Artificial Neural Network Discrimination of Multi-PD Sources Detected by UHF Sensor

Kang-Won Lee*, Dong-Uk Jang*, Jae-Yeol Park*, Seong-Hwa Kang*, and Kee-Joe Lim*

Abstract - The waveforms of partial discharges (PDs) imply physical and structural properties of PD sources, so analyzing them give us information on the kind of PD sources and the location. Waveforms of PD as a time series function have variable amplitudes but sustain a certain uniform shape, which shows well the characteristics of the waveforms and frequency region. They can also be used as parameters having time and frequency information of PD signals and applied to classification of multiple PDs sources via Artificial Neural Network with back propagation (BP) learning.

Keywords: Artificial Neural Network(ANN), partial discharges(PDs), electromagnetic wave, pattern recognition technigue.

1. Introduction

Conventional HV power equipment has many constraints due to residential environments. Therefore, many requirements existed for high compact HV power equipment. The higher the compact density of the power equipment, the higher the insulation strength needed. By limiting insulation strength, defects from manufacturing and set-up of HV equipments become fatal. Various defects occur, like gas accidentally mixed in the oil, accidental sparking, and so on. The partial discharge (PD) phenomenon is very important for the feasibility of measuring dangerous situations involving HV power apparatus, providing information about insulation abnormalities, preventing potential accidents. PD produced by defects can be detected by variable sensing methods, such as AE (acoustic emission) sensors, UHF (ultra high frequency) sensors (or antennas), CTs (current transformers), and so forth[1-3]. PD pulse signals have a very wide frequency band (several MHz to GHz), which causes environmental noise to be confused with PD signals and distinguishing between them is difficult. Many investigations regarding differentiating between two signals were performed by feature extraction and pattern recognition using the Phase Resolved Partial Discharge (PRPD) preprocessing method, such as ϕ-q-n statistical distribution [4] and Pulse Sequence Analysis (PSA)[5], most of which were successful for differentiating between two signal sources but experienced difficulty in discriminating between more signal sources. Power equipment may be used in an environment surrounded by not only one or two instruments, but also three or more pieces of high voltage equipment, the noise from which interferes with detecting the correct PD source. This paper shows that multiple PD or signal sources can be classified by an Artificial Neural Network (ANN) using a back-propagation (BP) learning rule, which uses, as ANN input frequencies, features of signals obtained by a UHF sensor. An ANN using a BP rule will hereafter be referred to as a BP-ANN.

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2. Back-Propagation Neural Network

A BP-ANN is very useful for pattern classification and especially for recognizing PD patterns [6]. A BP-ANN is a supervised multilayer perceptron, which consists of an input layer, a hidden layer, and an output layer. A frequency feature is applied to the input layer and classified PD sources come from output layer as a result. Fig. 1 depicts the feed forward neural network structure sent from the input layer to the hidden layer and from the hidden layer to

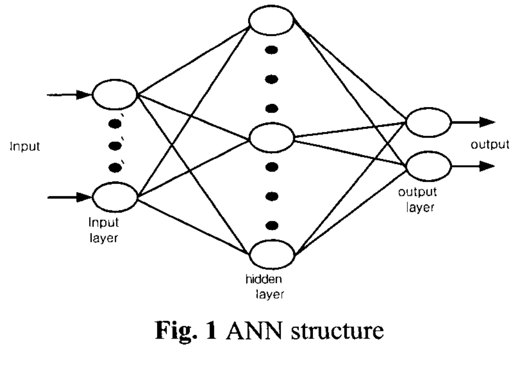
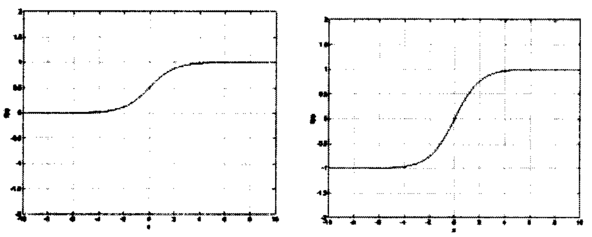


Fig. 1 ANN structure

the output layer. Connection strengths between layers are given as weight values and both hidden layer neurons and output layer neurons are defined by active functions. The relation of the input layer and the output layer is 「output layer = f(input layer×weight value)」 and here f(·) represents an active function. A logistic function (1) and hyperbolic tangent function (2) are generally used as an active function of an ANN, as is shown in Fig. 2.

