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TRANSFORMER FAULT CLASSIFICATION USING SUPPORT VECTOR MACHINE METHOD

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Abstract— Power transformers are important equipments in power system. Smooth functioning is the key to ensure hossle-free operation. Dissolved Gas Analysis (DGA) is a well known technique to analyze faults in Transformers. Rogers ratio method was attempted for transformer fault diagnosis and the same is reported. To improve the diagnosis accuracy soft computing techniques are generally used. There are several soft computing Techniques available for diagnosis. This work proposes a new method of DGA diagnosis based on Support Vector Machine (SVM) method. SVM can change a non-linear learning problem into a linear learning problem to reduce the algorithm complexity. Experimental data from TC 10 database is used to illustrate the performance of the SVM method.

Keywords— component DGA diagnosis, IEC TC 10, gas ratio, new method.

I. INTRODUCTION

Power transformer is an important equipment and a valuable asset of an electrical power system for providing stable and reliable energy. When a transformer in service fails due to deterioration, it can have a huge negative impact on an electrical power system, and repairing and maintaining a transformer is very expensive and difficult. Therefore, inspecting internal failures in an initial stage have become essential. when abnormal phenomena with specific energy, i.e., overheating, partial discharges, arc discharges and insulation breakdown occur inside oil-filled equipment such as a transformer, insulation materials, insulating oil or insulators being in physical contact with such abnormal phenomena, are affected and decomposed by the energy and produce gases. Such gases are dissolved into the insulating oil.

Dissolved gas analysis (DGA) diagnosis is widely used to analyze gases dissolved into the insulating oil used for transformer cooling and insulation and to evaluate whether there is an internal abnormality or not and how Serious it is, based on the volume and composition of The gases. DGA diagnosis is one of the oldest available, and is proven to be reliable . Methods of DGA diagnosis to detect internal defects are defined in IEEE C57.104 and IEC 60599 standards. Most users of oil-filled electric power equipment and apparatus determine internal faults, by using diagnosis methods described in international standards, and most of them are able to identify the different types of faults. Some utilities, laboratories and countries also use in-house methods. However, DGA interpretation is not an easy task since DGA methods often cannot provide a diagnosis or will give a wrong diagnosis. Several soft computing methods are available for transformer fault diagnosis. Prominent among them are Neural Net work, Fuzzy Logic, Neuro-Fuzzy, Support Vector Machine method etc. In this project support vector machine with Genetic algorithm is proposed to predict the transformer faults based on Dissolved Gas analysis results. Support vector machine method offers several advantages. It has excellent generalization ability in the situation of small sample. In addition, SVM can change a non-linear learning problem into a linear learning problem in order to reduce the algorithm complexity by using the kernel function idea.

II. DISSOLVED GAS ANALYSIS (DGA)

DGA is the study of dissolved gases in insulating fluid such as transformer oil. Insulating Materials within transformers and electrical equipment break down to liberate gases within the unit. The distribution of these gases can be related to the type of electrical fault, and the rate of gas generation can indicate the severity of the fault. The identity of the gases being generated by a particular unit can be very useful information in any preventative maintenance program. The collection and analysis of gases in an oil-insulated transformer was discussed as early as1928. Many years of empirical and theoretical study have gone into the analysis of transformer fault gases.

DGA usually consists of three steps: Sampling, extraction, analysis. Modern technology is changing this process with innovation of DGA units that can be transported and used on site as well as some that come directly connected to the transformer itself. Online monitoring of electrical equipment is an integral part of the smart grid. Though this new technology is promising often oil quality, labs are still utilized as third party verification. Also upgrading all equipment to meet the goals of the smart grid can be cost prohibitive.

Major power transformers are filled with a fluid that serves several purposes. The fluid acts as a dielectric media, an insulator, and as a heat transfer agent. The insulating fluid is in contact with most internal components and by evaluating the dissolved gases much diagnostic information can be gathered. Since these gases can reveal the fault of a transformer, they are known as Fault Gases. They are formed in transformer oil, due to natural ageing and as a result of fault inside the transformer. The causes of fault gases can be divided into three categories; corona or partial discharge, pyrolysis or thermal heating, and arcing. These three categories to oxidation, vaporization, insulation decomposition, oil breakdown and electrolytic action. The most severe intensity of energy dissipation occurs with arcing, less with heating, and least with corona.

