Machine Learning Techniques for Power Transformer Insulation Diagnosis

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***Abstract*— Power transformers are one of the most critical equipments in electricity network. A number of techniques such as dissolved gas analysis (DGA), polarization and depolarization currents (PDC) measurement and frequency domain spectroscopy (FDS) have been adopted across utilities for transformer insulation diagnosis. However, there are still considerable challenges remaining in interpreting measured data of these techniques. This paper develops machine learning algorithms, which utilise archived data for making insulation diagnosis on the transformer of interest. Analysis and interpretation of field test data are presented in the paper.**

***Index Terms*— dielectric response (frequency and time domain), dissolved gas analysis, machine learning, self-organizing map (SOM), support vector machine (SVM), transformer insulation.**

I. INTRODUCTION

Power transformers are one of the most expensive and critical equipments in power network. It is necessary to develop effective techniques for monitoring and diagnosis of transformer insulation system [1]. Recent years a number of techniques including dissolved gas analysis (DGA), polarization and depolarization currents (PDC) measurement and frequency domain spectroscopy (FDS) have been adopted across utilities for transformer insulation diagnosis [2]-[4]. However, there are still considerable challenges remaining in correlating measured data to actual transformer insulation conditions.

Current interpretation schemes of PDC and FDS are normally based on the data measured on the transformer of interest, depicting time (frequency) dependant current (impedance) curves and heuristically making diagnosis on transformer insulation [3],[4]. These heuristic based interpretation schemes may vary from one researcher to another researcher; sometimes the diagnostic results could even be controversial. Therefore, it would be a significant attribute if a computer program (algorithm) can be trained to acquire the knowledge of underlying statistical dependency between historical data and the conditions of corresponding transformers; such knowledge is then used to assist in evaluating the condition of a present transformer [5]-[7].

This paper develops machine learning algorithms, namely self-organizing map (SOM) and support vector machine (SVM) for automatically analyzing measurement data and making diagnosis on transformers insulation systems. Assuming for a number of transformers, their measurement data are available and the corresponding insulation conditions of these transformers are known, the machine learning algorithms attempts to build a model to approximate the underlying dependency between the measured data and the transformer conditions. The model later will be applied to make insulation diagnosis on other transformers [5]-[7].

This paper is organized as follows. Section II briefly reviews DGA, PDC and FDS techniques. Section III presents the mathematic formulation of SOM and SVM algorithms. Section IV presents the case studies in which the developed algorithms are applied to the diagnosis of transformer insulation. The paper is concluded in Section V.

II. BRIEF REVIEW OF DGA, PDC, AND FDS TECHNIQUES

A. *DGA Techniques* [2]

Operating under excessive thermal and electrical stresses, transformer insulation will form by-product gases such as hydrogen (H_2), methane (CH_4), acetylene (C_2H_2), ethylene (C_2H_4), ethane (C_2H_6), carbon monoxide (CO) and carbon dioxide (CO_2). Conventional DGA interpretation scheme makes use of the concentrations or relative proportions of these gases for transformer fault diagnosis. The artificial intelligent (AI) techniques have also been developed to recognize different fault conditions of transformers [8].

B. *PDC Techniques* [3]

In PDC measurement a step DC voltage U_0 is applied across the transformer insulation and the resultant current is:

$$I_{pol}(t) = \left\{\frac{\sigma}{\epsilon_0} + f(t)\right\} C_0 U_0 \tag{1}$$

where C_0 is the geometrical capacitance of transformer insulation, σ is the average conductivity of the transformer insulation, ε_0 is the permittivity of free space, and $f(t)$is the dielectric response function. At time $t = t_0$ the above U_0 is removed and transformer insulation is externally short circuited. The depolarization current flowing through the transformer insulation is:

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$$I_{depol}(t) = -\{f(t) - f(t + t_0)\}C_0U_0 \quad (2)$$

If the transformer insulation is charged for a sufficiently long time, the effect of $f(t + t_0)$ on Equation (2) can be neglected and Equation (2) becomes

$$I_{depol}(t) = -f(t) \times C_0U_0 \quad (3)$$

Equation (3) implies that the depolarization current can be approximated by deducting the conductivity current (first part in Equation 1) from the polarization current given the charging time is sufficiently long.

Transformer insulation system can be represented by a number of parallel connected resistors and capacitors branches as shown in Fig.1. The parameters (resistances and capacitances) in Fig.1 can be calculated from the polarization and depolarization currents [9].

