A Novel Wavelet Transform Technique for On-line Partial Discharge Measurements Part 1: WT De-noising Algorithm

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ABSTRACT

Medium and high voltage power cables are widely used in the electrical industry with substantial growth over the last 20-30 years ago, particular in the use of XLPE insulated systems. Ageing of the cable insulation is becoming an increasing problem that requires development of reliable methods for on-line condition assessment. For insulation condition assessment of MV and HV cables, partial discharge (PD) monitoring is one of the most effective techniques. However on-site and on-line PD measurements are affected by electromagnetic interference (EMI) that makes sensitive PD detection very difficult, if not impossible. This paper describes implementation of wavelet transform techniques to reject noise from on-line partial discharge measurements on cables. A new wavelet threshold determination method is proposed with the technique. With implementation of this novel de-noising method, PD measurement sensitivity has been greatly improved. In addition, a full ac cycle data recovery can be achieved instead of focusing only on recovering individual PD pulses. Other wavelet threshold de-noising methods are discussed and examined under a noisy environment to compare their performance with the new method proposed here. The method described here has been found to be superior to the other wavelet-based methods.

Index Terms - **Partial discharge, wavelet transforms, cables, interference suppression, online measurement.**

1 INTRODUCTION

MEDIUM and high voltage power cables represent a large capital investment for electrical utilities and have to be highly reliable. Failure of the insulation of power cables can lead to costly disruption of supply. However, as a result of deregulation and the current economic stringencies in the electrical supply industry, even cables of advanced age are still being used at high and, in some cases, increasing load factors. Cable insulation ageing is thus becoming an increasing asset management problem. Thus, the earlier insulation degradation can be detected the easier replacement or refurbishment will be arranged before failure. As such failure usually starts with PD activity; PD measurement can be used as a diagnostic method for detecting degradation and preventing major insulation breakdown. To do this requires development of a reliable method of continuous on-line PD detection.

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PD activity in cables can result from breakdown of gas in a cavity, breakdown of gas in an electrical tree channel, breakdown along an interface or breakdown between an energized electrode and a floating conductor [1,2]. The damage due to the discharge can be estimated depending on the type of discharge; for example, internal or surface discharge, termination discharge, corona, electrical treeing, etc [3]. For XLPE cable internal PD activity is regarded as the most dangerous as progressive deterioration due to internal PDs develops very quickly to ultimate failure.

PD monitoring is arguably the most effective technique of cable insulation assessment. On-line PD diagnostic measurement is more desirable as it has two major advantages: there is no interruption to operational service of the cable needed and also it provides continuous monitoring. However on-line PD monitoring has the major problem of electromagnetic interference (EMI). This noise often subsumes completely the very low level PD signals picked up by the sensors. This makes

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on-line PD detection difficult, particularly for monitoring low level PDs to determine insulation degradation trends. Thus, post-processing using sophisticated signal processing techniques is needed.

Traditionally, the main techniques used to reject noise from PD signals could be realized in either the time domain (with knowledge of some repetitive noise such as thyristor firing) or in the frequency domain (using fast Fourier transforms to extract PD events when PD and noise present different frequency characteristics). However when signal processing is done in the frequency domain the time domain information is lost. The wavelet transform (WT) technique provides a new analysis tool able to be implemented in both the time and frequency domains.

Previous applications of wavelets have been done to reject noise mostly in off-line tests and these are not satisfactory for on-line applications. This paper addresses the problem of on-line noise reduction and proposes a new wavelet transform method suitable for on-line PD measurements in high EMI environments. A robust novel WT threshold value selection algorithm is presented through continuously modeling the noise characteristic. With this the WT threshold value can be determined automatically without making any assumption of noise distribution model.

