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Chaotic characteristics of time series of partial discharges in oil-paper insulation and their applications in pattern recognition

***Abstract**. In order to recognize partial discharges (PD), five kinds of typical defects in oil-paper insulation are built and measured with current pulse method, and chaos method is used to research the time series of PD signals. The results revealed that the PD is of obvious chaotic characteristic, and the PD process is chaotic one. The PD patterns can be qualitatively analyzed and recognized by using the chaotic time series of PD and their chaotic attractors. Phase space reconstruction parameters and post-reconstruction chaotic characteristic quantities can be selected to quantify the PD's chaotic characteristics. Verification and comparison on pattern recognition effects of PRPD and CAPD were performed respectively by adopting the neural network of radial basis function (RBF), and the result showed that the effects of both were good and had their own advantages. Besides, statistical operators in PRPD mode and chaotic characteristic quantities in CAPD mode were comprehensively selected as the input vectors of neural network, and the average recognition rate can reach 95%, this result showed that the recognition on PD was improved by a relatively large scale.*

***Streszczenie.** Przeprowadzono badania pięciu typowych przypadków defektów izolacji papierowo-olejowej. Sygnały wyładowań niezupełnych przetworzono w szeregi czasowe. Stwierdzono że process ma character chaotyczny. Wykorzystano teorię przebiegów chaotycznych do analizy sygnału iklasyfikacji wad. (**Analiza przebiegów chaotycznych wyładowań niezupełnych w izolacji papierowo-olejowej**)*

Keywords: Oil-Paper Insulation; Partial Discharge; Time Series; Chaos; Pattern Recognition
Słowa kluczowe: izolacja papierowa, wyładowania niezupełne, rozpoznawanie obrazów.

Introduction

Partial discharge(PD) is a major cause of insulation deterioration of power equipment and accidents in power system and meanwhile the main characteristic and manifestation of insulation deterioration. Monitoring and recognizing technology for PD is an important method to evaluate the ageing condition of power equipment's insulation and forecast the insulation fault at present. Effective analysis on the discharge's signal is the key to successful monitoring and recognition of PD [1-3].

In recent decades, researchers have done a lot of work on studying the statistical characteristic of PD signal and put forward many analysis methods, among which the method of phase resolved partial discharge (PRPD) is extensively used to recognize the pattern of discharge source. Carried out in the phase domain, it adopts technologies like neural network, fractal theory, etc. to improve the accuracy of recognition and classification on PD. However, parameters extracted by these methods, i.e. kurtosis, are not physical parameters but a kind of statistical characteristics which are hard to interpret[4]; besides, the memory effect of PD is seldom considered.

Studying on the pulse time series of PD is another effective channel for recognition of its pattern and feature due to its implication of the physical characteristic [5, 6]. Along with the increasing application of DC power transmission, analysis on the time series of PD seems more urgent, because under this condition, there has been no phase reference for many kinds of DC equipment. And during contactless measurement of PD in either AC or DC equipment, both applied voltage and its change are unavailable, so the analysis on time series of discharge can only use other parameters under this condition.

The chaotic characteristic analysis on the time series of PD has been studied in recent ten years. In 1999, Y. Mizukami analyzed the PD signal of power cable from the view of non-linear dynamics. The discharge parameter studied mainly was the time interval between continuous discharges. Based on the time series constituted, the max. Lyapunov exponent was extracted, and the correlation integral were calculated [7].

Since 1999, Y. S. Lim continuously took the time series constituted by three parameters -- applied voltage "v", pulse amplitude "p" and time "t" -- in case of PD in power equipment like XLPE power cable, etc. as the study object, carried out phase space reconstruction on the time series through selecting proper reconstruction parameters, such as time delay and embedding dimension, and extracted such characteristic quantities as the max. Lyapunov exponent and correlation according to the multidimensional chaotic attractors obtained through reconstruction. The result not only showed that the PD phenomenon was a definitive chaotic process but also quantitatively characterized the chaotic characteristic of PD [8-10]. The study bore fruit and put forward the concept of CAPD [11, 12]. However, CAPD (chaotic analysis of partial discharge) itself doesn't contain the connotation of time series. What's more important, intelligent recognition on the chaotic characteristics of time series of various PD patterns are seldom reported.