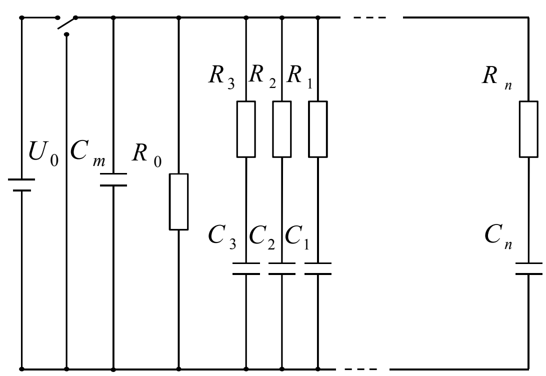

Fig.1 Circuitry representation of transformer insulation system ($1/R_0$ is the DC conduction and *Cm* is the measured capacitance at power frequency).

C. *FDS Techniques* [4], [12]

In FDS measurement a sinusoidal excitation is applied to the insulation and the magnitude and phase of resultant currents are measured. For a particular frequency of the applied voltage, the resultant current can be written as:

$$I^*(\omega) = j\omega\{C'(\omega) - jC''(\omega)\}U^*(\omega) \quad (4)$$

where $U^*(\omega)$ is the applied voltage, $C'(\omega)$ and $C''(\omega)$ are the real and imaginary parts of complex capacitance $C^*(\omega)$.

If the insulation geometrical capacitance C_0 is known, Equation (4) provides the possibility for calculating complex permittivity by measuring magnitude and phase of the response current. If the insulation geometrical capacitance C_0 is unknown, the frequency dependent loss factor $tan\delta(\omega)$ can be used to present the measured result as

$$tan\delta(\omega) = \frac{\epsilon''(\omega)}{\epsilon'(\omega)} = \frac{c''(\omega)}{c'(\omega)} \quad (5)$$

However in such a case information on some important dielectric parameters such as absolute dielectric loss and relative permittivity in high frequency cannot be obtained.

III. FORMULATION OF SOM AND SVM ALGORITHMS

This section briefly describes the formulation of SOM and SVM algorithms. The detailed derivations and implementations of SOM and SVM algorithms for transformer insulation diagnosis can be found in the authors' previous publication [5]-[7].

A. *Self-organizing map (SOM)*

SOM algorithm is a clustering algorithm. It transforms the data in a high dimensional input space to a series of processing units, which are scatted over a low dimensional feature space. The data points in the original input space are represented by these processing units in that the distance and proximity relationships are preserved as much as possible [10].

Given a sequence of input data $\mathbf{X} = [\,\mathbf{x}_1, \dots, \mathbf{x}_N\,]$, SOM is trained iteratively to transform data points in $\mathbf{X}$ to feature space such that the neighbouring data points in the input space are mapped into processing units that are neighbouring in the feature space. Each processing unit is represented by a weight vector $\mathbf{m}_i = [\alpha_i^1, \alpha_i^2, \cdots, \alpha_i^D]$, where D is equal to the dimension of the input data. The Euclidian distance between each input data $\mathbf{x}_k$ and the weight vector of each processing unit $\mathbf{m}_i$ is computed. And the weight vectors are updated [10]:

$$\mathbf{m}_i(t+1) = \mathbf{m}_i(t) + \alpha(t)h_{b_k,\,i}(t)\,[\,\mathbf{x}_k(t) - \mathbf{m}_i(t)] \quad (6)$$

where t is the iteration step, $\alpha(t)$ is the learning rate and $h_{b_k,\,i}(t)$ is the neighbourhood function, which decreases monotonically with increasing distance on the map grid.

B. *Support vector machine (SVM)*

The above SOM algorithm is capable of creating spatially organized "internal representations" and providing the visualization of relations amongst original data points. However, SOM is usually not effective for resolving the class ambiguity over all the regions of the state space. Consequently it may not be able to cope well in discriminating all patterns upon receiving new data. Therefore, in this paper SVM algorithm is employed due to its capability in constructing near perfect decision boundaries over all regions of the state space. SVM algorithm involves a trade-off between the accuracy attained on the training data and the "capacity" of prediction on new data without error [11].

