On-Line Estimation of Partial Discharge Location in Power Transformer

Yong-Han Yoon, Jae-Chul Kim, Chan-Soo Chung, Hee-Ro Kwak, and Dong-Jin Kweon

Abstract

This paper presents a neural network approach for on-line estimation of partial discharge(PD) location using advanced correlation technique in power transformer. Ultrasonic sensors detect ultrasonic signals generated by a PD and the proposed method calculates time difference between the ultrasonic signals at each sensor pair using the cross-correlation technique applied by moving average and the Hamming window. The neural network takes distance difference as inputs converted from time difference, and estimates the PD location. Case studies showed that the proposed method using advanced correlation technique and a neural network estimated the PD location better than conventional methods.

I. Introduction

Recently diagnosis and monitoring of power transformers is getting important due to the increase of power transformer failure. Specially, PD at large capacity power transformers can result in serious insulation damage. Therefore PD detection or estimation of its location is one of many diagnosis method. [1-6]

PD generates electrical and ultrasonic signals in transformers. In general, electrical signals could be detected by the Rogowsky coil mounted on the ground wire of the transformer tank or of the neutral line. Electrical signals propagate at light speed(3×10^8[m/sec]) which the propagation time is relatively negligible. Ultrasonic signals could be detected by the ultrasonic sensors mounted on the tank surface of the transformer tank. The ultrasonic signal velocity in the transformer oil is about 1400[m/sec] at 25[℃].

To estimate the PD location, the electrical-ultrasonic signal method and ultrasonic-ultrasonic signal method have been studied. [4] The electrical-ultrasonic signal method uses time difference between electrical signal and ultrasonic signal to reach each sensors from PD position. The ultrasonic-ultrasonic signal method uses time difference between ultrasonic signals to reach each sensors from PD position. The time difference resulting from the signals measured in each sensors can be used to estimate PD location. However, these approaches have the disadvantage such as inaccuracy and not adaptability.

Neural networks have been applied to power systems in the areas of control, analysis, planning, monitoring, and diagnosis. The neural network is a system composed of many simple processing elements(neurons) operating in parallel whose functions are determined by network structure, connection strengths, and the computing performed at neurons. The neural network with back-propagation of error is fit mapping relationships of complex, non-linear systems that are difficult to describe explicitly. Also, neural networks are good in interpolation, but not in extrapolation.

In this paper, we select the ultrasonic-ultrasonic signal method since it is inexpensive, highly sensitive, and highly resistive to external noise like air corona. To increase its accuracy and adaptability, this method use the advanced correlation technique and the neural network for on-line estimation of the PD location in power transformer. Case studies showed that we could estimate the PD location better than conventional methods.

II. Detection and Analysis of Ultrasonic Signal

1. Partial discharge measuring system [4]

Fig.1 shows the block diagram of PD measuring system

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using ultrasonic sensors. Fig.2 shows the position of ultrasonic sensors mounted on the tank surface of an experimental transformer of size $0.4\times0.8\times0.5$[m]. When PD generates in the experimental transformer, ultrasonic signals can be detected with ultrasonic sensors of PD measuring system. Fig.3 shows the ultrasonic signals detected with the ultrasonic sensors of PD measuring system.

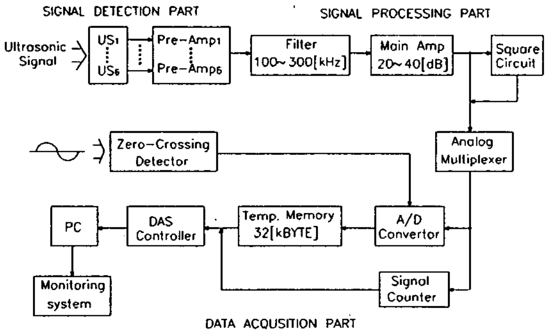
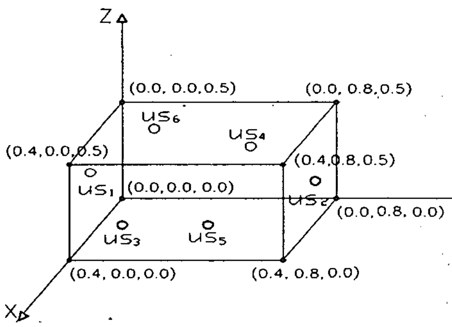


Fig. 1. Block diagram of partial discharge measuring system using ultrasonic sensors.