2 ON-LINE PARTIAL DISCHARGE MEASUREMENT SYSTEM

The on-line partial discharge measurement system used contains a PD sensor, an radio frequency (RF) amplifier, an oscilloscope and a computer for recording and post processing of data. The PD sensor is a clip-on type high frequency current transformer (HF-CT), which is clamped around the conductor that connects the cable metallic screen to the earth [4]. Other PD sensor types have been tested and evaluated in this program, including both capacitive and inductive couplers around the cable sheath. In terms of universal applicability, sensitivity and frequency response, it has been found that the HF-CT around the earth connection gives the best result. The HFCT frequency response is up to 40 MHz: this is high enough to cover the main range of PD activity. As the signal from the HFCT is in the range of a few milli-volts, an amplifier is needed. A wideband amplifier is necessary to avoid PD signal distortion. Careful attention must be paid to amplifier design to avoid introducing extra interference.

On-line PD measurement on-site is arranged as shown in Figure 1. Partial discharges in the power cable cause HF electrical pulses to propagate through the earthing conductor and thus they can be detected by the HF-CT. The output signal from the HF-CT is fed via a long 50-ohm coaxial cable to the acquisition system [4]. Here, the signal is amplified and sent to a digital oscilloscope with very high data storage capability. This enables recording of a substantial amount of data for post-processing.

Because PDs may last less than a microsecond a high sampling rate is necessary. To ensure the signal capture is distortion-free the sampling rate has to be at least two times the highest signal frequency. In consideration of signal resolution and coordination of the HFCT frequency response, a rate of 100 Msample/s has been adopted. A long recording time is also necessary because of the infrequent nature of the PDs.

Based on the above considerations all PD events are recorded over a whole ac cycle of 20 ms with a sampling rate of 100 Msample/s. As the signal is recorded and triggered over a whole ac cycle, the recorded data can also provide phase-resolved PD characteristics.

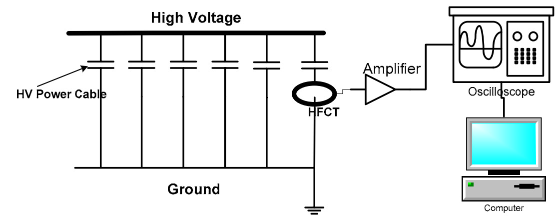

Figure 1. Test Arrangement, Each capacitance represents a separate cable.

3 ON-LINE PARTIAL DISCHARGE MEASUREMENT DIFFICULTIES

On-line PD measurement is desirable because of its obvious inherent advantages over off-line measurement. However, until recently PD techniques were restricted to off-line measurement because of recording limitations and noise problems. In on–line PD measurement the noise level often swamps the PD signal of interest. To restore PD signals that are often totally buried by on-line EMI is a major challenge in on-line PD measurement is conducted.

3.1 ON-LINE NOISE CHARACTERISTICS

The ability to discriminate PDs from noise improves with an increased knowledge of both the PD and noise characteristics [5]. Such knowledge might include PD bandwidth, dominant frequency, waveform, phase information relative to power frequency voltage, PD attenuation characteristics, the type of noise, the noise phase position, the noise bandwidth and attenuation characteristics.

PDs are normally low-level pulses with fast rise time and short duration, typically no more than a few hundred nanoseconds. Its waveform varies depending on the fault type, the PD detection sensor, insulation characteristics and physical connection. PDs cover a wide signal bandwidth.

Any or all of the following effects can cause interference that couples into on-line PD sensors [6]:

1. Discrete spectral interference (DSI), e.g. communication and amplitude modulation (AM)/ frequency modulation (FM) radio emissions;
2. Repetitive pulses, e.g. from power electronics;
3. Random pulses, e.g. from switching operations or lightning or RF corona emitted from HV equipment;
4. Other noise sources such as ambient and amplifier noise

In terms of its nature, the EMI noise on-site can be classified as sinusoidal noise (DSI), pulse-type noise (repetitive and random pulse), white noise (amplifier and ambient noise) and stochastic noise.

DSI is a narrow band noise signal; the other three types of noise are wide band signals.

