

WAVELET-BASED PARTIAL DISCHARGE SIGNAL ANALYSIS FOR CONDITION MONITORING OF HIGH-VOLTAGE POWER CABLES

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Abstract

Partial discharges (PDs) are widely recognized as early warning indicators of insulation deterioration in high-voltage power cables, making their timely detection essential for maintaining power system reliability. In this study, a wavelet-based signal analysis framework was presented to enhance the detection of weak PD activity under noisy measurement conditions. Simulated PD signals were generated as Gaussian-modulated sinusoidal pulses with a central frequency of 300 kHz and a pulse width of 50 μ s, sampled at 2MHz. To reflect realistic operating environments, the signals were further corrupted with 30% additive white Gaussian noise. Both Continuous Wavelet Transform (CWT) and Wavelet Packet Transform (WPT) were employed to extract detailed time–frequency features from the PD signals, while Discrete Wavelet Transform (DWT)–based denoising was used to suppress noise and improve signal clarity. The denoising process led to a noticeable improvement in signal-to-noise ratio, allowing clearer visualization and identification of individual discharge pulses. Quantitative analysis showed that the denoised PD signals exhibited an average normalized pulse amplitude of 0.48, a mean signal energy of 0.0.0007, and a total envelope energy of 5.4204. About 16 distinct PD events were successfully detected within the 2ms observation window. Frequency-domain energy analysis further revealed that PD activity was predominantly concentrated in the 250–400 kHz band, which aligns well with typical discharge behavior observed in high-voltage cable insulation. The findings confirm that wavelet-based techniques provide a robust and noise-resilient approach for PD feature extraction, offering strong potential for insulation condition assessment and early fault detection in high-voltage power systems.

Keywords: Partial Discharge, High Voltage Power Cable, Wavelet Transforms, Insulation Condition, Dynamic Modelling.

Introduction

High-voltage (HV) power cables play a vital role in modern electrical transmission and distribution systems by enabling the safe and reliable transfer of electrical energy from generation sources to consumers. During long-term operation, these cables are continuously exposed to a combination of electrical, thermal, mechanical, and environmental stresses [1], [2], [3]. The cumulative effect of these stresses gradually accelerates insulation aging, leading to deterioration of dielectric properties and, ultimately, a reduction in system reliability and service life if not properly monitored and managed [4], [5]. Partial discharges (PDs) are among the earliest and most reliable indicators of insulation degradation in high-voltage equipment. They are localized dielectric breakdowns that occur within insulation defects and generate high-frequency transient pulses without completely bridging the electrodes [6]. When left undetected, repeated PD activity accelerates insulation aging and can eventually cause catastrophic failures, leading to unplanned outages, equipment damage, and significant economic losses [7], [8].

The detection and analysis of partial discharge (PD) signals are therefore critical for predictive maintenance and effective asset management in high-voltage (HV) power systems. PD signals are inherently non-stationary and contain high-frequency components, typically spanning from tens of kilohertz to several megahertz [9]. In practical environments, these signals are often masked by substantial electromagnetic interference arising from switching operations, corona discharges, and

other industrial noise sources, which makes reliable PD detection a challenging signal-processing task [10], [11].

To address these challenges, wavelet-based signal processing techniques have gained wide acceptance as a robust and effective approach for partial discharge (PD) analysis. Unlike conventional Fourier-based methods, which provide only global frequency information, wavelet transforms enable multi-resolution time–frequency analysis, allowing transient PD events to be accurately localized in both time and frequency domains [12]. The Continuous Wavelet Transform (CWT) is particularly well suited for visualizing the temporal evolution of high-frequency PD pulses, offering intuitive time–frequency representations that highlight transient discharge activity [13]. The Discrete Wavelet Transform (DWT) is commonly employed for PD signal filtering and energy-based analysis, as it efficiently separates useful discharge components from noise. Furthermore, the Wavelet Packet Transform (WPT) extends this capability by decomposing the signal into uniformly spaced frequency sub-bands, enabling detailed energy feature extraction. Such fine-grained analysis is essential for characterizing the severity, repetition rate, and spectral content of PD events [14]. Although wavelet-based methods have significantly improved partial discharge (PD) analysis, accurately detecting weak PD signals in noisy environments remains challenging [15]. Many studies still lack robust quantitative evaluation of critical PD features such as pulse amplitude, discharge energy, and event count, which are essential for reliable insulation condition assessment and predictive maintenance. In addition, effective graphical visualization tools, including scalograms, spectrograms, and envelope plots, are vital for interpreting the time–frequency behavior of PD activity and supporting informed diagnostic decision [16], [17].

