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Research Article

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Fault diagnosis of power transformer based on chemical properties of insulation oil

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ABSTRACT

Failure of a large power transformer not only results in the loss of very expensive equipment, but it can cause significant collateral damage as well. Replacement of that transformer can take up to a year if the failure is not catastrophic and can result in tremendous revenue losses and fines. DGA is a technique used to assess incipient faults of the transformer by analyzing specific dissolved gas concentrations arising from the deterioration of the transformer. DGA is used not only as a diagnostic tool but also to stem apparatus failure. Forecasting of dissolved gases content in power transformer oil is very significant to detect incipient failures of transformer early and ensure normal operation of endure power system. In this study Multi class Support vector Machine is proposed to forecast dissolved gases content in power transformer oil, among which cross validation used to determine free parameters of support vector machine. The experimental data from the electric power company are used to illustrate the performance of proposed SVM model.

Key words: Power Transformer, Dissolved gas analysis, Support vector machine, Multi class SVM.

INTRODUCTION

Transformer acts as a link between generating station and at the point of utilization. In order to give trouble free long service, maintenance of transformer is very important. So, reliable and continued performance of power transformer is a main aspect for profitable generation and transmission of electric power. Hence it is very significant to detect the failure of power transformer as early as possible. Dissolved gas analysis is one of the most widely used techniques for Transformer fault diagnosis. DGA helps in identifying the faults without dismantling the transformer. Transformer in service is subjected to electrical and thermal stresses. The insulating oil will degrade and breakdown due to above stresses. Arcing, Corona discharge ,low energy sparking, severe over loading and overheating of insulation system are some of the problems causing decomposition of the insulating material. This process will produce gases which dissolved in oil. The concentrations of the gas analysis are indication of the type and severity of the fault in transformer. The source of generation of gases are basically from transformer windings, loose joints, tap changer, core laminations and bushings and excessive level of gas may indicate insulation deterioration. The significant gases generated by the decomposition of oil insulation are Hydrogen (H_2), Methane (CH_4), Ethane (C_2H_6), Ethylene (C_2H_4), and Acetylene (C_2H_2). Due to fault in cellulosic materials Carbon Dioxide (CO_2) and Carbon Monoxide (CO) are also generated. Over years there are various interpretative methods such as Key gas method and Ratio methods used for DGA. For evaluating the analysis of gases, covered in IEC:599/IS:10593 standards. While absolute values of Key gas are considered, the key gas method becomes applicable to Transformer with developed faults. Where Ratio method has to be employed in the incipient fault diagnosis. Also to check the severity of fault the Rogers method have to be employed in conjunction with Key gas method to check the severity of fault. If transformer fault is present they can provide an accurate diagnostic. However these methods are based on cumulative experience on large number of transformers. Hence these criterions are heuristic in nature and interpretation may vary from time to time. So some refinement necessary on some specific types of Transformer.

REPEATABILITY & REPRODUCIBILITY

Accuracy of DGA depends primarily on the methods used in oil sampling, storage of samples and gas extraction. This aspect of gas analysis is not good especially in cases where the values determined are nearer to the limiting values of detection. The samples must be taken where the oil circulates freely and following a failure it is necessary to wait for some time to allow fault gases to disperse in oil. Thus for high gas concentration, the result can be obtain within 10% accuracy. Due to the Scattering of the key gas concentration and ratios of the gas concentration being used in the different standards to detect certain fault, the following guidelines have been proposed.

i) Transformer classification
ii) Evaluation of the dissolved gas analysis.