In short, current study on the chaotic characteristic of time series of PD and its intelligent recognition is still in its infancy. In this article, the chaotic characteristics of time series signals of typical PD patterns for a transformer are analyzed comprehensively, and the chaotic characteristic quantities are attempted to apply to the intelligent recognition of PD pattern.

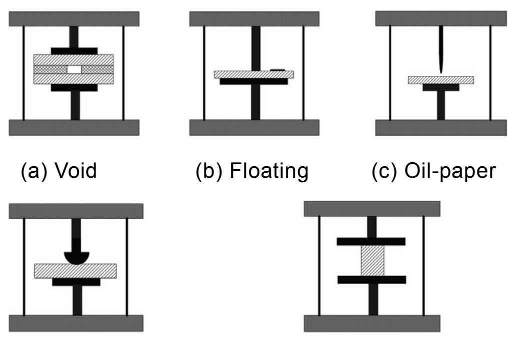


Fig. 1. 5 Typical PD Models of Oil-immersed Transformer

Establishment of PD models

Most discharge positions in the oil-paper insulation are oil gap, oil wedge, void in paper, metal with floating potential, sharp point of conductor and solid surface. Thus the multiple typical discharge models are summarized as oil-paper discharge, void discharge inside paper (paperboard), discharge along surface of paper (paperboard) and discharge of floating potential. The experimental models established are as shown in Fig. 1.

Data Compression and Preprocessing

Applied power frequency voltage on PD models, the measurement was with current pulse method. For the PD signal acquired each time, envelope obtaining is the first step, followed by sharpening, that is, selecting the maximum in one discharge acquired to represent this discharge magnitude, and setting all the other data into zero.

To facilitate comparison and analysis of time series data of different PDs acquired by the same measurement system, the data including discharge pulse amplitude p, applied voltage difference v and time interval Δt between two adjacent discharges obtained in experiments are always normalized, and the commonly-used normalization method is:

(1) $$x_n = (x - x_{\min}) / (x_{\max} - x_{\min})$$

where x is p or v.

(2) $$t_n = \Delta t / \Delta t_{\max}$$

Thus, the unidimensional chaotic time series of three corresponding basic parameters p_n, v_n and t_n can be acquired. The p_n series of floating discharge is shown in Fig. 2.

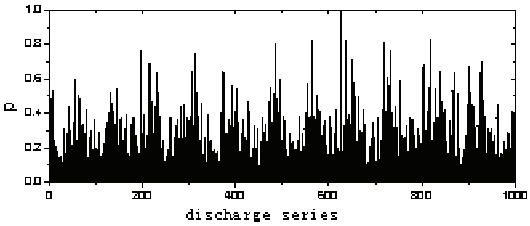


Fig. 2. p_n Series of Floating Discharge

Chaotic Characteristic and Feature Extraction of Time Series of PD

Phase Space Reconstruction

Being the comprehensive reflection of interactions among many physical factors, the time series embodies traces of all variables involved in the movement. Only when the time series is expanded to phase space of 3D and even higher dimension can the information in it be shown adequately. This is the phase space reconstruction of time series [13, 14].

One of the objectives of phase space reconstruction is to restore the chaotic attractors in the high-dimensional phase space. The chaotic attractor is one of the features of chaotic system, and the trace generated by a chaotic system will move regularly finally and be a regular and tangible trace (chaotic attractors) after a certain period of change. Because driving factors of the chaotic system interact, the data points generated in succession are correlated. Packard et al. suggested using the delay coordinate of a variable in the original system to reconstruct the phase space, and Takens proved a suitable embedding dimension could be obtained, that is to say, if the delay coordinate dimension $m \geq 2d+1$, with d being the dimension of dynamic system, the regular trace (attractor) could be restored from the space of this embedding dimension.