Assuming there are N samples $\mathbf{X} = [\,\mathbf{x}_1, \dots, \mathbf{x}_N\,]$ and each sample belongs to one of the T independent categories $\{\,y_1, \dots, y_T\}$, the SVM algorithm is tasked to correctly assign each sample to its corresponding class. SVM algorithm transforms dataset $\mathbf{X}$ from the original data space $\Re^m$ to a higher dimensional feature space $\mathcal{F}$ through $\mathbf{h} = \emptyset(\mathbf{x})$. It then searches for an optimal separation hyper plane in that feature space by solving a quadratic programming (QP) problem [11]:

$$\text{Maximize} \quad \sum_{k=1}^{N} \boldsymbol{\alpha_k} - \frac{1}{2}\sum_{\mathbf{k=1}}^{\mathbf{N}}\sum_{\mathbf{j=1}}^{\mathbf{N}} \boldsymbol{\alpha_k}\,\boldsymbol{\alpha_j} y_k y_j \mathbf{h_k h_j} \quad (7)$$

$$\text{Subject to} \quad \sum_{k=1}^{N} \boldsymbol{\alpha_k}\mathbf{h_k} = 0 \quad 0 \le \boldsymbol{\alpha_k} \le C \quad k = 1, \dots, N \quad (8)$$

where α_k is the Lagrange multiples, and C is the regularization parameter which balances the margin maximization and classification violation. After obtaining the optimal hyper plane, SVM algorithm can predict the class label for a new data sample $\mathbf{x}_*$:

$$z^* = \mathrm{sign}\{\sum_{k=1}^{N_s} \boldsymbol{\alpha_k} y_k \mathbf{h_k} \cdot \mathbf{h}_* + b\} \qquad (9)$$

where N_s is the number of support vectors.

IV. CASE STUDIES

In this section, SOM and SVM algorithms are applied to interpret the measurement data on a number of field transformers, which information are provided in Table I.

TABLE I
FIELD TRANSFORMERS INFORMATION

Transformer	Power (MVA)	Voltage (kV)	Manufacture year
T1	375	330	2008
T2	133	330	1974
T3	530	390	1981
T4	45	23	1982
T5	45	23	1982

A. DGA Interpretation for Transformer Insulation Diagnosis

The SVM algorithm is applied to recognize normal operating and faults conditions for the above transformers. A dataset consisting of 390 DGA records provided by a utility company is used as training dataset for the SVM algorithm. The gas concentrations, i.e., C_2H_2, C_2H_4, CH_4, H_2 and C_2H_6 in volume are used as discriminated features (input) of the algorithm, i.e. the input vector for training the algorithm is a data array with dimensions of 390×5.

In SVM algorithm, the radial-based function (RBF) kernel $K(x_i, x_j) = e^{-\gamma(\|x_i - x_j\|)^2}$ is adopted. Once the optimal parameters of (C, γ) is found, tenfold cross-validation is performed on the above training dataset. The classification accuracy of the tenfold cross-validation is 88.9% (standard deviation ±1.3%). The trained SVM model is applied to recognize the fault conditions of the field transformers listed in Table I.

The SVM recognition result indicates that transformers T1, T2, T4, and T5 are in normal operation condition. Transformer T3 has 88% chance of normal operating condition and 12% chance of lower to medium range thermal fault. This implies that T3 might be slightly deteriorating toward thermal fault from its normal operating condition. The PDC interpretation results presented in the next section will reveal that the oil insulation of T3 is more degraded compared to that of other four transformers T1, T2, T4, and T5.

B. PDC Interpretation for Transformer Insulation Diagnosis

The PDC measurements were conducted for the above five transformers T1 to T5. The tests were carried out at the charging voltage of 200 V_{dc} and with 10^4 s charging periods. Fig.2 plots the polarization currents of T1 to T5. The measured currents of each transformer in Fig.2 were normalized by the corresponding testing voltage and geometric capacitance values. Such normalization provides an equivalent base of geometry and charging voltage for easier comparison between different transformers. The significant current drop of transformer T1 at initial stage in Fig.2 might be due to the measurement error.

