Neuro Fuzzy Recognition of Ultra-High Frequency Partial Discharges in Transformers

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Abstract — **In this paper, partial discharge (PD) signals in the ultra-high frequency (UHF) range were investigated. A spectrum analyzer functioning in the zero span mode was applied to capture and record the PD signal component at a specific frequency over a time interval. Different PD sources produce different PD patterns, thus it is possible to recognize the PD sources from the captured PD patterns. Here, the PD patterns produced by 3 different laboratory models representing defects in transformer windings (void, floating metal, and surface discharge) are recorded and analyzed. From the PD pattern data, 6 features are extracted using 3 statistical parameters, i.e. mean, skewness and kurtosis for both positive and negative voltage half-cycles. The 6 features were used to recognize the PD sources by applying neuro fuzzy method to classify the PD pattern. ANFIS, a MatLab function, was used to train the fuzzy inference system (FIS). The trained FIS was then used to recognize the source of the PDs. Result shows the trained FIS has a high success rate to recognize and thus classify the PD sources.**

Keywords - partial discharge, ultra high frequency, neuro fuzzy systems, zero span method.

I. INTRODUCTION

High-voltage power transformer failures are mostly due to breakdown of the insulation. The applied electric stress during normal operation can cause partial discharges (PD) within the transformer insulation and lead to physical damage and deterioration of the insulation. If this is allowed to continue over time, the discharge activity will grow to a high level and lead to a catastrophic failure.

To detect the occurrences of PD inside transformer insulation, the ultra-high frequency (UHF) detection method is one that can be applied. A PD event typically generates a very short signal with less than 1 ns rise time [1]. Thus the PD signals contain frequency components well into the GHz range. The UHF detection method has a number of advantages over other methods such as the conventional IEC60270 whereby the detection frequency range is below 1MHz. The main advantage of the UHF method is a relatively lower level of noise and thus a better signal-to-noise ratio.

The zero span capturing mode available from a standard spectrum analyzer can be used to selectively detect a PD signal component at a specific frequency over a certain recording time interval. This method will capture the electromagnetic signals emitted by PD sources and show the two dimensions (v, φ) of the phase resolved partial discharge (PRPD) patterns, i.e. the discharge patterns in relation to the applied AC voltage cycle (20ms for 50Hz supply systems). Thus the PRPD patterns can be readily obtained for both positive and negative voltage half-cycles.

Apart from PD detection, the ability to recognize the PD patterns is an important aspect of transformer insulation diagnosis. Knowing the PD defect type will enable the engineer to determine the possible location and the severity of the PD deterioration. This in turn will help to determine corrective actions that have to be taken.

In order to classify the PD sources, two essential components are required: the classifier, and the signal features or finger prints as the classifier inputs. A number of PD pattern recognition methods can be used as a classifier such as genetic algorithm [2], support vector machine [3], neural network [4] and fuzzy logic [5]. Among all these methods, fuzzy logic and neural network show the highest success rate. The classifier input can be a group of features extracted from the PD pattern [2,3,4] or the PD signal itself [5]. However, the latter suffers from the complexity of the analysis due to the large amount of data inputs.

In this paper, PD signals were recorded by the UHF zero span method and then their patterns were classified by the neuro fuzzy method. Three statistical parameters were used to extract features from the PD patterns: mean, skewness and kurtosis for both positive and negative voltage half-cycle distributions. These features were then applied as inputs to train the fuzzy inference system (FIS) by using the MatLab toolbox ANFIS.

II. EXPERIMENT

Three defects were set up to generate PDs in the experiment: void, floating metal and surface discharge. All were constructed by using three layers of insulation, two bottom layers are pressboard and the top layer is Kraft paper. The sample dimension and the electrode arrangement are shown in Figure 1. Both void and floating metal have the same diameter size of 5 mm carved in the centre of the PD defect samples. The diameter of the PD defect model is 6.5 cm.

