Cluster Classification of Partial Discharges in Oil-impregnated Paper Insulation

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***Abstract*—Recognition of multiple partial discharge (PD) sources in high voltage equipment has been a challenging task until now. The work reported here, aims to recognize multiple PD sources in oil-impregnated paper using Cluster Analysis (CA) and Fuzzy Logic (FL). The typical sources of PD in transformer are identified and the corresponding single source PD defect laboratory models are fabricated. From the measured PD signals, the necessary statistical parameters are extracted by applying CA for classification. A Fuzzy based algorithm has been developed to recognize single source PDs. The developed algorithm has also been applied to recognize multiple PD sources.**

***Index Terms*—PDs, multiple PD sources, oil-impregnated paper insulation, PD classification, cluster analysis**

I. Introduction

The reliability of the power system depends on the insulation characteristics of the power equipment connected in the system. As many of the reported failures of the power equipment are due to the insulation failure, a continuous assessment of the state of the insulation becomes necessary. The PD monitoring has been recognized as one of the major insulation monitoring methods. The characteristics of the partial discharge signals generated by a particular insulation system may be used as a fingerprint for identifying the different PD sources [2].

In general, the internal insulation of power equipment is degraded due to various aging effects such as, thermal stress, chemical reaction and electrical stress, etc., over the service years. In addition, the defects in the insulation during manufacturing may also decrease the lifetime of the insulation. In the case of power transformer, oil-impregnated paper and pressboard are used as major insulations. A number of investigations have been conducted to determine the partial discharge characteristics of new and aged oil-impregnated paper insulation in Power transformers [1]. As the sources of PD in a transformer insulation system are different, like corona, surface, cavity, floating and wedge, the corresponding PD signals will also have their own characteristic features. These characterizing features are expressed in terms of the statistical parameters and phase resolved PD patterns (image) and they used for classification of the PD types and locations.

A number of different approaches has been attempted in PD pattern recognition for over a decade. Form templates for different PD patterns and template matching tool were utilized as recognition tools for multiple PD patterns [3]. Image and statistical features of different discharge sources are used as recognition parameters for multi source PD recognition through feed forward back propagation neural network [4]. Fuzzy logic artificial intelligence routine method is used to discriminate among internal, surface and corona PD, and influence of external activities are also reduced [5]. The different cavity sizes in high-density polyethylene are recognized using Fuzzy Decision Tree approach [6]. Combination of cluster analysis (CA) with neural network (NN) or fuzzy logic (FL) is the best-suited method to identify PD sources in real world problems such as Condition Monitoring Multi Agent System [7] and Principle Component with Hierarchical Cluster Analysis [8].

In this work, a Cluster based algorithm is developed to classify the single source PD using the developed PD defect models and it is utilized for PD classification of both single and multiple PD sources.

II. Samples and Electrode Configuration

PD defect simulation based on laboratory fabricated PD defect models, as in power equipment, has been the major adopted procedure for PD pattern recognition for over a decade. Based on the report of the transformer faults, various authors reported different types of single PD sources with different electrode configuration with Kraft paper and press board [9, 10 and 11]. From the various PD defect models, the following five typical single PD sources in oilpaper composite insulation are modeled.

A. Oil Corona

In transformers, the discharges occur due to sharp edges in the composite insulating medium of oil and paper. Presence of conductive particles in oil, which would have originated from the manufacturing process, mechanical distortion or replacement of oil and sharp edges of grounded parts in the transformer tanks also act as sources of the corona.

B. Surface Discharge

Surface discharge arises in cases where the maximum electrical field occurs along the interface of the two dielectric media resulting in the deterioration of the insulating material, in the case of transformer at the interface between paper and oil. Sometimes it may be due to the trapped bubble of the insulation or the de-lamination of the pressboard layers.

C. Cavity Discharge

Cavities can appear due to bad impregnation of oil in paper, mechanical damage during transportation or due to the ageing of the paper insulation.

