Partial Discharge Pattern Classification Using the Fuzzy Decision Tree Approach

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***Abstract*—Partial discharge (PD) measurement is a proven flaw detection technique for finding cavities that are defects in the insulating material. In this paper, a novel approach for the classification of cavity sizes, based on their maximum PD charge transfer-applied voltage (ΔQ-V) characteristics using a fuzzy decision tree system, is proposed. The (ΔQ-V) partial discharge patterns for different cavity sizes are represented by features extracted from their pulse shapes, and the classification rules are directly extracted from the data using the decision tree. The decision rules obtained from the decision tree are then converted to the fuzzy IF-then rules, and the back-propagation algorithm is utilized to tune the parameters of the membership functions employed in the fuzzy classifier. The neuro-fuzzy classification technique is shown to provide successful classification of void sizes in an easily interpretive fashion.**

***Index Terms*—Cavity size classification, decision tree, fuzzy logic, machine learning, partial discharges.**

I. Introduction

THE measured PD intensity in electrical power apparatus and cables is mainly dependent upon the size and type of the discharge source and the energy loss within. The recorded PD patterns of the pulse amplitude and epoch (phase) distributions are also contingent upon the cavity's geometry and location within the insulating system structure. For example, in cables, the PD pulse patterns will differ depending upon whether a given cavity is enclosed entirely within the dielectric or is adjacent to a conducting surface [1]. This dependency also applies to the form or shape of the discharge current pulses themselves. In addition, the recorded PD pulse distribution and pulse forms will be affected by the attenuation characteristics of the cable. Consequently, the PD pulse distribution pattern and the shape of the emanating pulses characterizing a given cavity further away from the cable end (where PD measurements are carried out) will appear different from those of an identical cavity of the same size and geometry, which is situated in the vicinity of the cable end. In addition, if the size of the discharging cavities within the cable differs only slightly, there may be considerable difficulty in differentiating between the two cavities, even if their displacement from the measuring cable end is equidistant. It is, therefore, of great practical importance to examine and ascertain carefully the PD pattern and classification capabilities of the proposed intelligent algorithms, using idealized cavities with well-controlled dimensions and geometry before those pattern recognition systems are applied in practice on actual cable specimens. The specimens may contain a distribution of cavity sizes with differing locations along the cable that may give rise to very complex overall discharge pulse shapes and distributions.

Throughout the last decade, there has been appreciable effort focused on the application of statistical analysis methods and neural networks (NNs) on partial discharge pattern recognition so as to render the latter task less subject to interpretational errors by human observers [2]–[13]. Successful attempts were described employing artificial NNs, utilizing a multilayer perceptron technique to distinguish between discharge pulse shapes as a function of void size and void surface electrode characteristics when comparisons of single discharge sources were made on a one-to-one basis [7], [11], [12]. However, it is apparent that because the cavity sizes in high voltage cables may be distributed over a wide range of values, the resultant PD pulse amplitude patterns will represent the superposition of all the individual pulse amplitude patterns of the discrete cavities. Meaningful interpretation of such complex patterns by a NN, which has been taught only to recognize individual pulse patterns of single discrete cavities, becomes substantially less feasible. Interpretational difficulties may arise even with a small number of cavities in cases where the few cavities involved are very close in size and the resultant pulse discharge patterns of the individual cavities exhibit only small differences in their respective discharge pulse amplitudes. Furthermore, NNs learn data via training examples and are incapable of giving explanations of the criteria upon which their decision-making is based.

In view of the foregoing pulse discharge pattern recognition difficulties, it may be advantageous to identify the PD pulse patterns in more vague, or at least less specific terms, such as describing void sizes in terms of being large, medium and small cavities. Generalizing the identification of PD pulse patterns in terms of a range of the cavity sizes producing the pattern, fuzzifies the approach to discharge pattern recognition. Such an approach necessarily involves the use of fuzzy logic systems.