According to the theory of phase space reconstruction, select a certain time delay τ for a group of time series actually measured x_i ($i = 1, 2, \cdots, N$), and reconstruct x_i in the d dimensional phase space; then a new d dimensional time series y_i, $i = 1, 2, \cdots, (N-(d-1)\tau)$ can be obtained:

$$y_1 = [x_1, x_{1+\tau}, x_{1+2\tau}, \cdots, x_{1+(d-1)\tau}]$$
$$y_2 = [x_2, x_{2+\tau}, x_{2+2\tau}, \cdots, x_{2+(d-1)\tau}]$$

$$y_{N-(d-1)\tau} = [x_{N-(d-1)\tau}, x_{N-(d-1)\tau+\tau}, x_{N-(d-1)\tau+2\tau}, \cdots, x_{N-(d-1)\tau+(d-1)\tau}]$$

The d dimensional phase space after reconstruction is:

(3) $$\begin{pmatrix} x_1 & x_2 & \cdots & x_N \\ x_{1+\tau} & x_{2+\tau} & \cdots & x_{N+\tau} \\ \vdots & \vdots & \ddots & \vdots \\ x_{1+(d-1)\tau} & x_{2+(d-1)\tau} & \cdots & x_{N+(d-1)\tau} \end{pmatrix}$$

In the phase space reconstruction by the delay-coordinate method, it is very important as well as difficult to select the best time delay τ and the min. embedding dimension d.

Selections in this article are based on the opinion that the selections of the best time delay τ and the min. embedding dimension d are independent.

Selection of Reconstruction Parameters

1) Determination of the best time delay τ

The best time delay τ is determined by adopting the mutual information method. The expression of mutual information I is [15]:

(4) $$I(\tau) = H(x_n) + H(y_n) - H(x_n, y_n)$$

where $H(x_n)$ is the entropy of unidimensional time series x_n,

(5) $$H(x_n) = -\sum_{i=1}^{N} P(x(i)) \log_2 P(x(i))$$

$H(y_n)$ is the entropy of new unidimensional time series y_n obtained from x_n after delay τ, and $H(x_n, y_n)$ is the joint entropy of x_n and y_n.

The diagram of relation between mutual information I and time delay τ can be obtained from formula (5), and the time delay τ corresponding to the minimum in the curve reached for the first time in the diagram is the best time delay.

2) Determination of embedding dimension d

In the article, the min. embedding dimension is determined by adopting the method of false nearest neighbors (FNN) put forward by Cao[15], and the calculation process is as follows:

As for the unidimensional time series x_n, the vector acquired by reconstruction in the d dimensional phase space should be $\{y_i(d)\}$, where

(6) $$y_i(d) = (x_i, x_{i+\tau}, \ldots, x_{i+(d-1)\tau}),$$
$$i = 1, 2, \ldots, N-(d-1)\tau$$

$y_i(d)$ is the i^{th} reconstructed vector in the d dimensional embedding space.

Define

(7) $$a(i,d)=\frac{\left\|y_i(d+1)-y_{n(i,d)}(d+1)\right\|}{\left\|y_i(d)-y_{n(i,d)}(d)\right\|}$$

$$i=1,2,\ldots,N-(d-1)\tau$$

where, $n(i,d)$ is integer, and $1\le n(i,d)\le N-d\tau$; $y_{n(i,d)}(d)$ is the neighbor of $y_i(d)$ in the reconstructed d dimensional phase space; $\|\bullet\|$ is the measure of Euclidean distance.

$a(i,d)$ indicates the separation degree in the reconstructed $d+1$ dimensional phase space between two adjacent vectors in the reconstructed d dimensional phase space, and its average value is

(9) $$E(d)=\sum_{i=1}^{N-d\tau}a(i,d)\Big/N-d\tau$$

In order to study the change of $a(i,d)$ from the reconstructed d dimensional phase space to that of $d+1$ dimension, the following variable is defined:

(10) $$E1(d)=E(d+1)/E(d)$$

When the embedding dimension d is larger than a value d_0, $E1(d)$ will stop changing. Take d_0+1 as the best embedding dimension. During practical operation, d_0+1 at the time that $E1(d)$ increases above 0.90 for the first time is generally selected as the best embedding dimension in consideration of the noise impact.

