A Study on the Partial Discharge Patterns from Multi-Defect Insulating Systems

June-Ho Lee and Tatsuki Okamoto

Abstract

In practice, there may be various defects in an insulating system, so that the PD signals can be produced from these defects simultaneously. Regarding these situations, we have to discriminate the type of defect as well as to determine whether the PD occurs or not. In this paper, some analysis results of the PD signals from multi-defects insulating system were presented. We measure the PD signals by using three kind of electrode system; IEC(b), Needle-Plane and mixed electrodes. To simulate multi-defect systems, we combined two electrode systems and apply test voltage simultaneously. Neural network, statistical analysis methods were tried, and the possibilities and limitations of each method were clarified.

I. Introduction

The PD is one of the most important quantities to know the status of many electrical apparatus because the PD signal can carry information on the condition of insulating system in the form of electrical signal. Therefore, the precise measurement and proper analysis of the PD signals are very essential to develop reliable diagnostic methods and to put it to practical use.

There have been many works on the PD analysis, most of which was concentrated on single-defect insulating systems. The basic parameters of the PD pattern can be classified into three quantities, those are, phase angle(φ), repetition rate(n) and discharge magnitude(q) of PD pulse.

Recently, by virtue of advanced measurement systems with high speed data processing, more detailed and precise information about these quantities could be obtained, and a lot of works with regard to analyzing the PD patterns have been performed using the φ-q-n patterns, which can represent all of three quantities on one graph [1, 2].

In practice various defects may exist in a insulating system, so that the PD signals can simultaneously be generated from multiple discharge sources. Considering the multi-defect insulating system, it is of importance to discriminate the type of defect as well as to know whether the PD occurs or not. In this paper we will discuss discriminating the type of defect by analysis of measured PD signals which are generated from simulated multi-defect electrode systems. The neural network(NN) and cross-correlation have been used as tools for discriminating defect types, and their possibilities and limitation will be reported.

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II. Experiment and PD pattern

PD pulses were measured from three kinds of electrode systems; IEC(b), needle-plane and mixed electrode system. Their configurations are shown in Fig. 1. The mixed electrode system simulates a multi-defect insulating system. To be sure that the PD occurs at the same voltage, we adjusted distance between needle tip and PET film or changed the thickness of PET film layer. Applied ac voltage was 1.5kVrms of 50 Hz and time interval between one measurement and another was 30 seconds. One cycle of applied ac voltage was divided into 200 phase angle windows in the PD pulse analyzer, resulting in time resolution of 100 μsec. 20 measurements from each electrode system have been performed.

Fig. 2 is an example of PD patterns constructed by the measured PD data. Horizontal and vertical axis correspond to 200 phase angle of applied voltage and arbitrarily scaled pulse magnitude, respectively. Each dot means the magnitude of one PD pulse generated at the phase angle. From this example it can be noticed that the PD pattern of mixed electrode is nearly overlapped with PD patterns of IEC(b) and needle-plane electrode.

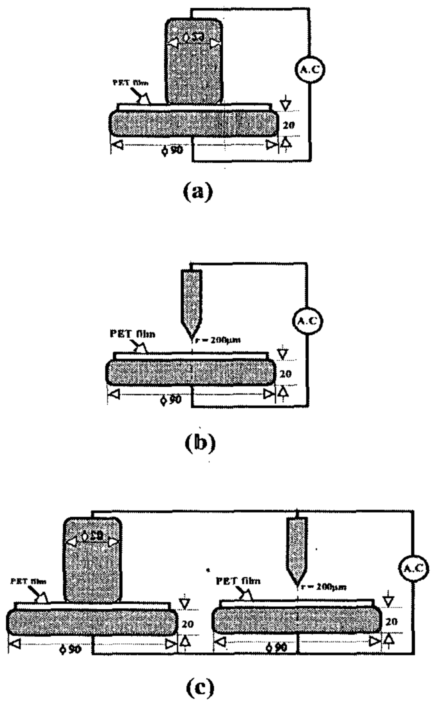

Fig. 1. Configurations of (a) IEC(b) electrode, (b) needle-plane electrode, (c) mixed electrode.

