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Wavelet the Tool for P.D. Pattern Recognition

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ABSTRACT:
Ageing of the cable insulation is becoming an increasing problem that requires development of reliable methods for on-line condition/off-line assessment. For insulation condition assessment of MV and HV devices, partial discharge (PD) monitoring is one of the most effective techniques. A partial discharge (PD) is a localised dielectric breakdown of a small portion of a solid or liquid electrical insulation system under high voltage stress. That is why PD detection is used in power systems to monitor the state of health of high voltage devices. If such problems are not detected and repaired, the strength and frequency of PDs increases and eventually leads to the failure of the HV devices, which can cause external equipment damage, fires and loss of revenue due to an unscheduled outage. PD measurements are affected by interferences (noises) that makes sensitive PD detection very difficult, This paper describes implementation of wavelet transform techniques to reject noise from partial discharge measurements on HV devices. The denoising technique includes the discrete wavelet transform decomposition, thresholding of wavelet coefficients, and signal recovery by inverse discrete wavelet transform. The threshold limits are selected using Shim's method to remove the noises for each level of wavelet coefficients. The results indicate that this method could extract the PD spike from the noisy measurement effectively.

KEY WORDS: Partial Discharge, Electrical PD Detection, Wavelet, Decomposed signal, Continuous Wavelet Transform

INTRODUCTION:

Large numbers of installed Medium Voltage or High Voltage devices, such as transformers, cables etc. are now of advanced age and have gradual insulation deterioration problems. Based on the present replacement rate of installed MV/HV devices, it would take a few hundred years to replace the entire network. The only option available to maintain these devices in good condition is to improve asset management method. Asset management in a modern power system is focused on what is termed life cycle management of the equipment, which is critical to understanding ageing process of the equipment components and the consequent impact on the equipment performance.

Many breakdowns in HV devices are caused by the damage due to the internal faults in the insulation system. MV/HV devices represent a large capital investment thus failure of those transmission and distribution-class can cause long periods of service interruption and blackouts, with costly repairs and loss of revenue.

PARTIAL DISCHARGE:

The term "Partial Discharge" (PD) is defined as a localized electrical discharge that only partially bridges the insulation between conductors and which may or may not occur adjacent to a conductor [1]. Usually a PD has a very short rise time of a few nanoseconds and a duration of a few to hundred of nanoseconds.

PD activity in a MV/HV devices might be caused by various defects or ageing, such as voids, shield protrusions, contaminants etc. In addition to causing electrical ageing, PD activity may also be a symptom of thermal, mechanical and environmental ageing in high voltage apparatus.

A partial discharge (PD) is short release of current caused by the buildup of electric field intensity in a finite region. The most likely sources of PDs are coronas, contaminants and voids. Insulation breakdown is physically manifested as small cracks, *i.e.* voids, in the insulation; therefore, only void sources will be considered here.

Voids are defined as gaps in a more dense dielectric material, such as gas bubbles in oil that fills the transformer tank, or cracks and fissures in the paper insulation lining the transformer walls. The void region has a lower dielectric constant than the surrounding material, creating a capacitance. A partial discharge can then occur when the electric field difference across the void exceeds minimum breakdown field strength (Inception level). However, reaching this minimum field strength does not guarantee an immediate partial discharge. When a PD pulse occurs in a void, there is a very fast of electrons from one side of the gas filled void to the other side.

In summary, in order for a PD to occur, a free electron must be present within a voltage dependent volume while the electric field strength is high enough to cause a cascading flow of electrons from the movement of a single free accelerated electron. This need for free electrons makes the PD phenomenon very unpredictable and a PD can occur within minutes or within hours of reaching the breakdown field strength within the void. The resulting discharge manifests itself as an observable electrical, acoustic, and sometimes optical signal.