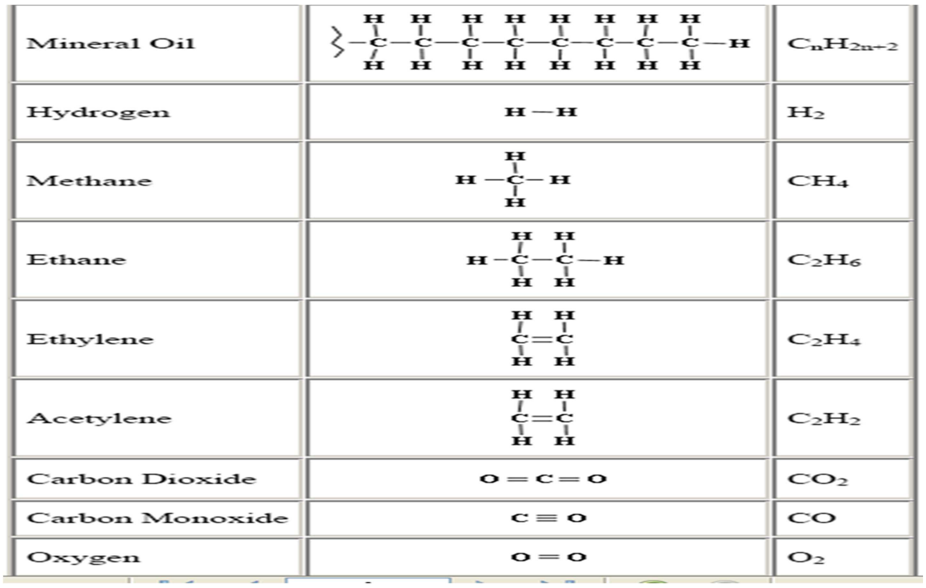
TRANSFORMER CLASSIFICATION

History of transformer is very much essential interpretation of DGA results. Incomplete data regarding history of transformer can lead erroneous fault diagnosis. Hence the approach has been selected regarding transformer classification. Basically Transformer is classified by its breathing system as open breathing system and closed breathing system. In each of the above said types it can further classified based on 1)Core construction(Core & Shell), 2)Cooling(Forced oil circulation & Normal oil circulation) 3) Temperature (Oil Temperature variation) 4) Load variation (Strong load & weak load0 5) Over voltage (Many &Few) 6) Tap changer type (On load & No load) 7) Oil preservation (Gas tight & Open to vessel) 8) Transformer application (Generation, Transmission, Industrial &Railway)

EVALUATION OF THE DISSOLVED GAS ANALYSIS

A DGA analysis is done first classify faults as thermal or electrical [6]. The next step is to determine the involvement of different areas that can produce this fault. Depending on DGA fault type, thermal, electrical faults are assessed.

Table.1 Structure of dissolved gases in transformer oil



Mineral Oil		C_nH_{2n+2}
Hydrogen	H — H	H_2
Methane		CH_4
Ethane		C_2H_6
Ethylene		C_2H_4
Acetylene		C_2H_2
Carbon Dioxide	O = C = O	CO_2
Carbon Monoxide	C ≡ O	CO
Oxygen	O = O	O_2