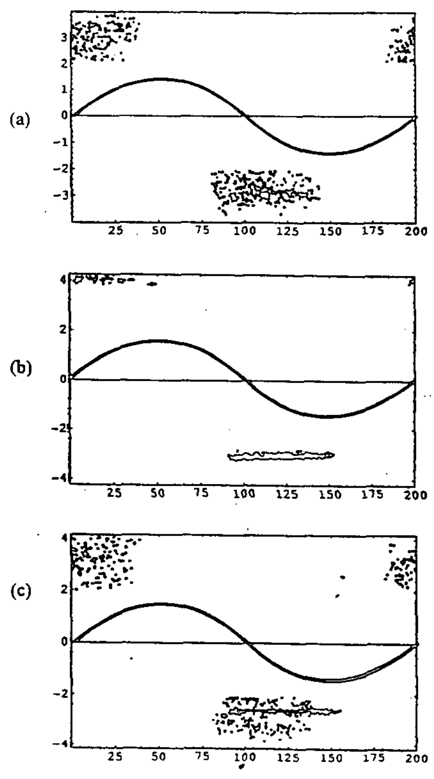

Fig. 2. Example of PD patterns from (a) IEC(b) electrode, (b) needle-plane electrode, (c) mixed electrode.

III. Neural Network

In recent years a lot of research groups have used the neural network algorithm to recognize PD patterns and authors have also reported that the NN with proper pre-process could discriminate phase-shifted PD patterns successfully[3][4][5].

In this research, we used a three layer perceptron as a NN structure. The number of input units of input, hidden and output layer were 320, 40 and 3, respectively.

Firstly we made a set of fifteen 320-element input vectors as a training matrix. The first 5 input vectors of the training matrix were randomly selected from the 20 measured PD data of IEC(b) electrode and next 5 input vectors were selected from those of needle-plane electrode and last 5 vectors were from mixed electrode.

The NN was trained that the 3 units of network output layer became (1,0,0), (0,1,0) and (0,0,1) when the input training vectors from IEC(b) electrode, needle-plane electrode and mixed electrode were presented to the network, respectively. After training process was finished, a test matrix was presented to this trained network. The test matrix was sixty 320-element input vectors, of which each 20 vectors consisted of the 20 measured PD data of IEC(b), needle-plane and mixed electrode, respectively.

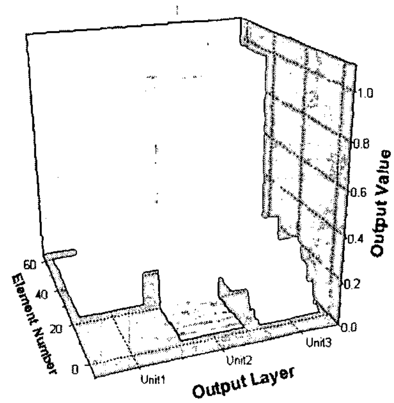

Fig. 3. Output result of the NN trained with PD data of three electrode systems

Fig. 3 shows the output result of the NN trained with PD data of three electrode system. This result indicates that well-trained NN can successfully discriminate defect types of PD signals if some prototypes of PD patterns of each electrode are provided during training process.

Next, we trained the NN with a training matrix which had no input vectors from the mixed electrode. Therefore the training matrix was a set of ten 320-element input vectors; the first 5 input vectors were from IEC(b) electrode and the rest 5 vectors were from needle-plane electrode. Fig. 4 shows the output result of the NN trained without PD data from mixed electrode when the test matrix was presented to the network. As show in the Fig., the most networks output corresponding to input vectors of mixed electrode PD data became (1,0,0) instead of (0,0,1). This means that the NN recognized PD pattern of mixed electrode as that of IEC(b) electrode. As a consequence, the neural network has a good recognition performance to the PD patterns similar to the trained ones, but has poor recognition performance even makes incorrect answers to the not-trained PD pattern.

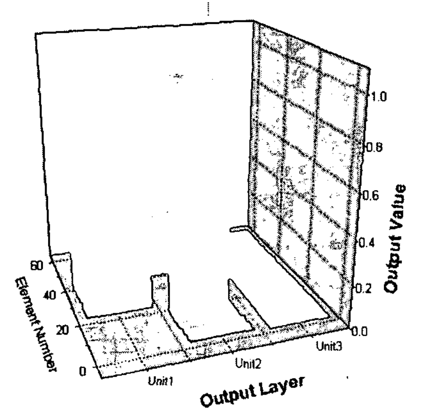

Fig. 4. Output result of the NN trained without PD data of mixed electrode system

IV. Cross Correlation

The cross correlation(CC) is a coefficient which indicates the degree of similarity between two signals or two images. The CC between signals f(x, y) and h(x, y) can be calculated by Equation.1

$$CC = \int\int f(x,y)h(x,y)dxdy \quad (1)$$

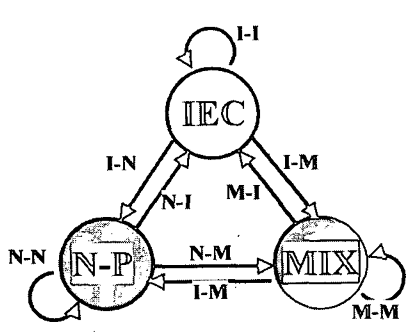

Fig. 5. Abbreviated words of the calculated CC between PD pattern groups

Based on the property of the CC, we can use the CC operator as a matched filtering between reference pattern and test patterns[6]. In this research, the CCs between the PD patterns from different electrode system as well as from same electrode system were.calculated. The maximum value of the CC was determined as degree of similarity between two PD patterns. Fig. 5 shows the abbreviations for calculated CCs. For example, I-M means a set of 20 maximum CCs which is calculated between one test PD pattern from IEC electrode system and each of 20 reference PD patterns from needle-plane electrode.