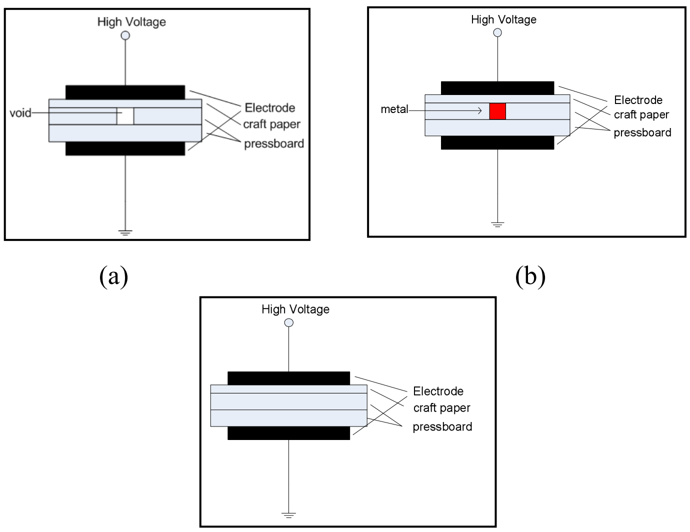


Figure 1. PD defect models (a) void, (b) floating metal and (c) surface discharge

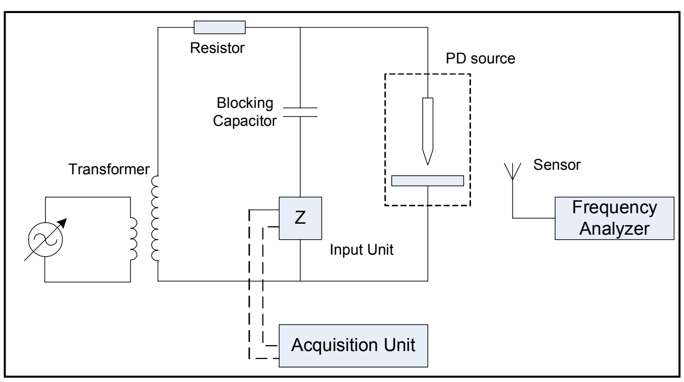


Figure 2. Test circuit.

All PD defect models were immersed in a small distribution transformer tank filled with oil but with the core and windings removed. The UHF sensor was positioned 75 cm from the PD source and its output connected to a spectrum analyzer via a 50Ω coaxial signal cable. In addition, a direct coupling detection circuit (blocking capacitor in series with a quadripole) was also used to measure the PD level based on the conventional PD detection method, i.e. IEC60270 Standard. The circuit setup is shown in Figure 2. The voltage was increased until the PD inception occurs and the PD magnitude Q_{IEC} can be read from the Mtronix digital PD detector. The voltage was 6 kV, 7, kV and 10.5 kV and produced PDs of 140 pC, 100 pC and 150 pC for void, floating metal, and surface discharge respectively.

III. PD PATTERN SIGNATURES

A. Zero Span Method

One of the advantages of the spectrum analyzer over the oscilloscope is its ability to capture signal in a single frequency and displays results over a desired time span period [1]. By applying this so-called zero span method, the PD pattern in relation to the supply voltage cycle can be captured and recorded. Here, the time span is determined by the frequency of the power supply system, e.g. 20 ms for a 50 Hz AC supply system. Figure 3 and 4 show a typical PD pattern captured by operating the spectrum analyzer in the zero span mode.

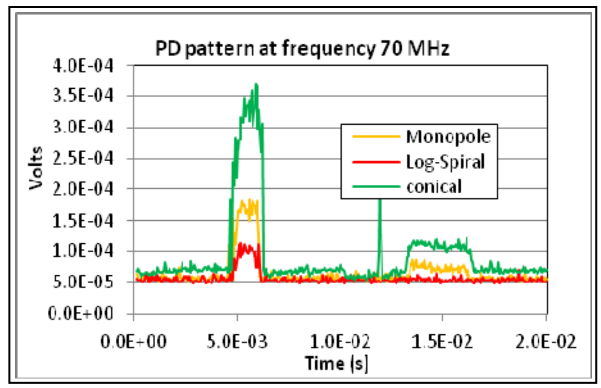


Figure 3. PD pattern captured by three different types of sensor.