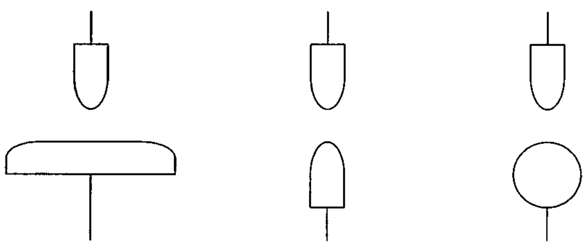


(a) (b)

Fig. 2 Graphs of logistic function (a) and tanh (b)

3. Experimental Setup

To simulate PD sources, three kinds of electrode systems, needle to plane (N-P), needle to needle (N-N) and needle to sphere (N-S) are made as shown in Fig. 3. All of the electrode systems have a gap distance of 1 cm and the tip radius of the needle is 0.5 mm. The upper needle electrode is connected to high voltage and the lower electrode is connected to earth. The applied voltage was AC 6 kV (60 Hz), which was provided through a corona free transformer. Fig. 4 shows the experimental configuration. The PD has a very wide frequency band and is radiated in the form of an electromagnetic wave, which can be detected by a UHF antenna (30 kHz to 2 GHz). The signals obtained from the UHF antenna are pre-amplified and sent to a 1GHz, Tektronix digital oscilloscope via a 50Ω BNC cable. Data stored in the digital oscilloscope is analyzed by a PC through a GPIB bus.



(a) N-P (b) N-N (c)N-S

Fig. 3 Electrode systems

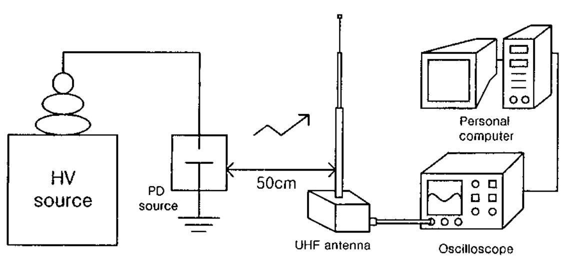
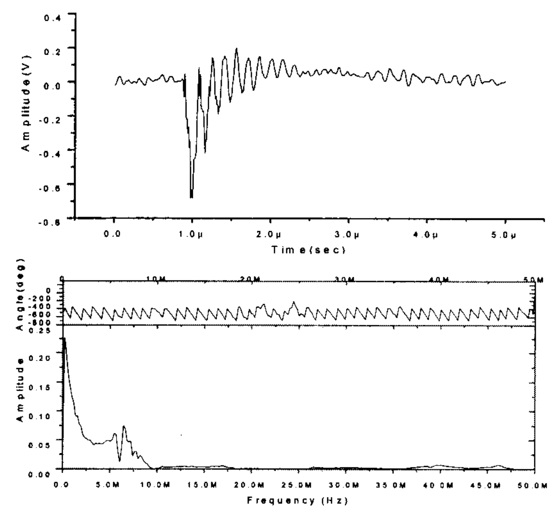


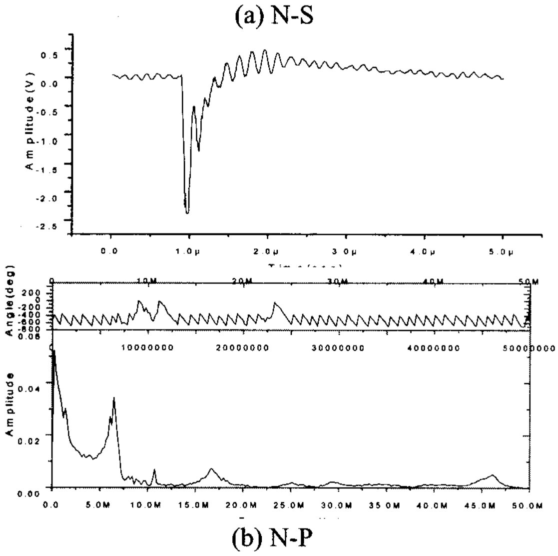
Fig. 4 Experimental setup

4. Results and Discussion

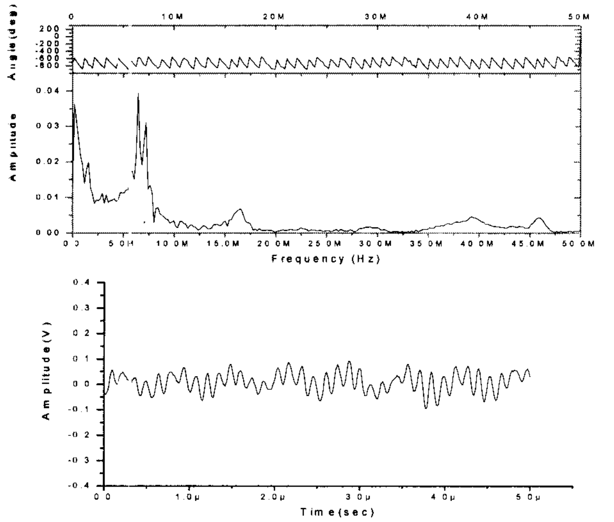
Fig. 5 displays signal waveforms (a, b, and c) measured from PD sources as shown in Fig. 3, a background noise waveform (d), and results of FFT for each signal waveform. Signal waveforms measured by the digital storage oscilloscope were triggered only for negative waveforms because the positive waveforms are so weak compared to negative waveforms, which have a bigger overshoot. The waveform of Fig. 5(a) has shape distortion in the front and a relatively big vibrating shape in the rear. The waveform of Fig 5(b) has smoothly descending and ascending shape in the both front and rear.