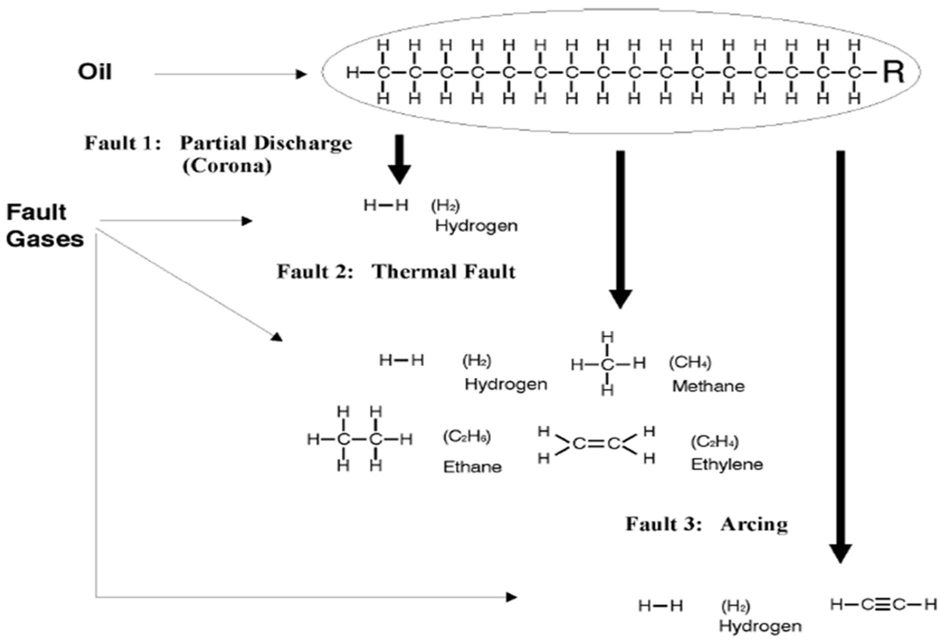


Fig.1 Fault classification

Based on this a multi class SVM modal for incipient fault detection in power transformer is presented.

SUPPORT VECTOR MACHINE

SVM was first introduced by Vapnik[1]. It is a supervised learning algorithm and shown excellent performance in the field of some pattern recognition application. SVM finds an optimal hyper plane that correctly classifies data points by separating the points of two or more classes as much possible. In Support Vector Classification, the separating function can be expressed as a linear combination of Kernels associated with the Support Vectors as,

$$f(x) = \sum_{x_j \in s} \propto_j y_j K(x_j, x) + b \qquad (1)$$

Where,

X_j= Training Pattern- dissolved gases with transformer conditions

$Y_j \in (+1,-1)$ = corresponding class labels

S = set of support vectors.

The dual formulation yields,

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

Where,

$\propto_i$ = corresponding coefficient

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 Karush – Kunn Tucker condition are first order necessary conditions for a solution in nonlinear programming to be optimal, provided that some regularity conditions are satisfied (Sun Xiaoyun AN,2009). The KarnshKunn – Tucker condition for dual can be expressed as,

$$g_i = \frac{\partial w}{\partial \alpha_i} = \sum_i Q_{ij} \alpha_j + y_i b - 1 \qquad (3)$$

$= y_i$ f $(x_i) - 1$

And,

$$\frac{\partial w}{\partial b} = \sum_j y_j \alpha_j = 0 \quad (4)$$

These partitions the training set into,
(i) S the support vector set $(0 < \alpha_i << c , g_i = 0)$
(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.The kernel parameter selection was done by Cho et al (2001). The Kernel function is modified as

$$k'(x_i,x_j) = k(x_i, x_j) + \frac{1}{c'} \partial_{ij} \quad (5)$$

Where
$\partial_{ij} = 1$ if i = j
$\partial_{ij} = 0$ otherwise.

The advantage of this formulation is that the SVM reduces the problem to that of a linearly separable case. Training of SVM involves quadratic optimization problem which requires the use of optimization routines from numerical libraries. This step is computationally intensive, subject to stability problems and nontrivial to implement.

MULTICLASS SVM
There is much type of approaches for multiclass SVM[3]. They are multilevel 1-v-1, 1-v- r, Directed acyclic graph SVM (DAGSVM), etc. Reference [4]has shown that 1-v-1 algorithm based SVM classifier has better performance in practical applications.1-v-r method will construct KSVM model where K is the number of classes. If there are many training samples there will take more time. So using 1-v-r method, SVM 1 is trained with the all the training samples to separate normal state from other fault types. Then using 1-v-1 method, by construct K * (K-1)/2 classifiers to diagnosis fault types.

FAULT DIAGNOSIS
To improve the effect of diagnosis we use H_2, CH_4, C_2H_2, C_2H_6 and C_2H_4. Thus five features used for fault diagnosis and an input vector $[H_2, CH_4, C_2H_2, C_2H_6, C_2H_4]^T$ composed for identification. For output vector DGA is divided in to six types of transformer state as [Normal unit, Corona, Sparking, Low overheating, severe Overheating, Arc] ^{T}. So it needs to construct 5 * (5 -1)/ 2 = 10 classifiers. Example for sparking, the output vector will be [0 0 1 0 0 0].