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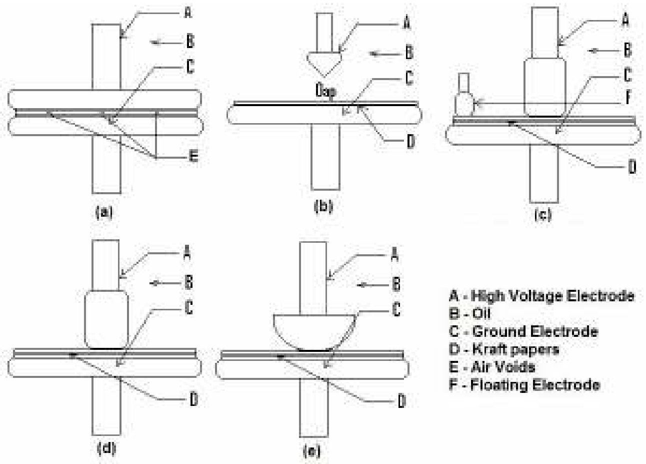

Figure 1. PD defect Models (a) Cavity Discharge, (b) Corona Discharge, (c) Floating Discharge, (d) Surface Discharge, (e) Oil Wedge.

D. Oil Wedge

Discharges across the corners of the coil under the wedge can lead to significant damage to the insulation.

E. Floating Discharge

Badly earthed objects near the high voltage circuit would produce this type of discharges [12].

III. Conventional PD Measurement System

The conventional experimental setup for PD measurement is shown in Fig.. 2. The utilized PD test circuit for measurement and calibration procedure follows the IEC-60270 Standard [13]. The specimens with different PD defects are used as test specimen in the PD test circuit.

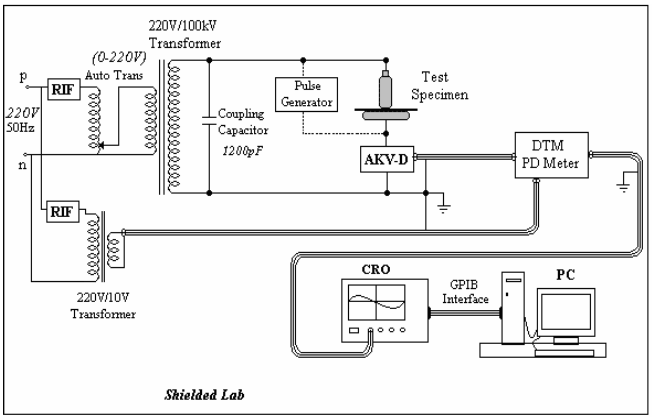

Figure 2. Conventional PD measurement system.

A MWB make PD measurement system consists of a 100 kV high voltage transformer, discharge free Coupling capacitor (1200 pC), measuring quadruple (RLC) and a PD detector (DTM). The PD signals are acquired using a Digital Storage Oscilloscope (Agilent 54621A) transferred to a personal computer using IEEE 488.2 GPIB card. The PD meter is calibrated by injecting 50 pC PD pulses across the test specimen (PD models) using standard PD pulse generator (PDG) and then the ambient pC level is noted. The input voltage is increased with the help of the autotransformer until the inception of PD (PDIV).

The voltage is further increased to 1.6 times PDIV and the PD discharges over 25 power cycles (80,000 data points per power cycle) are acquired and transferred to PC through GPIB. For all the five individual PD models, PD data are acquired 20 times and used as reference discharge samples.

IV. Statistical Analysis

An algorithm has been developed to extract the necessary statistical parameters from the measured reference PD sample data using statistical tool in MATLAB. Each reference discharge sample data with 25 data cycles is segregated into 25 single data cycle, each cycle period is divided into 800 windows and the corresponding ***peak*** and ***mean*** PD distributions are found out. For each type of PD, ***skewness+***(Sk+)*,* ***skewness-***(Sk-)*,* ***kurtosis+***(Ku+)*,* ***kurtosis-***(Ku-) and ***cross correlation*** (CC) for both mean and peak PD distribution are considered for further analysis as recognition vectors for Cluster analysis.

V. PD Pattern Classification

Fuzzy clustering analysis is a technique for statistical procedures designed to identify groups of observations that have similar attributes. The objective of cluster analysis is to group the observed data in such a way that the entities within a cluster are more similar to each other than to those in other clusters. A Fuzzy C-Means Clustering (FCM) based PD pattern recognition method is proposed and implemented using MATLAB fuzzy logic toolbox. The proposed algorithm is explained below:

1. Formation of clusters among the reference PD recognition vectors;
2. Calculation of the centers of clusters using FCM technique;
3. Identification of the significant statistical parameter pairs for better recognition;
4. Computation of classification tree by decision tree approach;
5. Extraction of the membership functions from the classification tree;
6. Formation of the fuzzy rules for pattern classification using membership functions;
7. Testing of the above developed algorithm for known reference PD patterns;
8. Identification of different discharges from unknown PD sources.

