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A Nonlinear Analysis of Partial Discharge Signal

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Abstract - The partial discharge(PD) signal, may seems to be stochastic and merely random, was investigated using the method to discern between chaos and random signal, e.g. correlation integral, Lyapunov characteristic exponents and etc. For the purpose of obtaining experimental data, partial discharge detecting system via computer aided acoustic sensor, detect PD signal from the insulating system, was used. While this method is very different from typical statistical analysis from the point of view of a nonlinear analysis, it can provide better interpretable criterion according to the time evolution with a degradation process in the same type insulating system.

Key Words : Partial Discharge, Correlation Integral, Lyapunov Exponents

1. Introduction

For a long time, various computer-aided evaluation methods of Partial Discharge phenomena have been developed for the purpose of testing the reliability of HV power equipment[1]. For the purpose of obtaining Partial Discharge signal, Acoustic Emission(AE) system was used. The advantages of AE system are adaptability for non-transparent materials, complicated electrode arrangements, immunity for electrical magnetic interferences, and the possibility for real time observation of tree propagation[2].

The data obtained from the AE system take the form of a "time series", which is to say, a series of values sampled at unique interval[1]. If a time series has chaotic characteristics, the system which generates the time series can be considered as deterministic and nonlinear. Conversely, the dynamical rule of the system can be represented by the obtained time series.

There are two general criterion to discern chaotic signal from merely random signal. The one is "qualitative information (topological characteristics)", which is to say, return(or Poincarè) map, strange attractors and correlation integral etc., the other is "quantitative information (dynamical characteristics)", which is to say, Lyapunov exponents, correlation dimension and Lyapunov dimension etc.

In this paper, to reveal the chaotic characteristics of PD signal, PD data will be reconstructed in the phase space, then Lyapunov dimension and correlation dimension of PD signal will be determined. Detail process and notations will be appear sequently in the following sections.

2. EXPERIMENTAL SETUP AND DATA PREPARATION

2. 1. Experimental Setup

Figure 1 illustrates the block diagram of the computer aided PD detection system.

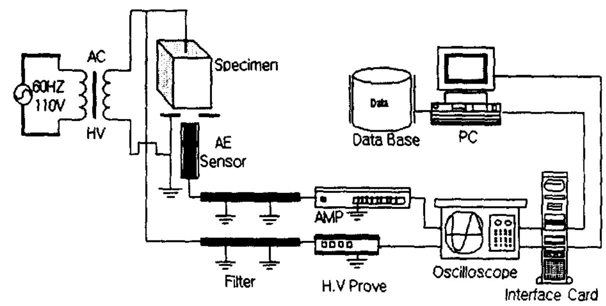

Fig. 1 Block diagram of the experimental devices

The basic elements of this system are specimen, AE sensor, high-resolution digital oscilloscope, and personal

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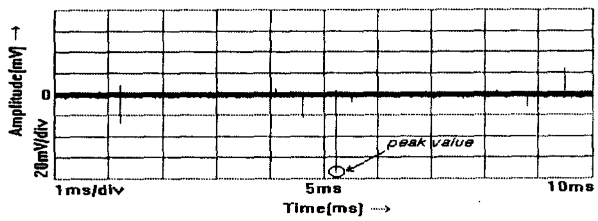
computer. The specimen is fabricated to has needle-plane electrode with XLPE. This specimen is the modeling of local high electric field due to the protuberance of semiconductive layer In power cable and the voltage of the HV is fixed at 15KV. The AE sensor is used for detecting PD signal in the treeing propagation and the pre-amplifier is used for amplifying the PD signal. The output frequency of the AE sensor takes from 400Khz to 1Mhz, and the resonant frequency is 600Khz. Therefore, the pre-amplifier used in this paper has the resonance frequency 600Khz. The signal detected from the AE sensor is digitized by the oscilloscope and saved in the personal computer through the interface card.