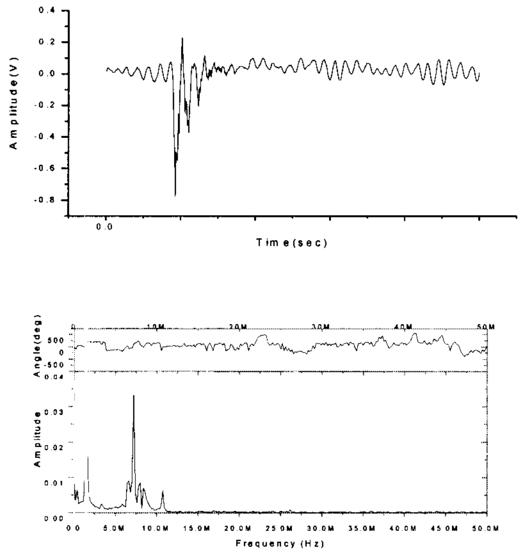
(a) N-S



(b) N-P



(c) N-N



(d) Noise

Fig. 5 Waveforms and FFT results of multiple-sources of PD signals

The waveform of Fig. 5(c) has a very sharp shape on the whole. The characteristics of these waveforms are reflected to frequency domains by FFT as shown in Fig 5. Noise of Fig. 5(d), which is assumed to be a free flying electromagnetic wave from a broadcast station or other sources, was measured while applying no high voltage. These FFT results are varied and uninfluenced by the starting point, which can cause some problems in the time domain. These differences make it possible to use the FFT results as features for classifying multiple PD sources. Features extracted from FFT results were configured with 250 points values and used as 250 input neurons of the ANN. To differentiate among the four PD sources, the output values of the ANN are defined by binary values 0 and 1; N-P (0,0), N-N (1,0), Noise (0,1), and N-S (1,1). The number of input neurons and output neurons of the ANN is determined to be 250 and 2, respectively. To make a complete ANN, the next task is to select an active function and the number of hidden layer neurons.

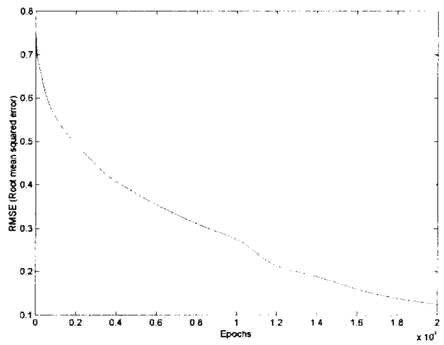
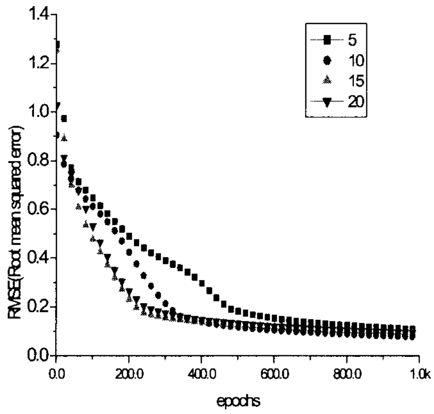


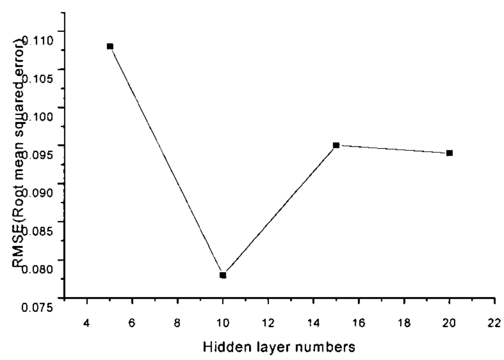
Fig. 6 RMSE result using logistic function (RMSE: 0.12 after 20,000 epochs)

Fig. 6 shows the result of using a logistic function as an active function that has 20,000 epochs to bring the root mean squared error (RMSE) to 0.12. Decreasing the RMSE to less than 0.12 will require too many epochs over 20,000.