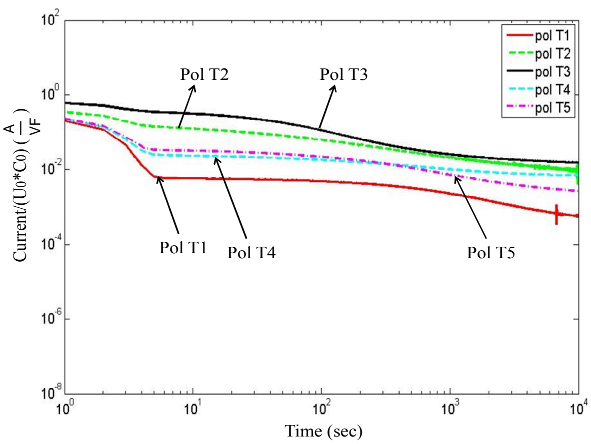

Fig.2 Polarization currents of transformers T1 to T5.

It can be observed from Fig.2 that overall polarization current of T1 is lower than that of T2 to T5. This implies that the overall insulation condition of T1 is better than that of T2, T3, T4 and T5. Therefore, in this case study T1 is selected as the *reference transformer* for diagnosing the insulation condition of T2 to T5 (named as the *testing transformers*)

As mentioned in Section II, in this paper the depolarization current is obtained by deducting the conductivity current from the polarization current. The PDC interpretation process starts with computing RC parameters and oil and paper conductivities from the polarization and depolarization currents of the reference transformer T1 (refer to Fig.1). The RC values of the two largest branches and paper conductivity are selected as features to represent the condition of paper insulation while the RC values of the two smallest branches and oil conductivity are selected as features to represent the condition of oil insulation [7]. These parameters are then processed as follows.

1. For oil insulation: applying a scalar coefficient $\alpha = 1, 2, ...,$ etc to the resistance and capacitance of the two smallest RC branches and oil conductivity.

$$\begin{aligned} R'_{-1} &= \frac{1}{\alpha} \times R_{-1}, \quad R'_{-2} = \frac{1}{\alpha} \times R_{-2} \\ C'_{-1} &= \alpha \times C_{-1}, \quad C'_{-2} = \alpha \times C_{-2} \\ \sigma'_{oil} &= \alpha \times \sigma_{oil} \end{aligned} \qquad (10)$$

2. For paper insulation: applying a scalar coefficient $\beta = 1, 2, ...,$ etc to the resistance and capacitance of the two largest RC branches and paper conductivity.

$$\begin{aligned} R'_1 &= \frac{1}{\beta} \times R_1, \quad R'_2 = \frac{1}{\beta} \times R_2 \\ C'_1 &= \beta \times C_1, \quad C'_2 = \beta \times C_2 \\ \sigma'_{paper} &= \beta \times \sigma_{paper} \end{aligned} \qquad (11)$$

In the above equations, subscripts 1 and 2 refer to the two largest RC branches and subscripts -1 and -2 refer to the two smallest RC branches of the equivalent circuit, σ_{paper} and σ_{oil} are the conductivities of paper and oil, respectively.

To simulate different insulation conditions with respect to that of the reference transformer, in Equations (10) and (11) the scaling coefficients α and β are assigned different values, which include (1) α=1, 2, 3,…, etc for the cases in which the oil insulation is worse than that of the reference transformer; (2) β=1, 2, 3 …, etc for the cases in which the paper insulation is worse than that of the reference transformer. Consequently, a dataset can be generated consisting of a number of data points describing various insulation conditions. This dataset is used to train the SVM algorithm. The trained SVM model is then applied to assess the oil and paper insulation conditions of testing transformers.

To assess the insulation condition of a testing transformer, the representative parameters of this transformer including RC parameters and oil and paper conductivities are firstly calculated from its PDC measurement. These parameters are then fed into the above trained SVM model, which will be applied to assess the insulation condition of this test transformer. By adopting the same reference transformer, the insulation conditions of different testing transformers can be compared.

However, for a testing transformer, its insulation condition might be varying in a very large range compared to the insulation condition of the reference transformer. Consequently, the exact values of the above scaling coefficients α and β in Equations (10) and (11) cannot be readily decided for SVM algorithm. Therefore, SOM algorithm is firstly employed to reveal the insulation condition of the testing transformer in a certain range with respect to the insulation condition of the reference transformer. Fig.3 shows SOM clustering result for insulation condition of transformer T2 with the reference to that of transformer T1. In Fig.3, each cell corresponds to the data points that have similar property (i.e. similar insulation condition) and the numbers in brackets are the number of data points in that cell [10].