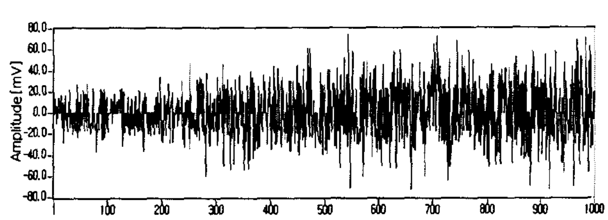
2. 2. Data Preparation : Peak Detection

The oscilloscope is set to sample the data at $f_s = 20Mhz$, this rate is 20 times higher than the highest output frequency of the sensor. Recall that the sampling rate f_s must be at least twice the highest frequency found in the signal to prevent aliasing.

But, the time series obtained from each reading of the oscilloscope is not proper to some of the data analysis by itself, because it contains too many zero values. Therefore, in this paper, each peak value of the reading of the oscilloscope is used to make time series. So, the sampling time step of the each point in a time series(Δt) is fixed at 1 second. Figure 2 shows an example of the time series.



(a) A sample time series obtained from each reading of the oscilloscope(1ms/div, 2×10^5points)



(b) A time series made by each peak value(1s/point). 1000points out of 9800 obtained are displayed.

Fig. 2 An example of the time series

3. NONLINEAR ANALYSIS OF THE DATA

3. 1. Phase-Space Reconstruction From a Time Series

Phase-space reconstruction was, for the first, suggested by Packard et. al[3]. These authors conjectured that phase-space pictures could be reconstructed from time derivatives formed from the observation of a single coordinate of any dissipative dynamical system. Another method of phase-space pictures reconstruction was suggested independently by Takens[4] and improved associated with the process of measurement by Broomhead and Gregory[5]. The later method is known as the "delay coordinate embedding" and will be used in this paper as a tool to reconstruct trajectory in phase-space, which is to say "attractor" that illustrates trajectory in phase space following time evolution in dynamical system.

The basic idea of the reconstruction (embedding) is that to specify the state of any dimensional system at given time, therefore any independent quantities should be sufficient to specify the state of the system. However, unfortunately, in many cases the experimentalist has no prior knowledge of how many dimensions would require, nor the quantities appropriate to the construction of such a phase-space.

Scalar time series, which is a result of measurement, can be presented as follows;

$$x(t+1) = x(t+\Delta t) \tag{1}$$

where, Δt is a sampling time step. From the set of time series, vectors in d_E dimensional space,

$$X_n = (x(t), x(t+\tau), \ldots, (x(t+(d_E-1)\tau),$$

i.e.

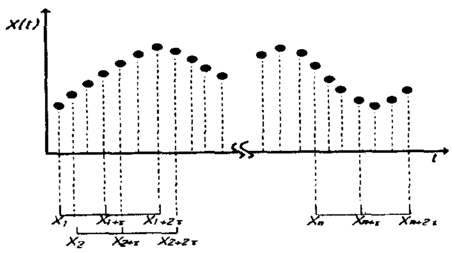
$$X_1 = [x(1), x(1+\tau), \ldots, x(1+(d_E-1)\tau)]$$

$$X_2 = [x(2), x(2+\tau), \ldots, x(2+(d_E-1)\tau)]$$

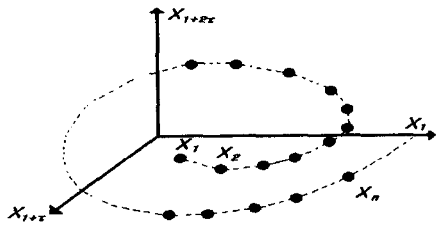
$$\cdots\cdots\cdots\cdots\cdots$$

$$X_n = [x(n), x(n+\tau), \ldots, x(n+(d_E-1)\tau)] \tag{2}$$

are used to trace out the trajectory of the system. Where, τ is a delay time and d_E is an embedding dimension, respectively. The time series, equation (1), are a projection of the state space of the system onto the one dimensional coordinate of the $x(n)$. Therefore, the purpose of delay coordinate embedding is to unfold the projection back to a phase space which is representative of the original system[6]. Hence, a set of d_E dimensional column vectors X_n represent points in the d_E dimensional phase space and a trajectory is constructed by connecting these points, at the same time, each row vectors $\{x(i) \mid i=1,2,\ldots,n\}$, $\{x(i+\tau) \mid i=1,2,\ldots,n\}$ and etc. will build each coordinates. Figure 3(a) illustrates a schematic diagram of making of 3-dimensional vectors from a time series and reconstructed trajectory with 3-dimensional vectors obtained by equation (2) is shown in figure 2(b).