High-voltage power cables are essential to electricity networks, but insulation degradation over time can lead to partial discharges that may cause severe failures if undetected. Because PD signals are short-duration, high-frequency transients often masked by noise, conventional time-domain techniques are inadequate for early detection. Reliable PD monitoring is therefore critical to prevent insulation failure, reduce maintenance costs, and improve power system reliability.

This study aims to develop and evaluate a wavelet-based approach for analyzing partial discharge signals in high-voltage cables, with particular emphasis on effective noise suppression, reliable feature extraction, and quantitative characterization of PD activity using MATLAB-based modelling and simulation.

1. Materials and Method

The methodology adopted in this study combines modelling simulation-based generation of partial discharge (PD) signals with advanced wavelet-based signal processing techniques, including noise suppression, feature extraction, and graphical visualization. This integrated approach enables a comprehensive assessment of PD activity in high-voltage power cables. Each stage of the methodology is carefully examined to highlight its specific role in improving the accuracy of PD detection and enhancing the reliability of quantitative PD analysis.

Conceptual System Mathematical Modelling

A. Partial Discharge Signal Model

Partial discharge (PD) events in power cables are transient high-frequency phenomena. A single PD pulse can be modeled as a Gaussian-modulated sinusoid [7], [8].

$$x(t) = A \sin(2\pi f_0 t) \cdot \exp\left[-\left(\frac{t-t_0}{\sigma}\right)^2\right] + n(t) \quad (1)$$

Where:

$x(t)$ = is the observed PD signal at time t

A = is the peak amplitude of the PD pulse

f_0 = is the central frequency of the PD pulse (Hz)

t_0 = is the pulse center time

σ = is the width controlling decay

$n(t)$ = is the additive white Gaussian noise (AWGN) representing measurement and environment for multiple PD events.

The signal can be represented as a superposition of N pulses [17].

$$x(t) = \sum_{i=1}^N A_i \sin(2\pi f_{0i}t) \cdot \exp\left[-\left(\frac{t-t_{0,i}}{\sigma}\right)^2\right] + n(t) \quad (2)$$

2.1.2. Continuous Wavelet Transform (CWT)

CWT was applied using the Morlet wavelet to obtain a time-frequency representation of the PD signals. This enables the detection of high-frequency transients and visualization of PD events [9].

The CWT Signal is defined as:

$$W(a, b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} x(t) \psi^*\left(\frac{t-b}{a}\right) dt \quad (3)$$

Where:

$W(a, b)$ = is the wavelet coefficient at scale a and translation b

a = is the scale factor; relate to frequency

b = is the translation related to time shift

$\psi(t)$ = it the Morlet wavelet function

$*$ = this denote the complex conjugate

Morlet Wavelet is defined as [12]:

$$\psi(t) = \pi^{-1/4} e^{j2\pi f_e t} e^{-t^2/2} \quad (4)$$

CWT coefficient represents the energy distribution of the signal across scales and time allowing detection of transient PD pulses even in noisy environments [18].

Discrete Wavelet Transform (DWT) Model

DWT was employed with Daubechies 4 ('db4') wavelet combined with soft threshold for de-noising [19]. The DWT decomposes a signal into approximation and detail coefficients at multiple levels [12].

$$x(t) = A_L + \sum_{i=1}^L D_i \quad (5)$$

Where:

A_L = approximation coefficients at level L

D_l = is the detail coefficients at level l

L = is the decomposition level

2.1.4. Noise Thresholding:

For soft-thresholding de-noising, coefficients are modified as [13]:

$$\bar{D}_l = \text{sign}(D_l) \cdot \max(|D_l| - \lambda, 0) \quad (6)$$

Where:

$\lambda = \sigma \sqrt{2 \ln N}$, a universal threshold

σ = Estimate of noise standard deviation

N = is the number of samples

The reconstructed signal is express as:

$$\bar{x}(t) = A_L + \sum_{i=1}^L \bar{D}_i \quad (7)$$

This enhances PD signal visibility by suppressing noise while preserving transient features [20].

