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Condition Assessment of Power Transformer Using Dissolved Gas Analysis

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ABSTRACT: The possibility of power transformer failure increases over the time as the age and rate of utilization increases. Since internal faults specially are the main cause of these failures, there are many ways and methods used to predict incipient fault and thus preventing the power transformer from failing by monitoring its condition. In oil immersed transformers, the Dissolved Gas Analysis (DGA) is used as one of the well-established tool to predict incipient faults occurring inside the body of power transformer. With already in existence of more than 5 known methods of DGA fault interpretation; there is the chance that all may give different conditions/results for the same sample. Using a combination of more than one of the methods and Support Vector Machine will result in increased accuracy of the interpretation and so reduces the uncertainty of the transformer condition monitoring.

KEYWORDS: Dissolved Gas Analysis (DGA), Power Transformer, Condition Monitoring, Fault Diagnosis, Support Vector Machine (SVM).

I.INTRODUCTION

In operation power transformers will go through electrical and thermal stresses, which will cause deterioration of insulation in power transformer and the deterioration products are gases, which get dissolved in transformer oil may be fully or partially. In transformer oil these gases can be easily detected at very low levels by gas chromatography, infrared analytical method, mass spectrometry etc. Dissolved Gas Analysis (DGA) is effective and reliable method used for monitoring the condition of oil filled power transformers. Hence this widely accepted technique is used in routine maintenance of power transformer. Transformer oil not only provide insulation to the transformer windings but also helps in cooling and quenching arcs. Transformer oil have dissolved gases which are resulted due to deterioration of oil, moisture in oil and due to deterioration of paper insulation which is usually cellulose, moisture come from the surrounding. The most common type of oil used in power transformer is mineral oil.

All oil immersed power transformers produce small amount of gases, especially carbon dioxide (CO2) and carbon monoxide (CO) to some extent at normal operating condition, slight overheating and corona. When transformer is under operating condition it get subjected to various thermal and electrical stresses which results in decomposition of oil and generate various gases . Different pattern of gases are result of different amount of energy released by different kind of faults present in power transformers. The dissolved gas availability in an oil sample makes it possible to find type of a fault by gas types and their ratios. DGA is performed accordance with American Society for Testing and Materials (ASTM) D3612 or IEC (International Electro technical Commission) 60567.

II. FAULT TYPES AND DGA METHODS VARIOUS TRANSFORMER FAULTS

IEC Publications 60599 gives a customary encoded no. of faults in power transformer which can be identified using DGA.

a) Partial discharge (PD)/ Corona:

PD usually occurs within voids or gas bubbles. It’s terribly simple to detect by DGA, however, as a result of its creation over a long periods of time and at intervals, it deteriorate the massive volume of cellulose paper insulation. It always create massive amount of chemical element from paper insulation deterioration.

b) Low energy electric discharges (D1):

D1 like corona discharge for longer period, uninterrupted sparking discharges and small arcs is simply identified by DGA, as a result of comfortable quantity of gas is generated.

c) High energy electric discharges (D2):

High energy electric discharges are identified from great amount of metal fusion, carbonization and regular tripping of the instrument.

d) Thermal fault Temperature 150°C -300°C (T1):

T1 fault can be identified by paper colour, as colour of paper insulation turns brown.

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e) Thermal faults 300 ºC -700 ºC (T2):
T2 fault can be identified by paper carbonization.
f) Thermal faults Temp.; 700 ºC (T3):
T3 fault can be identified by oil carbonizations, metal coloration or metal fusion.

2.1. DGA fault classification methods:
So many interpretive techniques are reported within the recent years to forecast fault development like IEC 60599 standard's Basic quantitative relation technique, Institute of Electrical and Electronics Engineers (IEEE) standards, Doernenburg's and Roger's quantitative relation codes, the Key gas technique, CIGRE(Council on Large Electric Systems) technique and graphical techniques like Duval triangle technique. These DGA interpretation technique area unit supported verifiable assumptions and sensible information gathered by specialists worldwide.
- Key Gas method;
- Ratio methods;
- The graphical illustration technique.

2.2. KEY GAS METHODs:
In key gas methods, we have five types of gases i.e. H2, CH4, C2H2, C2H4 and C2H6 with their concentrations are continuously present for continuous interpretation of the results. Table 1 shows various gas concentration values to classify fault based on them. The fault classification results provide information which is used as basis for further investigation. It is not much accurate method for power transformer fault classification.

Table 1: Interpretation of results from gas present in oil sample.

