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Improvement in Power Transformer Intelligent Dissolved Gas Analysis Method

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***Abstract*—**Non-Destructive evaluation of in-service power transformer condition is necessary for avoiding catastrophic failures. Dissolved Gas Analysis (DGA) is one of the important methods. Traditional, statistical and intelligent DGA approaches have been adopted for accurate classification of incipient fault sources. Unfortunately, there are not often enough faulty patterns required for sufficient training of intelligent systems. By bootstrapping the shortcoming is expected to be alleviated and algorithms with better classification success rates to be obtained. In this paper the performance of an artificial neural network, K-Nearest Neighbour and support vector machine methods using bootstrapped data are detailed and shown that while the success rate of the ANN algorithms improves remarkably, the outcome of the others do not benefit so much from the provided enlarged data space. For assessment, two databases are employed: IEC TC10 and a dataset collected from reported data in papers. High average test success rate well exhibits the remarkable outcome.

***Keywords*—**Dissolved gas analysis, Transformer incipient fault, Artificial Neural Network, Support Vector Machine (SVM), K-Nearest Neighbor (KNN)

I. INTRODUCTION

POWER transformers are always under the impact of electrical, mechanical, thermal and environmental stresses that degrade their insulation quality. To avoid the power failure, periodically monitoring of the conditions of transformers is necessary. Results of early detection of fault are large savings in operation and maintenance costs and preventing any premature breakdown/failure.

There are routine maintenance procedure for power transformers such as dissolved gas analysis (DGA), moisture analysis in transformer oil [1, 2], oil breakdown voltage test, the tan (delta) test, resistivity test, acidity test, sludge test, interfacial tension test and partial discharge (PD) acoustic emission sensing. Among these methods, DGA is an effective one for the early detection of incipient faults [3].

It is well known that overheating, arcing, partial discharge, winding circulating currents, and continuous sparking are the main factors in deteriorating transformer condition. These phenomena develop certain dissolved gaseous in the insulation oil. The gases include hydrocarbons such as: methane (CH4), ethane (C2H6), ethylene (C2H4), acetylene (C2H2) and others such as: hydrogen (H2), carbon dioxide (CO2), and etc.

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The gases are extracted from the oil under high vacuum and analyzed by Gas Chromatograph, to get each gas concentration separately. By interpretation of the gas contents, the developing faults in the power transformers can be diagnosed.

Many diagnostic criteria have been developed to establish relationships between the gases and the fault conditions, which some are obvious and some are not (hidden relationships). The gas concentrations, generation rates, specific gas ratios, and the total combustible gas are important parameters for interpreting the result of DGA. But the actual diagnosis must also consider other information of transformer such as size, volume of oil, type of transformer etc. Therefore, much of diagnostic relies on experts to interpret the results correctly.

To automatize the procedure of power transformer fault classification, several algorithms have been studied. Presently, the conventional ratio methods, statistical schemes and artificial-intelligence (AI) methods are the major interpreting approaches. The conventional ratio methods mainly include Rogers Ratios [4], Duval Triangle [5], and IEC Ratios [6]. Since conventional ratios' boundaries are sharp, they are unable to provide interpretation for every possible combination of ratio values [7].

The Artificial Neural Network methods have also been used to explore the nonlinear and complex relation between the gases concentration and the type of faults. Multilayer back propagation (MLP) [8], [9], self-organizing map network [10], Adaptive Back-propagation learning algorithm [11] and Extension NN [12, 13] are among them. ANN training suffers from trapping in local minima; therefore evolutionary training algorithms have got deserved attention in this field [7], [14], [15]. Other methods that have been investigated are wavelet decomposition [15], SVM [15], KNN [15] and fuzzy learning vector quantization network [16], [12].

In this paper SVM, KNN and ANN are considered for fault classification. The data sets are IEC TC10 and database 1, a collection of data gathered from many research papers. It is observed that the number of faulty patterns for each class is not equal and enough for well training of intelligent schemes. As a remedy, the bootstrapping technique is employed to equalize the number of faulty patterns for each class of the transformer condition. The results show that the method based on ANN takes more advantage of the bootstrapped input and renders remarkable improvement in the performance while the other two methods do not show such advances.

In section 2 the three classification methods are briefly reviewed. Section 3 discusses data preparation and pre-processing. Simulations are detailed in section 4 and finally, conclusion comes in section 5.

II. Classification Methods

A. Intelligent Method: Neural network

What makes artificial neural net algorithms valuable is that they can be taught to perform a particular task, such as recognizing patterns inherent in an incoming data set, curve fitting and data clustering.

In order for the artificial neural net to carry out a useful task, one must connect the neurons in a particular configuration, set the weights, and choose the layer functions. Fig. 1 shows a Multilayer Perceptron NN having "I" inputs, a hidden layer of "*J*" nodes and an output layer of "K" nodes. Weights w_{ij} and w_{jk} link the corresponding nodes to each other. In this network, all links are from left to right without jumps. Layers also have an extra node called bias where its value is often set to -1. Neurons of each layer have a specific type of function '*F*' that is mainly nonlinear such as tansig (tangent-sigmoid), logsig (log-sigmoid) and so on.