The reliability of HV apparatus is affected significantly by the presence of defects in its insulation. Thus the identification and characterization of insulation defects is a fundamental requirement for the purpose of maintenance. Since almost all the insulation breakdowns starts from Partial Discharge (PD) activity, monitoring of PD activity and its detection in the early stages of development is thus an important means of prevention of insulation failure.

The rise time of a PD pulse normally is in the range of a few nanoseconds and the corresponding frequency is up to several hundred megahertz. Thus any sensor sensitive to the higher frequencies can be used to detect the PD pulse current.

ELECTRICAL PD DETECTION SYSTEM:

Electrical PD detection systems are more convenient, sensitive and simply to apply. An electrical detection system is able to measure the internal discharge, surface discharge and corona discharge. The electrical PD detection methods can be further divided into two different groups: intrusive and non-intrusive methods.

An intrusive method requires the sensing element of the electrical detection system to be placed inside the power equipment to detect the PD pulses. In contrast, with the non-intrusive technique, the sensor is located outside the equipment [3]. Correspondingly, the most commonly used two techniques in PD testing in the case of transformer are Direct Coupling and Indirect Coupling sensing methods.

The direct coupling method is the most common means of PD measurement. It detects the current by using a high voltage capacitor connected to the high voltage terminal of the test object. Such direct coupling to the HV connection of a testing object is also recognized as a conventional discharge detector. A standard test circuit mainly consists of a Test object, a Coupling Capacitor, Measuring Impedance, and the PD Display and the Recording Unit. The PD current (or voltage) is detected directly through a capacitive coupler, with a band width ranging from few hundred kHz, is also called narrow band PD detector. Such a PD detector acts as a low pass filter or integrator. The narrow band PD detector integrates all frequencies in pC, which is the standard unit of partial discharge activity. A Schematic diagram of the PD detection circuit using direct coupling method is shown in the Figure.1

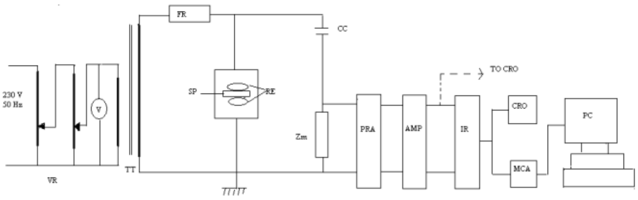


Figure 1. WAVELET

TRANSFORM:

WAVELET HISTORY AND APPLICATIONS:

The first recorded mention of what we now call a "wavelet seems to be in 1909, in a thesis by Haar [4]. The concept of wavelets in its present theoretical form was first proposed by Morlet. The methods of wavelet analysis have been developed and disseminated mainly by Meyer. The main algorithm dates back to the work of Mallat in 1988. Since then, it had been widely used in many areas for a variety of transient analysis applications, including: signal synthesis and analysis, de-noising and compression, pattern recognition and signal and image processing [5 -6]. The wavelet transform has been used previously for partial discharge detection in noisy backgrounds.

Ma et al applied continuous wavelet transforms for PD pattern recognition. They also implemented wavelet transforms to separate PDs from electrical noise and proposed an automated wavelet transform threshold value selection method [7]. Hang et al described application of the wavelet transform to extract PDs from barrow-band interference. Ming et al reported wavelet applications for characterization of PDs based on laboratory studies. Satish et al [8] employed wavelet transforms, 128 tap FIR filtering and IIR filtering for PD denoising and compared their performance with various noise sources. Shim et al [9] proposed using wavelet transforms to improve their capability for detection and location of PDs.

"A wavelet is a kind of mathematical function used to divide a given function in to its different frequency components and study each component with a resolution that matches its scale".

Wavelet transform theory has been well explained by many authors. Briefly the wavelet transform decomposes a signal from the time domain into a time-scale domain with expression of a set of shifted and scaled versions of a single prototype function $\psi(t)$, the basis function also known as the mother wavelet [10]. The Fourier Transform decomposes a signal from time domain into a set of sinusoids with varied frequencies, and then loses the original signal time information. With the wavelet however, it is possible to recover the original time domain signal without losing any information from the decomposed signal in wavelet transformation.

