

## Removal of Interferences from Partial Discharge Pulses using Wavelet Transform

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### Abstrak

*Pendeteksian pelepasan sebagian (PD) sebagai gejala gangguan isolasi pada aplikasi tegangan tinggi (HV) adalah penting. Namun akurasi pengukuran tersebut sering terdegradasi karena adanya derau pada sinyal. Transformasi wavelet (WT) tampaknya lebih cocok dari Transform Fourier tradisional dalam menganalisa sinyal dengan informasi transien yang menarik seperti sinyal PD. Pada makalah ini metode WT dengan thresholding lunak digunakan untuk denoising sinyal. Sinyal PD dan korona yang diperoleh dari pengukuran aktual dengan magnituda tegangan yang berbeda adalah diolah. Sinyal terolah menunjukkan hasil yang lebih baik.*

**Kata kunci:** Daubecheis, sinyal pelepasan sebagian, thresholding lunak, transformasi Wavelet

### Abstract

*It is essential to detect partial discharge (PD) as a symptom of insulation breakdown in high voltage (HV) applications. However accuracy of such measurement is often degraded due to the existence of noise in the signal. Wavelet Transform (WT) seems to be more suitable than traditional Fourier Transform in analyzing signals with interesting transient information such as partial discharge (PD) signals. In this paper a WT method with soft thresholding is used for signal denoising. PD signals and corona obtained from actual measurements with different voltage magnitudes are processed. Processed signals show the better result.*

**Keywords:** Daubecheis, partial discharge signals, soft thresholding, wavelet transform

### 1. Introduction

Failure of the solid insulating systems of high voltage (HV) equipment (rotating machines, transformers, and bushings) can lead to catastrophic failure of equipments. It is imperative that degradation of the insulation in such systems be detected and quantified at an early stage in its development so that, appropriate replacement/refurbishment can be arranged at the appropriate time. When degradation occurs in such systems, irrespective of the causative mechanism, it generally results in partial discharges (PD) being generated. Once prevalent, PDs are one of the dominant mechanisms of degradation. For this reason, detection and characterization of partial discharge activity is a key approach in insulation system condition monitoring [1].

An electrical discharge characterized by a corona, occurring when one of two conducting surfaces (such as electrodes) of differing voltages has a pointed shape, resulting in a highly concentrated electric field at its tip that ionizes the air (or other gas) around it. Corona can generate audible and radio-frequency noise, particularly near electric power transmission lines. They also represent a power loss, and their action on atmospheric particulates, along with associated ozone and NO<sub>x</sub> production, can also be disadvantageous to human health where power lines run through built-up areas. Therefore, power transmission equipment is designed to minimize the formation of corona discharge [2].

Insulation degradation process of HV machines include delaminating, shrinkage of wedges and/or side packing permitting vibration and abrasion, and loss of function of gradient control coatings. All these processes are almost invariably accompanied by partial discharges which increase in severity as the deterioration progresses, usually making and additional

contribution to the insulation damage rate. PD test is one of the most important post-production quality checks that is normally carried out on HV equipment insulation in laboratories. PD measurements are done using commercially available PD detectors, which satisfy requirements stipulated by National and International standards. The majority of them display the PD pulses as patterns on an elliptic or equivalent time base. The possibility of accessing the nature and type of defect from a study of PD patterns has facilitated its acceptance in industry and test equipments. The measurements, however, are seriously affected by the interference signals resulting from different sources, like the high frequency sinusoidal signals from radio broadcasts and/or carrier wave communications. These noise signals are coupled electromagnetically and their amplitude is often higher than the amplitude of the PD signal itself. These noises greatly reduce the sensitivity and resolution of the PD detector and even prevent meaningful measurements [3]-[7].

In the present work, wavelet transform (WT) for denoising the PD signals is considered. Since, the often encountered difficulty in PD measurement is to discriminate PD signals from various noises; a more sophisticated filtering method is required to detect PD signals correctly. WT has been a new and powerful tool for signal processing in recent years. It has been successfully applied in many fields. WT can give information both in time and frequency domains. Multiresolution (multiscale), the main characteristics of WT, makes it more suitable than traditional Fourier transform in analyzing signals with interesting transient information such as PD signals. Before discussing the proposed method, a concise introduction to common sources of interferences and wavelet signal representation is presented [8]-[20].