From the above mentioned five statistical parameters of q mean PD distribution, ten clusters (sub plots) (Sk-:Ku-), (Sk-:Ku+), (Sk-:Sk+), (Sk-:CC), (Sk+:Ku+), (Sk+:Ku-), (Sk+:CC), (Ku-:Ku+), (Ku-:CC), (Ku+:CC) are formed. The similar subplots are formed for q max PD distribution.

FCM technique is used to identify the significant statistical parameters to be used for classification of discharges based on centers of the clusters. From the analysis, q mean PD clusters of (Sk-: Ku-), (Sk-: CC), (Sk+: Ku+), (Sk+: CC), (Ku-: CC), and (Ku+: CC) are identified as significant contributing parameters for better classification and they are shown in Fig. 3.

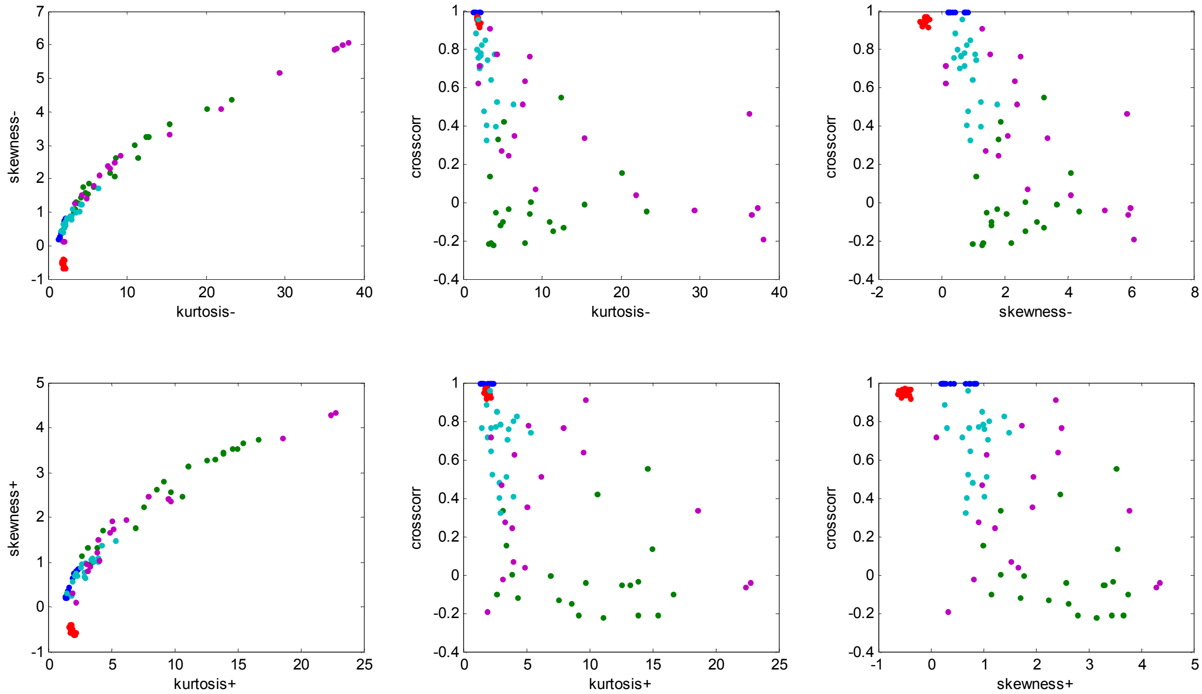

Figure 3. Identified Cluster sub plots of q mean PD distribution.

For classification, different methods like linear Discrimination analysis, Quadratic Discrimination analysis, Decision tree method and Simplified Decision tree method are tried and the misclassification error is found to be minimum with decision tree method. Table I gives the misclassification error for the Sk- and CC recognition vector pair.