Partial lists of fault gases that can be found within a unit are shown in the following three groups. It had been realized that under thermal and electrical stresses, the hydrocarbon molecules of mineral oil can decompose and from active hydrogen and hydrocarbon fragments, and that these fragments can combine with each other to form gases like hydrogen (H_2), methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4), acetylene (C_2H_2), etc [1].

It was also found that the amount of each individual gas is dependent on the temperature in the neighbourhood of the stressed point. The gases are generated in the following order with an increase of temperature: $H_2 \rightarrow CH_4 \rightarrow C_2H_6 \rightarrow C_2H_4 \rightarrow C_2H_2$. Hydrogen is generated at low temperature and its amount steadily increases, while acetylene is generated at a very high temperature (close to 1000°C) and also steadily increases its amount.

Transformer solid insulation degradation is conventionally diagnosed according to the amount and ratio of dissolved carbon monoxide (CO) and carbon dioxide (CO_2) [IEC599]. Their amount is found to increase dramatically above a threshold temperature of about 140°C-150°C.

When cellulose insulation decomposes due to overheating, chemicals, in addition to CO and CO2, are released and dissolved in the oil. These chemical compounds are known as furnace compounds, or furans. In healthy transformers, there are no detectable furans in the oil (< 100 ppb). As the cellulose degrades, the furan levels will increase. Furan leaves of 500 to 1000 ppb are indicative of accelerated cellulose aging, with furan levels > 1500 ppb having a high risk of insulation failure.

The gases will accumulate in the oil, as well as in the gas blanket of those units with a head space, as a result of various faults. Their distribution will be effected by the nature of the insulating materials involved in the fault and nature of the fault itself.

III. SUPPORT VECTOR MACHINE

Back-propagation algorithm and feed forward networks of these neural networks are universal approximation in their own ways. Another category of universal feed forward networks, it is known as Support Vector Machine.

It is a linear machine with some very nice properties. Like multilayer perceptrons and radial-basis function networks, support vector machine can be used for pattern classification and nonlinear regression. The support vector machine learning algorithm to construct the following three types of learning machines:

1. Polynomial learning machines
2. Radial-basis function networks
3. Two-layer perceptions.

Various kernel functions are follows:

1. Polynomial Kernel function:

$$K(x, x') = (c + x.\, x')^d$$

2. Gaussian radial basis function:

$$K(x, x') = \exp\left(-\frac{||x-x'||^2}{2\sigma^2}\right)$$

3. Sigmoid kernel function:

$$K(x, x') = \tan(\alpha_0(x, x') + \beta_0)$$

Classify algorithms of support vector machine include linear and nonlinear algorithm. When the sample data are linear, the

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samples data are fitted by linear classify function f(x) the optimal separating hyper-plane. Where w is the weight vector, b is the bias term. When the sample data are nonlinearly the original data x into a higher dimensional feature space, and then build optimal separating hyper-plane in high dimensional space, by which maximize the distance between training sample point and the optimal separating hyper-plane to separate the training samples. Hence, given the sample data, input vector is corresponding output value and l is the total number of sample data.

3.1 Basic Concepts of SVM

SVM analysis seeks to find an optimal separating hyper-plane by maximizing the margin between the separating data, as illustrated in fig.1[2], where the filled circles are the support vector and the unfilled circle are the training data.

The regression approximation estimates a function according to a given data set T = {x_k , y_k}km, where x_k denotes the input vector, $y_k \in$ {-1;1} denotes the corresponding output Table-I Fault Diagnosis For IEC Data value and 'm' denotes the total number of data patterns.