Wavelet Packet Transform (WPT) Energy Model

Wavelet Packet Transform (WPT) was employed to decompose the partial discharge (PD) signals into uniformly spaced frequency sub-bands, allowing the energy content of each node to be accurately computed and analyzed [14].

For a signal $x(t)$, the energy of each WPT node is:

$$E_i = \sum_{k=1}^{N_i} |c_{i,k}|^2 \quad (8)$$

Where:

$c_{i,k}$ = is the wavelet packet coefficient of the $i - th$ node

N_i = is the number of coefficients in node i

E_i = is the total energy of node i

The total energy is preserved across nodes:

$$E_{total} = \sum_{i=1}^M E_i \quad (9)$$

Where M is the total number of leaf nodes [15].

Envelop Detection

The Hilbert transform was applied to obtain the envelope of the denoised PD signal.

The analytic signal of the denoised PD signal $\tilde{x}(t)$ is [21], [22]:

$$z(t) = \tilde{x}(t) + j\mathbb{H}\{\tilde{x}(t)\} \quad (10)$$

Where $\mathbb{H}(\cdot)$ is the Hilbert transform; the signal envelop is:

$$\text{env}(t) = |z(t)| = \sqrt{\tilde{x}^2(t) + \mathbb{H}\{\tilde{x}(t)\}^2} \quad (11)$$

The envelope emphasizes PD pulse peaks and allows accurate peak detection for amplitude and timing measurement [23].

Feature Vector Extraction

From the denoised PG signal and it's enveloped, a feature vector F was introduced to numerical foundation for PD characterization [10], [18].

$$F = \begin{bmatrix} A_{max} \\ E_{mean} \\ \sigma_x \\ E_{total} \end{bmatrix} = \begin{bmatrix} \max(\tilde{x}(t)) \\ \frac{1}{N} \sum_{k=1}^N \tilde{x}^2(t_k) \\ \sqrt{\frac{1}{N} \sum_{k=1}^N (\tilde{x}(t_k) - \tilde{x})^2} \\ \sum_{k=1}^N \text{env}^2(t_k) \end{bmatrix} \quad (12)$$

Where:

A_{max} = is maximum PD amplitude

E_{mean} = is the mean energy

σ_x = is the standard deviation of amplitude

E_{total} = is the total envelop energy

These features are useful for condition monitoring, trend analysis, and machine learning-based PD classification [17].