4.3 Multidimensional Chaotic Attractors of PD

Through the qualitative analysis on the chaotic characteristic of PD, the chaotic attractors can be designed. Reconstruction of unidimensional time series in a higher-dimensional phase space is an effective method to obtain the attractors. Here, time series of p_n, t_n and v_n are mainly exploited to construct various simple attractors, which are then analyzed and studied intuitively. Based on different emphases of researches, the qualitative analysis can be performed from different angles to obtain different attractors accordingly; study on these attractors can acquire qualitatively features of different discharges. The analysis is mainly carried out from two aspects, the correlations between adjacent discharges and the relations between discharge parameters. The definitions of attractors don't descripted here, you can get them by reading correlative books about chaos.

1) Correlations between adjacent discharges

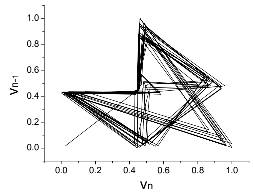
In the phase space, univariate 2D and 3D attractors respectively of time series of discharge parameters p_n, t_n and v_n, are constructed. And the correlations between adjacent discharges respectively of various discharge models, as well as the discharge characteristics of these models, can be shown by these attractors.

Sub graphs in Fig. 3 are v_n 2D attractors of the five typical oil-paper insulation PD models. Such attractors are in regular shapes and of distinctive features respectively.

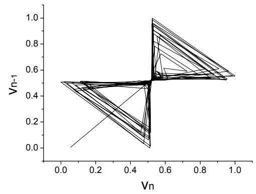
2) Relations between discharge parameters

Studying the relations between PD parameters p_n, t_n and v_n is an effective method to acquire the characteristic information of discharge between continuous discharge pulses. On the basis of time series of p_n, t_n and v_n, the three 2D attractors constructed by any two of them and the 3D attractor constructed by all of them can intuitively show the internal relations and interactions between any two or three of the parameters p_n, t_n and v_n.

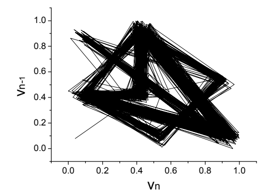
Sub graphs in Fig. 4 are t_n-v_n 2D attractors respectively of various PD models. Such attractors are in different shapes and of distinctive features respectively.



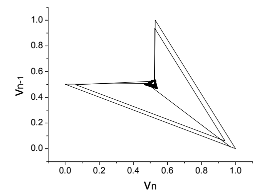
(a) Void discharge



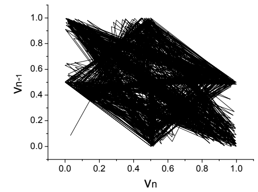
(b) Floating discharge



(c) Oil-paper discharge

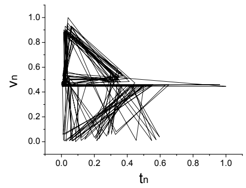


(d) Oil wedge discharge

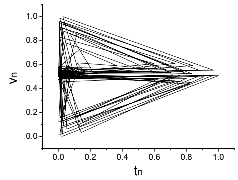


(e) Discharge along surface

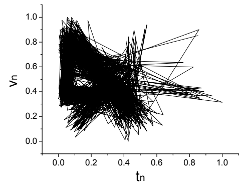
Fig. 3. v_n 2D Attractors of 5 Typical PD Models