Much research work in the area of machine intelligence is focused lately on integrating two or more intelligent techniques to obtain a hybrid model of improved numerical convergence or better classification capability [17]–[19]. The aim of the present work has been to go a step further in the application of a combined structure (decision trees in addition to a neuro-fuzzy technique) of more than one easily handled intelligent tool for the classification of void types based on PD patterns. This particular approach adopts a fuzzy inference system for PD pulse pattern recognition. The identification of the structure of the fuzzy

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classifier and the tuning of its parameters are the basic two steps required to build a fuzzy classification system. The structures of the fuzzy logic as well as the tuning of the parameters are usually done by the expert in the field. However, according to previous experience [14], it is difficult to identify such structure and tune the membership parameters by hand even for a moderate size system. The difficulty is readily circumvented in this work by means of a data driven approach for generating a set of inference rules, using pulse shape analysis in conjunction with a database for different cavity sizes [15]. This strategy combines the advantage of a rule-based system and minimizes the tedious work and time associated with adjustment of border values for the fuzzy system parameters. The proposed rule-based system can be easily modified to accommodate any change on the system parameters; and a fuzzy logic for easily interpreted PD pattern recognition is, thus, implemented.

In this paper, a two-step approach is proposed to build a fuzzy logic classifier. In the first step, the preprocessing stage, a decision tree infers the identification rules directly from the input data; and this is further utilized to identify the structure of the fuzzy logic classifier [16]. In the second step, the back-propagation algorithm is used to tune the parameters of the fuzzy logic classifier. The suggested method overcomes the difficulty of identifying the structure of the fuzzy logic classifier, and it also permits tuning the fuzzy logic rule parameters and renders it possible to build the system directly from the data, which means large savings in expert's effort and developing time. Meanwhile, it provides comparable results with previously implemented fuzzy techniques [14].

The remainder of this paper is organized as follows. First, the PD measurement procedure is detailed in Section II. In Section III, the extracted pulse shape features are given. An overview of inductive inference technique along with the description of the C4.5 algorithm is provided in Section IV. The fuzzy logic approach is introduced in Section V. The test results are discussed in Section VI, and, finally, Section VII concludes the paper.

II. Experimental Procedure

All test specimens were constructed of high-density polyethylene (HDPE), with the cylindrical cavities being formed by alignment and bonding of two HDPE sheets into which were drilled two symmetrical halves of the cylindrical cavity. The opposite ends of the cylindrical cavities, having a diameter of 2 mm and consisting of the HDPE dielectric, were placed 1.0, 1.5, or 2.0 mm apart. The flat sheet polymeric specimens, containing the artificial air filled cavities, were of an overall thickness of 6 mm and a surface area of 33 $\times$ 33 mm. Before commencement of the partial discharge tests, each specimen was inserted between two metallic electrodes and the entire electrode assembly was submerged in transformer oil in order to prevent the occurrence of extraneous discharges at the edges of the electrodes. The pulse discharge patterns were obtained using metallic (chrome plated brass) electrodes for the three cavity depths; however, measurements were also performed on a 1 mm cavity with dielectric (acrylic) electrodes. All discharge patterns were obtained at the discharge inception voltage, the

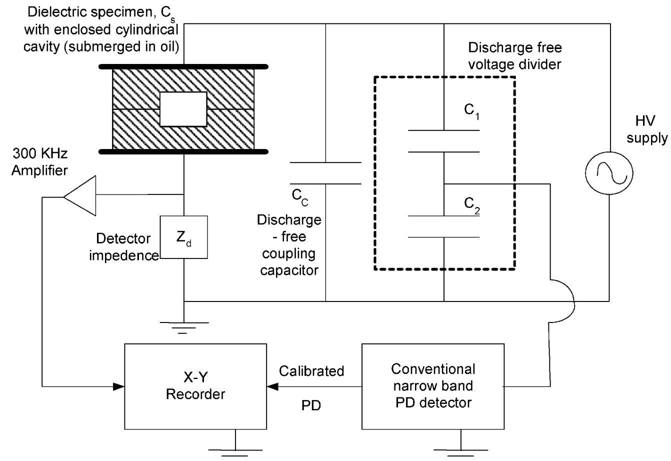

Fig. 1. Schematic diagram for the PD pulse detection circuit.

latter being defined as the value of the applied voltage at which the discharges once initiated does not disappear with time.