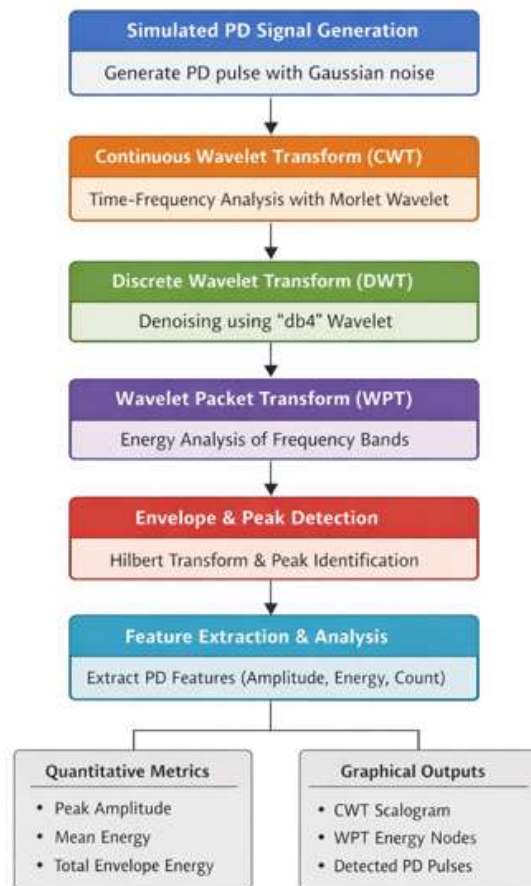


Figure 1: Flowchart of the Modelling Analysis Methodology

Results and Discussion

Table 1. Different Wavelet-Based Partial Discharge Signal, Values/Units

Parameters	Values/Units
Sampling frequency	2 MHz
Signal duration	2 ms
PD pulse central frequency	300 kHz
Pulse amplitude	1 (normalized)
Pulse width	50 μ s
Pulse center	1 ms
Noise level	30% of signal amplitude
CWT mother wavelet	Morlet ('amor')
DWT wavelet	Daubechies 4 ('db4')
DWT decomposition level	5
WPT decomposition level	4

Peak threshold	detection	0.2 (normalized)
Minimum distance	peak	50 samples

The simulation approach used in this study was based on a carefully selected set of parameters designed to realistically represent partial discharge (PD) behavior in high-voltage power cables. These parameters, which capture the vital characteristics of PD dynamics, are summarized in Table 1.

