0C to 700_0C or above.
C_2H_2	-----	Flashover without powerflow through	-------
C_2H_2& C_2H_6	-----	Tapchanger selector breaking current	
C_2H_2 & C_2H_4	------	Arc with power flow through or persistent sparking	Discharge of low energy or high energy
H_2	Corona	Corona,partial discharge	Partial discharge of low energy density
H_2 & C_2H_2	Arcing	----	Partial discharge of high energy density.

Table.2 Interpretation of rise in gas concentration:

Rise in Gas Concentration	**Interpretation**
Nil or not appreciable	Normal aging
H_2	Corona, Partial Discharge
CH_4 & C_2H_6	Thermal fault of low temperature upto 300^0C.
C_2H_4 with or without CH_4 ,C_2H_6,H_2.	Thermal fault of 300^0C to 700^0C or above
C_2H_2 with or withoutH_2, $_2H_4$,C_2H_6 and CH_4	Arc or Flashover

The main drawbacks [6] of this conventional method are unable to diagnosis the fault of a particular transformer owing to the lack of expert knowledge in them. [4].

3 Support Vector Machine

Support Vector Machine [5]-[6] has recently gained prominence in the field of machine learning and pattern classification. Classification is achieved by realizing a linear or non linear separation surface in the input space. In Support Vector Classification , the separating function can be expressed as a linear combination of Kernals associated with the Support Vectors as,

$$f(x) = \sum_{x_j \in s} \propto_j y_j K(x_j, x) + b$$

Where,

x j = Training Pattern

yj Є (+1 ,-1) = corresponding class labels

s = set of support vectors.

The dual formulation yields,

$$\min_{0 \le \propto_i \le c} w = \frac{1}{2} \sum_{i,j} \propto_i Q_{ij} \propto_j - \sum_i \propto_i + b \sum_i y_i \propto_i$$

Where,

$\propto_i$ = corresponding coefficients

b = offset

$Q_{ij} = y_i y_j K(x_i, x_j)$ = symmetric positive definite Kernal matrix.

C = parameter used to penalize error points.

The Karnsh Kunn – Tucker (KKT) condition for dual can be expressed as,

$$g_i = \frac{\partial w}{\partial \alpha_i} = \sum_i Q_{ij} \alpha_j + y_i b - 1$$

$$= y_i \text{ f } (x_i) - 1$$

And,

$$\frac{\partial w}{\partial b} = \sum_j y_j \alpha_j = 0$$

These partitions the training set into [6],

(i) S the support vector set $(0 < \alpha_i << c, \quad g_i = 0)$

(ii) E the Error set $(\alpha_i = c, \ g_i = 0)$

(iii) R well classified set ($\alpha_i = 0$, $g_i > 0$)

If the points in the error are penalized quadratically with the penalty factor c' then, it has been shown that the problem reduces to that of a separate case with c = α. [7] The Kernal function is modified as

$$k'(x_i,\ x_j) = k(x_i, x_j) + \frac{1}{c'}\ \partial_{ij}$$

Where $\partial_{ij} = 1$ if i = j

$\partial_{ij} = 0$ otherwise.

The advantage of this formulation is that the SVM problem reduces to that of a linearly separable case [8].It can be seen that training the SVM involves quadratic optimization problem which requires the use of optimization routines from numerical libraries. This step is computationally intensive, can be subject to stability problems and is nontrivial to implement. [9].

H_2 Ppm	CH_4 Ppm	C_2H_2 Ppm	C_2H_6 Ppm	C_2H_4 ppm	Remarks
46	60	1	15	104	Training Data
223	232	2	48	365	
180	182	6	45	334	
212	109	3	53	343	
123	188	3	77	519	
138	213	2	97	592	
103	199	3	145	699	
112	211	9	123	692	
116	252	2	134	794	Testing Data
121	261	2	121	781	

Table 1. Sample DGA data:

Fault type	No. of samples	Successful Diagnosis	efficiency
Normal Unit	21	21	100%
Arc, Corona	21	20	95.24%
Sparking	12	12	100%
Arc	11	11	100%

Table. 2. Results of statistical analysis using SVM

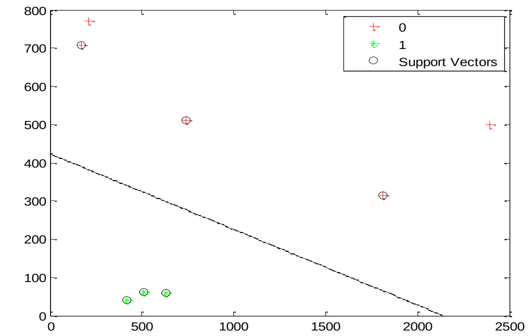

Fig.1 SVM Training Plot

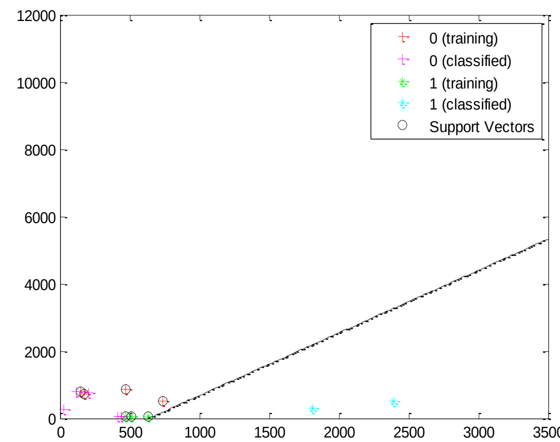

Fig.2 SVM Testing plot

In this study 125 samples of DGA were provided the national utility and 20 were taken from DGA results published in literature. They include power transformer with different ratings, voltage levels, operating conditions, age, and loading history etc. among this 80 samples were used for training and remaining 65 samples used for testing. The forecasting results shown in table II show that SVM has more accurate performance.

4. Conclusion

Determining Transformer condition based statistical analysis by using support vector machine on dissolved gas analysis is quite useful for large utilities with great number of power transformer..SVM has excellent performance because Using Kernal function it reduces the complexity by change a nonlinear learning problem into linear learning problem and it select the most suitable parameters to forecast dissolved gases by cross validation technique.

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