The wavelet transforms can be categorized as either continuous wavelet transforms (CWT) or discrete wavelet transform (DWT), in terms of the types of signals to be processed.

By performing scaling and shifting operations of the mother wavelet $\psi(t)$, a family of continuous wavelet transform (CWT) functions can be created as denoted by equation (1).

$$\psi_{s,\tau}(t) = \frac{1}{\sqrt{|s|}} \cdot \psi^*\left(\frac{t-\tau}{s}\right) \qquad (1)$$

Where s and τ are the wavelet scaling and shifting parameters respectively the wavelet transform allows localization in both time domain via shifting of the mother wavelet and in the scale (frequency) domain via dilation.

The CWT calculates the wavelet transform coefficients at every scale and long every time instant. Calculating wavelet transform coefficients at every scale is time consuming and generates much redundant data, which also potentially brings computational problems.

Choosing scales and positions based on powers of two gives a more efficient analysis with equal accuracy [11]. This Discrete Wavelet Transform (DWT) analysis is the discrete version of the CWT, where the scaling parameter s and shifting parameter τ are discrete, $s = 2^m$ and $b = n2^m$ (m,n are integer values). The discrete wavelet transform (DWT) can be obtained through use of multi-resolution signal decomposition. The time domain original signal is passed through a series of complementary high pass filters (H) and down-sampled by two to generate higher frequency coefficients (details), passed through low pass filters (L) and down-sampled by two to produce lower frequency coefficients (approximation) at different scales [12] as shown in figure (2). These filters are also called quadrature mirror filters (QMF).

QMF enable signals to be decomposed without any loss of original information and enable future inverse discrete wavelet transforms (IDWT) to reconstruct the original signal. Lower frequency coefficients can be further decomposed into next level approximation coefficients and detail until the desired resolution is achieved.

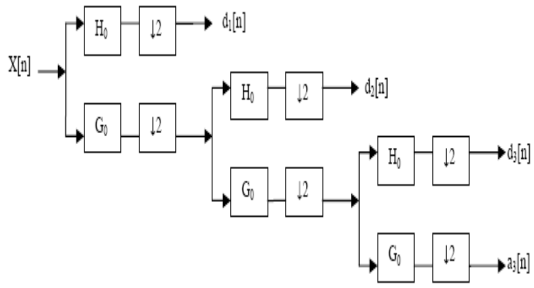


Fig.2 Three level decomposition of signal X[n].

Reconstruction of the signal is an inverse process of decomposition. Coefficients obtained through DWT or modified coefficients can be used to reconstruct the original signal as shown in figure (3).

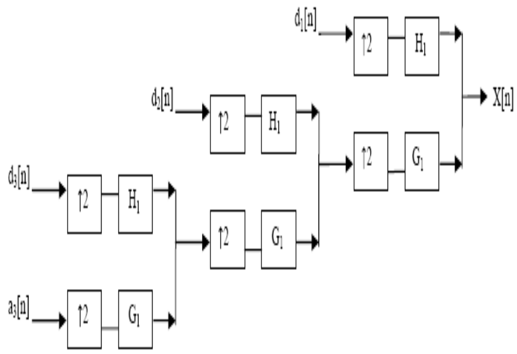


Fig.3 Three level reconstruction of signal X[n].

WAVELET DE-NOISING TECHNIQUE:

The general wavelet de-noising procedure involves three steps as detailed below:
1. Decomposition: Choose a wavelet, choose a level N and compute the wavelet
Decomposition coefficients of the signals at levels from 1 to N
2. Select threshold detail coefficients. For each level from 1 to N, select a threshold and apply a soft or hard threshold to the detail coefficients.
3 Reconstruction: To reconstruct signal by using original approximation coefficients and modified detail coefficients from levels 1 to N.