A commercial partial discharge detector, having an overall bandwidth of 40 to 400 kHz was employed to obtain the maximum apparent charge transfer, $\Delta \mathrm{Q_m}$, associated with the discrete discharge pulses as a function of the applied 60 Hz sinusoidal voltage. A schematic circuit diagram of the overall experimental arrangement is shown in Fig. 1, incorporating the cylindrical cavity specimen [20]. The PD detection circuit was of the RLC type, having a resonant frequency of 66 kHz with critical damping to provide the necessary detected unidirectional discharge pulse waveform. Representative discharge pulses, characterizing each electrode system and cavity depth were recorded and stored for further accessibility and analysis.

III. Feature Extraction

The apparent charge, $\Delta \mathrm{Q}$, has been widely used for quantizing partial discharge measurements, because it is directly related to the energy in the discharge as well as the size of the defect. Moreover, the apparent charge, $\Delta \mathrm{Q}$, can be readily measured by a PD detector or an oscilloscope using a suitable calibration procedure. In this work, the features extracted, concerning each characteristic pulse form, consisted of: 1) the peak apparent charge transfer, $\Delta \mathrm{Q_m}$ (equivalent to the calibrated pulse PD peak value), 2) the rise time $\mathrm{t_1}$ (ns), 3) the fall time $\mathrm{t_2}$ (ns), 4) the area under the partial discharge current pulse $\mathrm{A_1(A.s)}$, and, finally, 5) the pulse width

$$\text{where, } A_1 = \int_{t_1}^{t_2} i(t)dt \quad \mathrm{A.s.} \tag{1}$$

The foregoing PD pulse attributes, in addition to being dependent upon the cavity size, nature of inner surfaces and gas within, will be strongly affected by the physical and chemical degradation changes within the cavity that may alter the surface conductivities of the cavities with attending changes in the electric field within the cavities. These effects directly influence the rise time, amplitude, shape and phase of the discharge pulses; thus, there is a strong link between the pulse shape variation in a given train or segment of PD pulses and its corresponding pulse-height and pulse-shape distribution characteristics. Accordingly, pulse discharge pattern recognition may equally well be performed either in terms of discharge pulse shapes or discharge pulse distribution characteristics. The pulse shape feature approach offers an advantage in that the pulse output of the conventional discharge detector may be analyzed directly, without any further need of more sophisticated analytical techniques.

IV. Inductive Inference Algorithm

Inductive inference is defined as the process of reaching a general conclusion from specific examples. Thus, the inductive learning process is based on finding a hypothesis to approximate the function over a set of training examples, which leads to the determination of the target function over other unobserved examples. Decision trees, being immune to noisy data and capable of learning disjunctive expressions directly from the raw data, are one of the most widely used and practical methods for inductive inference.

A decision tree is a tree data structure consisting of a root node, decision nodes and leaf nodes. A decision tree classifies the size of the cavities by sorting them upwards the tree from the root to some particular leaf node, which identifies the cavity size. A decision node specifies a test over one of the features that characterizes the pulse shape, which is called the attribute (in our application we have five attributes, which describe the PD pulse shape) selected at the node, and each branch descending from that node corresponds to one of the possible values of the selected feature. A leaf identifies a class value (1-mm cavity size, 2-mm cavity size, etc). Decision tree algorithms use a set of partial discharge pulse forms $\mathrm{T_s}$, emanating from all cavity sizes under consideration. Each training case is specified with values for a collection of features as described in the previous section. Associated with each training case is a label representing the name of a class (1-mm cavity size, 1.5-mm cavity size, etc). Classes are denoted by specific names such as $\{\mathrm{C_1, C_2 \ldots, C_N}\}$. A divide and conquer strategy is used to construct the decision tree, that is the C4.5 algorithm; wherein each node in the tree is associated with a set of cases that may belong to different classes. At the beginning, the algorithm starts with the root node and the entire training cases $\mathrm{T_s}$; thereafter the divide and conquer algorithm is executed, continuously attempting to exploit the locally best choice with no backtracking allowance.

