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De-Noising of Partial Discharge Signals in HV XLPE Cables by Reference Noise based on the Wavelet Transform

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ABSTRACT

The use of underground XLPE cables in power systems is increasing due to the problems associated with overhead lines. However, insulation failure, primarily caused by partial discharge (PD) phenomenon, remains a major concern. Monitoring the insulation condition of XLPE cables, particularly the magnitude and trend of PDs, is crucial. Detecting and localizing PDs online pose a significant challenge due to the presence of various environmental noises that must be eliminated. In recent years, power system-introduced noises like impulse noises generated by power electronic devices have become prevalent. Therefore, effective de-noising techniques are required to filter out the noises and interferences from the detected PD signals. This paper proposes the use of wavelet transform, which encompasses both time and frequency domains, to remove various noises from PDs, considering their non-stationary nature. To determine the suitable mother wavelet transform, threshold, and number of decompositions, experimental tests are conducted to investigate the characteristics of PD signals in the cables. Additionally, background noise at the measurement site, which varies in substations, is recorded as reference noise for the wavelet-based noise removal process. Using MATLAB software, reference noises and noisy PD signals are measured in substations, and the de-noising process is executed. The proposed method is evaluated on a sample cable, and the results are discussed. Furthermore, the method is applied to detect PD signals in multiple 20 kV substations in Iran, utilizing high-frequency current transformers connected to shield wires, oscilloscopes with high-frequency bandwidth, and MATLAB software.

I. Introduction

A. Research Motivation

XLPE cables are commonly utilized in power systems as an alternative to overhead lines. The reliability of high-voltage equipment often hinges on the condition of its insulation. The primary cause of insulation failure in high-voltage devices is the occurrence of partial discharge within the insulation. Therefore, monitoring high-voltage equipment, such as cables, while they are operational, is crucial to timely detect any partial discharge and protect the cable insulation from further deterioration. Offline detection methods can also be employed for PD detection. However, applying offline methods is impractical for cables and other high-voltage equipment that cannot be easily de-energized during operation, and it may be too late by the time offline PD measurements are conducted.

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When online monitoring is employed for PD measurement, the presence of environmental noises and electromagnetic interference (EMI) can make it challenging to detect the PD signals. Thus, the removal of noise from PD signals is an essential task that must be carried out in the online monitoring of high-voltage equipment.

B. Literature Review

Due to the critical importance of detecting PD signals in high-voltage equipment, such as high-voltage XLPE cables, extensive research has been dedicated to denoising PD signals in these contexts. In reference [1], a novel wavelet selection scheme is introduced for detecting PDs that occur in environments with low signal-to-noise ratio conditions. This research recommends the use of a wavelet entropy-based wavelet selection scheme to eliminate noise from PD signals. In paper [2], a technique employing wavelet transform with histogram-based threshold estimation is applied for online noise removal from PD signals. The proposed approach determines two distinct threshold values for each wavelet sub-band and applies a significant threshold that preserves the original signal energy. The wavelet transform has proven to be a powerful tool, and as a result, it has been applied in various contexts, including the operation of networks comprising wind and photovoltaic units, detection of transmission line faults, and classification of power quality events [3-5]. In reference [3], a prediction method based on the wavelet transform, an artificial neural network with a nonlinear structure for enhanced training and learning, and the imperial competition algorithm is employed to conduct operational studies of wind farms, cascade hydro systems, photovoltaic units, and pumped-storage systems. Paper [4] introduces a single-ended approach for detecting the protection zone and identifying faults occurring behind the relays used in transmission lines. This paper utilizes the wavelet transform to classify different types of faults that may occur in transmission lines. In [5], a novel method based on discrete wavelet transform and correlation coefficient is implemented to detect and classify a wide range of power quality events. In [6], an improved generalized cross-correlation time delay estimation approach is utilized to locate partial discharge signals occurring in AC XLPE cables. Given the influence of electromagnetic noise and other factors, this paper suggests an online localization technique based on the generalized correlation algorithm for estimating the signal time delay. Paper [7] applies an improved wavelet spectrum segmentation algorithm based on the spectral kurtogram to detect partial discharge signals. This research presents an approach that eliminates the need for human intervention in selecting threshold parameters or decomposition layer numbers when detecting PDs in noisy environments. In [8], a novel adaptive method based on the total least-squares with Matern Kernel is proposed for locating partial discharges in cable systems. The algorithm is designed to suppress environmental noise from both the direct and reflected waves of the PD source while estimating the time difference used for locating PDs. Paper [9] employs a recursive continuous S-shaped approach to denoise PD signals occurring in cables. This research develops an adaptive filtering method to address both Gaussian and impulsive noises in PD signals. In [10], a partial discharge detection system is introduced for detecting PDs in XLPE cables. This research involves the development of an acoustic wave sensing system based on a fiber optic Mach-Zehnder interferometer to enhance the anti-interference capabilities and real-time performance of PD detection.

Paper [11] investigates the background noises, mechanisms, and coupling paths of partial discharge detection through experiments conducted in complex electromagnetic environments. Several denoising methods, including improved grounding, power isolation, and optimized wiring layouts, are analyzed in this paper. Paper [12] introduces a combined ultra-high frequency noise removal approach that integrates waveform correlation analysis, time-domain windowing techniques considering external noise signals, and a clustering approach based on the magnitude ratio associated with two consecutive sensors.

In [13], a deep learning method is applied for detecting partial discharge signals occurring in power lines. This paper suggests a novel end-to-end framework based on convolutional neural network methods to identify the pulses associated with partial discharges. Paper [14] utilizes the convolutional neural network method for classifying the noises present in the background of partial discharge signals. In this paper, a modified 10-fold cross-validation approach is proposed, where the convolutional neural network-based partial discharge classifier is trained using clean partial discharge data and tested with noisy partial discharge signals. In [15], power spectral subtraction is applied to eliminate different types of acoustic partial discharge signal noises. This method is used to detect partial discharge signals contaminated with white noises and study other discharges, including corona, surface, parallel, and void discharges.

In [16], the detection of partial discharge signals in environments with radio frequency noises is performed using multiple narrow-band antennas. This method is applied to detect partial discharge signals occurring in SF6 gas, and the results of this approach are compared with a standard wide-band Horn antenna. In [17], a review of radiometric approaches used for detecting partial discharge signals is conducted. The paper studies radiofrequency bands, including high frequency, very high frequency, and ultra-high frequency bands, used for partial discharge detection in cables and transformers. Finally, in [18], the detection and location of partial discharge signals occurring in medium-voltage cables in noisy industrial environments are performed. This paper describes the application of high-resolution data acquisition

devices for detecting PDs in medium-voltage cables equipped with high-frequency current transformers.

C. The Necessity of the Research based on Challenges of the Literature

According to the papers reviewed in the literature, various techniques such as wavelet transform, deep learning methods, convolutional neural network approaches, power spectral subtraction methods, multiple-narrow band antennas, radiometric approaches, and high-resolution data acquisition techniques are employed to detect PDs in high voltage apparatus.

TABLE 1
SUMMARY OF LITERATURE REVIEW

References	Description	Challenges
[1-2]-[7]-[19-20]	Wavelet transform is used for de-noising of PDs	Reference noise is not implemented
[3-5]	Wavelet transform is used for operation, transmission line fault detection and power quality event classification.	Detection and localization of PDs occurred in the XLPE cables are not performed.
[6]	Generalized cross-correlation method is used to locate PDs in cables.	Unlike the wavelet, transformation of PD signal in the time and frequency domains is not available, and so, noise removal is less accurate.
[8-9]	An adaptive method is used for de-noising PDs occurred in cables.	Reference noise is not implemented, and so, the accuracy of the method is low.
[10]	Acoustic wave sensing system based on fiber optic Mach-Zehnder interferometer is used for PDs detection.	Unlike the wavelet, transformation of PD signal in the time and frequency domains is not available, and so, noise removal is less accurate.
[11]	The type of background noises is studied	De-noising of PDs is not performed
[12]	Ultra-high frequency noise removing approach is studied	Reference noise is not implemented
[13]	Deep learning method is used for detecting PDs.	De-noising of PD signals is not performed.
[14]	Classification of background noises is performed.	De-noising of PD signals is not performed.
[15]	Power spectral subtraction is used for de-noising PDs.	Reference noise is not implemented
[16]	Multiple-narrow band antenna is used for de-noising PDs.	Only radio frequency noises are considered.
[17]	Radiometric methods for PD detection are reviewed.	De-noising of PD signals is not performed.
[18]	High resolution data acquisition device is used for detection of PDs.	De-noising of PD signals is not performed.

