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Application of Time Series Used on Recognition of Partial Discharge in Oil-Paper Insulation

***Abstract**. Five typical partial discharge (PD) models of oil-paper insulation are made in the article, time series of PD's amplitude are fetched from the results measured, after being pre-processed, they are fitted by auto regressive (AR) model, the coefficients of the AR model are used as feature vector to recognize the five typical partial discharges by BP Neural Network. In this article, different order AR models are used to fit the time series, the result shows that under the 4-order or 6-order AR model, the recognition accuracy rates of the five models are all as high as over 80%.*

***Streszczenie.** Zbadano pięć typowych modeli wyładowania niezupełnego w izolacji z papieru olejowego. Rezultaty pomiarów były przetworzone numerycznie tworząc model auto-regresywny AR. Współczynniki tego modelu mogą być używane do rozpoznawania rodzaju wyładowania. Do rozpoznawania użyto sieci neuronowych. (**Wykorzystanie szeregów czasowych do rozpoznawania wyładowania niezupełnego w izolacji z papieru olejowego**)*

Keywords: Oil-Paper Insulation; Partial Discharge (PD); Time Series; Auto Regressive (AR) model; BP Neural Network .
Słowa kluczowe: izolacja olejowa, wyładowanie niezupełne.

Introduction

With the advantage of low cost, high stability and high security, etc., oil-immersed power transformers is widely used in power system. In oil-immersed transformers, PD, which is the main cause of insulation deterioration, is also the main characteristics and manifestations. By the pattern recognition of PD, the type of PD can be identified, then a lot of defect information can be got, on the base of which, degree of insulation degradation can be assessed and the maintenance program can be determined[1-2].

In recent years, many pattern recognition algorithms of PD appear, such as genetic algorithms, artificial neural networks and statistical tools, etc., which are based on the PRPD spectrum[3-5]. However, studies have shown that the frequency phase Φ where PD occurs is not a so meaningful parameters[6], correlation information between adjacent pulses can not be studied through PRPD spectrum and the interaction between continuously pulses can not be studied either. Time-series analysis of PD will compensate for this.

In this paper, PD amplitude sequence are extracted, AR (auto regressive) model is used to fit the sequence, then parameters of AR model are used as input vector of BP neural network model to recognize the five PD patterns[7], concluded that when the lag fourth-order AR model is used, a better recognition results can be gotten.

Simulation experiment and results of oil-paper insulation system

A. Establishment of PD models

Most discharge positions in the oil-paper insulation are oil gap, void in paper, metal with floating potential, sharp point of conductor, solid surface, etc., five PD models are established in the paper, the specific structure of PD models are as follows, the ground electrode's radiuses of the five models are all 45mm.

(1) Corona discharge model

The corona discharge model is shown in Fig. 1(a). The medium is the pressboard whose thickness is 2mm and radius is 50mm, the high voltage electrode is the corona whose curvature radius is 80μm.

(2) Oil-gap discharge model

The Oil-gap discharge model is shown in Fig. 1(b). The medium is two slivers of 2mm pressboard which are clipped by two layers of 2mm thick paper.

(3) Void discharge model

The void discharge model is shown in Fig. 1(c). The medium is three layers of 2mm pressboard stick by epoxy; there is a hole whose radius is 4mm in the middle of the second layer of pressboard.

(4) Suspended discharge model

The suspended discharge model is shown in Fig. 1(d), the suspended electrode is a 0.4mm copper triangle stick on the pressboard by epoxy, and one angle of which is points to the high voltage electrode. The radius of high voltage electrode is 15mm.

(5) Surface discharge model

The surface discharge model is shown in Fig. 1(e), the medium is a pressboard whose thickness is 2mm and radius is 35mm, the radius of the high voltage electrode is 15mm.