C4.5 uses the concept of information gain to construct the decision tree [15] and then automatically infers the related "If-Then" rules for decision-making. The information gain can be described as the effective decrease in entropy resulting from making a choice as to which attribute to use and at what level.

V. Fuzzy Logic

Neuro fuzzy systems are found to be a powerful alternative strategy for developing a fuzzy system, since they are capable of learning and tuning the membership functions (MFs) in an explicit form [21], [22]. The adaptive network based fuzzy inference system (ANFIS) was used as a suitable tool for mapping the input PD features to the output void class based on both

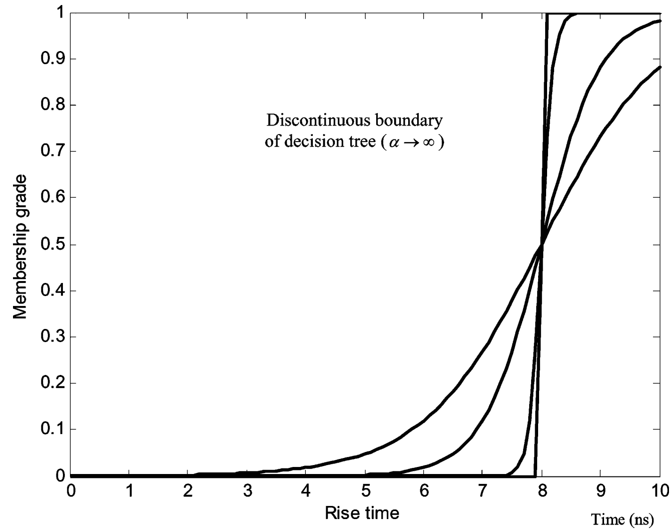

Fig. 2. Sigmoidal MFs with different αs for $\mathrm{Rise\ time} > \mathrm{c}$ (where $\mathrm{c} = 8$ ns).

knowledge in the form of "If-Then" rules generated formerly from the decision tree and the stipulated input-output data matrices.

A. Rule Construction

The decision tree is equivalent to a set of crisp rules in the form of "If A Then B." In our application, A is the boundary of the input feature and B is the void size class. An example of an output rule is:

$$\begin{aligned}&\mathrm{IF\quad Apparent\ charge} > 4814\ \mathrm{pc}\\&\quad\mathrm{And\quad Rise\ time} > 8.5\ \mathrm{ns}\\&\qquad\mathrm{THEN\ Class\ C_3}.\end{aligned}\tag{2}$$

The crispness of the rules reduces the computational tedium in constructing the tree as only the rules with the correct premises are fired; yet it gives undesired discontinuous boundaries. To smooth out the discontinuity at each split, fuzzy sets are used to represent the premise part of the rule. For instance, the statement $\mathrm{x} > \mathrm{k}$ can be represented as a fuzzy set characterized by either the sigmoidal MF with one parameter α

$$\mu_{x>c}(x;\alpha) = sig(x;\alpha,k) = \frac{1}{1+\exp[-\alpha(x-k)]}\tag{3}$$

or the extended S MF with two parameters α and γ

$$\begin{aligned}&\mu_{x>c}(x;\alpha,\gamma)\\&\quad = s(x;\alpha,k,\gamma)\\&\quad = \begin{cases}0, & \text{if } \mathrm{x} \le \mathrm{k}-\alpha\\ \frac{1}{2}\left[\frac{x-(k-\alpha)}{\alpha}\right]^{2\gamma}, & \text{if } \mathrm{k}-\alpha < \mathrm{x} \le \mathrm{k}\\ 1-\frac{1}{2}\left[\frac{c+\alpha-k}{\alpha}\right]^{2\gamma}, & \text{if } \mathrm{k} \le \mathrm{x} \le \mathrm{k}+\alpha\\ 1, & \text{if } \mathrm{k}+\alpha < \mathrm{x}\end{cases}.\end{aligned}\tag{4}$$

Thus, the condition of "$\mathrm{rise\ time} > 8$ ns" can be represented as a sigmoidal MF as shown in Fig. 2. Note that when $\alpha \to \infty$, the MF reduces to the step function and the fuzzy rule reduces to the original crisp rule.