In this case one IEC pattern is regarded as a test PD pattern of which we want to know the defect type, while 20 patterns is regarded as reference patterns.

The result of CC calculation between two groups of PD patterns was shown in Fig. 6. It can be noticed that maximum values of the CC between two PD patterns in the same group are greater than 0.8 except three points of the N-N, while the others such as I-N, M-N, etc. are less than 0.8.

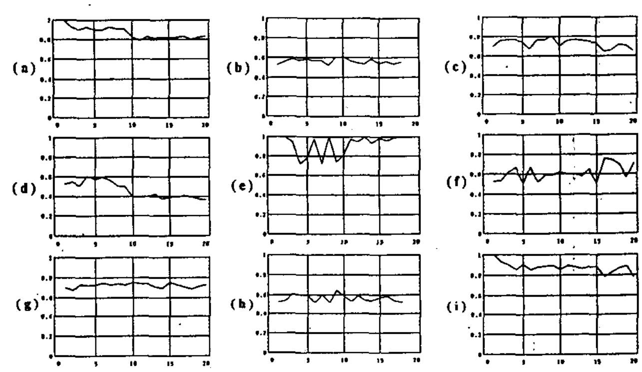

Fig. 6. Result of cross correlation between two groups of PD patterns ; (a)I-I, (b)I-N, (c)I-M, (d)N-I, (e)N-N, (f)N-M, (g)M-I, (h)M-N and (i)M-M.

The values of I-M are greater than those of I-N and less than those of I-I since the PD pattern of mixed electrode has more component of pattern of IEC(b) than that of needle to plane electrode. According to these results, maximum value of 0.8 may be used as a criterion level by which we determine whether a test pattern belongs to the reference group of PD patterns or not. Nevertheless, it seems to be difficult to apply the CC to discriminating defect type from PD pattern of mixed electrode system. On condition that we had only reference PD patterns of IEC(b) and needle-plane electrodes, all the values of CC related to PD patterns of mixed electrode is less than 0.8. For example the average values of I-N and M-N are almost same, so that the PD pattern of mixed electrode given as a test pattern can probably be decided as a pattern of the IEC(b) electrode.

V. Conclusions

For the purpose of analyzing PD signals from the multi-defect insulating system, we generated the PD signals using three electrode systems; IEC(b), needle-plane and combined electrode. The PD patterns made by measured signals were prepared for analysis process. The neural network and cross-correlation have been tested as tools for discriminating defect types.

The neural network showed good recognition performance to the PD patterns similar to the trained patterns, but had poor recognition performance, even made incorrect answers to the not-trained PD patterns.

It was clarified that the cross-correlation, one of statistical analysis operator, could be used as a matched filtering tool between reference PD pattern and test PD pattern. Nevertheless, the CC had some limitation for discriminating defect type from the PD patterns of mixed electrode.

From the above results, we could find the possibilities and limitation of neural network and cross-correlation as a tool for discriminating PD patterns from the multi-defect sources. For the realistic application, it seems to be better to make a recognition algorithm taking the advantage of each method It is expected that further improvement or new method development of recognition techniques for the multi-defect insulating system should be studied.

References

[1] N. Hozumi, T. Okamoto and T. Imajo, Discrimination of Partial Discharge Patterns Using a Neural Network, IEEE Trans. on Electr. Insul., Vol. 27, pp. 550-556, 1992.

[2] B. Fruth and L. Niemeyer, The Importance of Statistical Characteristics of partial Discharge Data, IEEE Trans. on Electr. Insul., Vol. 27, pp.60-69, 1992.

[3] J-H Lee, N. Hozumi and T. Okamoto, Discrimination of Phase-Shifted Partial Discharge Patterns by Neural Network using Standardization Method, Proc. 1994 IEEE Int. Symp. EI, pp.314-317, 1994

[4] A. Krivda, Automated Recognition of Partial Discharges, IEEE Trans. on DEI, Vol. 2, pp. 796-821, 1995.

[5] R. E. James and B. T. Phung, Development of Computer-based Measurements and their Applocation to PD pattern Analysis, IEEE Trans. on DEI, Vol. 2, pp. 838-865, 1995.

[6] M. Nadler and E. P. Smith, Pattern Recognition Engineering, John Wiley & Sons, 1993, pp. 57.

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