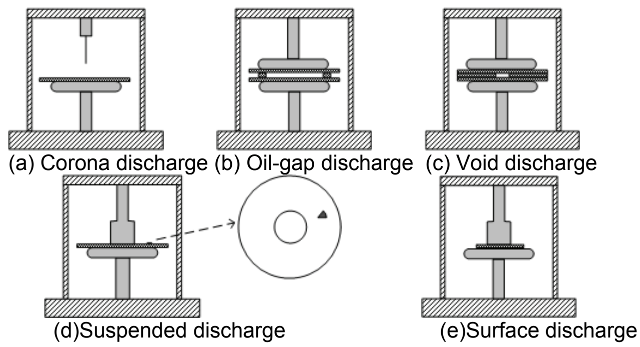


Fig.1 PD models of five typical oil-paper insulation

B. Establishment of experiment

In this study, pulse current method is used to measure partial discharge; the measurement system is shown is Fig.2.

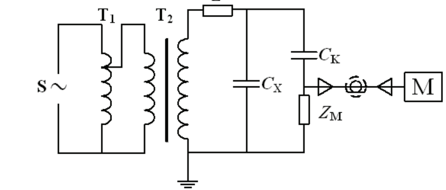
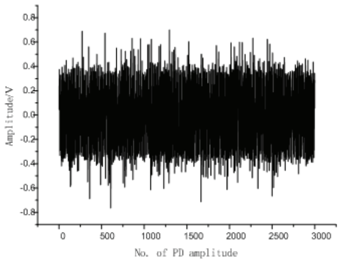


Fig.2 Measurement system of pulse current method

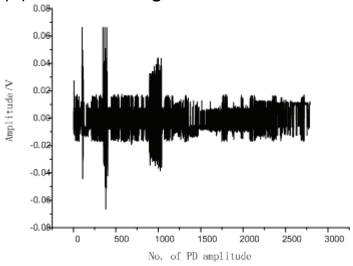
In Fig.2, S is AC, T_1 is voltage regulator, T_2 is non partial discharge testing transformer, Z is protection resistor, C_X is PD model, C_K is coupling capacitor, Z_M is detection impedance, M is PD detector.

C. Results and Discussion

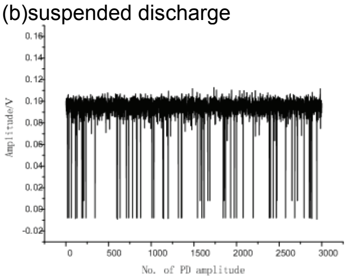
PD amplitude are extracted from the results of the experiment, PD amplitude sequence of the five kinds of PD are shown in Fig.3.



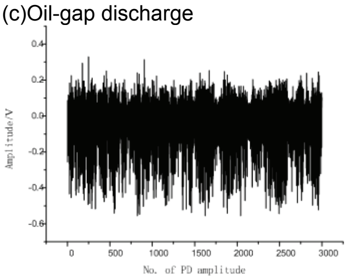
(a) Void discharge



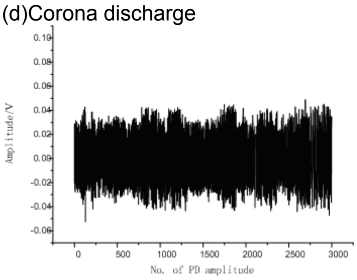
(b)suspended discharge



(c)Oil-gap discharge



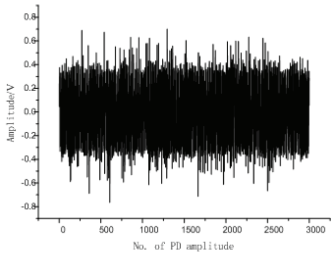
(d)Corona discharge



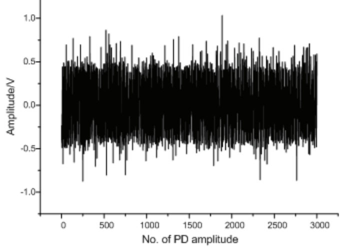
(e)Surface discharge

Fig.3 Time series of five typical PDs

From Fig.3 can be seen that void discharge, amplitude of void and surface discharge are similar in different period of time, while the other three kinds of discharge are different in different period of time, this is because the discharge of void and surface occur symmetrically in positive and negative cycles, include phase and amplitude. In this paper, amplitude is the interested factor while the phase is not. From (a)-(e) in Fig.3, it can be seen that the percentage of discharge points with different amplitude are quite different, which is just used to recognize the pattern of PD in this paper.



(a) Void discharge under 5kV



(b) Void discharge under 7.5kV

Fig.4 Void discharge

From Fig.4 can be seen that time series of the same kind of PD under different voltage are similar, the difference is the amplitude, by normalizing this can be solved.