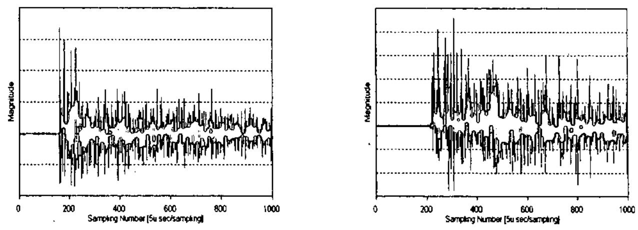
$US_1=(0.20\times0.00\times0.25)$ unit : [m]
$US_2=(0.20\times0.80\times0.25)$
$US_3=(0.40\times0.30\times0.30)$ $US_5=(0.40\times0.50\times0.20)$
$US_4=(0.00\times0.50\times0.20)$ $US_6=(0.00\times0.30\times0.30)$

Fig. 2. Position of ultrasonic sensors mounted on the tank surface of an experimental transformer.

2. *Advanced cross-correlation technique*

In the ultrasonic-ultrasonic signal method, the error of time difference is determined by the decision of the inception times of detected ultrasonic signals. To minimize errors, this paper improves the accuracy of the cross-correlation value by applying moving average and the Hamming window.[7]

The cross-correlation value of ultrasonic signals detected at each sensor pair can be calculated, after the decision of ultrasonic signals' inception time.



(a) US_1 (b) US_2

Fig. 3. Ultrasonic signals detected with the ultrasonic sensors US_1 and US_2.

For convenience of ultrasonic signal processing, the magnitude of detected signal is normalized as

$$\mathrm{nor}(n) = \frac{100\times U(n)}{\max|U(i)|} \tag{1}$$

where $U(\cdot)$ is the detected ultrasonic signal U, and n is sample ($1\le n\le N$). The sampling time (ΔT) is 5[μsec] and the number of samples(N) is 2000.

After the normalization of ultrasonic signals detected at ultrasonic sensors, the inception time of ultrasonic signal is determinated by a sample that is satisfied with Eq.(3) through moving average of Eq.(2)[7]

$$\mathrm{mv}(n) = \frac{1}{m_w}\sum_{k=0}^{m_w-1}|\mathrm{nor}(n-k)|,\quad m_w\le n\le N \tag{2}$$

where ($m_w=6$) indicates the range of moving average.

$$|\mathrm{nor}(n)| \ge \alpha\times \mathrm{mv}(n-1),\quad m_w+1\le n\le N \tag{3}$$

where ($\alpha=4$) is a constant.

After the decision of the inception time of the detected ultrasonic signal, the Hamming window function is applied with constant range around the inception time of ultrasonic signal. Out of constant range is coded by 0.

$$x(n) = \mathrm{nor}(n)\times H(n) \tag{4}$$

where $H(\cdot)$ is the value of the Hamming window function.[7]

$$H(p_T+k) = \begin{cases} 0 & ,|k| > \frac{H_M-1}{2} \\ 0.54+0.46\cos\left(\frac{2\pi k}{H_M-1}\right) & ,\text{otherwise} \end{cases} \tag{5}$$

where p_T is the inception time of detected ultrasonic signal and H_M is the range of the Hamming window ($H_M=59$, odd number). So, the above equations' parameters are determined through experimental works. And time difference between two ultrasonic signals is obtained from the condition of Eq.(7), after calculating cross-correlation value of Eq.(6).[7]

$$R_{xy}(n) = \frac{1}{N-n}\sum_{k=1}^{N-n} x(k)y(n\pm k),\quad 1\le n\le N \tag{6}$$

where, $\begin{cases} + : p_T \text{ of } x(\cdot) < p_T \text{ of } y(\cdot) \\ - : p_T \text{ of } x(\cdot) > p_T \text{ of } y(\cdot) \end{cases}$

$$T_D = (\max_n R_{xy}(n)) \times \Delta T, \quad 1 \le T_D \le N \tag{7}$$

Fig.4 shows the cross-correlation value of two ultrasonic signals applied by moving average and the Hamming window.