Gas Present	Fault
Oxygen (O2)	Transformer enclosing problem
Carbon Oxide and carbon Dioxide (CO and CO2)	Paper insulation deterioration
Hydrogen (H2)	Electrical discharges such as corona , low partial discharge etc.
Acetylene (C2H2)	Electrical faults such as arching
Ethylene (C2H4)	Thermal faults such as overheating up to 300 °C temp.
Ethane (C2H6)	Thermal fault above 300 °C and below 700 °C temp.
Methane (CH4)	Thermal faults above 700 °C temp.

The ppm values of gas concentration typical ranges are observed in accordance to IEC 60599 as written below in Table 2.

Table 2: Concentration ppm value ranges to be present in oil sample.

H_2	CH_4	C_2H_6	C_2H_4	C_2H_2	CO	CO_2
60-150	40-110	50-90	60-280	3-50	540-900	5100-13000

2.3. Ratios Method:
IEC, Doernenburg and Rogers are more commonly known in ratio methods classification. They give the relationship between gas types and concentrations. The key gas concentration values are utilized in all ratio techniques to form gas ratios. The IEC gas ratio method uses three gas ratios these are C2H2/C2H4, CH2/H2 and C2H4/C2H6. Table 3 shows the IEC gas ratios standard values for obtaining fault types. When key-gas ratios exceeds specified ratio values, any developing fault can be expected which can be classified using gas ratio methods.

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Table 3: Fault classification using the ratio method.

Fault types	C_2H_2 / C_2H_4	CH_4 / H_2	C_2H_4 / C_2H_6
PD	<0.1	<0.1	<0.2
D1	>1	0.1-0.5	>1
D2	0.6-2.5	0.1-1	>2
T1	<0.1	>1	<1
T2	<0.1	>1	1-4
T3	<0.1	>1	>4

2.4. The Graphical Representation Technique:

The graphical illustration technique is employed to examine various cases and gives their comparison. The coordinate values and their limits, thermal fault and electrical discharges zones in a Triangle are shown in Figure below. Where zone DT in Figure 1 indicates both electrical discharge and thermal fault.

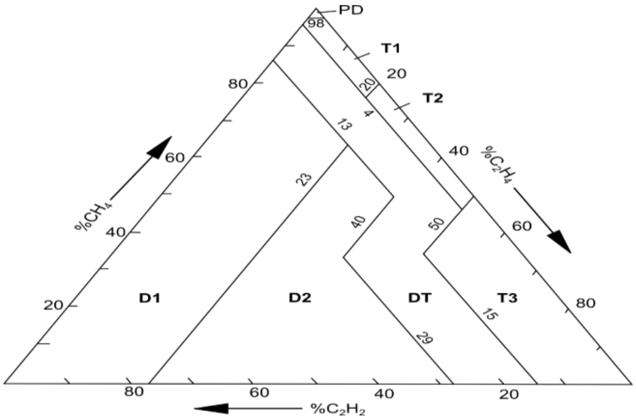

Figure 1: Duval Triangle.

2.5. Application Of Support Vector Machine:

Back-propagation algorithm and feed forward networks of these neural networks are universal approximation in their own ways. Another form of universal feed forward networks is recognized as Support Vector machine (SVM).

Support Vector machine (SVM) is a statistical theory based technique that can be seen as future of training classifiers based upon splines, radial basis function, neural network, polynomial functions etc. SVM use a hyper-plane linearly differentiating to form a classifier. Those classification problems which cannot be linearly differentiated in input space, these machines provide an opportunity to discover a solution by creating a non-linear transformations of the actual input space in a higher dimensional feature space, where an optimum differentiating hyper-plane can be seen. Those differentiating plane is optimal, it means i.e. a maximum margin classifier with respect to the training data set can be obtained.

Let one basic binary classification problem with a training data set of {(xk, yk)} nk =1, in this yk is the tag of I/P data class xk. In the binary classification study, yk ∈ {− 1, 1} and xk ∈ Rd, in which d is the dimensions of input vector. The support vector machine method aim to search a classifier in the form of:

$$y(x) = \text{sign} \sum_{k=1}^{n} ak\ yk\ K(xk\ , x) + b]\_\_ \qquad (2)$$

Where αk is the +ive real constant of LaGrange's multiplier, that is the solution of the bi-classification problem for the quadratic programming (QP) problem given below. Kernel function K (x_k, x) =f (x_k)T f(x), and f (X_k) presents the nonlinear mapping funcn from the non-linear original space to a high dimensional linear space.