(a) Making of vectors from an observed time series



(b) Reconstructed trajectory from the vectors

Fig. 3 Schematic diagram of trajectory reconstruction from an observed time series

There are two important parameters (embedding dimension d_E and delay time τ) for delay coordinate embedding and further application. In practice, what embedding dimension d_E and delay time τ to use in the reconstruction are very sensitive problem and various methods to determine d_E [5-9] and τ [10, 11] are suggested elsewhere. The method of determining τ, Mutual Information, will be discussed in the next section. And, in this paper, for the purpose of economizing to compute d_E , and have no prior knowledge on d_E , the method which Kennel[6] asserted "false nearest neighbors method", namely FNN method, was used for determining d_E. At the beginning of embedding, to compare result at various embedding dimensions and delay times with different experimental environment, the observed time series is normalized via $x^*(t)=\frac{(x(t)-x_{\min})}{(x_{\max}-x_{\min})}$, so that $0\le x^*(t)\le 1$.

3. 1. 1. Determining τ :Mutual Information $I(x(t),\ x(t+\tau))$

For infinite and noise-free time series, embedded attractors with different delay times are completely equivalent in their trajectory in principle. But for finite time series, different delay times in the reconstruction process may contain different dynamical information[12]. If delay time is too small, $x(t)$ and $x(t+\tau)$ are too correlated and if delay time is too large, $x(t)$ and $x(t+\tau)$ are uncorrelated as completely random variables. Therefore, an appropriate(or may be accurate) delay time is needed for phase-space reconstruction. In other words, to choose the appropriate delay time is that the coordinates $x(t)$ and $x(t+\tau)$ are independent but not completely uncorrelated so that they can be regarded as independent coordinates in reconstructed phase-space.

Various methods to determine appropriate delay time are suggested independently[10, 11]. While the suggested methods are very different from each other, from the figure 1 in Ref[10]. It may be seen clearly that the mutual information (namely, $N\log N$) method provides more appropriate delay time values than the autocorrelation method. Therefore, in this paper, the mutual information method is used for choosing delay time. The major concern which included in mutual information is that in measuring how dependent the values of $x(t+\tau)$ are on the values of $x(t)$, and at the same time each coordinate in the reconstructed phase-space must be independent each other. Therefore, taking the delay time which has the first minimum in I as an appropriate τ can be accepted reasonably.

The two sets of reconstructed data with delay time τ will have the form $\{x(t)\mid i=1,2,\ldots n\}$, $\{x(t+\tau)\mid i=1,2,\ldots n\}$ and let them $[s,q]=[x(t),x(t+\tau)]$, then the mutual information between these two sets of reconstructed data is(see Ref.[10] for more theoretical notion),

$$I(S,Q)=\frac{1}{N_0}F(R_0(K_0))-\log_2(N_0) \tag{3}$$

where, $I(S,Q)$ is a function of the joint probability distribution P_{sq} , N_0 is the total number of points observed in phase-space and $F(R_0(K_0))$ is the recursive function determined as follows ;

$$F(R_m(K_m))= \\ N(R_m(K_M))\log_2[N(R_m(K_m))]\ ; \\ \text{if there is no substructure in } R_m(K_m) \\ N(R_m(K_M))\log_2(4)+\sum_{j=0}^{3}N(R_{m+1}(K_{m,j}))\ ; \\ \text{if there is substructure in } R_m(K_m) \tag{4}$$

Mutual information was applied for peak detected PD data(Figure 2(b)), and then Figure 4 shows clearly that the delay time could be determined at 2(2 second). Because major concern included in mutual information is making independent coordinates in phase space, taking 2 as appropriate τ is resonable. In other words, the independency between $x(t)$ and $x(t+\tau)$ of peak detected PD data in phase space should be preserved at τ bigger than 2.