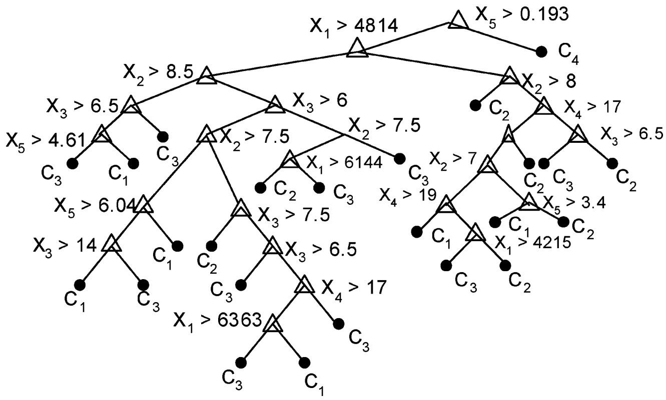

Fig. 3. Simplified output decision tree.

B. Training

The current application of the decision tree is generated after pruning a total of 13 rules to specify the void type. Generation of a fuzzy version of the rules is done by assigning fuzzy MF, as in (3) and (4), to each condition in the premise part of the rules. All the input variables are scaled to be in the range [0 1] to make the training process more efficient [17]. Based on these fuzzy-based rules, an ANFIS (adaptive neuro-fuzzy inference system tool in Matlab) structure is used for training, testing and analyzing the Sugeno type fuzzy inference system [21]. The output of each rule is a linear combination of input variables plus a constant term, and the final output is the weighted average of each rule's output. Such weights are adjusted automatically through the knowledge attained by the system throughout the input training set of features and their corresponding output void class. The adaptive network is a superset of all NN types with supervised learning capability. An adaptive network, as is well known, is a network structure consisting of nodes and directional links through which the nodes are connected. Moreover, part or all of the nodes are adaptive, which means that their outputs depend on parameters pertaining to these nodes, and the learning rule specifies how these parameters should be changed to minimize a prescribed error measure. The formulae for the node function vary from node to node, and the choice of each node depends on the overall input-output function, which the adaptive network is required to carry out. The parameter set of an adaptive network is the union of the parameter sets of each adaptive node. In order to achieve a desired input-output mapping, these parameters are updated according to the given training data.

VI. RESULTS AND DISCUSSION

A decision tree is applied to recognize the partial discharge patterns recorded on the different cavity size specimens. The parameters of the PD pulse waveform namely: apparent charge (X1) pC, rise time(X2) ns, fall time(X3) ns, A_1 (X5) and pulse width (X4) are used to build the decision tree. To construct the regression tree, C4.5 first grows the tree expressively based on the training data set and then prunes the tree back, based on a minimum cost complexity principle giving a final simplified output tree as shown in Fig. 3. Once the decision tree required for discriminating between the four cavity classes (C_1, C_2, C_3, and C_4) is determined using the specified input features, it is simple to obtain the associated "IF-Then" rules. This application provided thirteen output rules. Assigning fuzzy MFs to each undertaken feature, fuzzifies the crisp boundaries of the system rules. One example is the MFs assigned to the apparent charge, which are chosen to be either sigmoidal or trapezoidal in the Matlab fuzzy logic graphical user interface medium. The boundary values of the apparent charges, as given by the decision tree rules are either 4814 or 6363 pC as indicated in Fig. 4, which also shows the shape of the MFs of the apparent charge feature. In Fig. 4, the boundary values of 4814 and 6367 pC are equivalent to 0.72 and 1 p.u., respectively.