The two parallel hyper planes as shown in fig 1, it can be illustrated by the given two equations

$$w^T_{\varphi} (x_k) + b \geq +1 \text{ when } y_k = +1$$
$$w^T_{\varphi} (x_k) + b \leq -1 \text{ when } y_k = -1$$

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In above given equations w is the normal support vector and b is the constant of hyper plane. The margin distance is equal to 1/||w|| that means the minimum distance between the hyper plane and support vectors is 1/||w||.

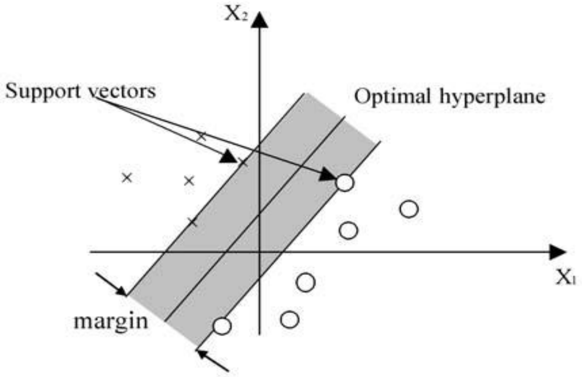

Figure 2: Separating two hyper planes by SVM.

There are four ways of support vector machine multi-classification problem:(1)one-to-many;(2) one-against-one method(one–to-one);(3) error-correcting output codes;(4) One-off Solution.

For classification problems such as fault classification, SVM technique itself is second class classifier. For K-class classification problems, one-to-many dissemination needs to be constructed K-SVM sub-classifier. In this i^{th} SVM classifier separates i^{th} class from the other classes. One-to-one algorithms will need to be constructed with 1/2K *(K-1) support vector machine classifier. The former method needs to construct much less SVM sub-classifier. However, one or several algorithms require the training process. The number of training samples presented to two categories in accordance with the form of DGA training sample data. For DGA training data sample numbers is large, and the training time is very long. However, one-on-one algorithm will take comparatively shorter time. Therefore, proposed method mainly uses one-on-one algorithm to construct the power transformer fault identification model. It has a total of six categories of failure, and need to construct 1/2k *(k-1) = 12 sub-classifiers. The SVM consists of 12 sub-SVM classifier. In this study, many sub-SVM models were accounted. In order to shorten the time taken by the training process, the least squares support vector machine was selected. The kernel function directly used the RBF kernel with a value of C = 6.25. In order to facilitate comparison with the three-ratio method and neural networks, during data processing five gases H2，CH4, C2H2, C2H4，C2H6 were selected as the input of text samples. The value method was still used to deal with the DGA original data normalization.

2.6. Existing Methodology:

Support Vector Machine is a machine learning technique based on Statistical Learning Theory (SLT). It is powerful for the real time practical problem with much less sampling time, non-linear data and higher dimensional space. Support Vector Machine is applied for identification of fault using dissolved gases concentrations present in power transformer oil sample. To find its feasibility in condition assessment of power transformer, the actual DGA sample data sets were used. The project work results indicated that SVM gives more accuracy in fault classification than Back Propagation technique. Various cases show that SVM has a better forecasting performance. Because, SVM is the statistical machine learning theory, which executes the concept of structural risk reducing rather than experimental one to make sure high generalization capability of SVM model in case of less number of samples. Support Vector Machine can convert a non-linear learning problem to a linear learning problem in order to minimize the level of complexity of algorithm by making use of kernel function. The Cross validation method is utilized to choose the optimal values to give more accurate dissolved gases analysis results, which make sure the generalization capability and fault classification accuracy should be maintained of SVM. Those proposed techniques have a large potential in fault classification as results are obtained, however, since SVM is commonly used in fault classification of power transformer using DGA, there are some problem related to it, such as choosing kernel function and the optimal values of parameters.