TABLE I. MISCLASSIFICATION ERROR FOR SK- AND CC

Sl. No.	Classification Methods	Misclassification Error in Percentage %
1	Linear Discriminant Analysis	18
2	Quadratic Discriminant Analysis	11
3	Decision Tree Method	03
4	Simplified Decision Tree Method	11

A. Decision Tree Method

Decision trees are being immune to noisy data. It is capable of learning disjunctive expressions directly from the raw data. The above would influence the method used widely in practical applications. A decision tree is a tree data structure consisting of a root node, decision nodes and leaf nodes. C4.5 algorithm is used to construct the decision tree [14]. The decision tree consists of a root node, decision nodes and leaf nodes. The C4.5 algorithm can create compact rules from its decision tree after pruning the tree, but we found them too compact for our purposes. Our system operates on the un-pruned tree obtained from C4.5. The process of creating rules is quite simple. A complete depth first search is performed on the decision tree and every time a path reaches a leaf, a rule is created. The class of the rule is the class of the leaf. For example, there would be twenty-four rules extracted from the classification tree of Sk-, CC.

From the chosen six recognition vector pairs, the corresponding six Classification trees are formed. The output classes are denoted as cavity, float, corona, surface and wedge. The tree classifies the classes from the root node by sorting them upwards to particular leaf nodes, which identifies different types of discharges. Fig. 4 shows the classification tree of Sk- and CC of mean PD distribution. In the tree, floating discharges are separated in first level leaf node based on Sk-. Second leaf node is the cavity discharge, based on Sk- and CC. Other discharge types are classified as the tree spreads downwards. The same procedure is repeated for all the other five recognition vector pairs.

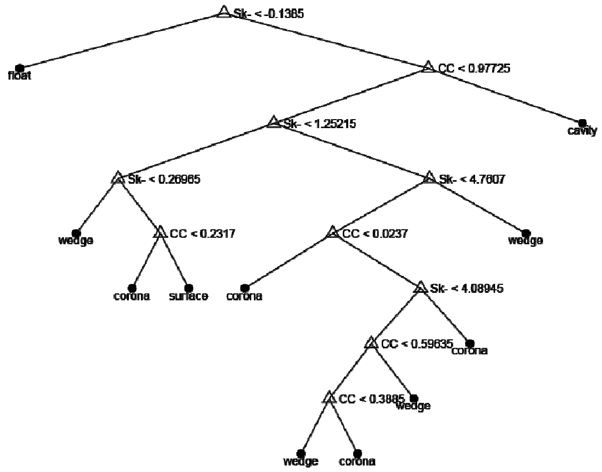

Figure 4. Classification tree for Sk- and CC.

B. Rules Construction

The decision tree is converted into a set of crisp rules such as

"IF Sk- < 0.26965 and CC < 0.2317
THEN **Corona discharge**
ELSE
Surface discharge"

Sets of crisp rules are formed from all the leaf nodes in the classification tree [15]. This is repeated for all the classification trees. The recognition algorithm is formed by using the above extracted crisp rules. The appropriate weight is given for each rule based on the recognition percentage obtained in each classification leaf nodes. The above-developed algorithm is checked for classification of different single sources and multiple PD sources, other than the reference five single PD models.

VI. MULTIPLE PD RECOGNITION

The detected PD in on-line PD monitoring of HV apparatus can be due to multiple sources. Therefore, separation of PD discharge sources is playing a vital role in the on line PD monitoring. In this work, a laboratory model for multiple PD in oilpaper composite insulation is developed. The model with two PD sources with void and surface is fabricated with oilpaper composite insulation as shown in the Fig. 5. The voids are created by punching the papers and the surface discharge is created by means of the extension of the ground electrode over the surface of the paper.

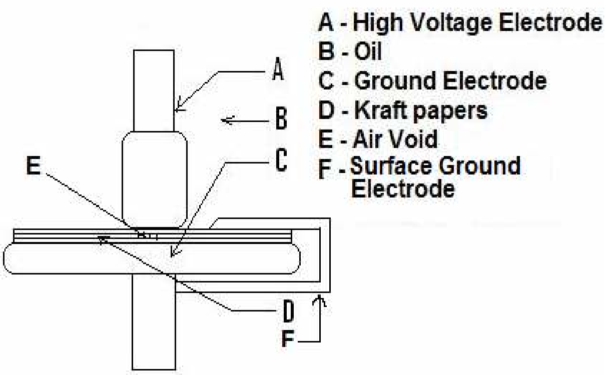

Figure 5. Multiple PD Source Cavity and Surface Discharges.

Discharges due to cavity alone were noticed initially, followed by surface discharges with increase in voltage. The PD signal with both the discharges is acquired and the necessary statistical parameters are extracted.

In this method, the classification efficiency for single source PD identification is more than 96%. Table II shows the classification for cavity-surface multiple discharges. The classification shows the cavity discharges as 72% and the surface discharges as 28%.