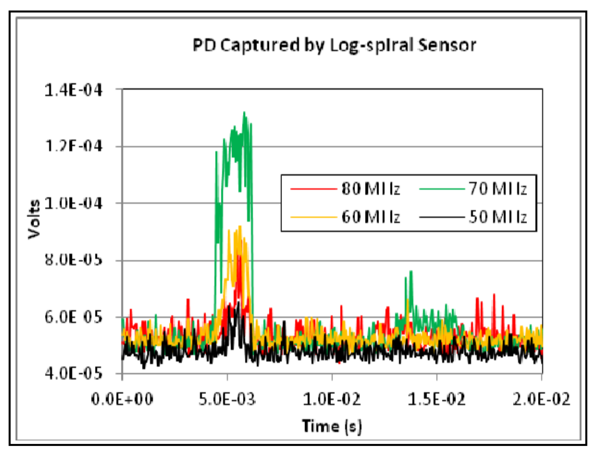


Figure 4. Typical PD pattern captured by the log-spiral sensor at a distance of 75 cm from the PD source.

The detected signal level of the PD pattern is very much dependent on the sensor characteristic. In previous experimental investigations by the authors, 5 different sensor types were built and tested for their capability to detect the PD signals. They are: monopole, conical, bowtie, spiral and log-spiral. It was found that the conical and log-spiral sensors have the best characteristics and response. The conical sensor has higher sensitivity whereas the log-spiral sensor has the flattest S11 and realized gain. Overall, the log-spiral sensor has the best response for the UHF range [6]. Thus, this sensor was used to capture all the PD signals in this paper.

B. UHF PD signatures

In this paper, a total of 107 PD patterns were recorded and analyzed. They comprise 26 void data, 40 floating metal data and 41 surface discharge data. From each PD pattern, 3 statistical operators were used to extract statistical values from the two voltage half-cycles (positive and negative). Thus, there are 6 parameters that can be used as inputs for the fuzzy analysis:

Mean (+), Mean (-): the first statistical moment (mean value) of the PD pattern for the positive and negative halves of the voltage cycle, respectively.

Sk (+), Sk (-): the third statistical moment (skewness coefficient) of the PD pattern for the positive and negative halves of the voltage cycle, respectively.

Ku (+), Ku (-): the fourth moment (kurtosis) of the PD pattern for the positive and negative halves of the voltage cycle, respectively.

For analysis purposes, the 107 data were divided into three groups. The first group consists of 73 data: 18 from void discharges, 32 from floating metal discharges and 33 from surface discharges. These data were used to train the fuzzy scheme by applying ANFIS. The second group consists of 3 data from each type of PD and used for checking the trained fuzzy scheme. The last group consists of 5 data from each PD type to test the trained fuzzy scheme ability to recognize the PD source. The first and second group data were arranged so they become a seven column matrix with the last column contains a single vector output data. This vector output data assigns the PD type to a specific number: 1 for void, 2 for floating metal and 3 for surface discharge.

IV. NEURO FUZZY

A. Neuro Fuzzy Method to Recognize the PD sources

ANFIS which stands for Adaptive Neural Network Fuzzy Inference System combines neural network and fuzzy system to determine the best fuzzy parameters [7]. The use of neural network removes the requirement of human expertise to determine the fuzzy parameters. In other words, fuzzy parameters are automatically optimized by the neural network. However, the fuzzy system itself must be firstly built by fuzzy logic and then ANFIS is applied to train the fuzzy scheme. The block diagram of using the neural network to recognize PD sources is shown in Figure 5.