Selection of the threshold value is the most difficult part of wavelet de-noising. For routine data de-noising processing a fully automatic threshold value selection algorithm must be developed. A successful threshold value determination algorithm must have both wide applicability and strong noise reduction capability. Satish et al proposed a semi-automatic and empirical wavelet-based method. For processing of a polluted PD signal by his method the signal is decomposed into up to 10 levels using a wavelet basis function, by inspection of all the components in those detail levels, i.e. D1 to D10, to determine which levels are relevant to the PD signal, those levels are retained and other levels are discarded. Finally PDs can be obtained by adding those PD relevant levels together. Thus the threshold values are fully determined by the operator's experience in this method. **Shim et al** applied a universal threshold rule developed by Donoho and Johnston, whereby the universal threshold level is set to be as in equation (2).

$$\lambda = \sigma * [(2 * \log nj)^{1/2}] \qquad (2)$$

Where σ is an estimate of the noise level and nj is the number of wavelet coefficients in the current level [13].

Thresholding by equation has been performed in certain scales in which PD pulses are dominant. The rest of the scales wavelet coefficients are set to zero. The 'true' PD signal is obtained by reconstructing the modified coefficients. The PD signal can be obtained by reconstructing those modified coefficients. Therefore even though this method gives a threshold value selection rule it is still only semi-automatic and empirical. Appropriate knowledge or an expert operator is required to complete data de-noising. Ma et al proposed a automated level-dependent threshold selection method, which is given by equation (3) :

$$\lambda j = \sigma j / 0.6745 * [(2 * \log n j)^{1/2} \qquad (3)$$

Where λ j is the threshold value at level j, σj is the level dependent noise estimated value at level j. nj is the number of wavelet coefficients at level j [15]. The 0.6745 rescaling factor makes equation (3) well suited for a zero mean Gaussian white noise model. The noisy signal is decomposed in to a certain level and each level wavelet coefficients are then thresholded by values defined by equation (3). The PD signal can be obtained by reconstructing those modified coefficients. This threshold value determination algorithm is totally automatic. No previous knowledge or expert operator is needed for a routine PD measurement even when noise is present.

Wavelet de-noising methods can be carried out using either hard or soft thresholding. Hard thresholding processes data in such a way that those wavelet coefficients whose absolute values are greater than the threshold are kept and those less than the threshold are set to zero:

$$\delta^H(x) = \begin{cases} x & if\ |x| > \lambda \\ 0 & if\ |x| \leq \lambda \end{cases} \qquad (4)$$

Soft thresholding sets the wavelet coefficients below the threshold to zero. The coefficients greater than threshold are kept and then shrunk towards zero:

$$\delta_{\lambda}^{s} = \begin{cases} x - \lambda & if\ x > \lambda \\ 0 & if\ |x| \leq \lambda \\ x + \lambda & if\ x > -\lambda \end{cases}$$

In comparison, hard thresholding is preferred in PD denoising due to the higher coefficients values associated with discharge events being kept without any modification and thus yielding an improved PD signal to noise ratio

RESULTS:

Results of different types of PD signals denoising using Shim's wavelet transform method are shown.
Sample 1 From Figure 4 (a-d) shows the PD pulses obtained at voltage 31.6 kV with inception voltage 15 kV. A random noise is added to this signal and then wavelet decomposition and reconstruction method is used for denoising the noisy signal.
The signal data for implementation is taken from reference [14].