From Fig.3 it can be seen that the paper insulation of T2 is in the regions of C and D, which means T2 paper insulation is around 15 to 20 times worse than the paper insulation of the reference transformer T1. The SVM algorithm is then applied to make further classification with probability in the above two regions. The SVM result indicates that T2 paper insulation has about 70% chance of around 15 times and about 30% chance of around 20 times worse than that of T1. Same process is applied to investigate the paper and oil insulation conditions of other transformers. Table II summarized the SOM and SVM diagnosis results on the insulation condition of transformers T2 to T5.

As shown in Table II, SVM classification result indicates that the oil insulation of T3 has about 90% chance of around 15 times worse than the paper insulation of T1. The oil insulation of T2, T4, and T5 has about 60% or 70% chance around five times worse than that of T1. Therefore, it can be concluded that the oil insulation of T3 is worse than that of T2, T4, and T5. This also coincides with DGA result as presented in the previous section, which indicates T3 might be slightly deteriorating toward thermal fault whereas T2, T4, and T5are in normal operating condition.

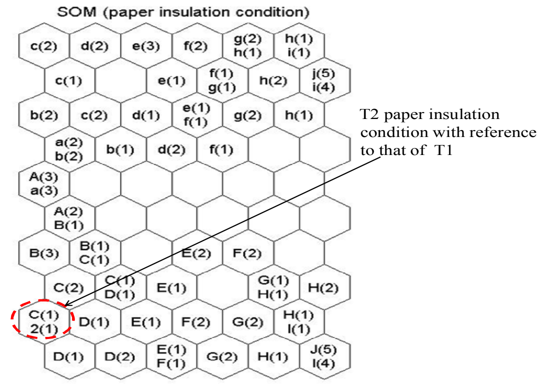

Fig.3 SOM clustering results of paper insulation of T2 with reference to that of T1. Alphabets A – J refer to the cases in which the paper insulation of testing transformer is around 5, 10, …, 50 times worse than that of reference transformer. Alphabets a – j refer to the cases in which the paper insulation of testing transformer is around 5, 10, …, 50 times better than that of the reference transformer (Note: "2" refers to the paper insulation of T2. The numbers in brackets are the number of data points in that case).

TABLE II
SOM AND SVM DIAGNOSIS RESULTS ON INSULATION CONDITION OF TRANSFORMERS T2 TO T5 (WITH REFERENCE TO THAT OF TRANSFORMER T1)

Insulation condition	SOM and SVM Diagnosis Results (with reference to transformer T1)
Oil (T2)	About 60% chance of around 5 times worse
Oil (T3)	About 90% chance of around **15** times worse
Oil (T4)	About 70% chance of around 5 times worse
Oil (T5)	About 70% chance of around 5 times worse
Paper (T2)	About 70% chance of around **15** times worse
Paper (T3)	About 70% chance of around **10** times worse
Paper (T4)	About 70% chance of around 5 times worse
Paper (T5)	About 65% chance of around 5 times worse

From Table II it can also conclude that the paper insulation of T4 and T5 are better than that of T2 and T3: the paper insulation of T4 and T5 has about 70% chance of around five times worse than that of T1; the paper insulation of T2 has about 70% chance of 15 times worse than that of T1; and the paper insulation of T3 has about 70% chance of around 10 times worse than that of T1. The FDS interpretation results presented in the next section will reveal that transformers T2 and T3 have higher moisture content in the paper insulation compared to transformers T4 and T5.

C. FDS Interpretation for Transformer Insulation Diagnosis

The moisture contents have significant impact on transformer paper insulation. SVM algorithm is also applied to estimate the moisture contents in the above transformers.

In FDS interpretation, a so-called X-Y model as depicted in Fig.4 [4] is used. A database containing data on dielectric properties of well-defined pressboard with varying water contents and temperatures is firstly formed. And then the dielectric response of composite duct insulation for different combination of X and Y is computed. Utilizing these computation results, a trial and error method can be applied to estimate the moisture contents in a field transformer from its

FDS measurement [12]. However, this paper adopts SVM algorithm to estimate moisture contents in the field transformers listed in Table I.