Output of each neuron is calculated by,

$$o_j = F_i\left(\sum_i w_{ij} o_i\right)$$

where "*j*" and "*i*" represent the index of the current and the preceding layer neurons, respectively [17].

In pattern recognition and cure fitting, network is trained based on a set of inputs and a set of desired outputs. This is called supervised learning against unsupervised learning that no desired output is introduced. Error backpropagation based on gradient descent method of optimization was a scheme that gave the NN idea a push. Other training methodologies are evolutionary methods, simulated annealing and so on.

B. Statistical methods

1) K-NN classifier

Among the various methods of supervised statistical pattern recognition, the K-Nearest Neighbor (K-NN) rule achieves consistently high performance, without a priori assumptions about the distributions from which the training examples are drawn. It is part of supervised learning that has been used in many applications in the field of statistical pattern recognition

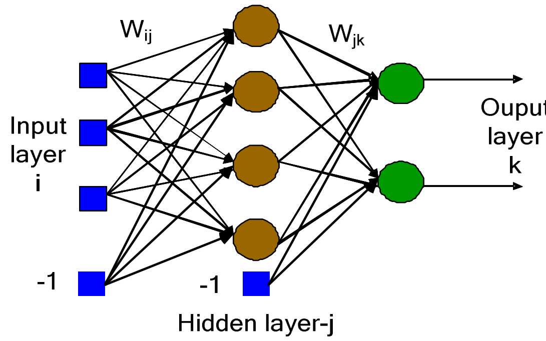

Fig. 1 A MLP neural network configuration

and many others. KNN categorizes objects into K class. K is a positive integer that is chosen appropriately [18]. It is usual to use the Euclidean distance, though other distance measures such as the Manhattan distance could in principle be used instead. Algorithm works as below:

1. Determine K=the problem dependent number of neighbors, beforehand.
2. Calculate the distance between the query-instance and all the training samples.
3. Sort the distances for all the training samples and determine the nearest neighbor based on the Kth minimum distance.
4. Since this is a supervised learning, get all the categories of the training data for the sorted value which fall under K.
5. Use the majority of nearest neighbors as the prediction value.

2) SVM classifier

Support vector machine is recognized as one of the standard tools for machine learning and data mining, which is based on advances in statistical learning theory. Originally developed to solve binary classification problems, SVM determines a number of support vectors from training samples and converts them into a feature space using various kernel functions, among which the most commonly used are Gaussian Radial Basis Function (RBF), polynomial, etc. [19]. Thus, by solving a quadratic optimization problem, the optimal separating hyper-plane with a maximal margin between the two classes is defined.

For the purpose of multi-category classification, various different binary classification methods are implemented, such as "one-against-all", "one-against-one" and binary tree. Binary tree needs "K-1" binary SVM for a K class problem while "one against all" requires K(K-1)/2 binary SVM [20].

III. DGA data preparation and pre-processing

A. Test Data

In this investigation two databases are used. The first is the well known IEC TC10 and the other is a dataset, called database 1 formed from a collection of data taken from various research papers. The IEC TC10 and database 1 contain 151 and 273 samples of various fault cases, respectively. Each sample comprises H_2, CH_4, C_2H_6, C_2H_4 and C2H2 gas concentration value and its respective fault classes. A set of 5 commonly used gas ratios is chosen as fault indicator and algorithm input as follows,

$$x = \left[\frac{C_2H_2}{C_2H_4} \quad \frac{CH_4}{H_2} \quad \frac{C_2H_4}{C_2H_6} \quad \frac{C_2H_2}{H_2} \quad \frac{C_2H_6}{C_2H_2}\right] \tag{1}$$

The fault types have been assigned to the samples by the diagnostic tools and industry experts. The transformer condition is categorized in six classes: Normal Condition (NC-class 1), Partial Discharges (PD-class 2), Low Energy Discharge (LED-class 3), High Energy Discharge (HED- class

4), Thermal Faults<700°C (TF1- class 5) and Thermal Faults>700°C (TF2- class6).

B. DGA data Bootstrapping

Since, in practice, the number of samples per fault type is not equal, it degrades the training and validation ability of classifiers. Therefore, the collected DGA data are firstly pre-processed by bootstrap to be equalized in the sample number for each fault type.

Bootstrap was first introduced by Efron [21] as a computer intensive re-sampling technique that draws a large number of re-samples from initial data repeatedly. This is designed to obtain reliable standard errors, confidence intervals, and other measures of uncertainty in cases when the initial sample number is not sufficient for accurate analysis by other statistical techniques. Because resampling is conducted in a random order, bootstrap assumes no particular distribution for the available input data, which gives more applicability with respect to other classical statistical methods [21].