SAMPLE 1

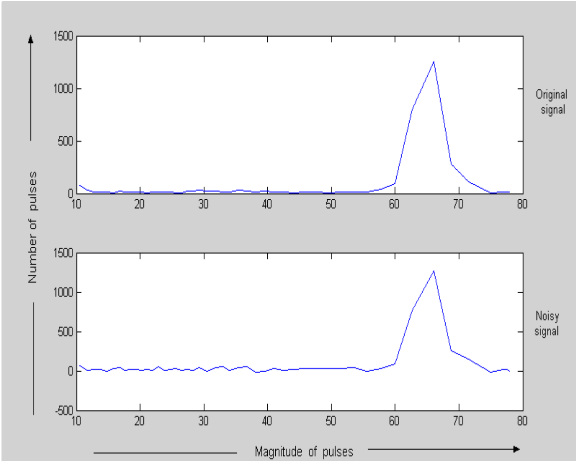


Fig 4 (a). Original signal and noisy signal

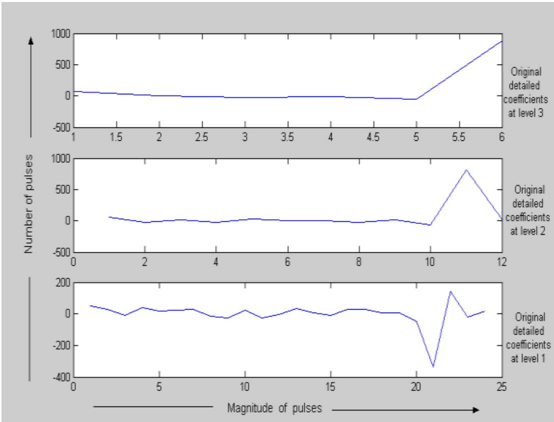


Fig. 4 (b) Original Detail coefficients

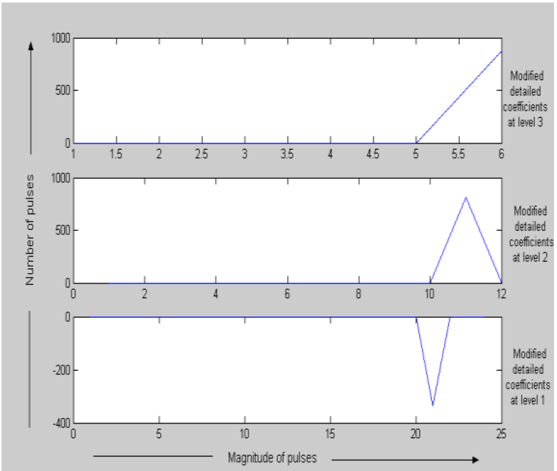
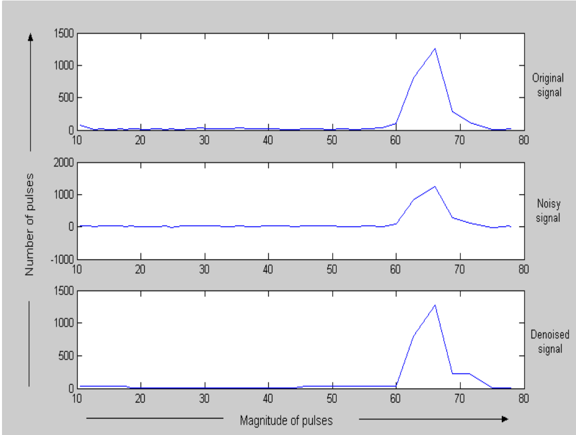


Fig.4 (c) Modified Detail coefficients



4 (d) Denoised signal.

SAMPLE 2

Sample (2) shows Figure 5(a-b) shows the PD pulses obtained at voltage 31.6 kV with inception voltage 15 kV. A random noise with is added to this signal and then wavelet decomposition and reconstruction method is used for denoising the noisy signal. Figure 5(b) shows denoised signal

