Electrical Power and Energy Systems 51 (2013) 27–34

Contents lists available at SciVerse ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

# Phase determination of partial discharge source in three-phase transmission lines using discrete wavelet transform and probabilistic neural networks

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ARTICLE INFO

*Article history:*
Received 28 November 2011
Received in revised form 23 February 2013
Accepted 2 March 2013
Available online 26 March 2013

*Keywords:*
Partial discharge
Three-phase
High frequency current transformer
Discrete wavelet transform
Probabilistic neural networks

ABSTRACT

This paper proposes an approach to determining the phase where partial discharges (PDs) occur in three-phase transmission lines with discrete wavelet transform (DWT) and probabilistic neural networks (PNNs) using the high frequency current transformer (HFCT). For accurately determine the PD source, the peak absolute value and average power of PD signal are used in the proposed method. The accurate ratios of the PD occurrence prediction using conventional observations of PD signals via oscilloscopes are improved by the proposed method. The standard PD pulse calibrator is installed and PD signals are individually injected into the power cable in each phase of three phase transmission lines. The electricity signal is simultaneously detected on the grounding line by the HFCTs. Furthermore, noises of measured signals are filtered by DWT for which a suitable mother function should be chosen. According to Kirchhoff's circuit law (KCL) and the concept of power delivery, the peak absolute value and average power of PD signal are applied as input of the PNN. Finally, experimental results validate that the proposed approach can precisely determine the phase location of PD sources in the field.



## 1. Introduction

The presence of the partial discharges (PDs) is one of the most prominent indicators of defects and ongoing degradation process of electrical insulation systems. Since PD process is started before severe damages, it is possible to issue necessary warnings by PD measurement and analysis. Not only the measurement tools and detectors should be selected carefully, but also two important procedures, detection of PD signals and determination of source location of PD signals should be employed during the measurement process. Detection of PD signals involves identification and classification of PD signals, which focuses on recognition and discrimination of different types of PD, such as corona, surface discharge, external discharge, and noise. Methods for identification of PD include ($\psi$–$q$–$n$) [1–4], neural network [5], fuzzy classification [6], neuron-fuzzy network [7] and support vector machine (SVM) [8,9], and the rise time of PD signals [10,11]. Tracking of source location of PD signals involves feature extraction using arrival time method and estimation of the power spectral density (PSD) [12–16]. Recent related works, in order to identify phase determination of PD source, the methods have simultaneous detection in the three-phase power cable [17], and polarity and magnitude of PD are measured signals for a defect attached on different positions in three-phase construction [18]. The simulation of PD propagation phenomenon is used in three-phase power cable [19]. Moreover, since the PNN classification method is adopted to discriminate the type of PD [20] and the feature extraction method is widely employed to locate the PD source [5–9]. The expert systems of fuzzy neural network also are applied to the failure diagnosis of power equipments [21,22]. This paper proposes an approach that combines the PNN classification method and the feature extraction method. According to the concept of power delivery, both the peak absolute value and the average power of PD signals are adopted as input variables of PNN. The proposed approach would precisely determine the phase location of PD sources, and the accurate ratios of PD occurrence prediction using the conventional observations of PD signals via oscilloscopes are improved by the proposed method. Furthermore, when different commercial instruments in three-phase transmission system yield different measurements results, this paper provides an alternative method to verify their measurements.

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http://dx.doi.org/10.1016/j.ijepes.2013.03.004

## 2. Experimental setup and data acquisition

### 2.1. Experimental setup

This paper adopts the 8-m power cable of 25-kV voltage grade and cross-linked polyethylene (XLPE) for PD signal measurement in the three-phase transmission lines. The calibrated pulse generator applied to the off-line PD testing method [23]. A standard PD pulse (LDIC LDC-5 PD Calibrator, in accordance to IEC 60270 [24]) is installed in the left side of Phase A, Phase B and Phase C, respectively [19,25–27]. The electrical signals are simultaneously measured on the grounding line by the HFCT, as shown in Fig. 1. The periodogram method is employed to estimate the power spectral density (PSD) for the PD signals [16], and the average power of the PSD can be calculated by the rectangle approximation integral method [28]. The waveform and PSD of detected signals are shown in Figs. 2a–c and 3a–c, respectively. The peak absolute values and average powers of the PD signals are indicated in Figs. 2d and 3d, respectively. To facilitate the observation, the signal values were normalized. Both the peak absolute value and the average power of the signal in the phase where PD occurs are the highest among the three phases.