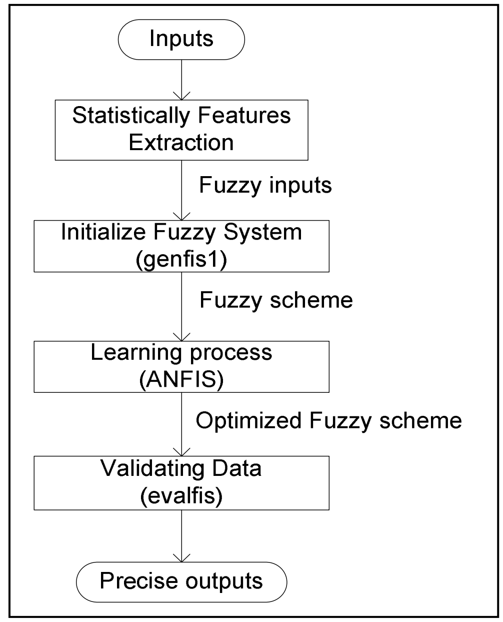


Figure 5. Flowchart of neuro-fuzzy recognizing method.

The fuzzy inference system (FIS) was built using MatLab ‘genfis1’ command. Figure 6 shows the FIS that was generated by using genfis1. The FIS was then trained by using ANFIS command to optimize the membership function. Finally, the optimized membership function was used to evaluate the data sets on which the FIS was not trained. The results will show how well the FIS model predicts the PD type of the corresponding data set.

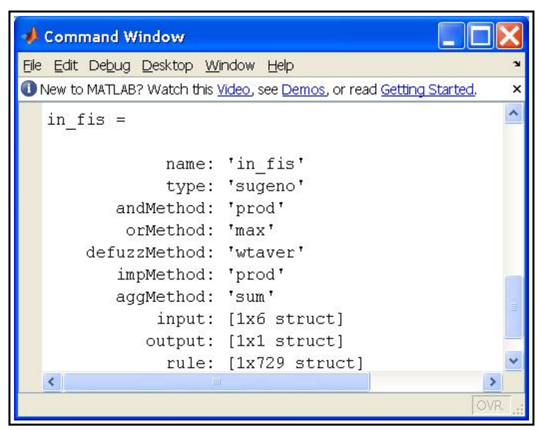


Figure 6. FIS generated by genfis1.

B. The ANFIS

ANFIS constructs a set of fuzzy 'if-then' rules with appropriate membership functions that can be used to generate the stipulated input-output pairs. To construct the fuzzy rules, ANFIS is based on a fuzzy Sugeno model [7].

Rule 1: If x is A_1 and y is B_1, then $f_1 = p_1x + q_1y + r_1$,

Rule 2: If x is A_2 and y is B_2, then $f_2 = p_2x + q_2y + r_2$.

The ANFIS architecture can be illustrated as shown in Figure 7 which consists of 5 layers.

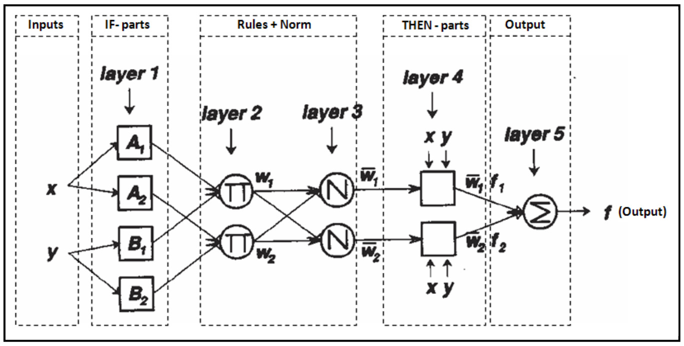


Figure 7. The ANFIS architecture [7].

Layer 1: In this first layer, all nodes (A_1, A_2, B_1, and B_2) are adaptive nodes. The outputs of layer 1 are the fuzzy membership grade of the inputs (x and y).

Layer 2: In this layer, all nodes are fixed and they perform as a simple multiplier of the incoming signals. The outputs that they produce are so-called firing strengths of the rules.

Layer 3: This layer normalizes the triggering strengths from the previous layer. All nodes on this layer are fixed nodes.