## **2. The Proposed Wavelet Technique**

### **2.1 Common Sources of Interferences**

Sensitivity and reliability of PD measurements are affected by ingress of various external interferences, and achieving acceptable levels of detection and sensitivity is many times not possible, as there are many sources of interferences of high magnitude even inside a well shielded laboratory. The condition that one encounters during online and onsite measurements can hence be easily imagined. Depending on the characteristics and origin of interferences, different suppression techniques have to be employed.

According to the time-domain properties, noises present in PD measurement can be broadly divided into three cases, namely: (i) discrete spectral interferences (DSI) from radio transmissions and power line carrier communication systems. (ii) Periodic pulse shaped interferences from power electronic devices are due to periodic switching. (iii) Stochastic pulse shaped interferences from frequent switching operations or lightning, arcing between adjacent metallic contacts, arcing from slip ring and brushes in rotating machines, PD and corona from the power system which can get coupled to the apparatus under test.

In addition to the above sources, other noise sources that can possibly exist in a PD measuring circuit are random noise from components, harmonics from the mains, pulsive interferences from transformers, and interferences from ground connections [6]-[8].

### **2.2 Wavelet Denoising Technique**

The general wavelet-based denoising method proceeds in three steps: decomposing the noisy signal, thresholding the wavelet coefficients, and reconstructing the signal as shown in Figure 1. In the first step, the signal is transformed into the wavelet domain and represented by weighted coefficients. This stage involves defining, the type and order of mother wavelet, and the decomposition levels [21], [22].

The second step is crucial in efficient noise cancellation. Wavelet denoising methods can be carried out using either hard or soft thresholding. Hard thresholding processes data in such a way that those wavelet coefficients whose absolute values ( $x$ ) are greater than the threshold ( $\lambda$ ) are kept and those less than the threshold are set to zero (equation 1). Soft thresholding sets the wavelet coefficients below the threshold to zero. The coefficients greater than threshold are kept and then shrunk towards zero (equation 2).

The reconstruction is defined by the Inverse Discrete Wavelet Transform which involves up-sampling and filtering steps. At the completion of this stage, the denoised signal is represented in time domain.

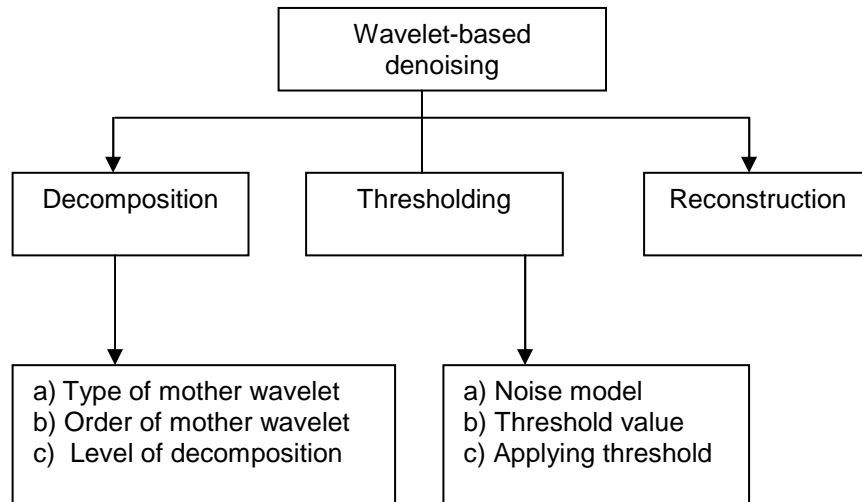


Figure 1. Wavelet-based denoising procedure

$$\delta_{\lambda}^H = \begin{cases} x & \text{if } |x| > \lambda \\ 0 & \text{if } |x| \leq \lambda \end{cases} \quad (1)$$

$$\delta_{\lambda}^S(x) = \begin{cases} x - \lambda & \text{if } |x| > \lambda \\ 0 & \text{if } |x| \leq \lambda \\ x + \lambda & \text{if } |x| > -\lambda \end{cases} \quad (2)$$