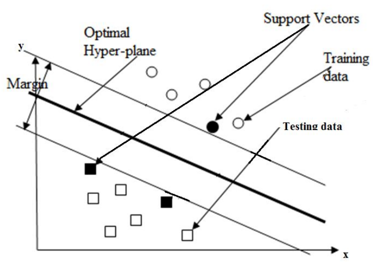

Fig.1.Separation of two classes by SVM

IV. EXSISTING METHODOLODY

SVM is a novel machine learning method based on Statistical Learning Theory (SLT). It is powerful for the practical problem with small sampling, nonlinear and high dimension. In this paper, SVM is applied for diagnosing dissolved gases content in power transformer oil. To investigate its feasibility in diagnosing power transformer fault, the real data sets are used. The experimental results indicate that SVM has more excellent performance than BP network in diagnosing power transformer fault. Several cases make SVM have a superior forecasting performance. Firstly, Support vector machine (SVM) is the statistical theory, which implements the principle of structural risk minimization in place of experiential one to ensure maximum generalization ability of model under the circumstance of small samples. Secondly, SVM can change a nonlinear learning problem into a linear learning problem in order to reduce the complexity of algorithm by using the kernel function.

Thirdly, the Cross – validation technique is used to select the most suitable parameters to forecast dissolved gases, which ensure the generalization ability and diagnosis accuracy of SVM. The proposed method has a large potential in practice according to the experimental results, however, since it is seldom applied to the fault diagnosis of power transformer, there still remain some problems, such as the selection of kernel function and the optimization of parameters, which need to be studied in future research.

V. PROPOSED METHODOLODY

5.1 Transformer Fault Diagnosis Model

In the paper, the transformer state are divided into normal, high energy discharge fault, low energy discharge fault, high thermal fault, middle and low thermal fault according to train four support vector models, the transformer fault diagnosis model is built by binary classification principle of SVM, based on the characteristics of different transformer fault types, four SVM classifiers are developed to identify the five fault types: normal state, high thermal heating, middle and low thermal heating, low-energy discharge , high energy discharge. With all training samples of four types, the first SVM (SVM1) classifier is trained to separate normal state from other four fault types (high thermal heating, middle and low thermal heating, low-energy discharge and high-energy discharge).

When input of SVM is a normal state sample, output of SVM1 is set to +1; otherwise -1. With sample of high thermal heating, middle and low thermal heating, low-energy discharge and high-energy discharge, the second SVM (SVM2) classifier is trained to separates thermal heating from the discharge fault types.

When input of SVM is a thermal heating sample, output of SVM2 is set to +1; otherwise -1. With samples of high thermal heating, middle and low thermal heating, the third SVM (SVM3) is set to +1; otherwise -1. With sample of high-energy discharge and low-energy discharge, the fourth SVM (SVM4)

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classifier is trained to separates them. When input of SVM is high-energy discharge, output of SVM4 is +1, otherwise-1.

Table -I
Fault Diagnosis Using Rogers RatioMethod

S.NO	R_2 (C_2H_2/C_2H_4)	R_1 (CH_4/H_2)	R_5 (C_2H_4/C_2H_6)	FAULT DIAGNOSIS
1	0.027650	.8372000	0.1146340	Unit Normal
2	0.038135	0.022850	0.9076900	Low Energy Density
3	0.800000	0.544400	5.3333000	Arcing High Energy Discharging
4	0.071420	0.750000	1.1666600	Low Temperature Thermal
5	0.010975	2.571420	4.5555000	Temperature> 700°C
6	0.016666	1.111111	2.0000000	Temperature< 700°C

Table-I shows training data used in transformer fault diagnosis based on Rogers Key Gas Ratio methods. In the Table-I R_2, R_1 and R_5 denotes C_2H_2/C_2H_4, CH_4/H_2 and C_2H_4/C_2H_6 [3].

Thus, the multi-layer SVM classifiers are obtained. The basic principle of fault diagnosis of power transformer based on multi –layer SVM classifier is shown in Fig.2[4].

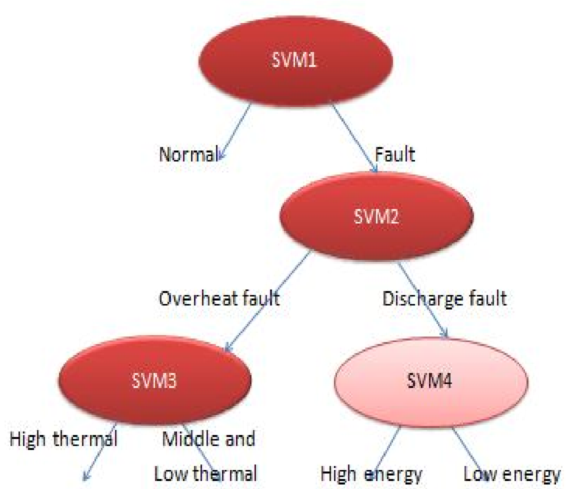

Fig.2. Model of Transformer Fault Classification

VI. RESULT ANALYSIS

6.1 Output Recognition of IEC Data

From the above result conventional method gives better accuracy. Now this work can be extended to analyze fault cases such as partial discharge and discharge of low energy based on IEC data.