The main challenges associated with these reviewed papers are presented in Table 1. According to the literature review, various methods are available for denoising PD signals detected in cables installed within energized substations. However, when the precise location of a failure or PD along the cable's length is a concern, a specialized denoising method becomes necessary. In certain PD localization methods, one must consider the reflection of the wave from the cable's end, where its travel time depends on the wave propagation speed at a specific frequency. Consequently, some denoising methods require the separation of PD-related frequencies from the frequencies associated with environmental noise. Therefore, an effective denoising method that encompasses both time and frequency domains becomes essential, and the wavelet transform has proven to be suitable for this purpose.

In this paper, we introduce PD detection circuits applied for online PD detection in XLPE cables, employing the wavelet transform for denoising. The method introduced by Shim et al [19] and Ma et al [20] does not employ reference noise; instead, it uses a Gaussian model to characterize various noise distributions. Given that a significant portion of environmental noise resembles white noise with a distribution similar to the standard Gaussian model, this approach appears suitable. However, in modern power systems equipped with power electronic devices, other noise distributions, such as impulsive noises generated by these devices, are prevalent. Therefore, because some of the existing noises do not follow a Gaussian distribution, this paper utilizes an antenna to capture the waveform of existing noises as reference noise. These reference noises are then utilized to remove noise from the PD signals.

D. Novelty and Main Contributions of the Paper

Based on the literature review and the identified research gap in the field of detecting PD signals in high voltage XLPE cables, this paper makes the following contributions:

- Investigation of the characteristics of partial discharge signals occurring in XLPE cables, with a particular focus on their frequency spectrum.
- Application of wavelet transform for denoising PD signals in high-voltage XLPE cables.
- Exploration of the characteristics of detected PD signals in XLPE cables within a high-voltage laboratory setting, aiming to determine the suitable mother wavelet, appropriate decomposition level, and the most effective denoising techniques.
- Introduction of a practical method that utilizes reference noise for denoising PD signals.
- Validation of the proposed method's effectiveness through several case studies.

E. Organization and Structure of the Paper

In accordance with the study's objectives, the paper is structured as follows:

In the second section, we introduce the detection circuit, including various sensors that can be utilized. The third section is dedicated to the proposed method based on wavelet

transform for addressing reference noises. Simulation results are presented in the fourth section. Finally, a summary of the paper in the last section is provided.

II. PD Phenomenon

Medium and high-voltage cables are widely used in power systems today. This is due to the improvement of their reliability in comparison with overhead lines. Many natural events interfere with the operation of power systems, such as lightning, tower breaking, and falling due to the snowfall, among others, but they do not have any effect on the operation of power systems when power cables are used and installed underground. Cross-linked polyethylene cables are one of the most reliable types of underground cables used in high voltage or extra-high voltage power system distribution and transmission networks. The specific structure of the polyethylene material allows this insulation to withstand high temperatures, reaching up to nearly 900 °C [21]. In electrical markets, the reliability of power systems is crucial, and customers are even willing to pay higher prices to ensure uninterrupted service. Thus, utilities should improve their system's reliability. One of the problems that increase the risk of failure in a power system is the failure of cable insulation. It is understood from experience that the occurrence of a partial discharge often leads to major insulation failure and service interruption if not detected through an online monitoring system.

Partial discharge is due to the existence of voids in the cable insulation. Air fills these voids, and since the dielectric resistance of air is lower than that of polyethylene, partial discharge occurs when the voltage over the void is higher than the air discharge inception voltage. However, if the magnitude of the partial discharge is kept lower than the permissible value, it poses no harm to the insulation. Serious increases in the magnitude of partial discharge over the life of the insulation can result in a breakdown.

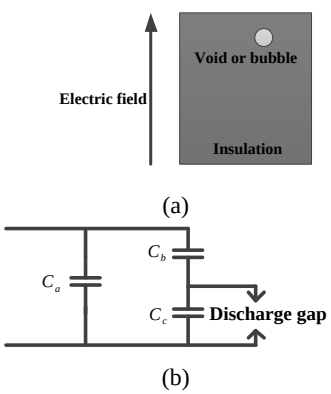


Fig. 1. The a-b-c model of PD (a) void or bubble in insulation, (b) a-b-c model [22]

The partial discharges that occur in high voltage XLPE cables arise from the presence of cavities, impurities, water drops, and air bubbles in the insulation, which reduce the insulation strength of the cable. By applying a high voltage across the cable insulation, the intensity of the created electric field may exceed the insulation strength, leading to currents with high-frequency impulses called PD. To study the partial discharges that occur in cables, the a-b-c model is used, as presented in Fig. 1. In this model, the cavity or bubble is presented by capacitor C_c, insulation placed in top and bottom of the cavity is modeled by C_b, and the insulation placed in right and left of the cavity is modeled by C_a. When, high voltage with magnitude V_a is applied to the insulation, according to the voltage division theorem, voltage with magnitude V_c is applied on capacitor C_c (cavity or bubble) that is calculated by:

$$V_c = \frac{C_b}{C_c + C_b} V_a \tag{1}$$

If the magnitude of voltage applied on cavity or bubble is more than the insulation strength, short circuit is occurred. Thus, the impulse currents are resulted as presented in Fig. 2. The amplitude of these impulse currents is calculated as:

$$i_{PD} = C_c \frac{dV_c}{dt} \tag{2}$$

When PDs occur in polymeric materials, due to the erosion of dielectric materials caused by physical and chemical mechanisms, they lead to the formation of pits and craters on the cavity surface. Some physical and chemical mechanisms created by PDs include the bombardment of the cavity surface by photons and charge carriers, an increase in the local temperature resulting from high-temperature discharge gases, and chemical reactions activated by excited molecules or chemical compounds in the gas and solid phases, especially ozone and oxygen [24].

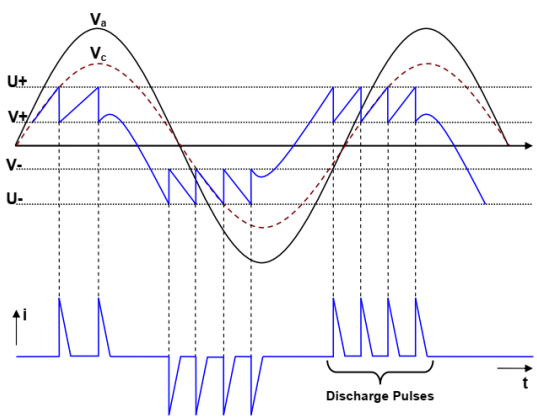


Fig. 2. The impulse currents of PDs [23]

III. The Circuit for Detecting PDs

After measuring the magnitude of the PD, if it exceeds the permissible value, it should be located along the length of the cable where it is occurring. Subsequently, necessary actions

must be taken to prevent its extension to other parts of the cable system. Online detection and location of partial discharge are imperative for this purpose. In online cable monitoring, the PD magnitude can be continuously measured while the power system is operational, and if necessary, warnings can be issued. To successfully measure online PD signals, it is essential to distinguish between the noises present at the measurement site (i.e., a substation) that can interfere with the PD signals. The differentiation between the detected signal and a genuine PD is necessary. Therefore, de-noising should be performed to extract the partial discharge signal from the detected signal.