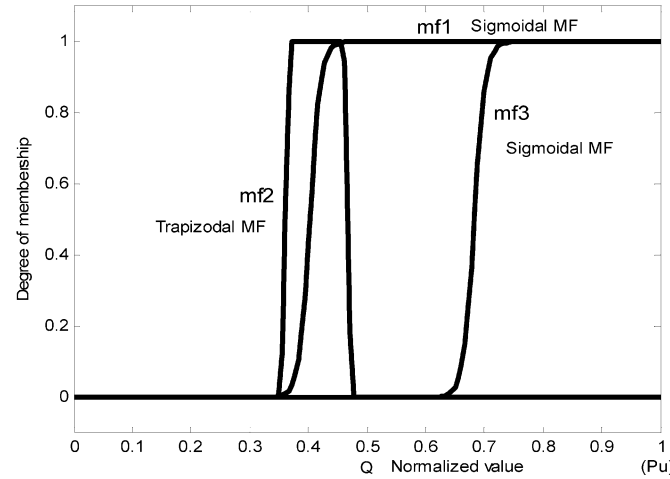

Fig. 4. MFs for the apparent charge (normalized, maximum apparent charge is utilized as the base).

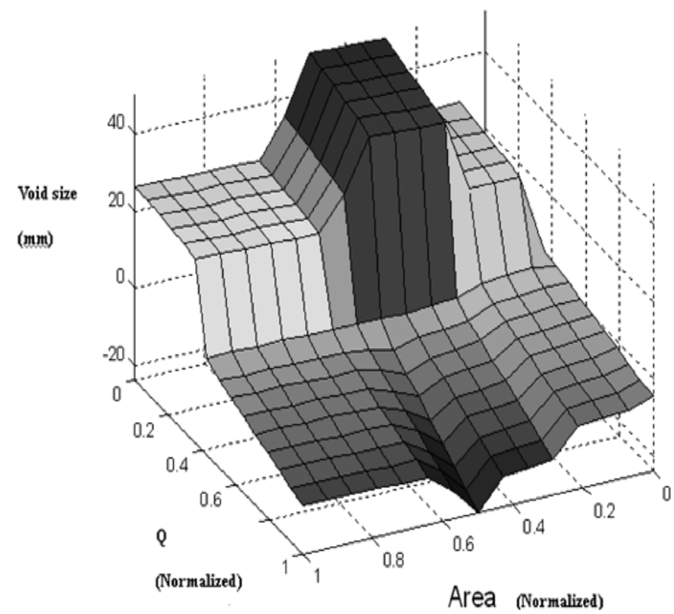

Fig. 5. Input-output surface of fuzzy inference system for apparent charge and area versus system output.

Based on the fuzzy version of the rules, an adaptive fuzzy inference system is built, which automatically adjusts the system parameters and finely tunes the chosen MFs for each rule to suit the system output given in the training set. The input-output surface of the fuzzy inference system is illustrated in Fig. 5 for two

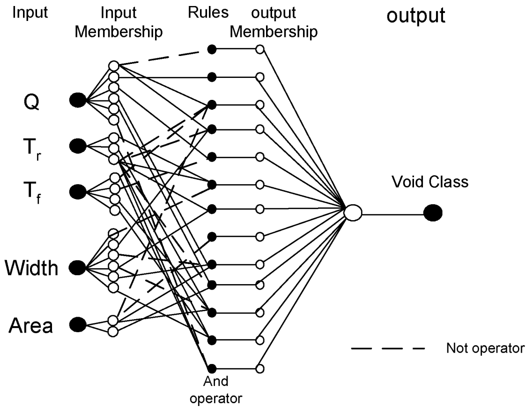

Fig. 6. Structure of the designed adaptive fuzzy inference system.

selected inputs of the chosen attributes along with the system output (void class).

Fig. 6 gives the architecture of the adaptive neuro-fuzzy system. It is basically a multilayer feed-forward network in which each node performs a particular function. The inputs to the system are our five features: apparent charge, rise time($\mathrm{t_r}$), fall time($\mathrm{t_f}$), $\mathrm{A_1}$ and pulse width, whereas the system output is basically a value of 1 divided into four quarters each corresponding to one of the four void size classes. Notice that the thirteen rules are essentially the outputs of the decision tree but with fuzzy MFs assigned for each attribute. All the nodes on the rules level are "and" nodes as dictated by the followed DT output rules. The links in the adaptive network adhered to indicate also the flow direction of signals between nodes; no weights are associated with the links. After almost 200 epochs, the average testing error for the undertaken network was found to be 9.65%, which is acceptable in such type of test.