The success of the noise cancellation can be assessed in a number of ways. One of the measures involve the signal-to-noise ratio (SNR) defined by equation 3. The goal of denoising is to improve the SNR. A positive value of SNR implies a greater power of the signal as compared to the noise and a negative value of SNR implies a greater power of noise as compared to the signal. It should be noted that it is only an approximate measure since signal is not entirely noise free. Another measure evaluates the mean squared error (MSE) between the input signal and denoised signal as defined in equation 4 and minimizes it. The denoising action is guided by a reasonable minimum MSE and reduction in pulse amplitude as defined in equation 5. In simulation study, since a pulse sequence is used, so the percentage reduction in the peak amplitude of the pulse recovered after denoising with respect to the corresponding pulse in the input sequence is calculated.

$$SNR = 10 * \log \frac{\sum_{i=1}^N Y(i)^2}{\sum_{i=1}^N (X(i) - Y(i))^2} \text{ dB} \quad (3)$$

$$MSE = \sum_{i=1}^N \frac{(Z(i) - Y(i))^2}{N} \quad (4)$$

$$\% \text{ Reduction} = \frac{X - Y}{X} * 100 \quad (5)$$

Where,  $X(i)$  is the original signal,  $Y(i)$  is the denoised signal,  $Z(i)$  is the noisy signal acquired,  $N$  is the number of pulses,  $X$  is the peak amplitude (positive going peak pulse in this case) of the original (reference) signal and  $Y$  is the peak amplitude of the recovered denoised pulse.

### 2.3 The Wavelet Technique with Soft Thresholding

In this work, a wavelet technique with soft thresholding and “minimaxi” thresh select was used. The selection of mother wavelet and decomposition levels was arrived at after considerable trial and error. The proposed technique is basically an off-line technique and has the advantages of low processing time and possibility of better reconstruction, because the suppression of noise/interferences is done in a joint time-frequency domain.

In this method, for a set of PD data in the presence of noise, the denoising can be performed through wavelet decomposition, thresholding of wavelet coefficients and wavelet reconstruction. Thresholding is of vital importance during denoising, which is considered by retaining the wavelet coefficients associated with discharge events and on the other hand, discarding all other discharge-free coefficients which characterize noise. Soft thresholding and “minimaxi” thresh select was used.

The “minimaxi” threshold select uses a fixed threshold chosen to yield “minimax” performance for mean square error against an ideal procedure. The “minimax” principle is used in statistics in order to design estimators. Since the denoised signal can be assimilated to the estimator of an unknown regression function, the “minimax” estimator is the one that realizes the minimum of the maximum mean square error obtained for the worst function in a given set. The “minimax” threshold selection rules are more conservative and convenient when small details of function lie in the noise range [21].

### 3. Research Method

The method was first applied to simulated signals and then to the actual PD signals obtained from experiments. In this paper, experiments to generate practical PD signals, processing of PD signals and the results of the denoising techniques applied to them are presented.

Figure 2 shows the schematic diagram of the experimental setup used to generate PD signals (Experiments were conducted at CPRI, Bangalore). A high voltage discharge free transformer of rating 20kVA, 100kV was used to supply high voltage to the PD test circuit. The input voltage to the HV transformer (HVT) was controlled by an auto transformer (AT) of rating 240V/270V, 40A. A coupling capacitance of 1000pF was connected in series with the input impedance  $Z_m$  to form the detection circuit. The PD data was collected using Discharge Detector Model 5, Bonar Instruments Limited, Manchester, England and recorded in a digital signal oscilloscope (DSO) in a shielded room.