The circuit utilized for PD measurement is depicted in Fig. 3. This system comprises several components. The sensor is an inductive type with a bandwidth of 100 MHz, essentially functioning as a high-frequency current transformer that detects the PD signal. This high-frequency PD signal is then amplified by a wide-band amplifier. An oscilloscope is employed to observe and record the waveform of the PD signal, with a bandwidth of 250 MHz. In this method, there is only one sensor for measuring the PD signal, which may pick up various environmental noises. There is no additional sensor in this circuit for measuring reference environmental noises. The length of the 11 kV XLPE cable used in this experiment is 2.4 meters. According to the rated values of the detection devices and the frequency characteristics of PD signals, the sampling rate for this experiment is set at 100 Mega samples per second.

Several sensors can be used for the detection of PD signals. In this section, two types of these sensors are introduced [24-26]. Inductive sensors detect the PD signals through the induced current, which is proportional to the magnetic field of this signal. The PD signal is a high-frequency current that has two components in the shield of the cables, as shown in Fig 4. One of these components is the current IZ that induces the current in the rectangular coil.

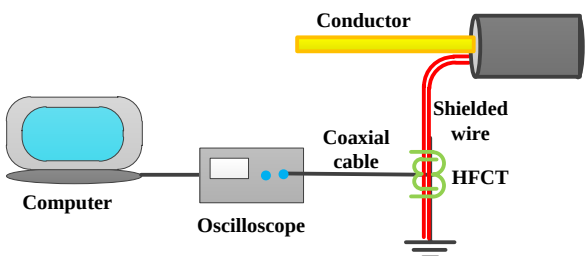


Fig. 3. The circuit for PD detection [25]

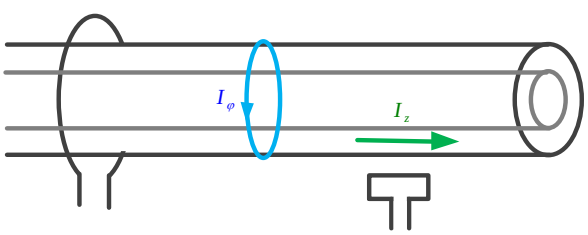


Fig. 4. Principle of an inductive sensor [25]

The other component of PD signal is I_φ that inducts a current in the circular coil as shown in Fig 4. The disadvantage of this sensor is its significant pick up of the external noises which affect the detected signals. In Fig 3, another type of inductive sensor (HFCT) is used for detection of PD signals in HV XLPE cables.

The various layers of XLPE cables consist of capacitive elements. These layers include an inner semi-conducting layer, insulation or dielectric, and an outer semi-conducting layer. The shield is connected to the ground. When a metallic ring is placed over the sheath, there will be four capacitive layers, and the PD signal voltage will be divided among them. By detecting the voltage on this ring, the PD signal can be identified. These sensors are also used to detect PD signals in power transformers. The copper strip serves as the capacitive sensor and is placed on the transformer HV bushing. The HV conductor of the transformer bushing and this copper strip create a capacitance that picks up the PD signal. By connecting this copper strip to the ground, the PD signal can be detected, initially by passing this connection through a high-frequency current transformer (Fig 5), and subsequently by adding a resistor in series and measuring its voltage (Fig 6).

In the high-voltage lab, voltages up to 20 kV were applied to an 11 kV XLPE cable with a 2.4 m length, connected as shown in Fig. 7, and the PD signal was detected. Fig. 8 presents the results of this experiment. Fig. 8.a shows the PD signal versus time. This signal is a damped oscillatory pulse in which a main oscillating signal with a period of 50 ns can be recognized. Its frequency spectrum is shown in Fig. 8.b.

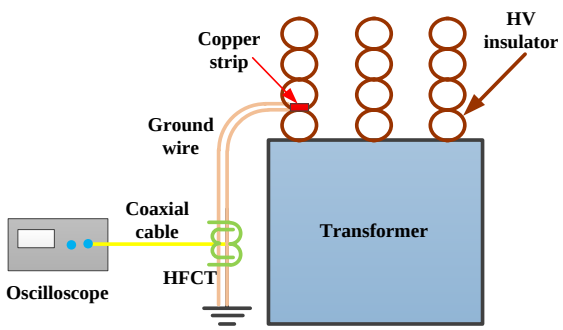


Fig. 5. Capacitive sensor in the power transformer and a HFCT for detection of partial discharge [26-27]

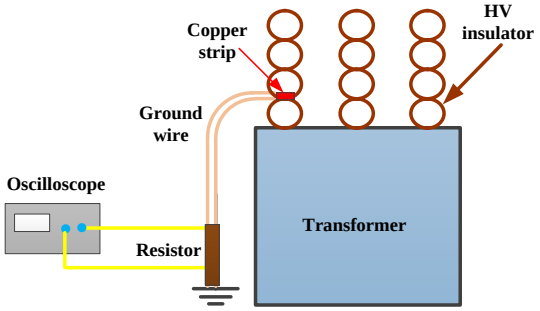


Fig. 6. Capacitive sensor in the power transformer and a HFCT for detection of partial discharge [26-27]

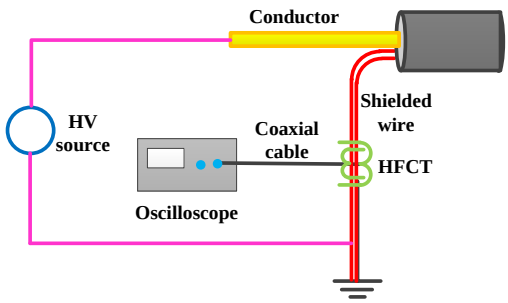
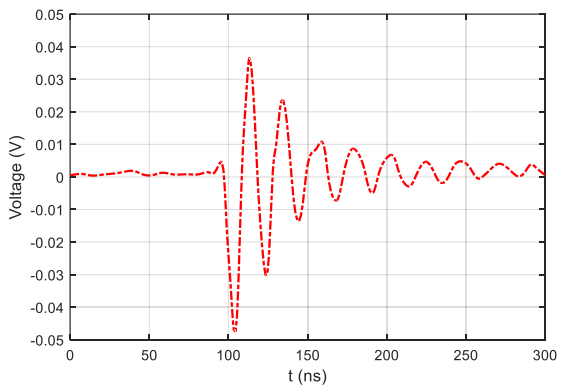
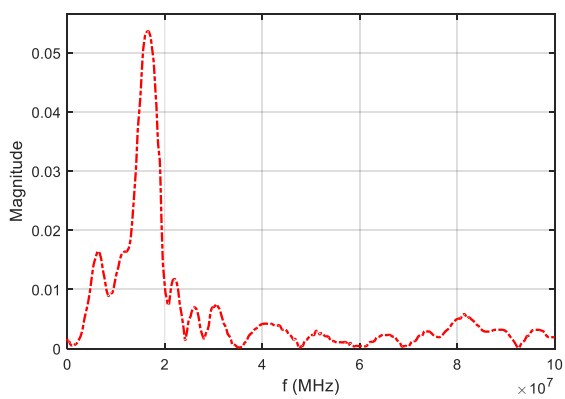


Fig. 7. The circuit employed in high voltage lab for PD detection in XLPE cable [25]



(a)



(b)

Fig. 8. (a)- PD signal in XLPE cable, (b)- Frequency spectrum PD signal in XLPE cables [25]

The PD signal of this XLPE cable involves a frequency spectrum around 20 MHz and it may have some higher frequencies. As can be seen in the figure, the amplitude of frequency components higher than 30 MHz is low. Thus, the sampling frequency for detecting PD signals occurred in the XLPE cables can be less than 30 MHz. For enhancing the accuracy of the proposed method, the HFCT used in this experiment have an acceptable transfer function up to 100 MHz.