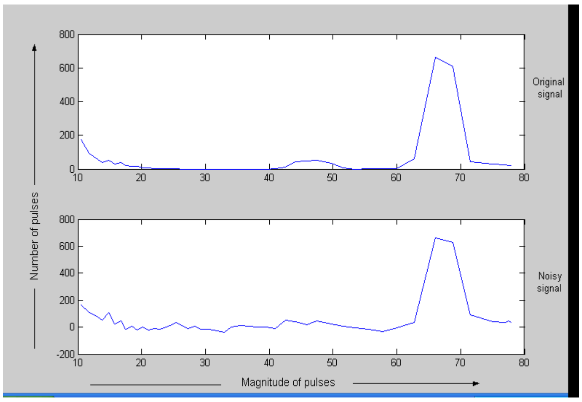


Fig. 5(a) Original signal and Noisy signal

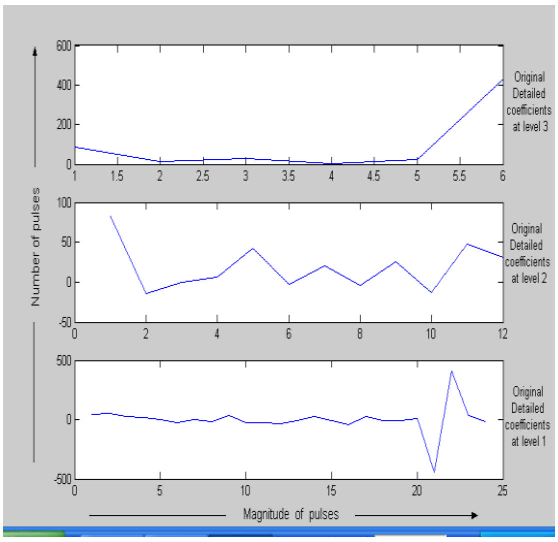


Fig. 5 (b) Original Detail coefficients

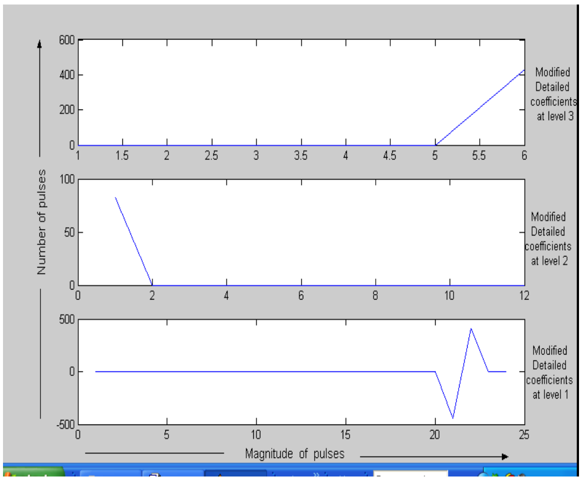


Fig.5 (c) Modified Detail coefficients

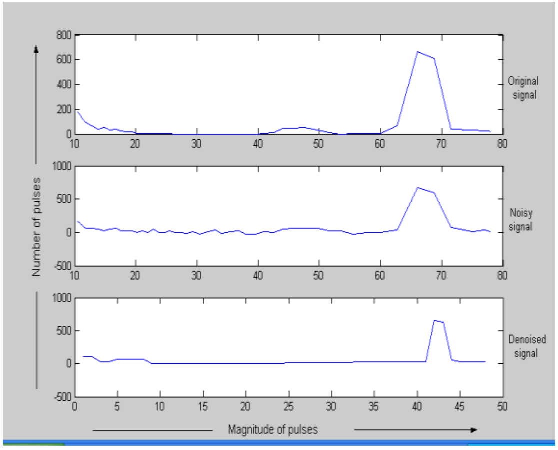


Fig. 5(d) Denoised signal

SAMPLE 3

Sample (3) shows Figure 6(a-b) shows the PD pulses obtained at voltage 25.6 kV with inception voltage 14 kV. A random noise is added to this signal and then wavelet decomposition and reconstruction method is used for denoising the noisy signal. Figure 6(b) shows denoised signal.