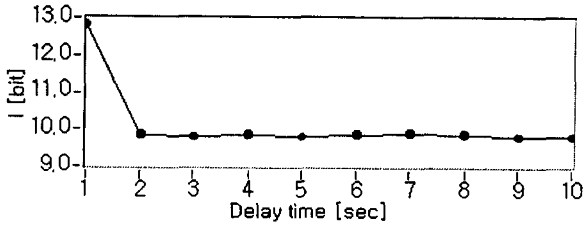


Fig. 4 Result graph of mutual information

3. 1. 2. Determining Embedding Dimension d_E : FNN Method

A false neighbor is a point in the data set appear to be nearest neighbors because the embedding space is too small. If one has taken a large enough embedding space, all neighbors of every orbit point in the phase space will be true neighbors. So, when the number of false nearest neighbors drops to zero, one can embed(unfold) the attractor in R^{d_E}.

In d_E dimensions, the rth nearest neighbor of X_i is able to be denoted by $X^{(r)}_i$, then from equation (2), the square of the Euclidean distance between the point X_i and $X^{(r)}_i$ is

$$E^2_{d_E}(i, r)= \sum_{k=0}^{d_E-1}[x(i+k\tau)-x^{(r)}(i+k\tau)]^2 \quad (5)$$

After the addition of the new coordinate, by delay time embedding, the distance between X_i and the rth nearest neighbor is

$$E^2_{d_E}+1(i, r) = R^2_{d_E}+ [x(i+kd_E\tau)-x^{(r)}(i+kd_E\tau)]^2 \quad (6)$$

Then, Kennel[4] has asserted a natural criterion for catching embedding errors using the increase in distance between X_i and $X^{(r)}_i$ is large when going from dimension d_E to d_E+1. This criterion is determined as follows;

$$\left[\frac{E^2 d_E+1(i, r)-E^2 d_E(i, r)}{E^2 d_E(i, r)}\right]^{1/2} > E_T \quad (7)$$

where, E_T is some threshold and Kennel[4] has verified that for $E_T \geq 10$ the false neighbors are clearly identified. And, they advise this criterion should be used with next criterion at the same time. The second criterion is

$$\frac{E_{d_E}+1}{E_A} > A_T \quad (8)$$

Where, A_T is some threshold(usually takes A_T = 2 [5]) and E_A is the size of attractor, respectively, determined as following equation.

$$E^2_A=\frac{1}{N}\sum_{n=1}^{N}(x(n)-\bar{x})^2,\ \bar{x}=\frac{1}{N}\sum_{n=1}^{N}x(n) \quad (9)$$

Then, the percentage of false nearest neighbors is computed as follows.

$$PFNN=\frac{(number\ of\ FNN)}{(number\ of\ point\ of\ the\ attractor)}\times 100[\%] \quad (10)$$

FNN method was applied for peak detected PD data. Theoretically, if the number of FNN drops to zero the time series can be embedded in R^{d_E} but in this paper the criterion for the number of FNN set to 0.5 and then Figure 5 shows that the embedding dimension could be determined at 6(delay time τ=2, as determined above).

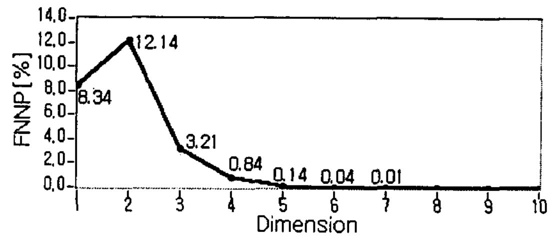


Fig. 5 Result graph of FNN

3. 2. Lyapunov Exponents and Dimension

Lyapunov exponents denote the rate of divergence of nearby trajectories. There are as many Lyapunov exponents as there are dimensions in the phase-space of the system, but the largest is usually the most important. In other words, the largest Lyapunov exponent is the time average logarithmic growth rate of the distance between two nearby trajectories and the largest positive Lyapunov exponents indicate that the system is nonlinear and chaotic. Some different methods to obtain all of the Lyapunov exponents were proposed independently in Ref.[13] and [14]. In this paper, the method out of Ref.[13] is used for convenience of computing, individually.