IV. Wavelet Transform Method for PD De-Noising

In the Fourier transform, a function is converted from the time domain to the frequency domain, and the time parameter is not present in the final domain. De-noising a signal using the Fourier transform involves identifying the frequency spectrum that corresponds to the noise and distinguishing it from the PD signal. By applying filters, the frequencies associated with noise are removed, leaving only the PD signal. The results of the PD measurement are also used to determine the location of the PD. This is achieved by calculating the time between the detection of the signal and its reflection from the end of the cable, taking into account the propagation speed of the PD signal in the cable shield.

As previously mentioned, the Fourier transform has been the most commonly used tool for analyzing the frequency characteristics of a given signal. However, after transformation, time information is lost, making it difficult to determine when a specific frequency occurs [28]. Traditional approaches for signal processing are generally based on either the time or frequency domain for analyzing and extracting PD events. In the case of the frequency domain, the Fourier transform assumes that signals can be represented as a sum of sine and cosine waveforms. While the signal can be analyzed throughout the frequency domain following the Fourier transform, time information is lost.

Partial discharge signals often exhibit non-periodic and fast transient features, which are not effectively revealed by the Fourier transform. This limitation has led to the recognition of the need for more powerful mathematical tools in signal analysis and processing by researchers and engineers. Among these tools, wavelet and Gabor transforms are employed to obtain two-dimensional information about PD pulses in both the time and frequency domains, allowing for the extraction of features from measurement data.

The Gabor transform is a special case of the short-time Fourier transform, which extracts sinusoidal frequency and phase content from local sections of a signal as they vary over time. The signal is first multiplied by a Gaussian function, acting as a window function, and then transformed using a Fourier transform to provide time-frequency analysis. The window function gives higher weight to the signal near the time being analyzed [30]. The Gabor transform represents a

signal as a set of properly shifted and modulated Gaussian elementary signals. However, its effectiveness is limited when dealing with PD signals containing non-Gaussian noise, and it can be computationally challenging to compute Gabor coefficients. For de-noising PD signals in power substations that involve various types of noise, the wavelet transform is a more suitable choice.

The continuous wavelet transform for a function, such as $f(t)$, is defined as follows [31].

$$CWT_{\psi}f\ (a,b) = W_f\ (b,a) = |a|^{\frac{1}{2}} \int_{-\infty}^{\infty} f(t)\psi^*(\frac{t-b}{a})dt \qquad (3)$$

In this equation $a,b \in R.\ a \neq 0$, 'b' is the value by which the function is shifted in the time domain and 'a' is the scale that multiplies by time and is used as the frequency factor. The function $\Psi(t)$ is mother wavelet and it has several different types such as Haar, Daubechies family, Coiflet1, Symlet2, Meyer, Morlet and Mexican Hat that the different types of wavelets are resulted of these types of mother wavelet functions [31]. For different application the specific types of this mother wavelet is used and for removing the noises from the PD signal Daubechies family can be applied. It is suitable for this purpose, since the waveforms of partial discharge signal is similar to these mother wavelet functions and the noises have the different characteristic that it is easy to remove them from the partial discharge signal. The waveform of the Daubechies mother wavelet functions is presented in Fig 9. In [31], discrete time wavelet transform definition is given.

Due to the similarity between PD signals occurring in HV cables as presented in Fig 7 and the mother wavelet of Daubechies7, Daubechies7 is applied for PD signal denoising in HV XLPE power cables in this paper.

For denoising using the wavelet transform method, there are three stages: First, the conversion of the waveform of the signal and noise to the wavelet domain is performed, and the level and the coefficients in this domain are determined. Then, in the wavelet domain, the separation of noise and PD is carried out, and finally, the denoised PD signal is reconstructed in the time domain. The procedure is illustrated in Fig 10.

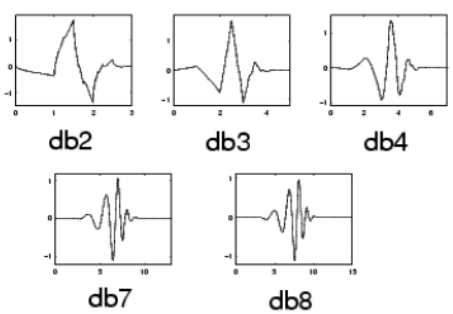


Fig. 9. Daubechies mother wavelet functions family [31]

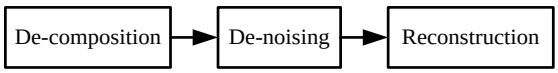


Fig. 10. De-noising procedure [27]

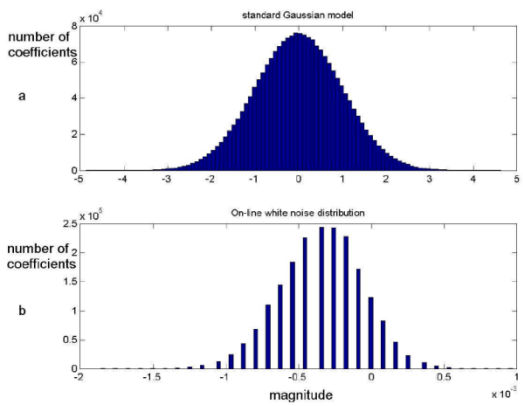


Fig. 11. Gaussian distribution function of white noise [32]

In the old method employed by Shim et al [19] and Ma et al [20], a Gaussian model is utilized to represent the noise distribution. Based on this model, noise removal is performed in the wavelet domain. This model is well-suited for white noises, such as ambient and random noises like thermal noise, and so on. However, in modern power substations, there exist various noises for which the standard Gaussian distribution is not suitable for modeling. These noises often exhibit amplitudes that may exceed the magnitude of partial discharge signals, making it challenging to detect partial discharge signals in their presence.

In the substations of power system, there are four types of noise that include [32]:

1- White noise: the environmental noises and the noises associated with amplifiers are placed in this category. This type of noises named white noise has Gaussian distribution function as presented in Fig. 11. To removing this type of noises from PD signals, the previous methods based on Gaussian noises that do not require to the reference noise can be used.

2- Discrete spectral interference (DSI) that includes telecommunication and radio signals such as modulated AM and FM signals. This type of noises has narrow band specification and to remove them from PD signals, digital filters such as notch filter and spectrum analysis method can be implemented.

3- Repetitive or pulse type noises that include the pulses are arisen from power electronic devices such as thyristor fire pulses. This type of noises has repetitive nature and is repeated regularly at each cycle of power frequency. The band width of these noises is wide and for removing them from PD signals, the methods in time domain such as gate circuits are applied.

4- Switching noises that are random high frequency

pulses. This type of noises is arisen from switching occurrence of different devices, lightning and corona discharge of high voltage apparatus. The switching pulses have wide bandwidth and are typical source of disturbances. The most problem for de-noising PD signals are arisen from this type of noises. The frequency characteristic of these noises is very similar to the PD signals, and so, the notch filters cannot be used for removing of them. On the other hand, due to the random nature of these noises, the gate circuits cannot be used for removing them.

By studying different types of noises, it is concluded that some of these noises do not have Gaussian model and we cannot apply the Gaussian model for them, thus the old method is not suitable for modeling all noises in substations. Fig. 12 presents the distribution of real noises in the substations and compares it with Gaussian distribution function that is suitable for modeling white noises. In the proposed method there are two sensors. One of them such as an antenna is applied for measurement of only noises. It samples the noises when the cable is out of the system and the breaker of this bay is disconnected. Thus the results of this sensor are only the noises that are used for the reference noises.

The second sensor is applied for measurement of the partial discharge signal that is noisy. This sensor records the signal by a specific sampling rate when that cable is alive. There are several options for measurements of the background noises; one is that the sensor measures the signals when the cable is out of service, second is to measure the signal when there are two bays and one of them is out of service, and in the last option, an antenna can be used to detect the noises available in the environment. Then conversion of the measured signal by the sensors to the wavelet domain is done and in this domain the coefficient of the reference noise is applied on the threshold to remove the noises from the detected signal.