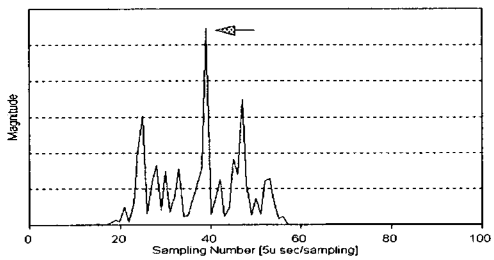


Fig. 4. The cross-correlation value of two ultrasonic signals applied by moving average and the Hamming window.

Distance difference from PD location to a pair of ultrasonic sensors can calculate using Eq.(8).

$$D_D = T_D \times V \tag{8}$$

where V is the ultrasonic signal velocity in transformer oil(V=1400[m/sec], 25[℃]).

III. Estimation of Partial Discharge Location Using Neural Networks

Conventional methods for on-line estimation of PD location based on mathematical analysis such as 3-dimensional drawing method and Newton-Raphson method. [4] However, because the detected ultrasonic signals can include noises and non-linear characteristics, conventional methods sometimes cannot estimate PD location due to the convergence problem.

In this paper, the error of time difference from PD location to a pair of ultrasonic sensors is minimized by applying moving average and the Hamming window. And the PD location can be estimated by the trained neural network. A multilayer neural network is trained with the back-propagation algorithm.[8]

In a trained neural network, input value is the distance differences from PD location to each sensor pair and output value is the PD location of 3-dimension rectangular coordinates in transformer.

1. Training samples

The training samples of neural networks for on-line estimation of PD location in transformers are obtained by Eq.(9)

$$d_{i(1-2)} = \sqrt{(x_p - x_{i1})^2 + (y_p - y_{i1})^2 + (z_p - z_{i1})^2} - \sqrt{(x_p - x_{i2})^2 + (y_p - y_{i2})^2 + (z_p - z_{i2})^2}, \quad (1 \le i \le 3) \tag{9}$$

where,

$d_{i(1-2)}$: distance difference[m] of sensor pair I between US_{i1} and US_{i2} from PD location

x_p, y_p, z_p : 3-dimension coordinates of PD location

x_{i1}, y_{i1}, z_{i1} : 3-dimension coordinates of US_{i1} among ultrasonic sensor pair i

x_{i2}, y_{i2}, z_{i2} : 3-dimension coordinates of US_{i2} among ultrasonic sensor pair i

Also, to reduce the number of training samples, the ranges of the possible PD location in transformer divided into the intervals of 0.05[m].

2. Learning and application

It is not that neural networks are programmed, but that they are learned. In other words, the human does not have to be able to explain the problem to the network. The advantage of this is that they can distinguish patterns from multi-dimensional data that a human may not be able to recognize. Therefore, this means that training samples need to comprise the complete pattern space that needs to be correctly classified during normal state. This directly impacts the sensitivity of the neural network in providing accurate results. For example, if training samples include a large range of numerical values, information provided by the small change of a certain parameter can be lost. Additionally, accuracy of the output depends upon the training tolerance and the range of numerical values. A major problem can occur if the output set consists of values comprising a relatively large range compared to the training tolerance of the output. The training tolerance is larger than the sensitivity of the neural network.

Table 1. The neural network parameters.

number of node of input layer	3
number of node of hidden layer	30
number of node of output layer	3
learning rate	0.7
momentum rate	0.5
training tolerance (maximum error)	0.01

The long time required for learning is another problem associated with neural networks. The training time may be long due to the high number of iterations required to adjust the connection strengths(weights) to the proper values to minimize the overall neural network error. However, once the neural network is trained response is very fast.