Consider a small ball of radius ε centered at the point X_j (j=1, 2, ...)on trajectory, and the set of points included in this ball { X_{ji} }(i=1, 2, ...). Then, the displacement vector Y^i between X_j and X_{ji} is calculated as follows ;

$$\{ Y^i \} = \{ X_{ji}-X_j \mid \|X_{ji}-X_j\| \leq \varepsilon \} \quad (11)$$

where, $\|\ldots\|$ denotes Euclidean norm. After the time step T ($=m\Delta t$, m is an integer), X_j and X_{j_i} are proceed to X_{j+m} and X_{j_i+m} , respectively. So, the displacement vector $\{Y^i\}$ is mapped to

$$\{Z^i\} = \{X_{ji+m} - X_{j+m} \mid \|X_{ji+m} - X_{j+m}\| \le \varepsilon\} \tag{12}$$

If the radius of ε is small enough Y^i and Z^i can be regarded as an approximation of tangent vectors in the tangent space. Then, Z^i can be represented using any matrix A_j by

$$Z^i = A_j Y^i \tag{13}$$

where, the matrix A_j is an approximation of the Jacobian matrix. The squared error norm between Z^i and $A_j Y^i$ can be minimized using least-square-error algorithm ;

$$\min S = \min \frac{1}{N} \sum_{i=1}^{N} \|Z^i - A_j Y^i\|^2 \tag{14}$$

and the matrix A_j can be computed approximately as follows (for $N > d_E$),

$$A_j V = C \Rightarrow A_j = C(V)^{-1}$$
$$(V)_{kl} = \frac{1}{N} \sum_{i=1}^{N} Y^{ik} Y^{il}, \quad (C)_{kl} = \frac{1}{N} \sum_{i=1}^{N} Z^{ik} Y^{il} \tag{15}$$

Then, Lyapunov exponents are computed as,

$$\lambda_i = \lim_{n \to \infty} \frac{1}{N} \sum_{j=1}^{N} \|A_j e_j^i\| \tag{16}$$

Then, from the Lyapunov spectrum, one of the fractal dimension of attractor, which is called the Lyapunov dimension, can be computed. The Lyapunov dimension is defined as

$$D_L = j + \frac{\sum_{i=1}^{j} \lambda_i}{|\lambda_i|} \tag{17}$$

where, j is the largest integer such that the sum $\sum_{i=1}^{j} \lambda_i$ of the Lyapunov exponents in the descending order is non negative[15]. If the sum of the Lyapunov exponents is positive, D_L is defined as the same value with the dimension of the state space.

Figure 6 shows the result of Lyapunov exponents according to iteration at embedding dimension 6, delay time 2(They were determined in the above section), initial center point 100, initial radius of a ball 0.01, and time step 10. Where, from the result, the largest exponent was 1.08 ±0.0028 and the Lyapunov dimension was 6(equal to d_E). This result, the largest exponent $\lambda_i > 0$, shows that the PD is originated from the deterministic chaotic dynamical system.

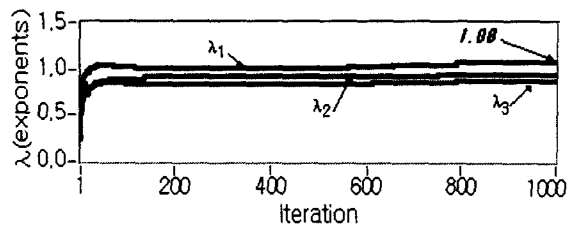


Fig. 6 Lyapunov exponents according to iteration. 3 exponents, descending order, were plotted out of 6 exponents