Secondly, the hyperbolic tangent function was evaluated as a replacement for the logistic function. Fig. 7(a) shows the RMSE result, which requires 1,000 epochs to achieve



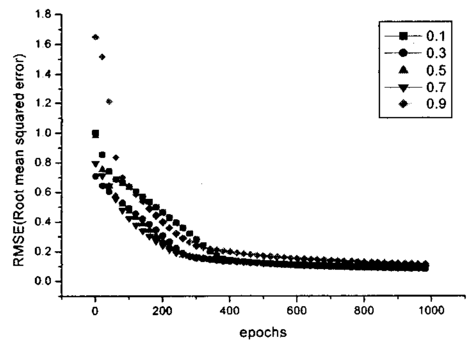
(a) RMSE curves (during 1,000 epoch)



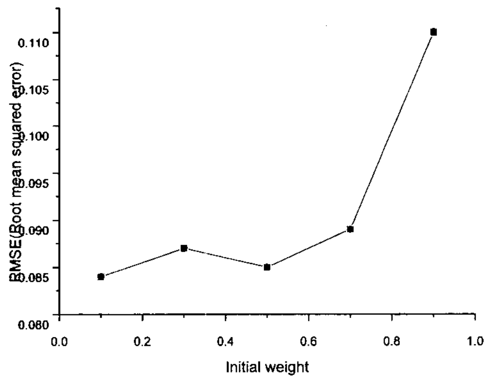
(b) RMSE results after 1000 epochs

Fig. 7 RMSE results on neuron numbers (5, 10, 15, 20) of the hidden layer an RMSE of less than 0.1. This epoch is quite small compared to that of the logistic function. The next task was to determine the number of neurons in the hidden layer. Each 5, 10, 15 and 20 neurons of the hidden layer was investigated as shown in Figs. 7(a) and (b).

Each results draws different curves in the region of less than 400 epochs but approaches similar values near 1,000 epochs. Ten neurons reached the least RMSE value and was selected as the number of neurons in the hidden layer. The BP learning is sensitive to the initial weighted value. If selected incorrectly, the BP learning is driven to the local minimum point. To investigate the effect of the initial weighted value for BP learning, the initial weighted values of 0.1, 0.3, 0.5, 0.7, and 0.9 are used and the results are shown in Figs. 8(a) and 8(b). The initial weighted value of 0.1 has the least RMSE. The completed ANN, with BP learning constructed, consists of an input layer (250), a hidden layer (10), an output layer (2), an active function (tanh) and an initial weighted value (0.1). The training data set is selected for determining the connecting strength (weight) of the ANN through BP learning, and the checking data set is selected for evaluating the classification performance among multiple PD sources using the ANN, which was already organized by the training data set. There are 15 sets per PD sources and the total number of sets was 120. Fig. 9(a) shows the perfect classification result of the training data set, and Fig. 9(b) show the classification per

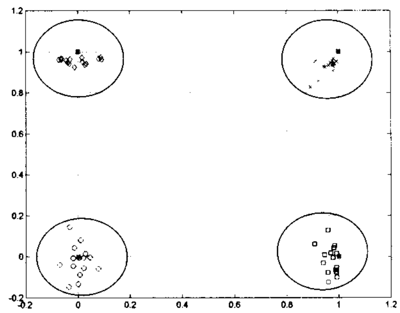


(a) RMSE curves (during 1,000 epochs)



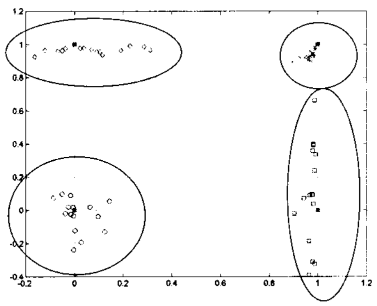
(b) RMSE results after 1,000 epochs

Fig. 8 RMSE results for initial weighted values



(0.1, 0.3, 0.5, 0.7, 0.9)

(a) Result using Training data set



(b) Result using checking data set

Fig. 9 Classification results by ANN (N-P (0,0), N-N (1,0), Noise (0,1), N-S (1,1).)

formance of the checking data set, which is good and has only one fault (noise) to divide into other source (N-S).

5. Conclusion

Signal waveforms from multiple PD sources vary as shown in the experiment results and their FFT results indicate more apparent differences than is shown in the signal waveforms. These differences of both the signal waveforms and their FFT results can be used as appropriate characteristics of PD. To discriminate among four PD sources, this paper adapted FFT results of the frequency domain as feature vectors and an ANN with BP learning as a classifier. This ANN consists of an input layer (250), a hidden layer (10), an output layer (2), an active function (tanh) and an initial weighted value (0.1) with 1,000 epochs. The performance of the ANN using the FFT results as an input is excellent for recognizing PD sources.

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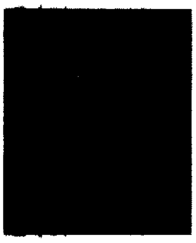

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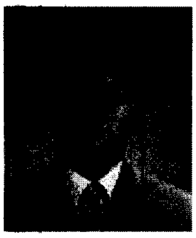

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