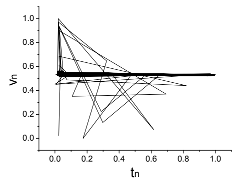
(a) Void discharge



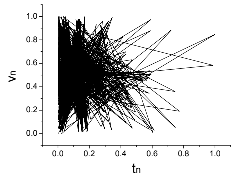
(b) Floating discharge



(c) Oil-paper discharge



(d) Oil wedge discharge



(e) Discharge along surface

Fig. 4. t_n-v_n 2D Attractors of 5 Typical PD Models

Extraction of Chaotic Characteristic Quantities

The analysis of the attractors is largely depend upon judgment by the shape difference visually and is at the qualitative stage, thereby being of subjective arbitrariness. Solutions to this problem are intelligent recognition on graphs and extraction of chaotic characteristic quantities. With respect to the later, after selection of the two parameters, namely the best time delay τ and the min. embedding dimension d, during reconstruction in a higher-dimensional phase space, the chaotic characteristic quantities, such as the max. Lyapunov exponent, correlation dimension, quadratic and cubic box dimension, quadratic and cubic information dimension and Kolmogorov entropy, could be calculated from the high-dimensional attractors.

With the method of extraction of chaotic characteristic quantities, the parameters of phase space reconstruction and these quantities are obtained from the chaotic time series of three uni-variables p_n, t_n and v_n respectively of five typical oil-paper insulation PD models. Among them, the max Lyapunov exponent, correlation dimension and Kolmogorov entropy are calculated after the corresponding best embedding dimension d and min. time delay τ in the table 1 are selected; while the box dimension and the information dimension are calculated upon the selection of the corresponding min. time delay τ in the table.

It can be observed from the table that the max. Lyapunov exponents corresponding to the time series of p_n, t_n and v_n of various discharge models are all larger than 0, and all the Kolmogorov entropies are also larger than 0 and less than ∞. According to the chaos criterion, the PD in the oil-paper insulation is not a completely random process but has chaotic characteristic, which indicates that the PD in the oil-paper insulation is a chaotic process.

Graph establishment and artificial recognition on the PD pattern to a certain extent can be performed for the parameters of phase space reconstruction and the various extracted chaotic characteristic quantities in table 1, but the large quantity of data makes the artificial recognition difficult. So they are constructed into the characteristic fingerprints of PD in oil-paper insulation to realize pattern recognition by the means of neural network technology.

Table 1. Characteristic Fingerprints Constructed by Phase Space Reconstruction Parameters and Chaotic Characteristic Quantities of Partial Discharges

Discharge Pattern	Parameter	Phase Space Reconstruction Parameters and Chaotic Characteristic Quantities								
		τ	d	λ_1	D_c	D_{b2}	D_{b3}	D_{i2}	D_{i3}	K_{kol}
Void discharge	p_n	4	8	2.2433	2.6896	1.6224	1.9721	1.9836	2.7190	0.2841
	t_n	8	10	2.1677	2.6268	1.0266	1.1254	1.6758	2.4431	0.2507
	v_n	7	15	2.0247	2.4445	1.3434	1.2871	1.3391	1.6596	0.2235
Floating discharge	p_n	2	10	1.9742	2.6865	1.6217	2.0604	1.9302	2.9265	0.3011
	t_n	4	10	1.2356	2.5046	1.1625	1.2873	1.7415	2.1953	0.2715
	v_n	9	13	1.7848	1.9368	1.3821	1.3035	1.3708	1.7775	0.1846
Oil-paper discharge	p_n	2	11	1.9935	2.2408	1.5500	1.5420	1.7859	2.2831	0.2223
	t_n	6	13	1.8725	2.7117	1.6266	1.9631	1.6858	2.1720	0.3472
	v_n	8	10	1.8416	2.4568	1.7668	2.0029	1.3993	2.1425	0.2883
Oil wedge ischarge	p_n	5	10	1.5310	2.4791	1.7493	2.1609	1.9259	2.5788	0.2012
	t_n	3	16	1.4016	2.6241	1.0951	1.2352	1.7259	2.2866	0.2346
	v_n	3	11	1.4382	2.5650	1.6339	1.5255	1.6988	1.9125	0.2158
Discharge along surface	p_n	2	9	3.0158	2.6386	1.5962	2.0579	1.9680	2.8806	0.2845
	t_n	5	11	2.9601	1.9498	1.4932	1.8699	1.6876	2.1093	0.1751
	v_n	6	14	2.7673	2.7062	1.8109	2.1617	1.4089	1.8019	0.2531

Note: τ is the best time delay; d : The best embedding dimension; λ_1 : The max. Lyapunov exponent; D_c : Correlation dimension; D_{b2} : Quadratic box dimension; D_{b3} : Cubic box dimension; D_{i2} : Quadratic information dimension; D_{i3} : Cubic information dimension; K_{kol} : Kolmogorov entropy.