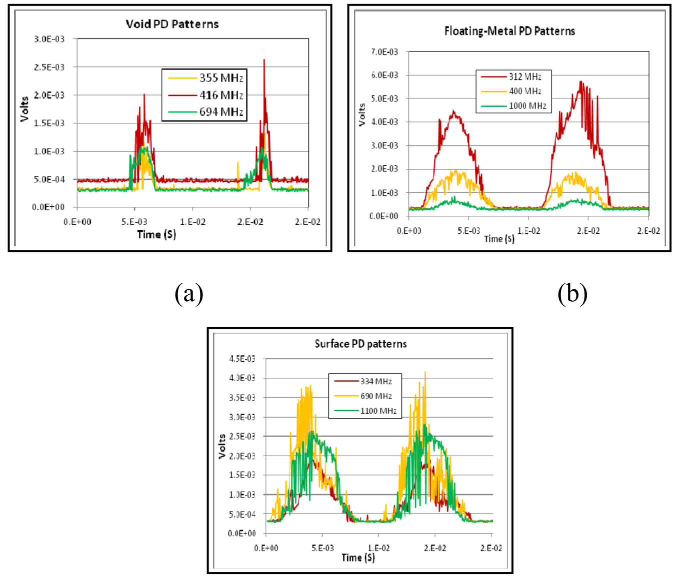
Layer 4: The outputs of this layer are the product of the normalized firing strength and a first order polynomial (for first-order Sugeno model). All the nodes in this layer are adaptive.

Layer 5: There is only one single fixed node in this layer that performs the summation of all incoming signals.

V. RESULT AND DISCUSSION

Three different defect models were used to generate the discharges. In total, 107 PD patterns were recorded which comprise 26 patterns from void discharges, 40 from floating metal discharges and 41 from surface discharges. The number of data for each PD defect model depends on the PD signal level in the UHF range (300 – 3000 MHz). Experiment results showed that PD signals associated with void occurs less than the other two PD defect models. The void PDs mainly occur in the lower frequency range of 300 – 600 MHz, while floating metal and surface discharge were produced in the higher frequency range up to more than 1000 MHz. Figure 8 shows the typical PD pattern for all PD defect models at various frequencies.

Note that Figures 3 and 4 show the corona patterns. These corona patterns were generated by a needle to plate electrode configuration. The applied voltage was increased well above the inception to get steady corona discharges which appeared on both half-cycles. From experimental results obtained, it was found that the corona spectrum is evident only in the low frequency range, mainly below 100 MHz. This is not within the UHF range. For this reason, the corona was not included as a test sample and thus excluded in the analysis.



(a) (b)

(c)

Figure 8. Typical PD patterns captured by sensor (a) void, (b) floating metal and (c) surface discharge.

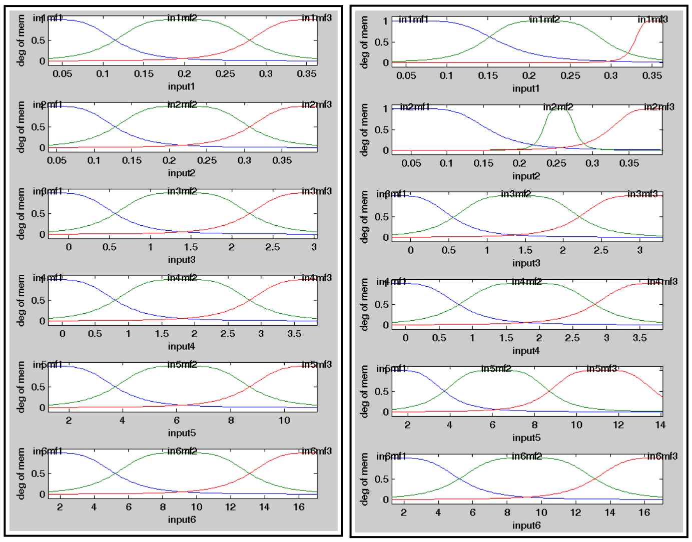
From the PD pattern data, 3 statistical parameters were extracted which are: mean, skewness and kurtosis for positive and negative voltage half-cycles (total 6 features). These data features were then divided into three groups and used (i) as input to build and train the fuzzy inference system, (ii) to check the fuzzy training, and (iii) as testing data. The three groups have similar compositions of 6 data columns for the 6 features. In addition, the first two groups have an extra column for marking code of the PD defect type. Table 1 shows the data arrangement for the checking data.