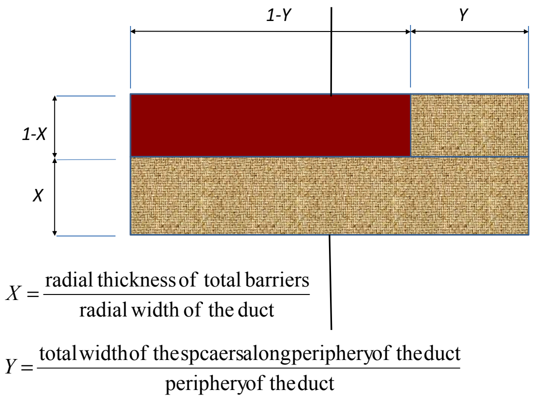

Fig. 4 X-Y representation of transformer main insulation [4].

The database used in the following analysis is developed by one of the authors of this paper [12]. It is formed from the frequency dependent dielectric measurements of well-characterized pressboard samples and contains complex permittivity values of pressboard with four different moisture contents (i.e. 1%, 2%, 3% and 4%) at three different temperature levels (i.e. 20 °C, 50 °C and 80 °C). A fitting algorithm is developed to further derive the complex permittivity values for pressboard at other moisture contents and temperature levels.

Based on the X-Y model, the above database is used to generate training dataset for SVM algorithm. The training dataset consists of complex permittivity of transformer paper insulation at different moisture contents, temperatures and combinations of X and Y. In the computations the relative permittivity of oil is set to 2.2 and the oil conductivity is estimated from PDC measurements. After training, the trained SVM model is applied to estimate moisture contents in paper insulation of the transformer based on its FDS measurement. The discrimination feature for SVM algorithm is the frequency dependent loss factor calculated from FDS measurement as depicted in Fig.5.

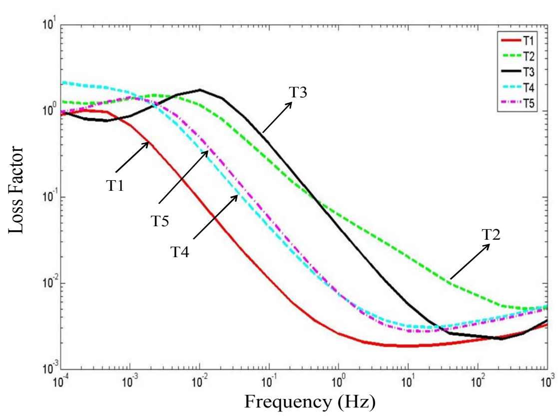

Fig.5 Loss factors of transformers T1 to T5.

The SVM algorithm estimated moisture contents in the paper insulation of transformers T1 to T5 are summarized in Table III.

TABLE III
SVM ALGORITHM ESTIMATION RESULTS ON MOISTURE CONTENTS IN PAPER INSULATION OF TRANSFORMERS T1 TO T5

Transformer	SVM Estimation Results
T1	2.5% moisture contents
T2	4.5% moisture contents
T3	4.5% moisture contents
T4	3.5% moisture contents
T5	3.5% moisture contents

From Table III, it can be observed that the estimated moisture contents in T2 and T3 paper insulation are 4.5% whereas the estimated moisture contents in T1 paper insulation is 2.5%. This coincides with the PDC results (Table II), which indicates that paper insulation of T2 and T3 is worse than that of T1. The moisture contents for both T4 and T5 are estimated as 3.5%. This also coincides with PDC results (Table II), which indicates that the paper insulation of T4 and T5 are better than that of T2 and T3.

Combined the interpretation results from DGA, PDC and FDS, the diagnosis on the insulation condition of transformers T1 to T5 can be drawn: (1) the overall insulation condition of T1 is better than that of T2 to T5; (2) the paper insulation of T4 and T5 is better than that of T2 and T3; and (3) the oil insulation of T3 is worse than that of T1, T2, T4, and T5, and T3 might be slightly deteriorating toward thermal fault from normal condition.

V. Conclusion

This paper developed machine learning algorithms, namely SOM and SVM for transformer insulation diagnosis. The key advantage of these algorithms is their capability of acquiring the knowledge of underlying statistical dependency between archived data and the conditions of corresponding transformers, and making use of such knowledge to assist in transformer insulation diagnosis. The case studies demonstrated the applicability of the developed algorithms. The results of case studies also show some correlations amongst different measurement techniques in transformer insulation diagnosis.

Current research work is focusing on incorporating more DGA, PDC and FDS results in enhancing the training database for the machine learning algorithms. Efforts are also being made to further investigate cross-correlation that may exist between DGA, PDC and FDS techniques.

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