Application of Chaotic Characteristics in Pattern Recognition of PD

RBF Neural Network and Data Processing

1) RBF Neural Network

As a self-adaptive pattern recognition technology, the artificial neural network has no need for prior knowledge and discriminate function related to the pattern; instead, it forms automatically the decision-making range required via self-learning mechanism, and the self-adaptive adjustment is available [16]. The recognition and classification of fault patterns is a process realizing the non-linear mapping from symptom set to fault set based on a given group of symptoms. As a result, the neural network has been widely used in the field of fault pattern recognition. In this network, the input node is corresponding to the fault symptom and the output node to the fault cause or pattern.

The 5 PD patterns are recognized by the neural network of radial basis function (RBF) in the article. With a structure similar to multi-layer forward network, RBF neural network is a 3-layer forward network as well as a single-hidden-layer feed forward network taking the radial basis function as the activation function for hidden nodes. Here, Gaussian function is selected as the transfer function of RBF neural network.

2) Normalization of sample data

If there is any singular sample in training samples in the input layer of neural network, or the data sample in the input layer is too large, the neuron nodes will be saturated very fast, resulting in paralysis of network, so the sample data need to be normalized. The following formula is adopted here for normalization:

(11) $$X(i) = \{x(i) - mean(x)\} / sd(x)$$

Where, $mean(x)$ is sample mean, and $sd(x)$ is standard deviation of sample.

3) Judgment rule for recognition

Judgment method for recognition results has a significant impact on the training of neural network. Assume a testing input vector belongs to pattern class i, and the vector of testing calculation output is y_i, $i = 1,2,\cdots,m$, where m is the sum of output neurons. Make

(12) $$Y = \begin{cases} \sum_{i=1}^{m} y_i, Y \ge 1 \\ 1, Y < 1 \end{cases}$$

Then its classification reliability rate is:

(13) $$P = {y_i}/{Y}$$

The judgment rule for correct recognition of data is defined as

(14) $$P = y_i / Y > 0.6$$

Pattern Recognition Results of PD

In the following pattern recognition process with the RBF neural network, the number of output neurons corresponding to the 5 PD patterns is assumed 5, the distribution constant and the training goal are set to 1.2 and 0.0001 respectively.

1) Based on phase space reconstruction parameters and chaotic characteristic quantities

Under this condition, the chaotic characteristic quantities of the time series of discharge parameters p_n, v_n and t_n are selected as the input vectors of the neural network, so the sum of input neurons is 27.

Column 3 in table 2 are the results of pattern recognition on PD based on phase space reconstruction parameters and chaotic characteristic quantities, here the CAPD concept is still used. The results of recognition on typical PD patterns in this way are favorable, with the average correct judgment rate up to 85%; among the results, the recognition effects on oil wedge and oil-paper discharges are the best, reaching 92.5% and 87.5% respectively; while the relatively poor effect happens on the discharge along surface, being only 77.5%.

Table 2. Pattern Recognition Results of PD in Case of Various Input Vectors

PD Pattern	Training Samples /Total Samples	Correct Judgment Rate (%)		
		CAPD	PRPD	CAPD & PRPD
Void discharge	20/60	85	80	90
Floating discharge	20/60	82.5	85	92.5
Oil-paper discharge	20/60	87.5	90	95
Oil wedge discharge	20/60	92.5	85	97.5
Discharge along surface	20/60	77.5	87.5	95

2) Based on PRPD

In order to compare with the pattern recognition results of PD based on phase space reconstruction parameters and chaotic characteristic quantities (CAPD), the commonly-used PRPD is also adopted in the article to analyze the experimental data and recognize the pattern. In this method, the statistical characteristic quantities of the 5 important 2D discharge spectrograms of PD, $H_{q\max}(\varphi)$, $H_{qn}(\varphi)$, $H_n(\varphi)$, $H(q)$ and $H(p)$, are extracted, and the 29 statistical operators obtained are shown in table 3, taking as the input neurons of RBF neural network.