In this case the number of data for each fault case is raised to 100 samples, extending the overall database sample to the amount of 600 samples. This is done for both data bases. In case that algorithm needs training and test sets, 70% are allocated for training and the remaining 30% are devoted to the test procedure. It should be noticed, that the assembled training and testing datasets are independent of each other and are employed to confirm the reliability and efficiency of the proposed ANN classifier.

IV. Classification methods and simulation results

The proposed method is a hybrid one, integrating bootstrap with ANN, K-NN and SVM classification methods. In the case of ANN a Multilayer Perceptron NN and in the case of SVM, a “one against all” multiclass SVM classifier is employed.

A. K-NN Classification

First, a K-NN classifier is used for classification of the transformer condition class. The K closest neighbors are found from the training dataset by calculating the Euclidean distance between the examined point and the training samples. The classification performance of KNN is listed in Table I, where the number of neighbors, K, is a parameter. As the result indicates the classification success rate of about 95% for IEC TC10 can be achieved with K=6. In this situation the success rate for the database 1 is as low as 83.33% which is not so good. With increase in K the algorithm outcome is seen to be deteriorated.

B. SVM Classification

For SVM classification, a One-against-all strategy is adopted. The results of tests have been depicted in Table II and III. The results show very low 51.67% success rate for IEC TC10 and 59.9% for the database 1. Choice of SVM parameter, λ, affects marginally the outcome of the algorithm; however, by no means somehow acceptable results are obtained.

C. ANN Classification

For ANN classification, a three-layer MLP (multilayer perception) structure with input, hidden and output layers is employed as the classifier for the transformer fault classification. The results have been depicted in Table IV and V for each of the databases.

TABLE I
TEST CLASSIFICATION ACCURACY OF THE *K*-NN METHOD FOR THE TWO DATABASES VERSUS K

K	**Classification Accuracy % TC10**	**Classification Accuracy % Database 1**
6	95	80.53
10	88.89	78.65
15	90	83.33
20	83.89	79.69
40	81.67	79.17
60	77.78	73.96

TABLE II
CLASSIFICATION ACCURACY OF THE SVM METHOD FOR IEC TC 10 VERSUS SVM λ PARAMETER

λ	**C=250**	**C=2500**
0.0001	47.78	38.33
0.0005	38.89	42.78
0.001	49.44	43.89
0.005	43.33	42.78
0.01	42.78	45.00
0.1	44.44	46.11
1	45.56	42.22
10	40.00	43.33
100	48.89	43.89
1000	50.56	51.11
2000	51.67	46.67

TABLE III
CLASSIFICATION ACCURACY OF THE SVM METOD FOR THE DATABASE 1 VERSUS SVM λ PARAMETER

λ	**C=250**	**C=2500**
0.0001	44.79	46.35
0.0005	46.35	45.31
0.001	50.00	45.31
0.005	40.10	48.96
0.01	45.83	43.75
0.1	39.58	39.06
1	47.92	45.83
10	44.27	52.08
100	54.69	49.48
1000	58.33	60.42
2000	59.90	57.29

TABLE IV
FAULT CLASSIFICATION ACCURACY (%) OF THE ANN METHOD VERSUS THE NNUMBER OF HIDDEN LAYER NEURONS APPLIED TO THE IEC TC10

neurons	**validation**	**training**	**test**
3	99.50	100	98.33
4	100	100	100
6	99	100	96.67
8	99.5	100	98.33
10	99.83	100	99.44
12	99	100	96.66
15	99.33	99.52	98.88
20	100	100	100

TABLE V
TEST CLASSIFICATION ACCURACY (%) OF THE ANN VERSUS THE NUMBER OF HODDEN LAYER NEURONS APPLIED TO THE DATABASE 1

neurons	**validation**	**training**	**test**
3	99.42	100	98.09
4	99.28	100	97.61
6	98.71	99.79	96.19
8	99.14	100	97.33
10	99.14	99.59	98.09
12	99.42	100	98.09
15	99	99.59	97.61
20	98.85	100	96.19

The number of hidden layer neurons is left as a parameter to change from 3 to 20. Increase in the number of neurons exhibits no improvement meaning that a small size network is adequate for the task.

For each row of the Table IV and V, several experiments are conducted and the average has been listed. The best accuracy is 100% that is higher than those obtained using KNN and SVM.

V. CONCLUSION

In this paper, three well-known classifiers: ANN, K-NN and SVM are used for DGA and power transformer incipient fault classification. Often due to the unequal samples for each fault classes, the training of the algorithms does not proceed well and test classification does not succeed appropriately. To manage the difficulty, the bootstrapping technique is employed to equalize the number of samples for each class. Categorizing the fault cases based on the bootstrapped preprocessed DGA data using ANN shows a remarkable improvement, however the treatment does nothing special for the two other statistical classifiers. The error in the achieved accuracy reaches less than 2% that a small size fast converging network can yield.

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