### 2.2. Discrete wavelet transform

Since the DWT preserves the time-domain characteristics, it is widely applied in transient and periodic signals. DWT which includes both decomposition and reconstruction is currently used in signal de-noising [29–35]. The decomposition of DWT involves many logarithmic filter trees, each of which comprises a pair of low-pass filter (LF) and high-pass filter (HF), as shown in Fig. 4. When an original signal is decomposed using the DWT, the signal is fed through the LF and the HF using a down-sampling algorithm. As shown in Table 1, the component of the LF and HF is known as approximation and detail, respectively. Each decomposition level eliminates the original signal length to half of the data in the previous level. According to the properties of the DWT filter bank, the frequency band for an approximation and a detail is given by (1) and (2), respectively.

$$Ca_L = \left[0, \quad \frac{f_s}{2^{L+1}}\right], \tag{1}$$

$$Cd_L = \left[\frac{f_s}{2^{L+1}}, \quad \frac{f_s}{2^L}\right], \tag{2}$$

where $L$ is the desired decomposition level.

From (1) and (2), the corresponding DWT decomposition bandwidths can be listed in Table 1. The sampling frequency is 100 MHz. The reconstruction process involves taking the information obtained from one or more decomposition levels and returning the signal representation to the time domain. The maximum number of levels with which a signal can be decomposed is determined by

$$J_{\max} = fix(\log_2(n/n_w - 1)), \tag{3}$$

where $n$ is the length of the signal, and $n_w$ is the length of the decomposition filter associated with the chosen mother wavelet.

The original signal can be perfectly reconstructed through an up-sampling algorithm, known as the inverse discrete wavelet decomposition (IDWT) shown in Fig. 4.

#### 2.2.1. Optimal wavelet selection

The optimal wavelet mother function is selected by the PD signal shape, which is detected from HFCT. The correlation coefficient is employed to select appropriate wavelet for PD plus de-noising. In addition to the Daubechies wavelets (db2, db3, db4, db5, db6, db7, db8, db9, db10, and db11), including the Symlets wavelets (sym2, sym3, sym4 and sym5) and the Coiflets wavelets (coif2, coif3 and coif4), the optimal wavelet can be determined using the correlation coefficients according to the knowledge of PD pulse characteristics obtained from the HFCT. The correlation coefficient is expressed as

$$\gamma(\%) = \frac{\sum[(X - \overline{X})(Y - \overline{Y})]}{\sqrt{\sum(X - \overline{X})^2 \sum(Y - \overline{Y})^2}} \times 100\%, \tag{4}$$

where $X$ denotes the actual PD pulse signal, $\overline{X}$ is the average value of the PD signal, $Y$ is the mother wavelet, and $\overline{Y}$ is the average value of the mother wavelet.

In this paper, the PD signal is detected by the HFCT, and comparisons between the PD signals and the determined optimal wavelets are shown in Fig. 5a. In Fig. 5b, the correlation coefficient of db4 is the highest in the comparisons between the wavelet mother functions and the PD signals; and hence, db4 is the optimal wavelet selected.

#### 2.2.2. Automatic thresholding rule

Wavelet de-noising methods involve either hard or soft thresholding. Hard thresholding retains large coefficients and sets the coefficients below a certain threshold to zero as given by

$$\delta_\lambda^{Hard} = \begin{cases} x(t), & if|x(t)| > \lambda \\ 0, & otherwise \end{cases}. \tag{5}$$

Soft thresholding claims to provide a more visually pleasing estimation than hard thresholding, and can be employed to avoid the discontinuity of signals. Soft thresholding can be described by

$$\delta_\lambda^{Soft} = \begin{cases} \mathrm{sgn}(x(t))(|x(t)| - \lambda), & if|x(t)| > \lambda \\ 0, & if|x(t)| \leqslant \lambda \end{cases}. \tag{6}$$

Many variants and improvements of their thresholding rules, including fixed threshold, minimum criteria and Stein's unbiased risk estimate, had been proposed in the statistical curve estimation literature. This paper adopts the automatic thresholding rule, which can effectively suppress noise, and the estimation procedure is expressed in (7). On the right-hand side of (7), $\sqrt{\log_2(n_j)}$ is used for calculating the basic threshold value with $m_j/0.6745$ being a rescaling factor.

$$\lambda_j = m_j/0.6745 \cdot \sqrt{\log_2(n_j)}, \tag{7}$$

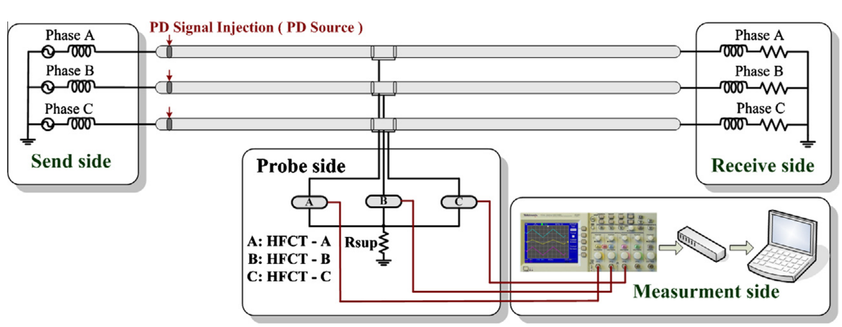


**Fig. 1.** Experimental setup for PD measurement in the three-phase transmission line.