Table 3. 29 Statistical Operators of PRPD

Discharge Spectrogram	Skewness S_k		Kurtosis K_u		Partial Peak Number P_e		Degree of Discharge Asymmetry Q	Degree of Phase Asymmetry φ	Cross-correlation Factor cc
	+	-	+	-	+	-			
$H_{q\max}(\varphi)$	√	√	√	√	√	√	√	—	√
$H_{qn}(\varphi)$	√	√	√	√	√	√	√	√	√
$H_n(\varphi)$	√	√	√	√	√	√	√	—	√
$H(q)$	◆		◆		—	—	—	—	—
$H(p)$	◆		◆		—	—	—	—	—

Note : "√", "—" and "◆" indicate that the statistical parameter corresponding to the distribution spectrogram is available, unavailable or optional respectively.

Column 4 in table 2 is the pattern recognition results of PD by PRPD. The correct rate of pattern recognition on typical partial discharges in this way is above 80%, and the effect is good; the recognition rate of oil-paper discharge is as high as 90%. Through comparison, it can be found that the pattern recognition results of PD obtained respectively by the two methods are relatively close, however the results of special PD pattern are different and the two methods may be complementary.

3) Based on the combination of PRPD and CAPD

Comprehensively select the characteristic quantities of PRPD and CAPD as the input vectors of the neural network to recognize the pattern of PD. As for the selection of characteristic quantities of both, after comparative study on several combinations, a combination with the best effect is selected: skewness S_k, kurtosis K_u and partial peak number P_e in PRPD mode as the statistical characteristic operators, and the max. Lyapunov exponent, correlation dimension, cubic information dimension and Kolmogorov entropy in CAPD as characteristic quantities. So the number of input neurons is 30.

Column 5 in table 2 lists the results of recognition on PD patterns by adopting the combination of PRPD and CAPD. It can be observed that the effect of recognition on typical PD patterns is favorable through comprehensively selecting chaotic characteristic quantities and statistical operators respectively in CAPD and PRPD as the input vectors, with the average correct judgment rate reaching 95.5% and the best recognition effect amounting to 97.5% on oil wedge discharge.

After comparing the three methods, we can find that the pattern recognition effects of PRPD & CAPD combination are improved greatly on all kinds of discharge. The improvements on floating discharge and discharge along surface are the largest.

In respect of the recognition method for PD patterns combining PRPD with CAPD, the selection of characteristic quantities directly influences the effect of recognition, therefore different combinations of characteristic quantities can still be tried. Besides, these methods are all used in the discharge models in labs currently and still need further verification in real oil-immersed electric equipment.

Conclusions

In this article, the chaotic characteristics of time series of five PD patterns in oil-paper insulation are studied, the results reveal that the discharge time series signal is of obvious chaotic characteristic and PD is a chaotic process.

The multiple time series of PD have distinctive features. And the 2D and 3D chaotic attractors obtained from time series differed greatly from each other by shapes in phase shape and of their own distinctive features, so they can be used in the qualitative analysis and recognition on the PD patterns.

Phase space reconstruction parameters of multiple time series of different discharge models as well as the extracted chaotic characteristic quantities are selected as the characteristic fingerprints applied to the pattern recognition by RBF neural network, the results show that the recognition effects on PD patterns are favorable. Compared with the recognition results based on PRPD, the overall effects of the two methods are relatively close, however the results of special PD pattern are different. Further the PRPD operators and chaotic characteristic quantities are used comprehensively for pattern recognition, and the recognition rate is increased greatly. Therefore the combination method can be used to improve the recognition effect.

Analysis on the chaotic characteristic of PD's time series is a new method emerging in recent years, and still requires further study and verification to achieve practical on-site effect.

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