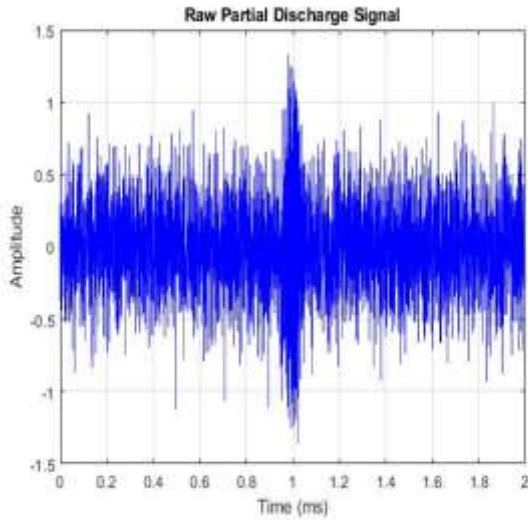


Figure 2: Raw Partial Discharge Signal

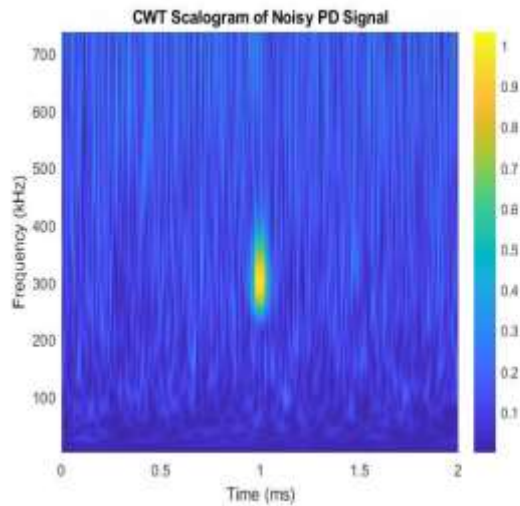


Figure 3: CWT Scalogram of Noisy PD Signal

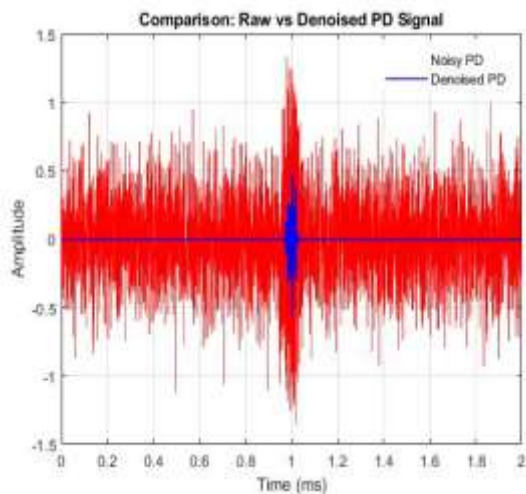


Figure 4: Comparison of Raw Against Denoised PD Signal

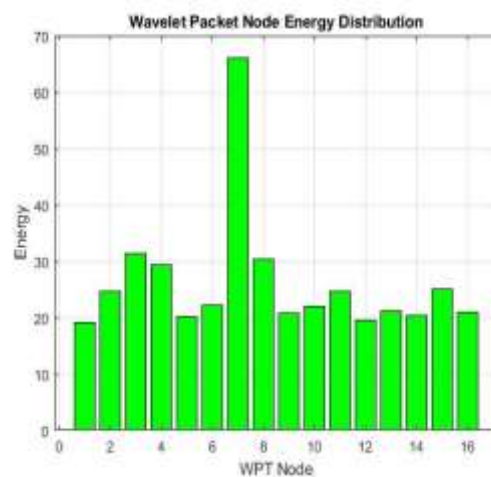


Figure 5: Wavelet Packet Node Energy Distribution

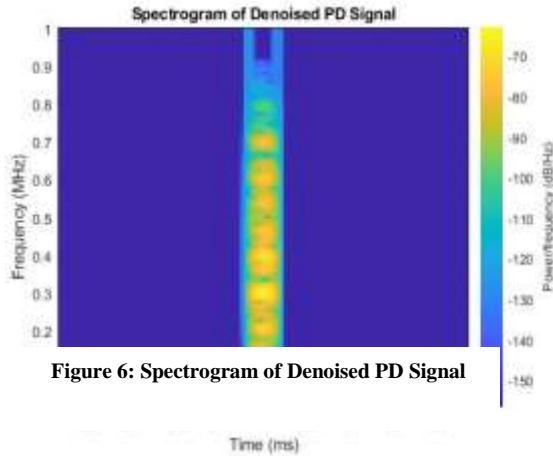


Figure 6: Spectrogram of Denoised PD Signal

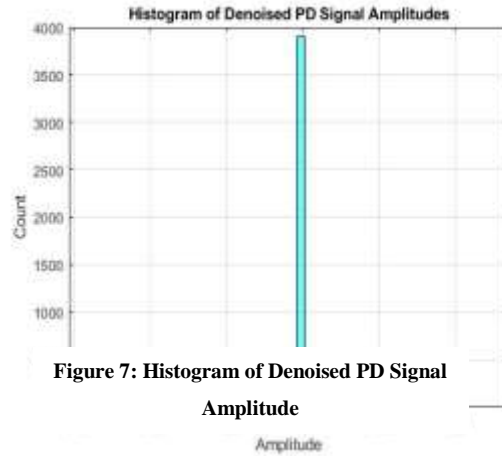


Figure 7: Histogram of Denoised PD Signal

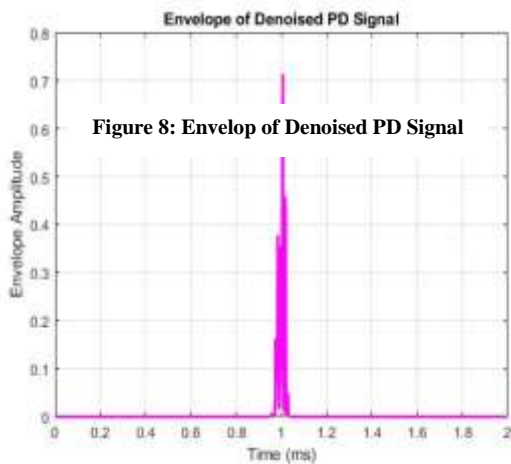


Figure 8: Envelop of Denoised PD Signal

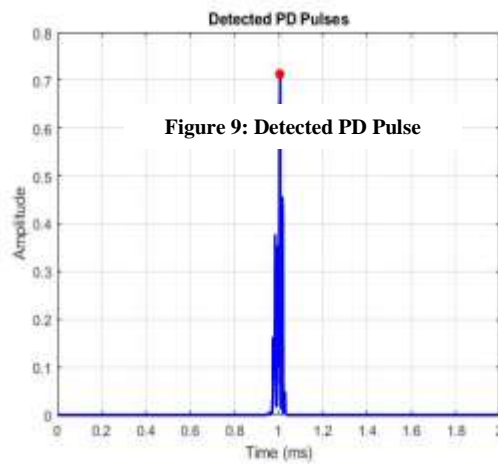


Figure 9: Detected PD Pulse

Table 2: Extracted Features of PD Characteristics

Extracted PD Features	Values
Max PD Amplitude	0.4885
Mean Energy	0.0007
Standard Deviation of the Amplitude	0.0260
Total Envelope Energy	5.4204