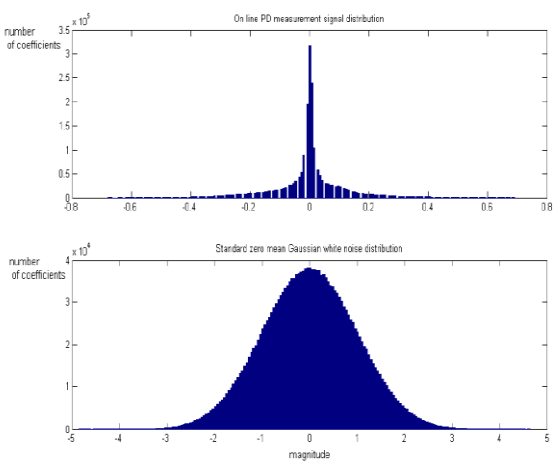


Fig. 12. Distribution function of white and real noises [32]

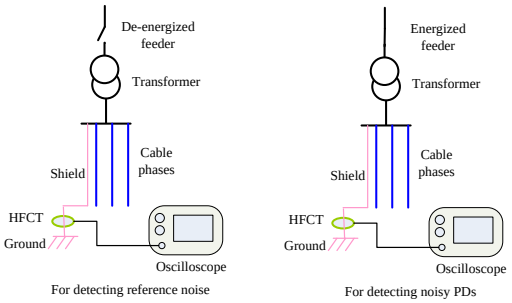


Fig. 13. Single line diagram of circuits proposed for detecting PDs

Thus, according to the proposed method, de-noising of PD signals is performed by following steps:

Step1. Using of HFCT, the noisy PD signals are detected and presented on oscilloscope. Then, data of noisy PDs is transferred to the computer.

Step 2. Reference noise is detected by an antenna or by HFCT when the feeder is de-energized. The single-line diagram of PD detecting system is presented in Fig. 12. As can be seen in the figure, when, the feeder is de-energized, the HFCT placed on cable shield detects noises, and when the feeder is energized, the HFCT detects noisy PDs.

Step 3. The reference noise is transferred to wavelet transform. The suitable mother wavelet, number of de-composition levels and de-noising technique are determined in the next part. The outcomes present that for de-noising PDs occurred in XLPE cables, db7 is an appropriate mother wavelet, between 5 to 20 decomposition levels is suitable and hard type de-noising technique is better than soft type de-noising method.

Step 4. The threshold level required for de-noising PDs is selected based on the reference noise.

Step 5. The noisy PD signal is transferred to the wavelet domain by considering suitable mother wavelet and appropriate de-composition level.

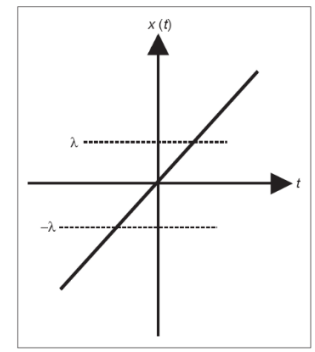
Step 6. By threshold determined in step 4, using hard de-noising technique, de-noising process is performed.

Step 7. The de-noised PD signals are reconstructed in time domain.

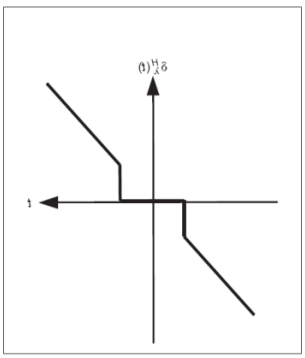
To compare the suitability of different mother wavelet for de-noising PD signals from noises, SNR index is calculated as:

$$SNR = 10 \log \frac{\sum_{i=1}^{n} y^2(i)}{\sum_{i=1}^{n} (x(i) - y(i))^2} \quad (4)$$

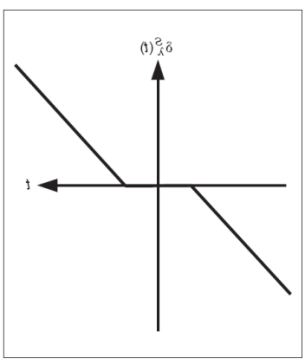
In (4), *x(i)* is the initial PD signal and *y(i)* is the de-noised PD signal. For de-noising by wavelet transform, two approaches including hard and soft techniques presented in Fig. 14 can be applied. According to the literature review, hard de-noising technique is better than soft de-noising technique [31].



(a)



(b)



(c)

Fig. 14. (a) initial signal (b) hard de-noising method (c) soft de-noising method [32]

V. Case Studies

In the first study, the following steps were performed to determine the suitable mother wavelet and de-noising technique:

1. A sample of partial discharge signals related to a specific cable, tested under the application of high voltage, was recorded by a digital scope with a 250 MHz bandwidth.

2. Based on the characteristic of PD signals occurring in XLPE cables, four samples were simulated using a mathematical function obtained by multiplying a sinusoidal function and an exponential function. These functions were combined with the noises measured in a substation to create a noisy signal.

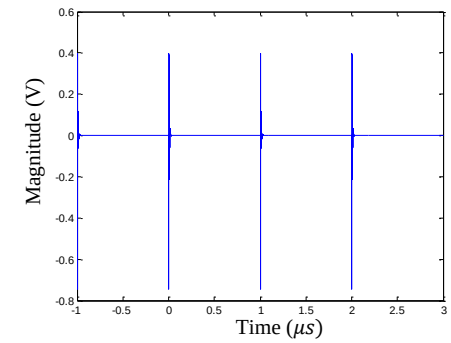
3. Different mother wavelet functions were employed to de-noise these noisy signals.

4. The de-noised signals were then compared with the corresponding original signals.

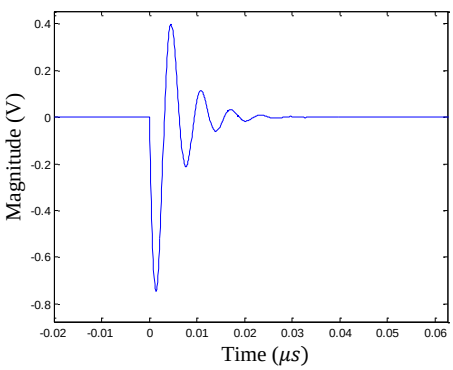
5. The signal-to-noise ratio (SNR) factor was used as a measure to evaluate the performance of the different mother wavelet functions. It was found that db7 had the highest SNR factor.

Fig. 15 presents the initial PD signals, the added noise, and the extracted PD signals for different mother wavelet applications. Additionally, in Figure 16, the steps of the proposed method performed in MATLAB software for de-noising PD signals with reference noise are presented. As shown in the figure, the proposed method follows seven steps to de-noise PD signals.

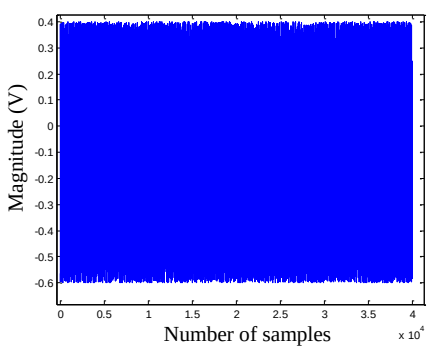
Table 2 presents the values of SNR obtained for different mother wavelet functions. The results present db7 is a suitable mother wavelet for de-noising PDs occurred in XLPE cables.