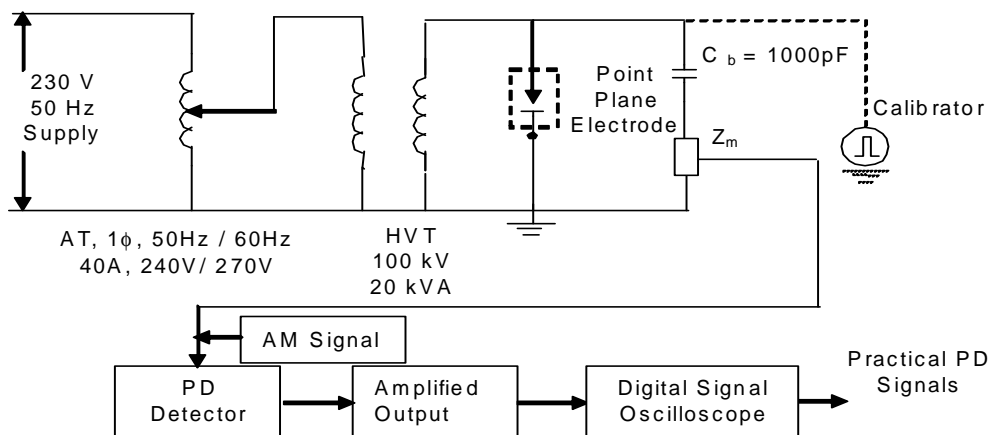


Figure 2. Schematic diagram of the experimental setup

PD pulses produced by the test object were detected by  $Z_m$  and fed through a cable to the PD detector along with a amplitude modulating signal (AM: which is a radio noise generated by a signal generator with carrier frequency adjusted to 615kHz and modulating frequency adjusted to 1.25kHz). This radio signal represents the DSI used for superimposition on the PD signals. This resultant signal, which represents the PD signals similar to signals acquired in online measurements, was fed to an amplifier. The magnitude of the resulting quasi-integrated PD signal is displayed on the DSO and by a process of calibration can be correlated to the apparent charge in pico-coulomb (pC).

A measuring bandwidth of 20-300 kHz was used to measure the PD signals. A calibrating pulse of 5pC was injected to the detection circuit to calibrate the PD detector. The sampling rate was chosen, such that the recorded signal corresponds to one power frequency cycle, which yielded 20ms of the signal. All data acquisition was carried out ensuring a maximum possible full-scale deflection on the DSO. Figure 3 shows the photograph of the acquisition unit used to acquire PD signals and Figure 4 shows the experimental setup in the shielded room. Figure 5 shows the signal acquired by using DSO.