SVM MODEL

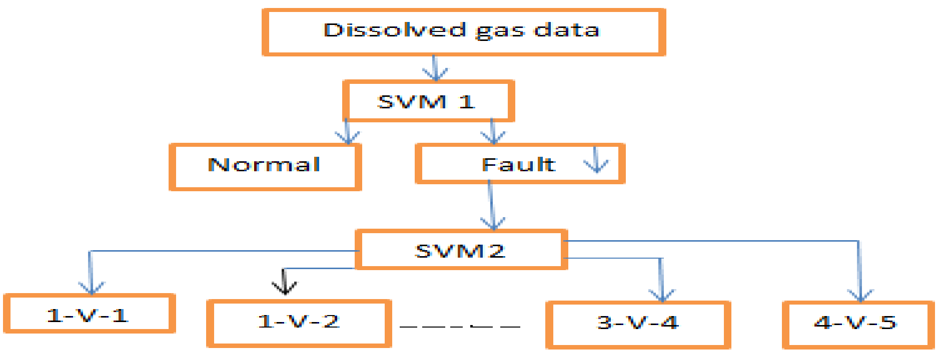


Fig.2 Multi class SVM Model

In this study 90 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 30 samples used for testing. The forecasting results shown in table III show that SVM has more accurate performance.

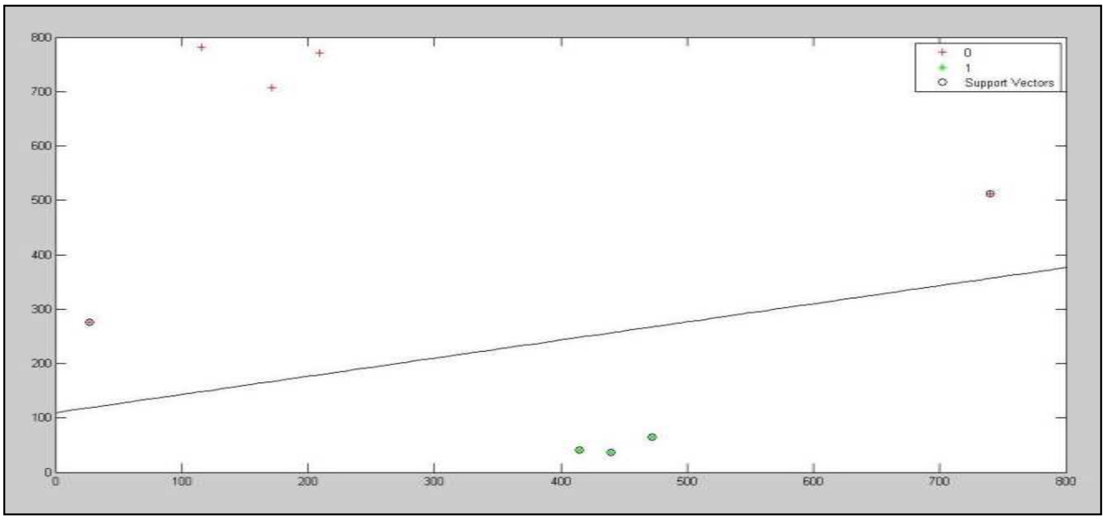


Fig.3 Characteristic Plot Using SVM

Table 2. Sample of Experimental Data

H_2 Ppm	CH_4 Ppm	C_2H_2 Ppm	C_2H_6 Ppm	C_2H_4 ppm
46	60	1	15	104
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
121	261	2	121	781

Table 3. Results of Statistical analysis Using SVM

Fault type	No. of samples	Successful Diagnosis	efficiency
Normal Unit	21	21	100%
Arc, Corona	21	20	95.24%
Sparking	12	12	100%
Low over heating	12	12	100%
Severe over heating	10	10	100%
Arc	11	11	100%
TOTAL	82	81	95.24%

CONCLUSION

A Transformer diagnostic system based on SVM and trained on several diagnosis criteria is quite useful for large utilities with great number of power transformer. SVM used as a tool to analyze DGA samples using several diagnosis criteria. 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. Further an evaluation of gases concentration with time has to be incorporated in future SVM models.

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