In this paper, the basic structure of a neural network is given table 1. The neural network is trained at SUN SPARC 10.

In table 1, the 0.01 of training tolerance means that the neural network trained until coordinate error has 1[cm]. Finally, the system diagram for on-line estimation of PD location is given Fig.5

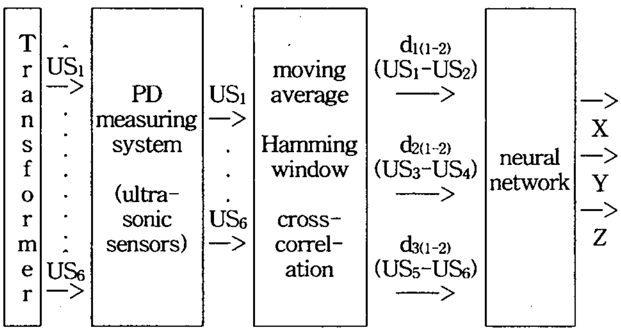


Fig. 5. System diagram for on-line estimation of partial discharge location.

IV. Case Studies

This paper studies two cases, the experimental transformer and the 3-phase transformer. Also, we present the comparison results of the proposed method and the mathematical (Newton-Raphson) method.

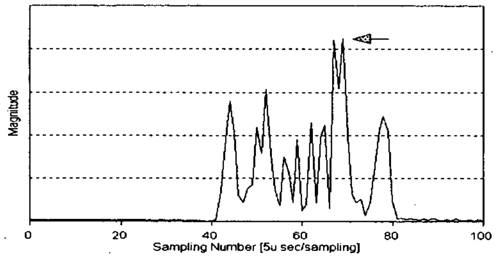
1. Experimental transformer

Table 2. The results of case studies in the experimental and 3-phase transformer.

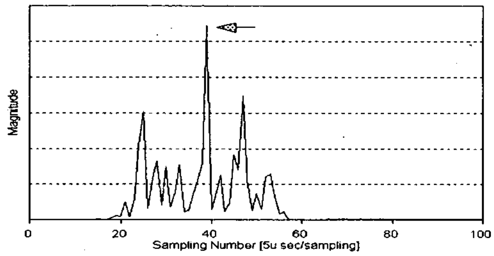
PD position		time difference between ultrasonic sensors			results of neural network		results of Newton-Raphson	
rectangular coordinates [m]	X Y Z	$d_{1(1-2)}$ D_D (US_1-US_2)	$d_{2(1-2)}$ D_D (US_3-US_4)	$d_{3(1-2)}$ D_D (US_5-US_6)	X Y Z	$error[m]_\infty$	X Y Z	$error[m]_\infty$
experimental transformer case 1	0.095	0.481	0.295	-0.036	0.099	0.050	no converge	
	0.655	0.483	0.273	-0.028	0.655			
	0.210				0.260			
experimental transformer case 2	0.210	-0.049	-0.006	-0.029	0.222	0.016	0.217	0.017
	0.375	-0.056	-0.014	-0.042	0.372		0.371	
	0.175				0.159		0.158	
experimental transformer case 3	0.155	-0.285	-0.059	0.201	0.148	0.025	0.150	0.017
	0.255	-0.294	-0.063	0.217	0.248		0.248	
	0.305				0.330		0.328	
3-phase transformer case 4	0.220	-0.330	-0.088	0.469	0.214	0.023	0.215	0.016
	0.430	-0.336	-0.098	0.476	0.422		0.434	
	0.580				0.557		0.564	