Feature Extraction of PD Based on Time Series

A. Data inspection and preprocessing

The time sequence shown in Fig.3 only describe the differences between various discharges qualitative, to recognize the partial discharge, quantitative analysis is required. Before the quantitative analysis, data must be tested and pre-processed, the aim of which is to test whether the sequence is a smooth time series, if not, and appropriate treatment should be applied to process the sequence to make it meet the requirements of stability. The amplitude sequence of PD is recorded as $\{PD_i\}$, if it is a non-stationary series, then the non-stationary items {di} is extracted, from formula (1), a smooth sequence $\{PD\_d_i\}$ will be gotten.

$$PD\_d_i = PD_i - d_i \tag{1}$$

The amplitude of different models under different voltage is different; these differences may bring side effect of pattern recognition, therefore zero meaning and normalizing are needed for a smoothed sequence. Let the mean of the sequence $\{PD\_d_i\}$ is μ, the maximum value and minimum value are PD_d_{max} and PD_d_{min}, by formula (2) a stationary, zero mean, normalized sequence is gotten.

$$x_i = \frac{PD\_d_i - \mu}{PD\_d_{\max} - PD\_d_{\min}} \tag{2}$$

B. Parameter Extraction of AR(p) Model

To recognize PD, input vectors need the same dimension, so the coefficient which are gotten from the fitted results of the PD amplitude sequence by the same order.

After the order is determined, the parameters should be estimated. Least square is a method of less computation, so it is the commonest method for parameter estimation in AR model.

The form of AR(p) model of stationary sequence $\{x_i\}$ in 2.1 are as formula (3).

(3) $$x_t = \sum_{i=1}^{p} a_i x_{t-i} + \varepsilon_t, t \in \mathbf{Z}$$

In formula, $\{\varepsilon_t\}$ is the residual of $\{x_t\}$.

For better estimation of a1,a2…ap in formula(3), the sum of squares of residual in formula (4) should be as small as possible.

(4) $$S(a_1, a_2 \dots a_p) = \sum_{j=p+1}^{N} [x_j - \sum_{i=1}^{p} (a_i \times x_{j-i})]^2$$

The point where $S(a_1,a_2 \dots a_p)$ in formula (4) get the minimum value is the least squares estimation of the regression coefficient.

The matrix form of AR(p) model is shown in formula (5).

(5) $$\mathbf{Y} = \mathbf{X}\mathbf{a} + \boldsymbol{\varepsilon}$$

In formula (5)

$$\mathbf{Y} = \left[x_{p+1}\ x_{p+2} \dots x_N\right]^{\mathrm{T}}, \quad \mathbf{a} = [a_1\ a_2 \dots a_N],$$

$$\boldsymbol{\varepsilon} = [\varepsilon_{p+1}\ \varepsilon_{p+2} \dots \varepsilon_N], \quad \mathbf{X} = \begin{bmatrix} x_p & x_{p-1} & \dots & x_1 \\ x_{p+1} & x_p & \dots & x_2 \\ \dots & \dots & \dots & \dots \\ x_{N-1} & x_{N-2} & \dots & x_{N-p} \end{bmatrix}$$

By the multiple regression theory, the least squares estimation of the parameter matrix are shown as formula (6).

(6) $$\mathbf{a} = (\mathbf{X}^{\mathrm{T}}\mathbf{X})^{-1}\mathbf{X}^{\mathrm{T}}\mathbf{Y}$$

For example, Fig (3) shows the sequences of gap discharge, after the pretreatment, a new sequence is gotten, by fitting it with third-order lag AR model ($X_t=a_1X_{t-1}+a_2X_{t-2}+a_3X_{t-3}+\varepsilon_t$), the parameters are computed as follows.

$a_1 = 0.598$, $a_2 = 0.178$, $a_3 = -0.147$

That is the PD amplitude sequence correspond to the equation as formula (7)

(7) $$X_t=0.598X_{t-1}+0.178X_{t-2}-0.147X_{t-3}+\varepsilon_t$$

The diagram of the fitted sequence is shown in Fig. 4.