TABLE I. DATA CHECKING ARRANGEMENT

PD sources	Mean (+)	Mean (-)	Skew (+)	Skew (-)	Kur (+)	Kur (-)
Void	0.0710	0.0308	3.9680	4.8835	19.0655	28.3938
Void	0.0532	0.0218	2.6332	3.8853	9.4247	18.2825
Void	0.0828	0.0435	2.2471	3.7006	6.7417	15.5048
Void	0.0655	0.0390	2.7235	4.2616	8.7747	20.5322
Void	0.0516	0.0443	2.6060	2.8877	8.4147	9.8055
FM*	0.3406	0.3227	0.3347	0.3806	1.4311	1.4325
FM	0.2740	0.3532	0.2824	0.3485	1.3487	1.5117
FM	0.1792	0.2110	1.0561	0.8507	2.4923	2.0518
FM	0.1782	0.2208	1.4825	1.2809	3.7568	3.1687
FM	0.3456	0.3207	0.5158	0.5951	1.6416	1.7277
SD**	0.2121	0.1883	0.6981	1.0043	1.9465	2.5452
SD	0.1893	0.1752	0.9200	1.0887	2.3846	2.6280
SD	0.2542	0.2476	0.5645	0.4689	2.4588	1.9036
SD	0.1667	0.1359	1.9981	0.3266	10.0550	1.9882
SD	0.1901	0.1578	1.6862	1.6790	4.7255	4.9129

*FM = floating metal, **SD = surface discharge

Figure 9(a) shows the un-trained membership functions generated by the 'genfis1' command. They correspond to 6 input parameters. Each function is divided into three regions, namely: low, medium, and high and built with the same 'gbellmf' type shape. Total data used to generate the FIS are 73 and produced 729 rules (Figure 6). Such a large number of rules made it impractical for direct implementation and thus the need for optimizing the membership functions.



(a) (b)

Figure 9. Membership function (a) before training (generated by Genfis1) and (b) after training using ANFIS

TABLE II. TEST RESULTS USING TRAINED FIS

PD sources	Evaluation result	Rounding	PD type
Void	0.885	1	1
Void	1.113	1	1
Void	0.781	1	1
Void	0.935	1	1
Void	0.674	1	1
*FM	1.967	2	2
FM	2.102	2	2
FM	2.099	2	2
FM	1.900	2	2
FM	1.821	2	2
**SD	3.251	3	3
SD	1.721	2	3
SD	3.080	3	3
SD	3.400	3	3
SD	2.736	3	3

*FM = floating metal, **SD = surface discharge

The optimized membership functions of the FIS are shown in Figure 9(b). ANFIS was used to train the FIS. These functions are arranged in the order (from top to bottom) of the mean, skewness and kurtosis for positive and negative voltage half-cycles. It can be seen that the most significant changes to the membership-function occur to the mean input for both voltage half-cycles. Also, changes can be easily recognized on the kurtosis of the positive half-cycle.

The ANFIS used 73 data patterns for training the membership function and 9 additional data patterns for checking the training result. After 50 training periods, the error value is 1.1549×10^{-3}.

After the training process was carried out and completed, 15 data records were used to evaluate the ability of ANFIS classifier to recognize the PD sources. The test results, summarized in Table 2, show excellent success rate. Out of 15 test data patterns, only 1 surface discharge source was misclassified as a floating metal discharge.

VI. CONCLUSION

In this work, 3 different PD models to simulate typical defects in transformer windings were developed and tested. The PD signals were captured using the UHF zero span measuring method. Corona discharge was not included in this investigation because its signal spectrum is below the minimum frequency of UHF range.

Three statistical operators were extracted from the phase-resolved PD distributions for both positive and negative voltage half-cycles and used as features for training a fuzzy inference system (FIS). The membership function of the FIS was obtained with the aid of MatLab function ANFIS. The training results show some significant changes of the membership functions for the mean and kurtosis.

The trained FIS was then applied to evaluate its accuracy to recognize the PD sources. Test results show high success rate. Thus, it is possible to recognize the source of PD based on its PD pattern captured by the UHF zero span method.

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