2.7. Classification Using SVM:

As presented below in Figure 3, the fault classification model includes six support vector machine classifiers; these classifiers are further used to classify seven states of power transformer: six faults such as T1, T2, T3, PD, D1, and D2

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and normal operating state. With all the training DGA data samples for each state, SVM1 go under training process to differentiate the normal operating condition from all faulty states. When input given to SVM1 is a DGA sample which represents the normal operating condition, value given by SVM1 is +1; it not then -1. With the DGA data samples having electrical discharge fault, SVM2 go under training process to classify the electric discharges faults from thermal faults. When input given to SVM2 is a DGA sample presenting electric discharge faults, value given by SVM2 is +1; if not then -1. With the DGA data samples having electrical discharge faults, SVM3 is trained to classify high energy electric discharges from low energy electrical discharges and partial discharge faults. When input given to SVM3 is a DGA sample presenting high energy electric discharge (D2) faults, value given by SVM3 is +1; if not then -1. With the DGA data samples having thermal fault, SVM4 go under training process to be able to classify the high temperature thermal fault (T3) from medium (T2) and low (T1) temperature thermal faults. When input given to SVM4 is a DGA data sample presenting high temperature thermal fault, value given by SVM4 is +1; if not then -1. With the DGA data samples having low and medium temperature thermal fault, SVM5 is trained to classify the medium temperature (T2) thermal faults. When input given to SVM5 is a DGA sample presenting medium temperature (T2) thermal fault, value given by SVM5 is +1; if not then -1. With the DGA data samples having thermal faults, SVM6 is trained to classify the low temperature (T1) thermal faults. When input given to SVM6 is a DGA sample presenting low temperature (T1) thermal fault, value given by SVM6 is +1; if not then -1.

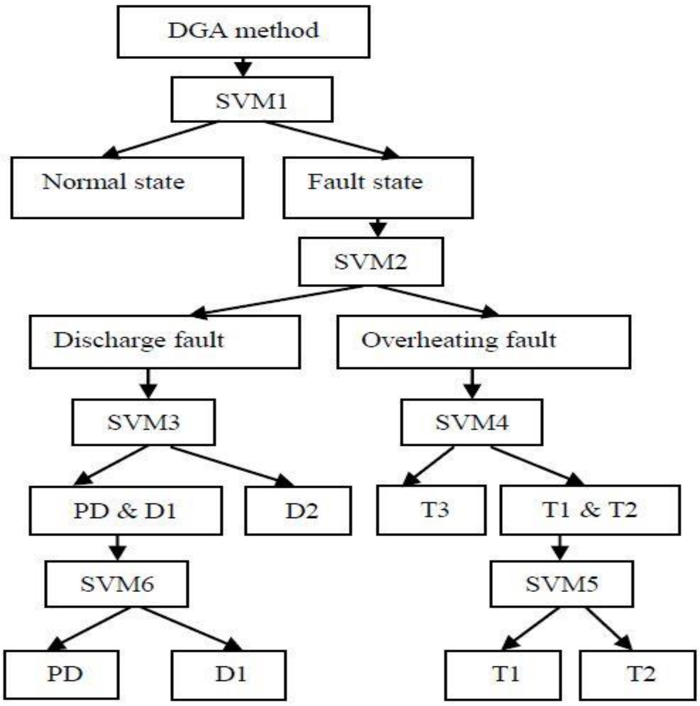

Figure 3: SVM based fault classification model for power transformer.

Table 4: Decoding of SVM model Output.

	SVM1	**SVM2**	**SVM3**	**SVM4**	**SVM5**	**SVM6**
No fault	+1					
PD	-1	+1	-1			-1
D1	-1	+1	-1			+1
D2	-1	+1	+1			
T1	-1	-1		-1	-1	
T2	-1	-1		-1	+1	
T3	-1	-1		+1		

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III. RESULTS AND ANALYSIS

To evaluate the proposed method, we used 150 samples of dissolved gas analysis (DGA), those were provided by Punjab State Transmission Corporation Limited. These DGA samples have included power transformer with different ratings, voltage levels, operating conditions, age, and loading history etc. employed all over Punjab among this 95 samples were used for training and remaining 55 samples used for testing. The forecasting results shown in table 6. Results obtained show that SVM has good performance in fault classification.

Table 5: Sample Data:

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 6: Result of described Model.

Fault types	No. of samples	Successful Identification	Efficiency
Normal State	21	20	95.23
Partial Discharge	21	19	90.47
Arching	16	14	87.5
Thermal Faults	19	18	94.73

IV. CONCLUSION

This proposed method with application of support vector machine for identification of fault in power transformer. Sixth order support vector machine model is used to solve power transformer fault identification problem. In this, electrical faults such as partial discharge, sparking and thermal faults such T1, T2 and T3 were diagnosed using SVM model for 55 DGA sample fault data. The SVM algorithm is coded in MATLAB environment and solved. Compared to other techniques used for fault diagnosis, SVM model provides higher accuracy in fault classification.

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