3. 3. Correlation Dimension

Correlation dimension D_c is one of the non-integer number of dimensions that characterizes the multifractal structure of the chaotic attractor. D_c can be evaluated using the correlation integral $C(\varepsilon)$, which is proposed by Grassberger and Procaccia[12, 16, 17]. For a trajectory of length N in the embedding space R^{d_E}, the correlation integral can be computed as follows ;

$$C_N(\varepsilon) = \frac{2}{N(N-1)} \sum_{i,j=1,\, i \ne j}^{N} \Theta(\varepsilon - \|X_j - X_i\|) \tag{18}$$

where, $\Theta(X)$ is the Heaviside function defined by $\Theta(X)$ =1(if $X \ge 0$); $\Theta(X)$=0(if $X < 0$), X_j is the center of a ball has any radius ε and X_i is the set of points included in the ball. Then, the correlation dimension D_C is given by

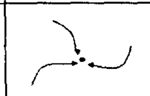
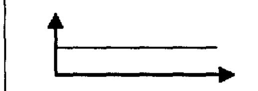
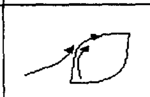
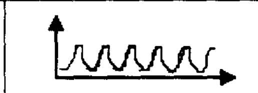
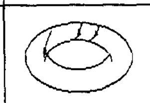
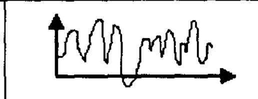
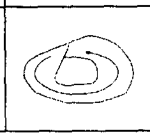
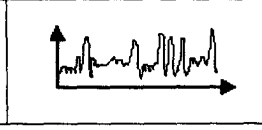
$$D_c = \lim_{\varepsilon \to 0} \lim_{N \to \infty} \frac{\log C_N(\varepsilon)}{\log(\varepsilon)} \tag{19}$$

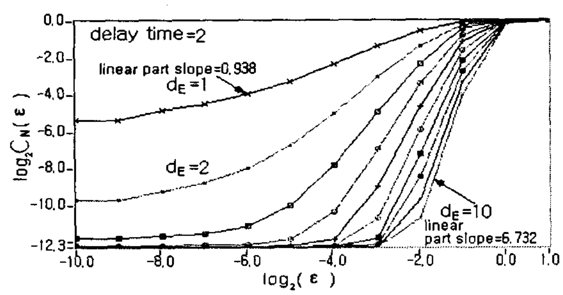
In practice, D_c usually can be estimated by computing the slope of the linear part of the plot of $\log C_N(\varepsilon)$ versus $\log \varepsilon$ for increasing values of embedding dimension d_E (or delay time τ) using the least squares fit method as follows.

$$D_c \approx \frac{l \sum_{i=1}^{l} \log(\varepsilon_i) \log C_N(\varepsilon_i) - l \sum_{i=1}^{l} \log(\varepsilon_i) \sum_{i=1}^{l} \log C_N(\varepsilon_i)}{l \sum_{i=1}^{l} \log^2(\varepsilon_i) - \left(\sum_{i=1}^{l} \log(\varepsilon_i)\right)^2} \tag{20}$$

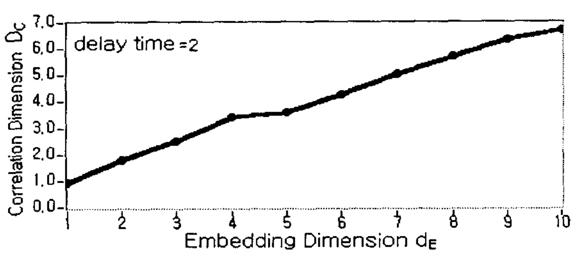
Figure 7 shows that the correlation dimension could be determined as 7 and 4. These results make clear that the attractor constructed from PD signal has multi fractal structures in phase space in that PD signal have non-integer D_c values.