In this method used in training set. Training set have a original data of content of the transformer. Original data of content of the transformer are applied in the Rogers ratios for finding fault diagnosis.

Results are tabulated in 5, and it shows that the results achieved for diagnosing faults for the test samples indicates 75% accuracy, the research are going on.

Table-II
Testing data on SVM4

S.NO	H_2	CH_4	C_2H_6	C_2H_4	C_2H_2
1	0.2181	0.0789	0.0488	1.0000	0.2776
2	1.0000	0.4015	0.1554	0.6400	0.8892
3	1.0000	0.3207	0.0658	0.8337	0.8884
4	1.0000	0.2000	0.0537	0.4269	0.5075
5	1.0000	0.2364	0.0672	0.5771	0.6468
6	1.0000	0.1704	0.0460	0.3969	0.4191
7	0.9019	0.2827	0.0240	0.5096	1.0000
8	0.7885	0.6731	0.1308	0.2308	1.0000
9	1.0000	0.2485	0.0061	0.0794	0.0978
10	0.7182	0.0820	0.0848	0.2477	1.0000
11	1.0000	0.1756	0.0385	0.1092	0.0878
12	0.6207	1.0000	0.3103	0.6034	0.1638
13	0.7119	1.0000	0.1356	0.4746	0.1356

Table-II shows training data used in transformer fault diagnosis based on Support Vector Machine by Bide Zhang , an Zhang , Yuchum Yuan & Zichun Pei , Yan Wang[5].

Also, Table.III shows training data used in transformer fault diagnosis based on Support Vector Machine by Bide Zhang , Yan Zhang , Yuchum Yuan & Zichun Pei , Yan Wang[5].

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Table-III
Training data on SVM4

S.NO	H_2	CH_4	C_2H_6	C_2H_4	C_2H_2
1	1.0000	0.4015	0.1554	0.6400	0.8892
2	1.0000	0.3207	0.0658	0.8337	0.8884
3	1.0000	0.1801	0.0127	0.2605	0.3919
4	0.3952	0.3355	0.2024	1.0000	0.1266
5	1.0000	0.1919	0.0214	0.2325	0.3928
6	1.0000	0.1704	0.0460	0.3969	0.4191
7	1.0000	0.1636	0.0455	0.3909	0.4121
8	0.9019	0.2827	0.0240	0.5096	1.0000
9	0.7182	0.0820	0.0848	1.0000	0.2477
10	0.3824	0.4300	0	1.0000	0.1241
11	1.0000	0.1756	0.0385	0.1092	0.0878
12	0.6207	1.0000	0.3103	0.6034	0.1638
13	1.0000	0.6667	0	0.6667	0.5833
14	1.0000	0.5010	0.1113	0.3225	0.3532
15	1.0000	0.0799	0.0538	0.0323	0

Table-IV
Output of SVM 4 Classifier

S.NO	Model	Training Set	Testing Set	SVM Algorithm	Accuracy
1	High Energy/ Low Energy	15	13	Polynomial	75%
		15	13	Kernel-Function, Linear	73%
		15	13	Quadratic	69%
		15	13	rbf	74%

VII. CONCLUSION

This project work describes the application of support vector machine method for diagnosing fault in a transformer. SVM model is proposed to transformer fault diagnosis . Fourth order SVM model can be used to solve transformer fault diagnosis related problem. Here, electrical faults such as partial discharge and discharge of low energy fault were diagnosed using SVM model for 36 fault data. The SVM algorithm is coded in MATLAB environment and solved. Compared to other techniques used for fault diagnosis, SVM technique gives higher accuracy.

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