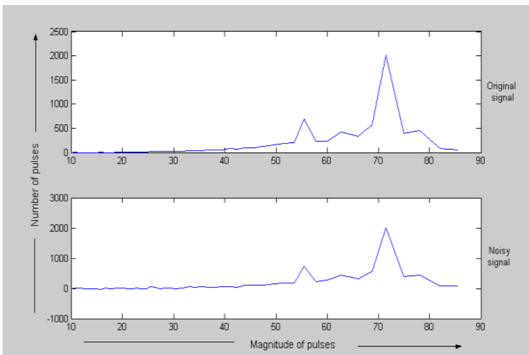


Fig. 6(a) Original signal and Noisy signal

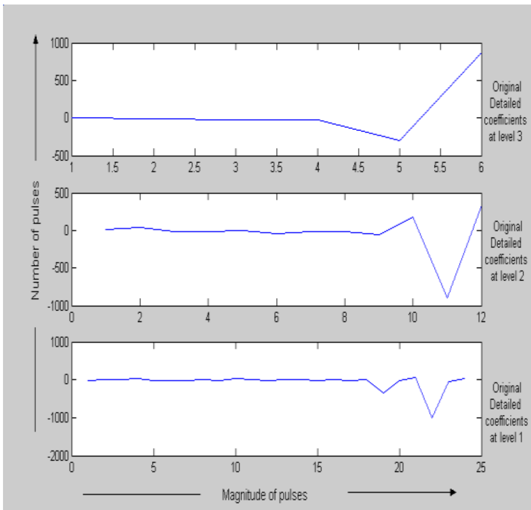


Fig. 6 (b) Original Detail coefficients

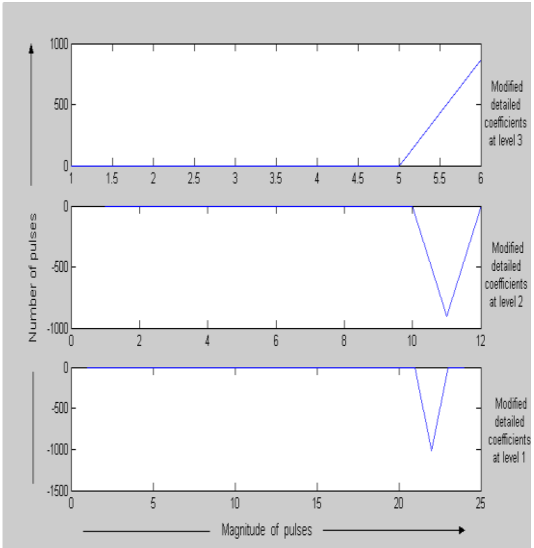


Fig.6 (c) Modified Detail coefficients

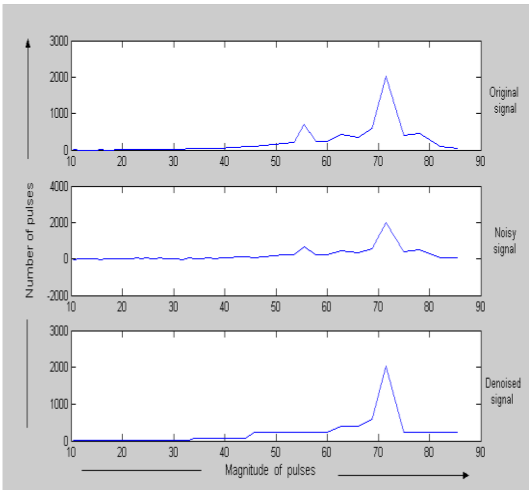


Fig. 6 (b) Denoised signal

CONCLUSION:

It is valuable to take wavelet transform into the PD diagnosis. This study has provided some useful insights into the practical application of WT to extracting PD signals from the noise background. Partial discharge detection and location in high voltage devices is an essential diagnostic tool for monitoring the state of health of electrical insulators within the devices. PDs make insulation damage worse because the event adds more electrical and mechanical stress to the developing flaw. Therefore, accurate detection and positioning is required to maintain these devices and limit the amount of diagnostic and repair time required.

The above results shows wavelet transform is a successful method of denoising. WT de-noising method can handle high noise levels and recover PD signals from noise.

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