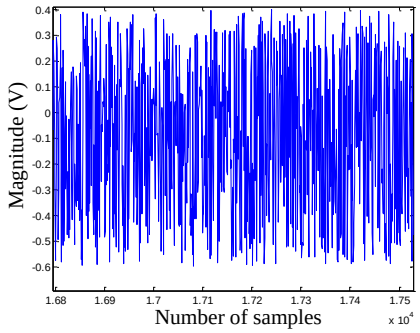
(a)



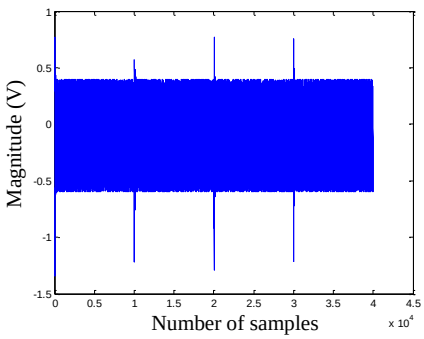
(b)



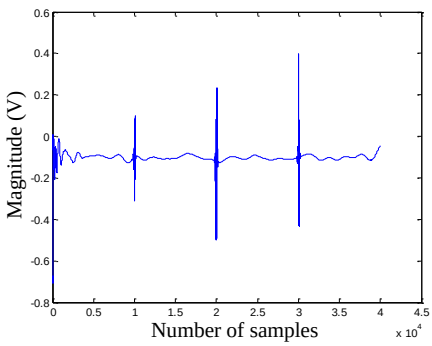
(c)



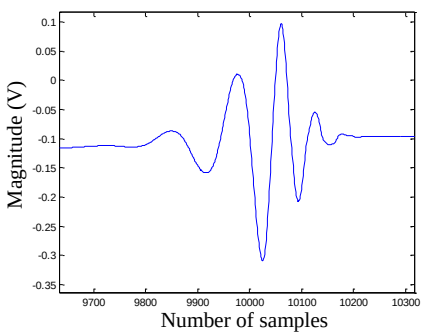
(d)



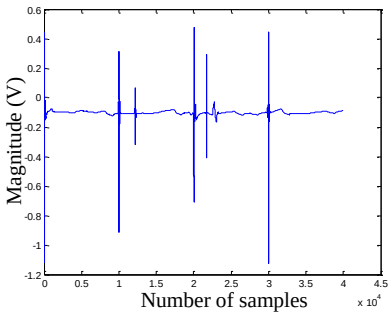
(e)



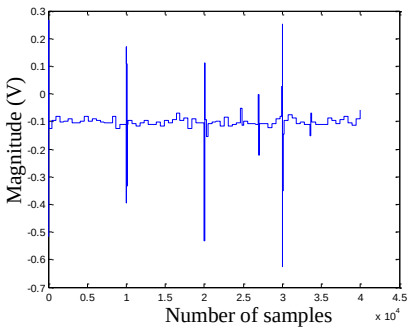
(f)



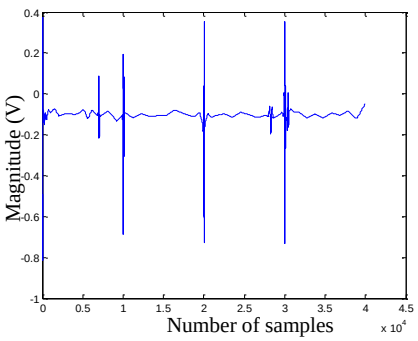
(g)



(h)

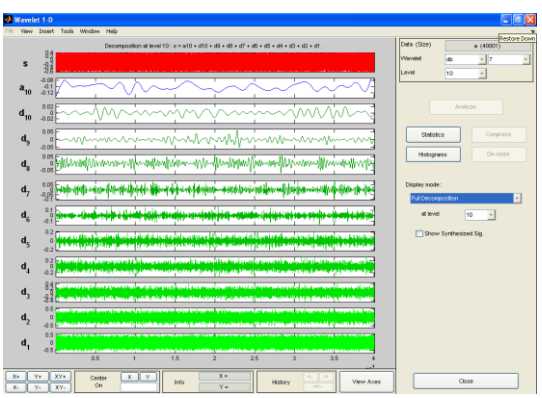


(i)

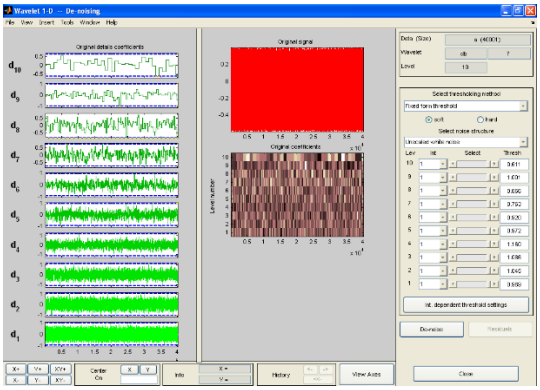


(j)

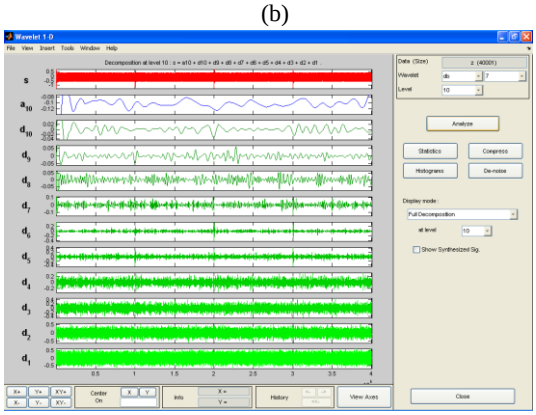
Fig. 15. (a) initial PDs (b) enlarged figure of PD (c) noises (d) enlarged figure of noises (e) noisy PDs (f) extracted PDs by db7 (g) enlarged extracted PD by db7 (h) extracted PDs by db2 (i) extracted PDs by Haar (j) extracted PDs by coiflet1



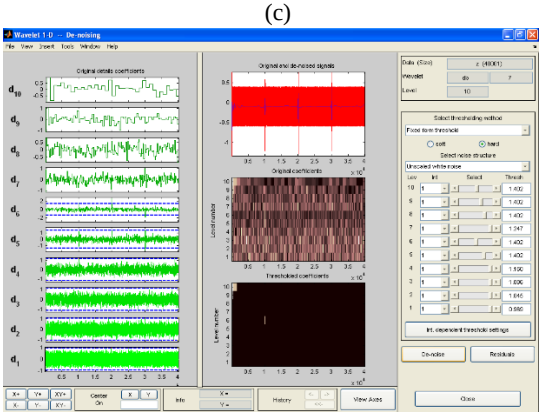
(a)



(b)



(c)

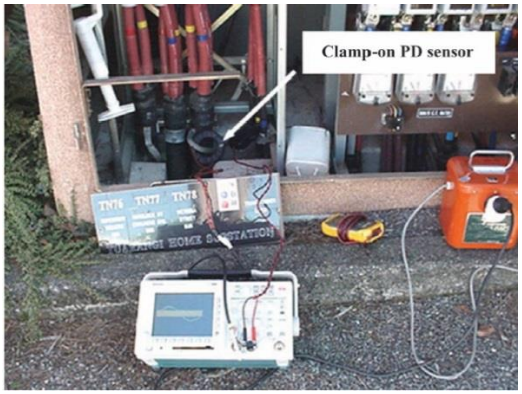


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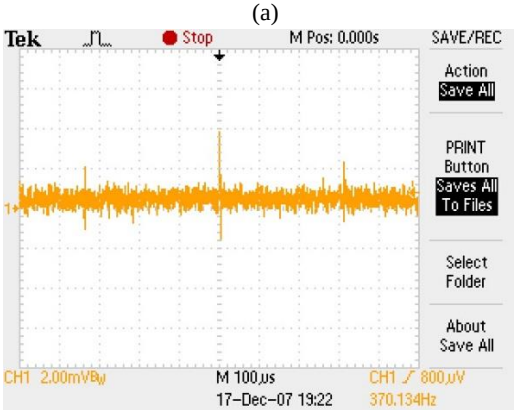
Fig. 16. (a) wavelet transform of reference noise (b) threshold determination by reference noise (c) wavelet transform of noisy PDs (d) noise removing of PDs