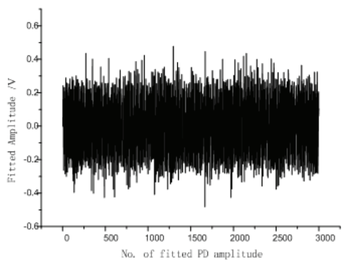


Fig.4 Fitting result of time series in Fig.1(a) by AR(3) model

In the paper, BP neural network is used for pattern recognition of the five kinds of PD; the input vector of network is the parameters obtained by fitting the PD amplitude sequence. Higher the order is, the greater amount of computation is needed, so in this paper, only 2 to 6 order lag model are used to fit the sequence, recognizing the PD in different orders, conclude that a better correct judgment rate can be gotten under some order lag model.

Pattern Recognition of PD

A. Model of BP Neural Network

In many artificial neural network models, back-propagation (BP) network has better classification ability, so it is often used for pattern recognition of fault diagnosis[8-10]. BP network is a multilayer feed-forward network, which is composed of input layer, one or more hidden layers and output layer, there are full interconnects between layers while there aren't connection in the same layer. The structure is shown in Fig.6.

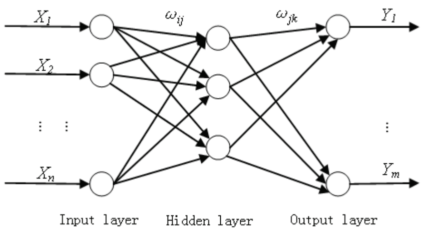


Fig.6 BP neural network

In Fig.6, X_1、X_2、…、X_n are the input values of BP neural network, Y_1、Y_2、…、Y_m are predictive values, ω_{ij} and ω_{jk} are the weights of BP neural network, BP neural network shown in Fig.6 expresses the mapping function from n independent variables to m dependent variables.

In this paper, pattern-matching principle is used for the recognition of PD. The computing process for the pattern recognition of PD series is shown in Fig.7, First, extracting PD sequence and do the preprocess, AR(p) model is used to fit the processed signal, the coefficient is the pattern of the signal, then compare the pattern to the reference patterns which have been known, the best match of the reference pattern is the recognition result of PD series signal.

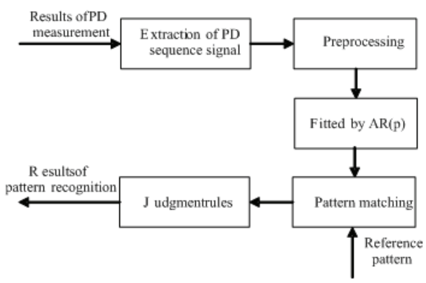


Fig.7 Process of PD recognition

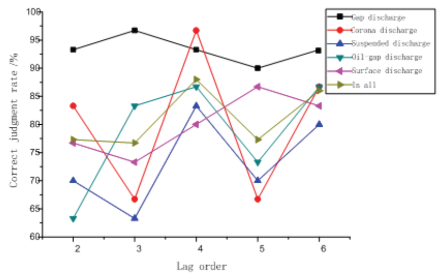


Fig.8 Results of recognition

B. Recognition Results

Second to sixth-order lag AR model are used to fit the processed PD sequence signal, the coefficients are the features of pattern recognition, 20 sets of data are chosen from each kind of PD to train the BP neural network, and 30 sets of data in each kind of PD for testing, the test results are shown in Fig. 8.

From Fig.8 can be seen, higher correct judgment rate will be gotten when the forth or the sixth order lag AR model used to fit the PD sequence, while other order only can recognize one or two kinds of PD correctly.

Conclusion

Because of the difference between the PD amplitude sequences, after processing the sequence signal and then fitting it by AR model, the coefficients of which are as the feature vector, BP neural network is used to recognize the five typical partial discharges. The result shows than under proper order lag AR model, such as forth order and sixth order, to fit PD sequence, higher correct judgment rate can be gotten, now the rate of each PD is above 80%.

Experiments in this paper is done in the laboratory, the background noise is much lower than the value of partial discharge, by setting proper trigger value, noise can be filtered. So the influence of noise can be eliminated.

So it can be known that when the value of partial discharge is higher than the background noise, PD amplitude sequences can be used to recognize the pattern of PD.

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