TABLE II. CLASSIFICATION OF MULTIPLE PD SOURCE CAVITY-SURFACE DISCHARGES

Sl. No.	Discharge types	Classification in %				
		Cavity	Corona	Floating	Surface	Wedge
1	Cavity	72	0	0	0	0
2	Corona	0	0	0	0	0
3	Floating	0	0	0	0	0
4	Surface	0	0	0	28	0
5	Wedge	0	0	0	0	0

Using the formulated six sets of membership functions obtained for single PD sources, the multiple discharges have been accurately classified.

VII. CONCLUSION

The common sources of PD in transformers are identified as cavity, corona, surface, floating and wedge. PD defects laboratory models with single PD sources are fabricated and the PD signals are measured. For all the single PD sources the relevant statistical features are calculated and discussed the inference between them using FCM. An algorithm has been developed to classify single PD sources on Decision Tree approach. Thus, formulated membership functions are successfully used to classify the unknown PD of both single and multiple sources.

REFERENCES

[1] L. E. Lundgaard, W. Hansen, D. Linhjell, T. J. Painter, "Aging of oil-impregnated paper in power transformers", IEEE Transactions on Power Delivery, Vol. 19, pp. 230-239, 2004.

[2] F.H. Kreuger et. al., "Classification of Partial Discharges", IEEE Transactions on Electrical Insulation, Vol. 28, No. 6, pp. 917-931, December 1993.

[3] A. Krivda and D. Birtwhistle, "Recognition of Multiple Partial Discharge Patterns", High Voltage Engineering Symposium, 22-27 August 1999 Conference Publication No. 467,O IEE, 1999.

[4] D. Suresh, "Feature Extraction for Multi Source Partial Discharge Pattern Recognition", IEEE Indicon 2005 Conference, Chennai, India, 1-13 Dec. 2005.

[5] A. Cavallini, G. C. Montanari, and F. Puletti, "Partial Discharge Analysis and Asset Management: Experiences on Monitoring of Power Apparatus", IEEE PES Transmission and Distribution Conference and Exposition, Latin America, Venezuela, 2006.

[6] T. K. Abdel-Galil, R. M. Sharkawy, M. M. A. Salama and R. Bartinikas, "Partial Discharge Pattern Classification Using the Fuzzy Decision Tree Approach", IEEE Transactions on Instrumentation and Measurement, Vol. 54, No. 6, pp. 2258-2263, December 2005.

[7] S. M. Strachan, S. Rudd, S. D. J. McArthur and M. D. Judd, "Knowledge-Based Diagnosis of Partial Discharges in Power Transformers", IEEE Transactions on Dielectrics and Electrical Insulation, Vol. 15, No. 1, February 2008.

[8] Tadeja Babnik, Raj K. Aggarwal and Philip J. Moore, "Principal Component and Hierarchical Cluster Analyses as Applied to Transformer Partial Discharge Data With Particular Reference to Transformer Condition Monitoring", IEEE Transactions on Power Delivery, 2008.

[9] C. R. Li, Wei Wang, Z. G. Tang, Y. S. Ding "PD Pattern Recognition in Transformer by Using UHF Technology", Conference Record of the 2004 IEEE International Symposium on Electrical Insulation, Indianapolis, IN USA, 19-22, September 2004.

[10] Jiang Lei, Jin Xianhe, "Partial Discharge Pattern Recognition of Insulation Models of Power Transformer", Proceedings of the 6th International Conference on Properties and Applications of Dielectric Materials, Xi'an Jiaotong University, China, June 21-26, 2000.

[11] Feliciano Massingue, Sander Meijer, Pantelis D. Agoris, Johan J. Smit and Jose Lopez-Roldan, "Partial Discharge Pattern Analysis of Modeled Insulation Defects in Transformer Insulation", Conference Record of the IEEE International Symposium on Electrical Insulation, 2006.

[12] F.H. Kreuger, Partial Discharge Detection in High-Voltage Equipment, Butterworth & Co, 1989.

[13] IEC 60270, Partial Discharge Measurements, 3rd edition, March 2001.

[14] J. R. Quinlan, "C4.5 Programs for Machine Learning", Morgan Kaufmann, 1993.

[15] L. O. Hall and P. Lande, "Generating fuzzy rules from data" in Proc. 5th IEEE Int. Conf. Fuzzy Systems, vol. 3, pp. 1757–1762, Sep. 8–11, 1996.