Table 1 Phase space states of various system and their Lyapunov spectrum

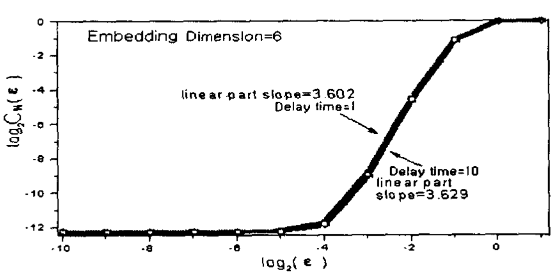
Class	Phase Space	System	Attractor	Dimension	Lyapunov Spectrum	Time Series
Fixed Point		Equilibrium	One Point	0	λ_i <0 (i=1, 2, ... ,n)	
Limit Cycle		Periodic Oscillation	Closed Curve	1	λ_1 =0 λ_i <0 (i=2, 3, ..., n)	
Doughnut		Quasiperiodic Oscillation	Doughnut	K	λ_1 = λ_k =0 λ_i <0 (i=k+1, ... , n)	
Strange Attractor		Chaos	Fractal	non-integer	λ_i >0 (i=1, ... , m-1) λ_m =0, λ_i <0 (i=m+1, ... , n)	



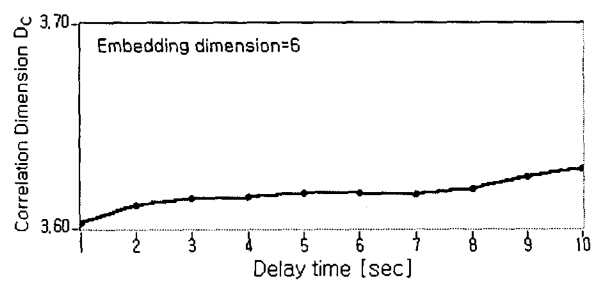
(a) Result graph of the correlation integral. τ was fixed at 2 and d_E was changed from 1 to 10.



(b) Graph of D_C with different d_E. Delay time τ is fixed at 2



(c) Result graph of the correlation integral. d_E was fixed at 6 and τ was changed from 1 to 10.



(d) Graph of D_C with different τ .(d_E is fixed at 6)

Fig. 7 Result graph of the correlation integral with different delay time and embedding dimension

4. RESULT AND CONCLUSION

In this paper, the chaotic characteristics of partial discharge signal were investigated using the method which discern between chaos and merely random signal.

The time series was obtained from the peak value of one reading of the oscilloscope and the sampling time step was fixed at 1 second. At the beginning of embedding, the observed time series was normalized to have value $0 \le x^*(t) \le 1$. Then, the delay time τ and embedding dimension d_E were determined using the method, namely Mutual Information and FNN, respectively. The normalized time series was reconstructed with the determined τ and D_E. Then, the Lyapunov exponents and Correlation dimension were computed using the reconstructed trajectory.

The largest Lyapunov exponent was 1.08±0.0028 and the correlation dimensions are considered 4 and 7(see above result graphs in Figure 7). These results indicate that the Partial Discharge is originated from the deterministic chaotic dynamical system. In Table 1 various phase space states of system and their Lyapunov spectrum were exemplified. If the largest Lyapunov exponent shows a positive value(see Table 1), system shows exponential orbital divergence that indicates system with a small initial differences behave quite differently with time - chaotic behavior. Therefore, one can easily recognize form Table 1 and Table 2 that PD signal havechaotic characteristics in that they have non-integer positive Lyapunov exponents and correlation dimension which mean multi-fractal structure in phase space. The results of this paper are summarized in Table 2.

Table 2 Summary of the results

Parameter	Values[unit]	Sub Parameters
Time series	-80 ~ 80[mV]	Sampling time step=1[s]
Dealy time(τ)	2[sec]	
Embedding dimension(d_E)	6	Delay time=2
The Largest λ_1	1.08 ± 0.0028	Delay time=2 Embedding dimension=6 Initial center point=100 Radius of a ball =0.01 Time step=10
Lyapunov dimension(D_L)	6	Delay time=2 Embedding dimension=6
Correlation dimension(D_c)	7	τ is fixed at 2
	4	D_E is fixed at 6

Indeed, it is considered that these quantitative results can be used as coefficients for the Neural Networks and nonlinear predictors. With these coefficients, more applications could be available such as life time predictor using nonlinear prediction algorithm.

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