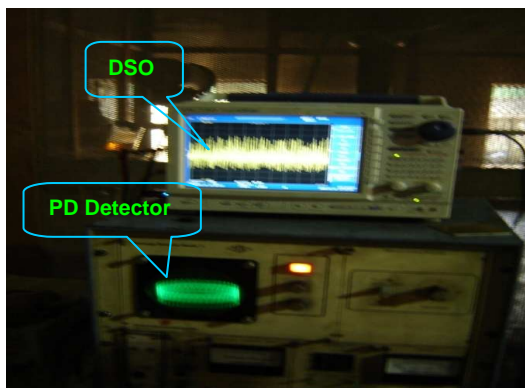


Figure 3. Photograph of the acquisition unit used to acquire PD signals

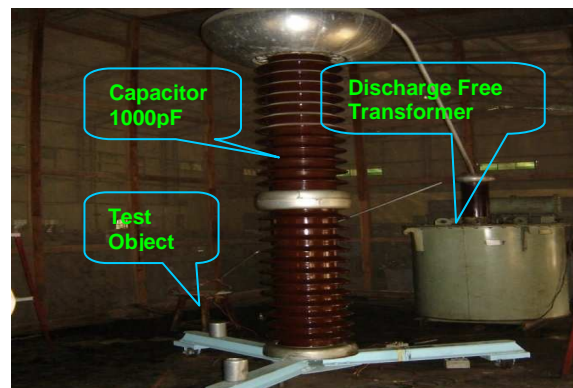


Figure 4. Photograph of the experimental setup in the shielded room

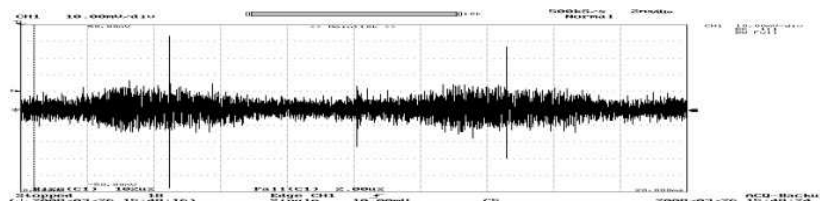


Figure 5. Signal acquired in DSO

#### 4. Results and Discussions

**Set 1:** The input signal to the PD detector was obtained by superimposing radio station noise i.e. DSI generated by signal generator with the calibration pulse of the calibrator. In this acquisition, the power supply to the circuit was connected, but not energized. The input signal to the PD detector consisted of a calibration pulse of 5pC and the noise generated in the experimental set up is shown in Figure 6(a). Figure 6(b) shows the denoised signal of Figure 6(a) by the proposed method. For processing the signal 6(a), signal was decomposed up to 10 levels by using "Daubechies1" as mother wavelet. The thresholding method used was soft and "minimaxi" thresh select. The pulse amplitude reduction was 24.98%. The shape of the calibrating pulse was greatly preserved as depicted in Figure 6.

**Set-2:** In this set, the test object was a point (needle) to ground configuration. Figure 7 shows the photograph of sharp needle as test sample.

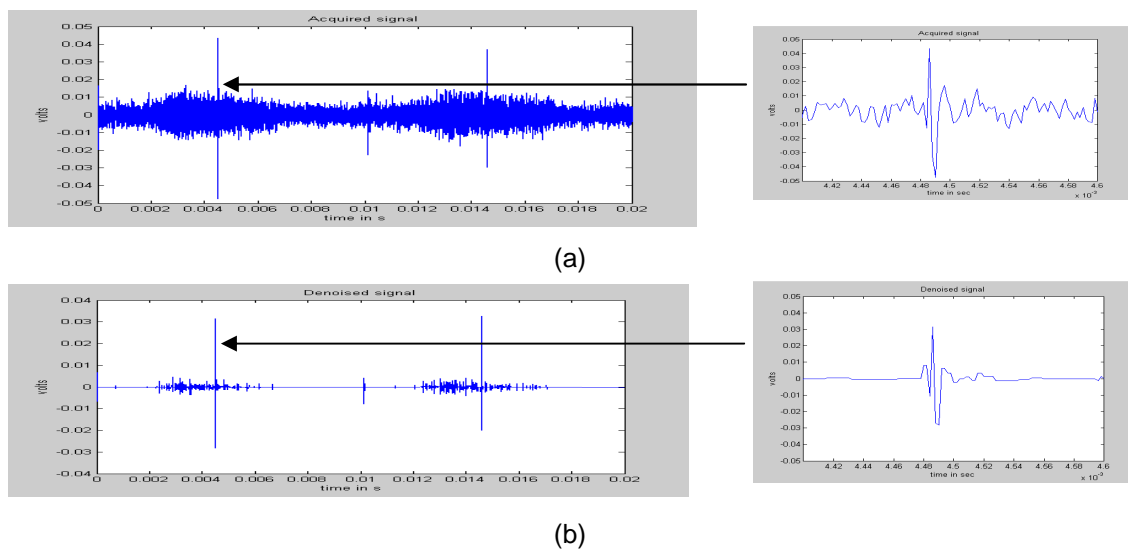


Figure 6. (a) PD signal of 69dB (set 1) and (b) denoised signal



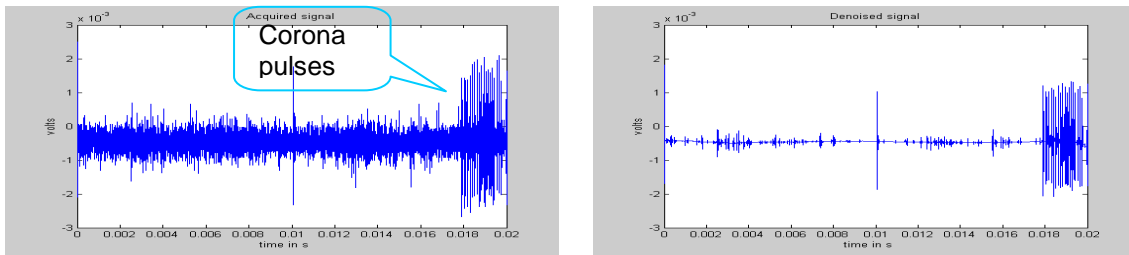
Figure 7. Photograph of sharp needle as test sample

**Set 2a:** The applied voltage was 5.8kV. The corona discharges along with the noise generated in the experimental set up were fed to the PD detector circuit. Figure 8(a) shows signal of set 2a. Figure 8(b) shows the denoised signal of Figure 8(a). For processing the signal 8(a), signal was decomposed up to 10 levels by using “Daubechies 4” as mother wavelet. The thresholding method used was soft and “minimaxi” thresh select. The pulse amplitude reduction was 27.36%.

