Statistical approach for Dissolved Gas Analysis on power Transformer

1K.Iyswarya Annapoorani, 2Dr.K.UdayaKumar, 3Dr.B.Umamaheswari

1Research Scholar, College of Engineering Guindy, Chennai-25, 9884077358, mail.id: iyswaryamail@gmail.com
2,3Professor, College of Engineering Guindy, Chennai -25.

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\textsubscript{2}) , Methane (CH\textsubscript{4}) , Acetylene (C\textsubscript{2}H\textsubscript{2}),Ethylene (C\textsubscript{2}H\textsubscript{4}) and Ethane (C\textsubscript{2}H\textsubscript{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 appreciable 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 continuous 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\textsubscript{2}H\textsubscript{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\textsubscript{2}H\textsubscript{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\textsubscript{2}H\textsubscript{2} and / or C\textsubscript{2}H\textsubscript{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 substantial 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>
<thead>
<tr>
<th>Rise in gas concentration</th>
<th>Key gas method</th>
<th>Rogers Method</th>
<th>IS.10593 standard</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nil</td>
<td>Normal aging</td>
<td>Normal aging</td>
<td>Normal aging</td>
</tr>
<tr>
<td>CH\textsubscript{4}</td>
<td>-----</td>
<td>Thermal Fault below 150°C</td>
<td>Thermal Fault from 150°C to 300°C</td>
</tr>
</tbody>
</table>

Table.1
Table 2 Interpretation of rise in gas concentration:

<table>
<thead>
<tr>
<th>Rise in Gas Concentration</th>
<th>Interpretation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nil or not appreciable</td>
<td>Normal aging</td>
</tr>
<tr>
<td>H₂</td>
<td>Corona, Partial Discharge</td>
</tr>
<tr>
<td>CH₄ &amp; C₂H₂</td>
<td>Thermal fault of low temperature upto 300°C</td>
</tr>
<tr>
<td>C₃H₄ with or without CH₄</td>
<td>Thermal fault of 300°C to 700°C or above</td>
</tr>
<tr>
<td>C₂H₃ with or without H₂, H₄, C₂H₄, and CH₄</td>
<td>Arc or Flashover</td>
</tr>
</tbody>
</table>

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 Kernels associated with the Support Vectors as,

\[ f(x) = \sum_{x_j \in s} \alpha_j y_j K(x_j, x) + b \]

Where,
- \( x_j \) = Training Pattern
- \( y_j \in (+1, -1) \) = corresponding class labels
- \( s \) = set of support vectors.

The dual formulation yields,

\[ \min_{\alpha \in \mathbb{R}^n} w = \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j Q_{ij} - \sum_i \alpha_i + b \sum_i y_i \alpha_i \]

Where,
- \( \alpha_i \) = 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,

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

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 \( \alpha_i = c, \quad g_i = 0 \)
(iii) R well classified set \( (\alpha_i = 0, \xi_i > 0) \)

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 \( c = \alpha \). [7] The kernel function is modified as

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

Where

\[
\partial_{ij} = 1 \text{ if } i = j \\
\partial_{ij} = 0 \text{ otherwise.}
\]

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].

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

Table 1. Sample DGA data:

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 transformers. SVM has excellent performance because Using Kernel 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.

References:


