Denoising different types of acoustic partial discharge signals using power spectral subtraction

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Abstract: Measuring acoustic emission (AE) of partial discharge (PD) phenomena can be adopted to estimate the condition of power transformers. However, the environmental noise encountered with AE of PD measurements negatively affects the accuracy of PD localisation and classification. Thus, efficient signal denoising techniques are required for noise suppression and hence, better detection accuracy. This study deals with white noise and it is a continuation of a previously published work that deals with random noise. The published work addresses the random noise suppression using a method named, power spectral subtraction denoising (PSSD). This study applies PSSD to the PD signals contaminated with white noise and uses a novel denoising performance and hence, the PD recognition accuracy.

1 Introduction

Power and distribution transformers are vital to the reliability of the power system. Any failure in the transformers and consequent unexpected outages can lead to catastrophic damages with massive costs for industrial, commercial, and residential customers. Therefore, on-line condition monitoring is crucial and necessary to prevent unexpected outages, maintain the reliability, extend lifetimes, and achieve the optimal performance of power transformers in service [1, 2].

There are several methods for condition monitoring of power transformers such as partial discharge (PD) measurement, dissolved gas analysis, and dielectric spectroscopy analysis. Among these methods, on-line PD measurement is very effective and non-destructive technique to detect PD at an early stage and hence assess the insulation condition of power transformers [3]. However, many sources of noise meddle with the measured PD recordings causing a serious impact on the PD diagnostic and detection accuracy. Therefore, signal denoising is considered an essential pre-processing step to remove the noise embedded in PD measurements. Frequently, there are four sorts of noise, to be specific: white noise, random noise, repetitive pulsative noise, and discrete spectral interferences (DSIs). The narrowband noise signals such as pulsative noise and DSIs can be easily removed using digital notch filters [4]. Meanwhile, the suppression of wideband noise signals such as white and random noises is more challenging, while they dwell in the whole frequency spectrum of PD signals [5]. Further, white and random noises represent the major sources of artefacts coupling with acoustic PD measurements [6].

Time-domain methods are rarely used for PD signal denoising since they operate only on the repetitive-pulse interference. They also lead to a considerable energy loss of the PD signal and can noticeably distort the PD signal shape [7]. Frequency-domain denoising methods are also proposed in the literature. The threshold filter method based on Fourier transform has been proposed in [8] to address the narrowband interfering noise. This method is computationally efficient, however, determining the optimal threshold value in real-time operations is challenging. This is because the embedded noise signal and its corresponding frequency spectrum change along with time [9].

Recently, wavelet transform based denoising methods are proven effective due to their abilities to suppress the different types of noise [10]. For instance, Shim et al. [11] have presented a discrete wavelet transform (DWT) based method to eliminate the different types of interferences embedded with the PD acquisition. Further, an analysis of wavelet packet transform (WPT) is interpreted in [12] to competently filter on-site PD signals. In this count, the statistical features of the embedded noise are used to find out the optimal wavelet tree. Evagorou et al. [13] have also employed the WPT for PD characterisation, while the moments of the density functions of the wavelet sub-bands are computed as delegate features for PD recognition.

Furthermore, considering the crucial role of the mother wavelet in controlling the denoising performance, an approach is presented in [14] to optimally select the mother wavelet relating to the recorded PD signals. This mother wavelet selection has boosted the denoising performance and hence, the PD recognition accuracy. Moreover, a hybrid method integrating pre-whitening and blind equalisation modules is introduced in [15] to process the PD signals that are totally buried in noise. Further, a DWT method with energy conservation-based thresholding is developed in [16] to accurately recover the original PD signals with minimum distortion.

Despite the promising results achieved by wavelet methods, the performance of wavelet-based denoising procedure is computationally intensive and might hinder real-time applications [17]. The spectral subtraction denoising (SSD), on the other side, is a frequency-domain-based denoising approach that achieves a comparable performance to those of wavelet methods in less computation time [18]. SSD is previously adopted to eliminate the environmental noise in different applications [19–21].

In this paper, we introduce a variation of SSD, named power SSD (PSSD) to suppress the noise embedded with acoustic emission (AE) of PD signals. PSSD is principally derived when the phases of the reference signal and noise are independent, which is the situation in PD measurements [18]. This paper is a continuation of a previously published work that addresses the challenge of PD denoising. The published work demonstrates the PSSD method for...
random noise rejection [22]. This paper applies PSSD to the PD signals contaminated with white noise, while using a novel scheme of noise power spectrum density (PSD) estimation. The PSSD method is evaluated on different types of PD signals and under various levels of noise intensity. Compared to the wavelet shrinkage denoising (WSD) method [23], PSSD produces better results with much lower computational complexity. Further, we introduce the modified PSSD (M-PSSD) method to handle the PD signals corrupted with real noise. It is shown that M-PSSD provides higher reductions in noise levels than those of WSD.

2 Laboratory setup for PD signals measurement

To assess the denoising performance of the proposed method, tests are applied to laboratory-measured PD signals polluted with synthetic and real noise. The experimental setup and circuit diagram are depicted in Figs. 1 and 2, respectively. Four common types of acoustic PD signals are considered in this study; PD from a sharp point to ground plane, surface discharge, PD from a semi-parallel plates and a PD from an air void in the insulation; as depicted in Fig. 3. Examples of these PD signals are displayed in Fig. 4.

The utilised tank with 1 m × 1 m × 0.5 m dimensions is filled with aged oil received from a local utility company. The high voltage source is 40 kV, 10 mA, 50/60 Hz AC tester and it is linked together with an adjustable electrode system in order to generate the four PD types under study. The bandwidth of the used AE sensor is 100–450 kHz with a resonance frequency at 150 kHz. The sensor was fixed around 0.5 m from the PD source at the shortest direct line path. The data acquisition system is composed of a 60 MHz digital oscilloscope interfaced with a PC. The sampling frequency was adjusted at 10 Msample/s for a time frame of 250 μs. The AE sensor is attached to the tank wall with a magnet and a silicone grease is used between the sensor and the tank wall to minimise the acoustic waves reflection.

3 Power spectral subtraction denoising

Spectral subtraction is shown to be effective as a noise suppression technique, particularly for the data corrupted with white noise [18]. A measured acoustic PD signal polluted with an environmental noise can be represented by

\[ x(i) = s(i) + v(i), \quad i = 0, 1, 2, \ldots, N \]  

(1)

where \( x(i) \) is the captured noisy PD signal, \( s(i) \) is the original noise-free PD signal, \( v(i) \) is the noise signal, \( i \) is the discrete time index, and \( N \) is the length of these signals.

3.1 PSSD for acoustic PD signals with synthetic noise

Assuming that the original PD signal and the interfering noise are uncorrelated, which is often the case in PD measurements, the PSD is obtained by applying fast Fourier transform (FFT) to both sides of (1); and that is

\[ X(e^{j\omega}) = S(e^{j\omega}) + V(e^{j\omega}) \]  

(2)

where \( X(e^{j\omega}) \), \( S(e^{j\omega}) \), and \( V(e^{j\omega}) \) are the Fourier transforms of noisy PD, noise-free PD, and noise signals, respectively; \( \omega \) is the
Fig. 5 Proposed SSD technique for the noisy PD signals contaminated with real noise

The denoised PD signal, \( z(i) \), can be obtained by applying the inverse FFT (IFFT) to the spectrum \( Z(e^{j\omega}) \).

3.2 M-PSSD for acoustic PD signals with real noise

In practice, the measured PD signals are contaminated with different sources of real noise. To mimic such a real noise, a DC motor is used at different speed conditions to generate different levels of noise. The motor is placed, on the ground, 5 cm from the transformer tank. The acquisition of surface, sharp, parallel, and void PD signals is executed simultaneously so that they are prone to the same level of noise. M-PSSD is proposed for noise suppression of the PD signals that are corrupted by real noise. The anonymous power spectrum of the embedded noise signal hinders the implementation of PSSD denoising method. Thus, we introduce an estimation scheme for the PSD of the surrounding embedded noise. Fig. 5 illustrates the framework of our proposed M-PSSD approach. After PD acquisition, DWT is used to decompose the PD signal into approximation and detail sub-bands. Assuming that the noise signal and the first detail sub-band have comparable characteristics [17], an estimate of the noise PSD (\( E|1V(e^{j\omega})|^2 \)) can be obtained and subtracted from the PSD of the captured PD signal. This subtraction process gives an estimate of the PSD of the denoised PD signal. Thus

\[
IZ(e^{j\omega})^2 = |X(e^{j\omega})|^2 - E|1V(e^{j\omega})|^2
\]

Since the distribution of the white noise is Gaussian, the noise PSD can be expressed as the root-mean-square noise power \( |V(e^{j\omega})|^2 \), such that

\[
|Z(e^{j\omega})|^2 = |X(e^{j\omega})|^2 - |V(e^{j\omega})|^2
\]

Referring to [19], the average noise power \( |V(e^{j\omega})|^2 \) can be expressed in terms of the noise variance and the length of the noise signal, as follows:

\[
|V(e^{j\omega})|^2 = N \cdot \sigma_v^2
\]

where \( \sigma_v^2 \) is the noise variance.

In practice, the noise signal is jumbled with the measured PD signal. Therefore, DWT is used to analyse the PD signal and assess the variance of the embedded noise signal. It decomposes the signal into one approximation \( A1 \) and one detail \( D1 \) sub-bands. Then, the noise signal and first detail sub-band are assumed to have the same statistical features and characteristics [17]. Thus

\[
Z(e^{j\omega}) = |Z(e^{j\omega})|e^{j\phi(Z(e^{j\omega}))}
\]
From (12), an estimate of the PSD of the denoised PD signal, compared to the WSD technique [23]. PSSD and WSD are first examined on PD signals defiled with synthetic noise. Second, we discuss the results obtained by applying M-PSSD and WSD to actual signals contaminated with real noise. Various performance evaluation metrics are considered to assess the denoising performance including:

i. Signal-to-noise ratio (SNR)

$$\text{SNR(dB)} = 10 \log \left( \frac{\sum_{i=1}^{N} |s(i)|^2}{\sum_{i=1}^{N} |v(i)|^2} \right)$$

where $s(i)$ and $v(i)$ denote the original PD signal and noise signal, respectively.

ii. Root mean square error (RMSE)

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} |z(i) - s(i)|^2}$$

RMSE is commonly used to evaluate how much distortion caused by denoising.

iii. Cross-correlation coefficient ($\rho_{xy}$)

$$\rho_{xy}(n) = \frac{\sum_{i=0}^{N-n-1} s(i)z(i+n)}{\sqrt{\sum_{i=0}^{N-1} s(i)^2 \sum_{i=0}^{N-1} z(i)^2}}$$

It calculates the correlation between the original and denoised PD signals.

iv. Reduction in noise level (RNL)

$$\text{RNL(dB)} = 10 \log \left( \frac{1}{N} \sum_{i=1}^{N} |x(i) - z(i)|^2 \right)$$

where $x(i)$ denote the noisy PD signal.

4 Results and discussions

This section discusses the denoising performance of PSSD compared to the WSD technique [23]. PSSD and WSD are first examined on PD signals defiled with synthetic noise. Second, we discuss the results obtained by applying M-PSSD and WSD to actual signals contaminated with real noise. Various performance evaluation metrics are considered to assess the denoising performance including:

i. Signal-to-noise ratio (SNR)

$$\text{SNR(dB)} = 10 \log \left( \frac{\sum_{i=1}^{N} |s(i)|^2}{\sum_{i=1}^{N} |v(i)|^2} \right)$$

where $s(i)$ and $v(i)$ denote the original PD signal and noise signal, respectively.

ii. Root mean square error (RMSE)

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It calculates the correlation between the original and denoised PD signals.

iv. Reduction in noise level (RNL)

$$\text{RNL(dB)} = 10 \log \left( \frac{1}{N} \sum_{i=1}^{N} |x(i) - z(i)|^2 \right)$$

where $x(i)$ denote the noisy PD signal.
the denoised PD signal by PSSD can adequately preserve the same behaviour of the original PD signal.

Fig. 4c shows a specimen of the parallel PDs that occur in electrical insulation systems. The PSSD technique is examined on two different forms of such parallel PD signal, one of them is polluted with a low level of noise, while the other one is extremely wrapped in noise. For the low level of noise, the parallel PD signal is contaminated with synthetic noise such that producing a noisy PD signal of 10 dB SNR. The denoising performance of this PD signal is reported in Table 3, whilst the evaluation metrics demonstrate that the similarity between the original and denoised PD signals obtained by PSSD is higher than the one obtained by WSD. Moreover, the performance evaluation metrics reported at high noise level (SNR = –10 dB) reinforce that PSSD can excavate the original PD signal from the noise-corrupted version with lower distortion than WSD.

A similar analysis is conducted on the void PDs, where two different levels of synthetic noise are artificially added to the noise-free void PD signal shown in Fig. 4d producing two noisy PD signals of 10 and –10 dB SNRs, respectively. At low noise level (SNR = 10 dB), the performance metrics reported in Table 4 reflect the capability of the PSSD method to obtain a denoised PD signal that is very analogous to the original void PD signal. At high noise level (SNR = –10 dB), the imperfect conditions negatively affect the void PD signal such that being immersed in noise. In this case, the denoising performance depicted in Table 4 shows that the PD signal de-noised by PSSD has smaller distortion than those de-noised by WSD.

4.2 Denoising results of signals with real noise

The denoising performance of the developed M-PSSD method is investigated on the noisy acoustic PD signals corrupted with real noise, where the noise levels are unknown. Figs. 8a, 9a, 10a, and 11a show samples of laboratory-measured noisy acoustic signals generated by surface, sharp, parallel, and void PDs, respectively. As depicted in Figs. 8b and c, it can be visually noted that the M-PSSD method as well as WSD method are capable of removing a considerable amount of noise that interferes with the captured PD signals.