Discussion:

Figure 2. Displays the raw PD signal in the time domain. The waveform consists of fast, high-frequency transient pulses characteristic of partial discharge events in high-voltage cables. Noise is clearly visible throughout the signal, which can obscure weaker PD pulses. The presence of noise simulates real-world measurement conditions, emphasizing the need for advanced signal processing techniques for reliable PD detection.

Figure 3. Presents a CWT scalogram of the noisy PD signal using the Morlet wavelet. The scalogram provides a time-frequency representation, revealing the localization of PD pulses in both time and frequency. The PD activity is concentrated around 300 kHz. The high time-frequency resolution of the CWT highlights individual PD events despite the presence of noise, demonstrating the technique’s ability to identify transient, high-frequency signals that are not easily visible in the raw time-domain event.

Figure 4. Compares the raw and DWT-denoised PD signals. The denoising process preserves the PD pulse structure while effectively reducing background noise. After denoising, PD pulses appear sharper and more distinguishable, aiding accurate identification and measurement of pulse amplitude and timing. This figure demonstrates the effectiveness of wavelet-based denoising in enhancing signal quality and increasing the reliability of PD analysis in noisy environments.

Figure 5. Shows the energy distribution across leaf nodes obtained from the WPT of the PD signal. Each bar represents the total energy of a specific frequency sub-band. This analysis quantitatively identifies which frequency bands dominate the PD signal, making WPT an effective tool for feature extraction and enabling classification of PD activity based on energy content.

Figure 6. Presents a spectrogram of the denoised PD signal. The spectrogram confirms the presence of high-frequency transient events and shows their distribution over time. The spectrogram provides complementary validation of PD activity and highlights the recurring nature of the pulses. This figure demonstrates that multiple analysis approaches converge to confirm the same PD characteristics.

Figure 7. Illustrates the amplitude distribution of the denoised PD signal. This reflects the typical statistical behavior of partial discharge activity. Histograms are useful for evaluating the severity and frequency of PD events, as increases in high-amplitude occurrences may indicate advancing insulation degradation. This figure supports quantitative assessment and monitoring of insulation health.

Figure 8. Displays the envelope of the denoised PD signal obtained using the Hilbert transform. The envelope accentuates the timing and amplitude of PD pulses, making peak identification easier. This technique effectively highlights the transient nature of PD activity and provides a clear representation of pulse occurrences, which is critical for assessing PD severity and frequency in high-voltage cables.

Figure 9. Presents the detected PD pulses overlaid on the signal envelope. Peaks corresponding to individual PD events are marked, allowing direct counting and amplitude measurement. This figure enables quantitative analysis of pulse characteristics such as amplitude, rate of occurrence, and timing, which are essential parameters for assessing insulation condition and identifying potential failure risks.

Table 2. Shows computed feature vector combining maximum amplitude, mean energy, standard deviation, and total envelope energy. These features summarize the PD signal characteristics and can be employed in automated PD classification or machine learning algorithms for insulation health assessment.

Conclusion

The results of this study demonstrate that wavelet-based techniques are highly effective for the detection and analysis of partial discharge signals in power cables, especially in the presence of significant noise. By enabling reliable identification and characterization of PD events in noisy high-voltage cable signals, these methods substantially improve the accuracy of PD monitoring. The integrated use of continuous wavelet transforms (CWT), discrete wavelet transform (DWT), and wavelet packet transform (WPT) provides a robust, quantitative, and noise-resilient framework for PD detection. As a result, the proposed wavelet-based methodology shows strong potential for enhancing insulation condition assessment and supporting proactive and predictive maintenance strategies in high-voltage power systems.

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