Inspection of the undertaken measurements and the output results of the classifier indicated that the PD patterns for the metallic electrode cavities ($\mathrm{C_1}$, $\mathrm{C_2}$, and $\mathrm{C_3}$) differ very markedly from those of the dielectric electrode cavity ($\mathrm{C_4}$). This becomes obvious when it is noted that the decision boundary was determined by testing the values of the area $\mathrm{A_1}$ in the first level of the decision tree. This is the result of the large pulse amplitudes measured for the metallic electrode bounded cavities ($\mathrm{C_1}$, $\mathrm{C_2}$, and $\mathrm{C_3}$). For cavity depths of 1, 1.5, and 2 mm, the apparent charge ranged from 2.2×10^3 to 13.3×10^3 pC with related areas ($\mathrm{A_1}$) ranging from 1.7 to 10.8 A.ns. These substantially elevated values were in marked contrast to those characterizing the dielectric electrode cavity ($\mathrm{C_4}$), where the apparent charge measured values ranged from 29 to 235 pC with corresponding area values of 0.036–0.191 A.ns. This means that there is no overlap between any of the tested metallic electrode void classes and the dielectric electrode cavity ($\mathrm{C_4}$), which resulted in error-free classification for class $\mathrm{C_4}$. Meanwhile, regarding the metallic electrode bounded cavities ($\mathrm{C_1}$, $\mathrm{C_2}$, $\mathrm{C_3}$), there was a large overlap of the feature values, making discrimination between these classes more difficult. The training is accomplished using 30 hysteresis traces for each cavity size. A separate frequency of occurrence vector is obtained for each cavity size under consideration in the training phase, which means that the total number of considered frequency of occurrence vectors is three, corresponding to the 1-, 1.5-, and 2-mm cavity size, respectively. After a separate frequency of occurrence vector is obtained for each of the cavity sizes in terms of the V-Q data, a set of data, which has never been used in the training procedure, is used to test the performance of the proposed algorithm. Table I gives the results of testing for the 30 different hysteresis traces of each cavity size. The adopted system classifies 74.4% of class $\mathrm{C_1}$, 74.8% of class $\mathrm{C_2}$ and 79.5% of class $\mathrm{C_3}$ correctly after 300 epochs of system iterations. The overall system performance classified the testing data up to 82.17%. This accuracy is very comparable to the accuracy reported by using ANN based classifier [12], and fuzzy logic based classifier [14].

TABLE I
PD VOID SIZE CLASSIFICATION RESULTS (DIAGONAL ELEMENTS SHOW CORRECT CLASSIFICATION RATES, OFF-DIAGONAL ELEMENTS SHOW MISCLASSIFICATION RATE)

	$\mathrm{C_1}$%	$\mathrm{C_2}$%	$\mathrm{C_3}$%	$\mathrm{C_4}$%
$\mathrm{C_1}$	74.4%	16.5%	9.1%	0%
$\mathrm{C_2}$	12.3%	74.8%	12.9%	0%
$\mathrm{C_3}$	6.4%	14.1%	79.5%	0%
$\mathrm{C_4}$	0%	0%	0%	100%
Classification Accuracy	82.2%			

VII. CONCLUSION

This paper presents a fuzzy decision tree based partial discharge pulse pattern recognition method. The basis of inductive inference as well as the fuzzy logic is introduced in this paper to pave the road for the implementation of the proposed method. The implementation of the fuzzy logic decision tree based classifier requires two consecutive steps. First, a C4.5 algorithm is utilized to produce a compact size "IF-Then" rule set by inferring them from the data. Then, the obtained rules are fuzzified in order to avoid classification surface discontinuity that results from crisp decision tree rules; a back-propagation training algorithm is further utilized to tune the parameters of fuzzy memberships. The proposed technique has the decided advantage of its being totally computerized, thus eliminating the tedious work and prior data analysis by the human expert for manual adjustment of MFs. Furthermore, the proposed system optimizes the number of the utilized "If-Then" rules.

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