| Table 1 | Denoising performance of WSD and PSSD for surface PD signal at low noise level (SNR = 10 dB) and high noise level (SNR = –10 dB), respectively |
|---|---|---|---|---|
| SNR | Method | SNR_D | RMSE | D_rho | RNL |
|---|---|---|---|---|---|
| 10 | WSD | 10.2487 | 0.1077 | 0.8901 | 57.5939 |
| | PSSD | 14.1865 | 0.0485 | 0.9788 | 61.6661 |
| –10 | WSD | 2.2445 | 0.1916 | 0.6090 | 43.8310 |
| | PSSD | 6.2702 | 0.1206 | 0.8749 | 44.3988 |

| Table 2 | Denoising performance of WSD and PSSD for corona PD signal at low noise level (SNR = 10 dB) and high noise level (SNR = –10 dB), respectively |
|---|---|---|---|---|
| SNR | Method | SNR_D | RMSE | D_rho | RNL |
|---|---|---|---|---|---|
| 10 | WSD | 11.4746 | 0.4286 | 0.9061 | 45.4030 |
| | PSSD | 16.4739 | 0.1521 | 0.9887 | 49.8771 |
| –10 | WSD | 1.9269 | 0.8117 | 0.7156 | 30.0297 |
| | PSSD | 5.5227 | 0.5365 | 0.8849 | 32.3412 |

| Table 3 | Denoising performance of WSD and PSSD for parallel PD signal at low noise level (SNR = 10 dB) and high noise level (SNR = –10 dB), respectively |
|---|---|---|---|---|
| SNR | Method | SNR_D | RMSE | D_rho | RNL |
|---|---|---|---|---|---|
| 10 | WSD | 12.0485 | 0.1826 | 0.8920 | 53.1115 |
| | PSSD | 17.1545 | 0.0571 | 0.9900 | 58.0904 |
| –10 | WSD | 1.2656 | 0.3554 | 0.5089 | 37.4713 |
| | PSSD | 4.1695 | 0.2544 | 0.7956 | 37.8677 |

| Table 4 | Denoising performance of WSD and PSSD for void PD signal at low noise level (SNR = 10 dB) and high noise level (SNR = –10 dB), respectively |
|---|---|---|---|---|
| SNR | Method | SNR_D | RMSE | D_rho | RNL |
|---|---|---|---|---|---|
| 10 | WSD | 12.3904 | 0.2666 | 0.9026 | 49.7374 |
| | PSSD | 18.8788 | 0.0710 | 0.9935 | 54.2922 |
| –10 | WSD | 1.8476 | 0.5047 | 0.6540 | 34.1257 |
| | PSSD | 4.6716 | 0.3646 | 0.8330 | 35.4434 |
surface PD signal. More importantly, M-PSSD achieves higher RNL than WSD, and hence, reproduces more clean signal.

A similar analysis is performed for another specimen of acoustic signals generated by sharp PD. Fig. 9a depicts the noisy sharp PD signal, whereas the denoised PD signals using WSD and M-PSSD are depicted in Figs. 9b and c, respectively. The RNL achieved by M-PSSD is higher than the one achieved by WSD by 0.9 dB disparity. Fig. 10a shows an example of actual parallel PD signals that are corrupted with real environmental noise. As shown in Figs. 10b and c, it can be visually observed that M-PSSD can maintain the behaviour of the reference PD signal and reproduce the cleanest PD signal.

To verify the strength of M-PSSD in field situations, its denoising performance is also examined on another real noise-corrupted signal generated by void PD, as shown in Fig. 11a. The environment where the void PD is measured comprises many sources of real noise such that the captured PD signal is entirely buried in noise. Figs. 11b and c denote the denoising results of WSD and M-PSSD, respectively. It can be observed that WSD loses the originality of the PD signal, while M-PSSD can efficiently suppress the majority of the existing noise. Furthermore, Figs. 8c, 9c, 10c, and 11c illustrate the potency and efficacy of the proposed M-PSSD method to sufficiently remove the embedded noise regardless of the PD signal type and noise level.

5 Conclusion

In this paper, a frequency-domain-based denoising method, named PSSD, is introduced to repress the white noise coupling with PD measurements. PSSD is examined on laboratory-measured AE signals generated by corona, surface, parallel, and void PDs. The first set of PD signals is contaminated with synthetic noise, where two different noise levels are added to noise-free PD signals such that the SNRs are 10 and –10 dB, respectively. Compared with the WSD method, it is shown that PSSD achieves superior denoising results with much lower computational complexity. Moreover, the captured PD signals in field measurements are contaminated with real noise of an anonymous PSD. Thus, we introduce the M-PSSD method that uses a novel estimation scheme of the embedded noise PSD. To evaluate the effectiveness of the proposed M-PSSD method, it is examined on another set of
laboratory-measured noisy PD signals polluted with real environmental noise. This set includes four samples of actual surface, sharp, parallel, and void PD signals. The RNLS achieved by M-PSSD verifies its capability to effectively handle the real noise-corrupted PD signals in real-life situations.

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7 References

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