**Set 2b:** The applied voltage was 7.1kV. The corona discharges along with the noise generated in the experimental set up were fed to the PD detector circuit. Figure 9(a) shows signal of set 2b. Figure 9(b) shows the denoised signal of Figure 9(a). For processing the signal 9(a), signal was decomposed up to 10 levels by using “Daubechies 1” as mother wavelet. The thresholding method used was soft and “minimaxi” thresh select. The pulse amplitude reduction was 12.01%.

**Set 2c:** The applied voltage was 5.2kV. The corona discharges along with the noise generated in the experimental set up were fed to the PD detector circuit. Figure 10(a) shows signal of set 2c. Figure 10(b) shows the denoised signal of Figure 10(a). For processing the signal 10(a), signal was decomposed up to 10 levels by using “Daubechies 4” as mother wavelet. The

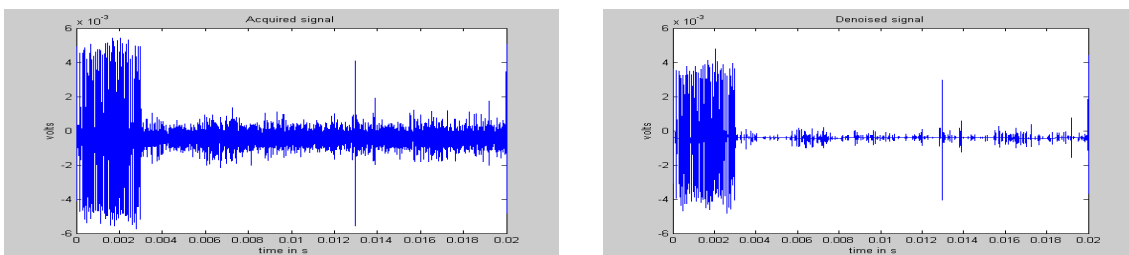
thresholding method used was soft and “minimaxi” thresh select. The pulse amplitude reduction was 14.97%.



(a)

(b)

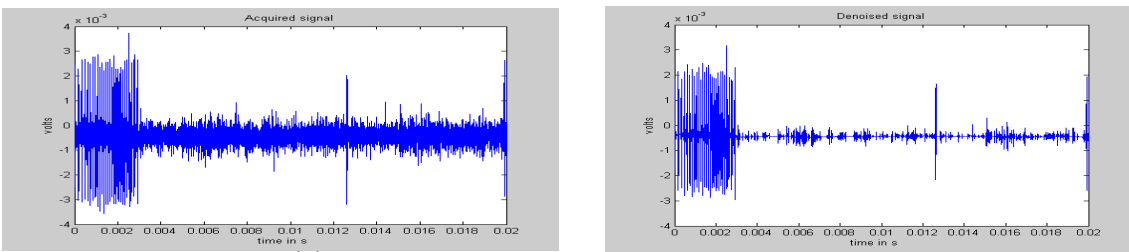
Figure 8 (a) Corona discharges acquired at the applied voltage of 5.8kV (set 2a), (b) denoised signal



(a)

(b)

Figure 9. (a) Corona discharges acquired at the applied voltage of 7.1kV (set 2b), (b) denoised signal



(a)

(b)

Figure 10. (a) Corona discharges acquired at the applied voltage of 5.2kV (set 2c), (b) denoised signal

## 5. Conclusion

PD signals were acquired by considering interferences which occurs during onsite and online measurements. The signals were acquired in laboratory in a realistic manner [14]. For processing the signals, the mother wavelet was selected after rigorous trials through ‘db1’ to ‘db45’ and ‘bior 1.1’ to ‘bior 6.8’. The “Daubechies” mother wavelets emerged as appreciably good mother wavelets for the proposed application. The results indicate that, the wavelet transform technique incorporated using “Daubechies” as mother wavelet is very effective in denoising PD signals mixed with DSI and white noise.

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