* The error tolerance of Newton-Raphson method : 0.03

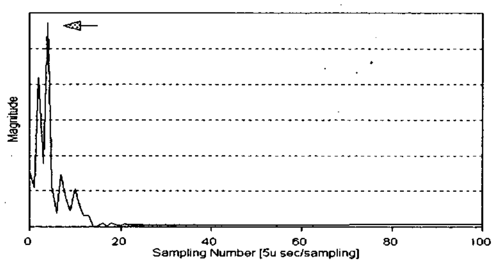
The experimental transformer consists of steel tank filled with oil, a piezoelectric vibrator for simulating the PD. The dimension of the steel tank is $0.4 \times 0.8 \times 0.5$[m] and it consisted of insulation oil and insulation paper without coil or core. The PD simulated at piezoelectric vibrator which is fixed at $0.095 \times 0.655 \times 0.210$[m]. In the neural network of this case study, the number of the training samples is 325, and the number of the training iterations is 237,586.



(a) Cross-correlation of ultrasonic sensor pair 1



(b) Cross-correlation of ultrasonic sensor pair 2



(c) Cross-correlation of ultrasonic sensor pair 3

Fig. 6. The cross-correlation of ultrasonic signals generated in the experimental transformer.

Fig.6 shows the cross-correlation of ultrasonic signals generated in the experimental transformer. Table 2 is the results of case studies by changing the PD location.

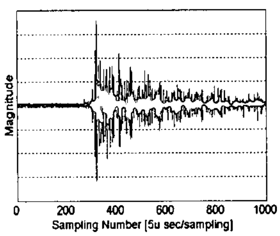
2. 3-phase transformer

The 3-phase transformer consists of steel tank filled with oil, an electrode for generating the PD. The dimension of the steel tank is $0.88 \times 0.53 \times 0.88$[m] and it consisted of insulation oil, insulation paper, coil and core. The 3-phase transformer is core type, rated capacity is 200[kVA]. The PD generated at the gap between needle and plate electrode which is fixed at $0.22\times0.43\times0.58$[m]. In the neural network of this case study, the number of the training samples is 2,210 and the number of the training iterations is 711,357.

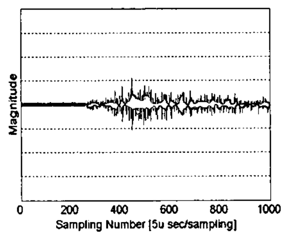
The location of ultrasonic sensors mounted on the tank surface of the 3-phase transformer is as follows:

$US_1=(0.22\times0.53\times0.58)$ unit : [m]
$US_2=(0.22\times0.00\times0.58)$
$US_3=(0.66\times0.53\times0.35)$ $US_5=(0.88\times0.26\times0.48)$
$US_4=(0.63\times0.00\times0.58)$ $US_6=(0.00\times0.43\times0.58)$

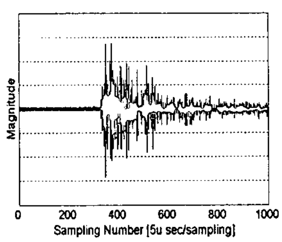
Fig.7 shows that detected ultrasonic signals in the 3-phase transformer. Fig.8 shows the cross-correlation of ultrasonic signals generated in the 3-phase transformer. Table 2 shows the results of case studies.



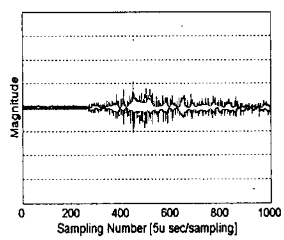
(a) US_1



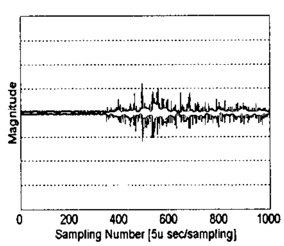
(b) US_2



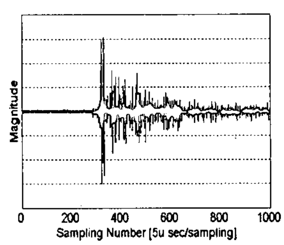
(c) US_3



(d) US_4



(e) US_5



(f) US_6

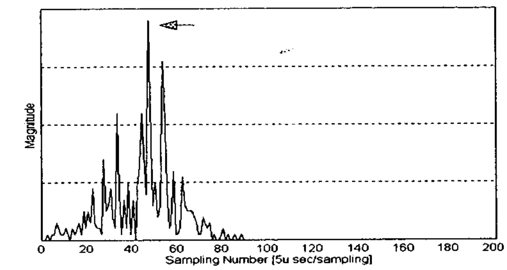
Fig. 7. Detected ultrasonic signals in the 3-phase transformer.