TABLE 2
SNR FOR DIFFERENT MOTHER WAVELET FUNCTIONS

Mother wavelet function	SNR (dB)
Haar	24.7
Coiflet1	19.6
Symlet2	27.1
Meyer	22.8
Morlet	36.5
Mexican Hat	40.1
Daubechies 2	37.3
Daubechies 3	38.2
Daubechies 4	43.5
Daubechies 7	49.6
Daubechies 8	45.2



(a)



(b)

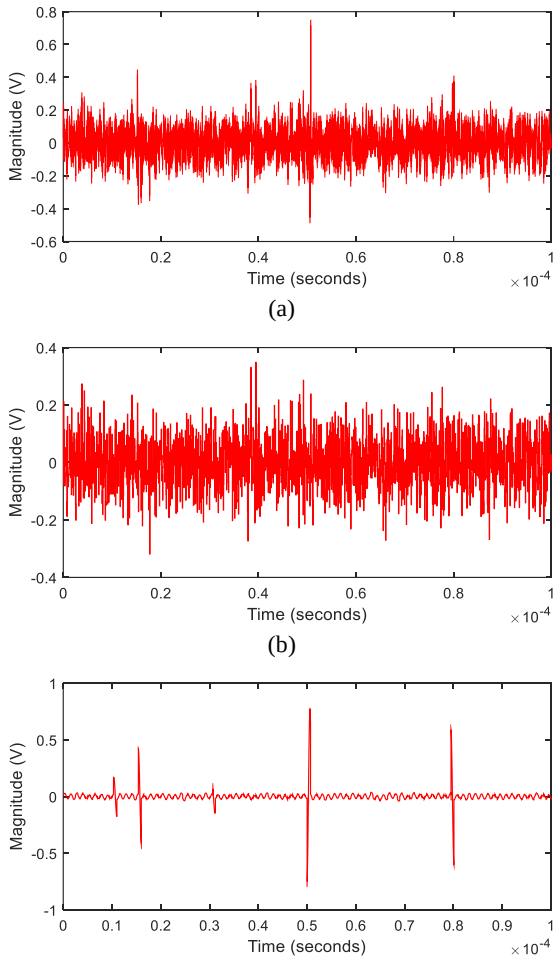
Fig. 17. (a) Test system used for detecting PDs in Poonak substation and (b) presented signal on oscilloscope

As for the second case study, in this section, the recorded measurements of a substation are utilized to be de-noised using the suggested method. The following presents the results of a PD test conducted on a 20 kV XLPE cable for the Nahal feeder in Poonak substation in Tehran.

During this test, the first stage involves de-energizing the feeder, and the HFCT connected to the shield detects the reference noise. In the second stage, the feeder is energized, and the HFCT connected to the shield detects the PD signals along with the accompanying noises. The oscilloscope used in this experiment has a bandwidth of 250 MHz, while the HFCT has a bandwidth of 100 MHz. The HFCT is connected to the oscilloscope via a coaxial cable, which includes a low-pass filter that filters out frequencies above 30 MHz. Fig. 17 presents the test system set up for this experiment.

In Fig 18, a, b and c are the noisy PD signal, the reference noise signal, and the PD signals after de-noising, respectively. In this method db7 mother wavelet up to level 10, hard threshold approach based on the reference noise and the wavelet toolbox of MATLAB are applied. As for the third case study, a substation in Fars province is being examined. The results of the PD measurement of the XLPE cable in Kheir-Abad substation are presented in the following figures. In this substation, a similar procedure to the one used in Poonak substation is being followed. The oscilloscope and HFCT used in this experiment have bandwidths of 250 and 100 MHz,

respectively. In this test, the db7 wavelet up to level 6, a hard threshold based on the reference noise, and the wavelet toolbox of MATLAB are being applied. Fig. 19 displays the detected signal (a), the reference noise (b), and the PD signal after de-noising (c). These coefficients represent the maximum magnitudes obtained from the wavelet decomposition of the reference noise.

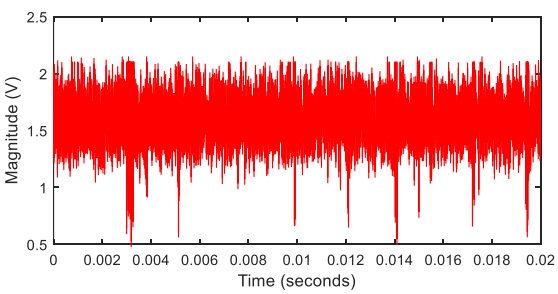


(a)

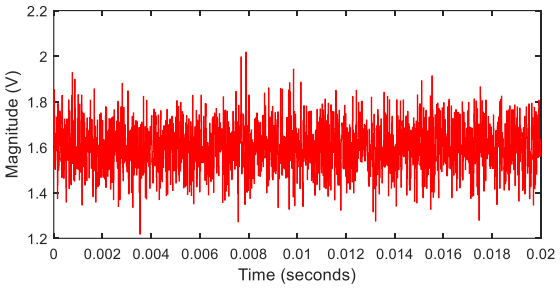
(b)

(c)

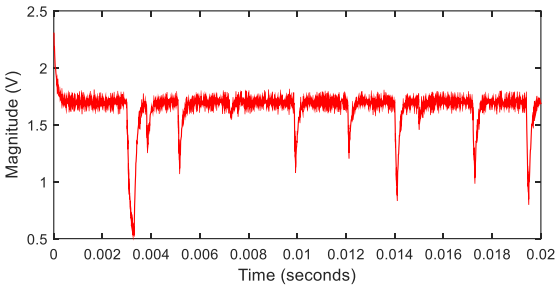
Fig. 18. Poonak substation (a)- Detected signal, (b)- Reference noise, (c)- PD signals after noise removing



(a)

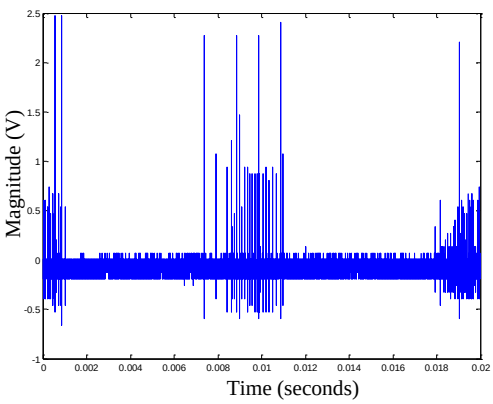


(b)

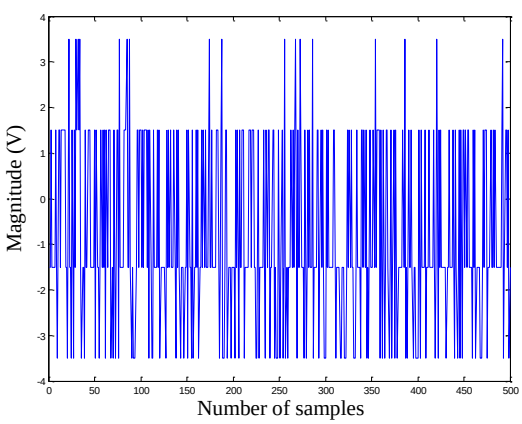


(c)

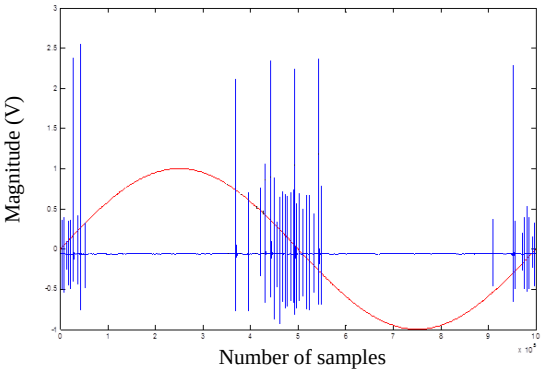
Fig. 19. Kheir-Abad substation (a)- The detected signal, (b)- Reference noise, (c)- The PD signal after noise removing



(a)



(b)



(c)

Fig. 20. Afsarieh Substation (a)- The detected signal, (b)- Reference noise, (c)- The PD signal after noise removing

For detecting PD signals in Afsarieh substation, similar procedure used in previous case studies is followed. The Afsarieh substation located in Tehran is a 230kv/63kv substation. The measurement devices are placed on 63 kv side. The noisy PDs, reference noise and PDs extracted from noisy signals are presented in Fig. 20. As can be seen in the figure, the proposed technique with good accuracy removes the noises of PDs.

VI. Sensitivity Analysis

To select the suitable de-noising method, we perform the de-noising of noisy PD signals using the soft de-noising approach based on the db7 mother wavelet. The initial PD signals, as presented in Fig. 15, are contaminated with noise. Then, following the soft de-noising method, we determine and present the extracted PD signals in Fig. 21. From the figure, it is evident that the performance of the hard de-noising method in removing noise from PD signals is superior to the soft de-noising approach. The SNR index associated with the soft de-noising method is 38.1, which is lower than the SNR index associated with the hard de-noising method, which is 49.6. In this stage, the impact of number of de-composition level on performance of PD signals de-noising is investigated.

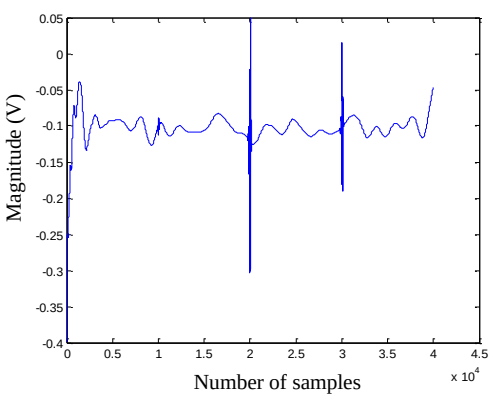


Fig. 21. PDs extracted by soft de-noising method

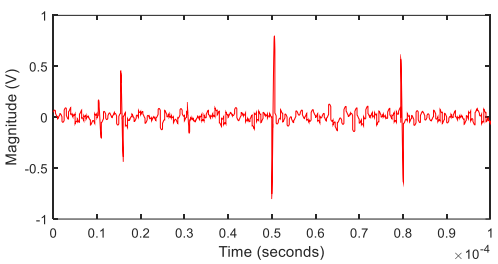
TABLE 3
SNR FOR DIFFERENT NUMBER FOR DE-COMPOSITION LEVEL

Number of de-composition	SNR (dB)	Number of de-composition	SNR (dB)
2	11.82	13	50.04
3	25.77	14	50.18
4	39.26	15	50.24
5	42.65	16	50.33
6	46.72	17	50.47
7	48.53	18	50.69
8	48.80	19	50.74
9	49.34	20	50.82
10	49.61	21	50.98
11	49.78	22	51.06
12	49.89	23	51.12

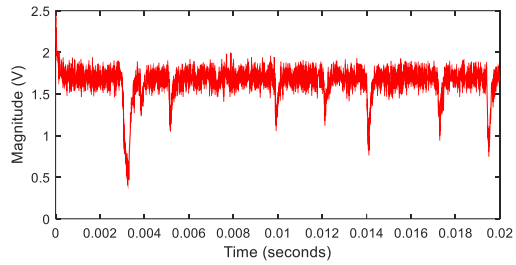
For this study, the number of de-composition level for de-noising of PD signals polluted by noises (presented in Fig. 15), is changed from 2 to 23, and by hard de-noising technique and db7 mother wavelet, the PD signals are extracted. The SNR indices associated with this study are calculated and presented in table 3. As can be seen in the table, for understudied PDs and noises, when the number of de-composition level increases from 7 to 2023 the value of SNR index do not change significantly. Thus, for preventing from high volume of computation, the suitable number of de-composition level is between 7 and 10.

VII. Discussion

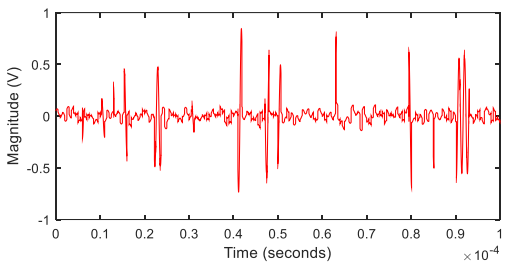
To study the effectiveness of the proposed method, de-noising of PD signals occurred in this substation is performed by old method that do not use the reference noise. By wavelet transform and without reference noise, de-noising of noisy PD signals presented in Figs. 18, 19 and 20 is performed. The results are presented in Fig. 22. As can be seen in the figure, the de-noised PD signal is still noisy. Thus, the proposed method has been able to separate the noise from the PD signals better than the method without reference noise.



(a)



(b)



(c)

Fig. 22. PD signals after noise removing without reference noise (a) Poonak substation (b) Kheir-Abad substation (c) Afsarieh substation

For comparing different methods mentioned in the literature review that can be used for de-noising of PDs with the proposed method based on the wavelet transform, the PD signals of first case study are used. According to the first case study, the PD signals are polluted with different noises. Then, by different methods including improved generalized cross-correlation time delay estimation approach as method 1, total least-square with Matern Kernel as method 2 and recursive continuous s-shaped approach as method 3, de-noising of polluted PDs is performed. The SNR related to the outcomes of these methods as well as the SNR related to the outcome of de-noising by proposed method are presented in table 4. As can be seen in the table, the accuracy of the proposed technique is more than other methods.

TABLE 4
SNR FOR DIFFERENT DE-NOISING METHODS

Methods	SNR (dB)
Proposed method	49.6
Method 1	39.2
Method 2	42.6
Method 3	39.8

VIII. Conclusions

In this paper, a method based on the wavelet transform approach, considering the reference noise, is employed to remove different noises from recorded partial discharge signals occurring in XLPE cables. This method utilizes the MATLAB toolbox associated with wavelet transform. The suitable mother wavelet, threshold for de-noising, number of decompositions, and noise rejection technique are selected based on the characteristics of PDs occurring in XLPE cables. The waveform of PDs leads to the selection of the db7 mother wavelet. Additionally, the background noise is obtained through off-line measurement, another sensor placed on a de-energized feeder, or an antenna, and is applied as the reference noise. The proposed approach effectively performs noise rejection on PD signals occurring in XLPE cables. It accurately detects the pulses of PDs, which can be used to determine the location of partial discharge. This method relies on the available data regarding the time between the PD signal and its reflection from the end of the cable. Two sensors are used in this method: one for measuring the PD signal mixed with noise and the other solely for measuring the background noises. For future work, one can explore other new methods introduced in the communication field for de-noising, such as blind source method, SVD method, adaptive filter, non-adaptive filter, and more.

Appendix

The characteristics of test systems and devices applied in the paper for detecting PDs occurred in XLPE cables are presented in Table 4.

TABLE 4
CHARACTERISTIC OF TEST SYSTEMS AND APLIED DEVICES

Characteristic	**Value**
Rated voltage of sample XLPE cable	11 kv
Poonak substation voltage	63kv/20kv
Kheir-Abad substation voltage	63kv/20kv
Afsarieh substation voltage	230kv/63kv
Oscilloscope bandwidth	250 MHz
HFCT bandwidth	100 MHz
Length of sample XLPE cable	2.4 m
Sampling rate	100 Msample/s
Used software for simulation	MATLAB
Used sensor for PD detection	HFCT

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