3. Analysis of the case studies

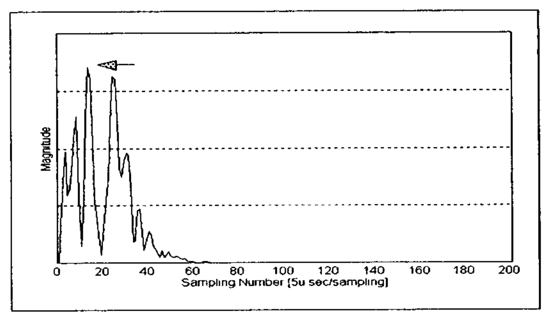
As pointed out in table 2, because of convergence problem in mathematical analysis, Newton-Raphson method sometimes cannot estimated PD location.

V. Conclusion

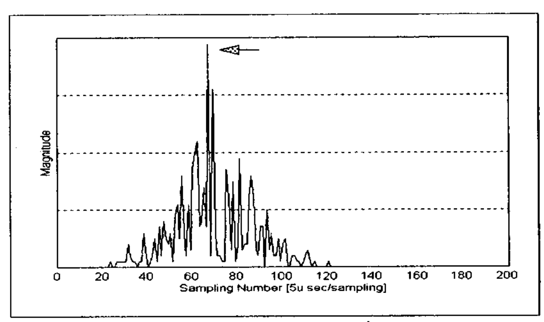
For improving the reliability of diagnosis and monitoring in power transformer, the on-line estimation of PD location could be used. And it reduces the time and cost for repairing the troubled transformer.



(a) Cross-correlation of ultrasonic sensor pair 1



(b) Cross-correlation of ultrasonic sensor pair 2



(c) Cross-correlation of ultrasonic sensor pair 3

Fig. 8. The cross-correlation of ultrasonic signals generated in the 3-phase transformer.

We present an application of the neural network in relation to estimate partial discharge location in power transformer. In addition, we propose a preprocessor stage before the neural network stage, consisting of moving average filter, Hamming window and cross-correlation technique. The advantage of this method is that it is adaptive. Because of noise in the detected ultrasonic signals and convergence problem in mathematical analysis, conventional methods such as Newton-Raphson method sometimes cannot estimated PD location. Also, in on-line operation, they appear the speed problem.

As the results of case studies, we can estimate PD location better than conventional methods. Therefore, the proposed method is adaptable on-line estimation to changing PD location in power transformer.

Acknowledgment

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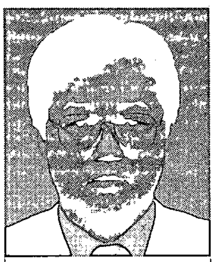
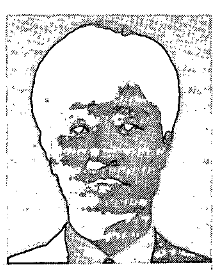


Chan-Soo Chung was born in Kyeongbuk Province, Korea in 1949. He received the B. E., M. E. and Ph. D. degrees in Electrical Engineering from Seoul National University, Seoul, Korea in 1972, 1980 and 1987, respectively. Currently he is a professor at the department of Electrical Engineering, Soongsil University and his areas of interests include adaptive control and signal processing, robust and optimal control, equipment diagnosis and active noise control applications. He is a member of the IEEE, KIEE, ASK(Acoustic Society of Korea) and so on.



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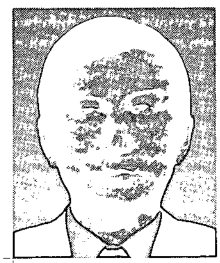

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