DSI can be removed by applying digital notch filters [7], with the help of a spectrum analyzer. Repetitive pulses can be rejected through gating circuits in the time domain. White noise and its WT coefficients can be described by a Gaussian model, as illustrated in Figure 2. Based on such distribution characteristics some noise reduction techniques can be implemented to reject white noise, as will be discussed later.

Random pulse interference is the most common interference source and presents the biggest problem to on-line PDs measurement. The pulse frequency characteristics are quite similar to PD signals so that notch filtering techniques are not effective. Because they rare random gating cannot help. An advanced technique has to be implemented to separate the PDs from the random noise pulses.

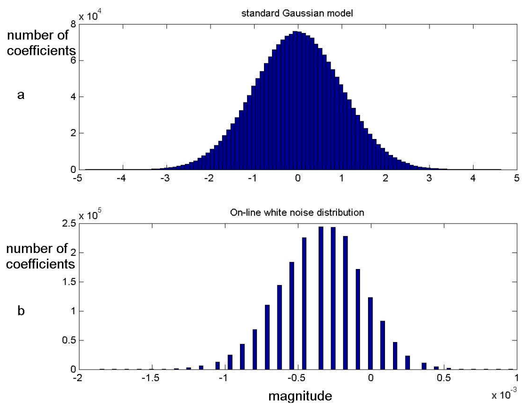

Figure 2. White noise histogram. Top trace Figure 2a is the standard Gaussian model, bottom trace Figure 2b is the measurement system white noise distribution

4 WAVELET TRANSFORM

4.1 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 [8]. 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 [8]. 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 [8-12]. The wavelet transform has been used previously for partial discharge detection in noisy backgrounds [13-19].

Ma et al [14] 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 [15]. Hang et al [16] described application of the wavelet transform to extract PDs from barrow-band interference. Zhang et al [7, 22] implemented wavelet transforms to remove narrow band interference and white noise in on-line PD measurement. Ming et al [17] reported wavelet applications for characterization of PDs based on laboratory studies. Satish et al [13] employed wavelet transforms, 128 tap FIR filtering and IIR filtering for PD de-noising and compared their performance with various noise sources. Shim et al [3, 18] proposed using wavelet transforms to improve their capability for detection and location of PDs in shielded distribution cables. Tian et al [19] applied wavelet transform de-noising techniques to improve SNR when using an HFCT to detect PDs within a prefabricated cable joint.

Almost all applications of wavelet transform de-noising techniques described above aim to remove DSI or measurement system white noise, which are the main interference sources during off-line testing. For on-line testing, the test object is not isolated and thus picks up the prevalent pulsive interference from the grid. It is now commonly accepted that the removal of pulsive interference is the main challenge. A successful method of on-line PD measurement must possess the capability of suppressing pulsive interference.

For precise insulation diagnosis PD magnitude and number vs. phase position are needed. These q-Φ and n-Φ characteristics are essential for PD type and insulation fault type determination. This is why any condition monitoring method requires the whole ac cycle data recovery capability.

Three of the above methods have greatly improved our capability of recovering off-line PDs from excessive EMI environments and have led to the development of the new wavelet transform de-noising method described here. Thus, the PD de-noising methods proposed by Ma et al. [15], Satish et al [13] and Shim et al [18] will be discussed later in detail with this proposed new method. Comparisons will be given in terms of their sensitivities, noise level and data acquisitions.

4.2 A BRIEF WAVELET TRANSFORM INTRODUCTION

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 ψ(t), the basis function [20]. By performing scaling and shifting operations of the mother wavelet ψ(t), a family of continuous wavelet transform(CWT) functions can be created as denoted by equation (1) [9];

$$\psi_{a,b}(t) = a^{-1/2} * \psi\left(\frac{t-b}{a}\right) \text{ , } a, b \in R, a \neq 0 \qquad (1)$$

where a and b are the wavelet scaling and shifting parameters respectively.

Choosing scales and positions based on powers of two gives a more efficient analysis with equal accuracy [21]. 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) [7] at different scales. 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.

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.

4.3 WAVELET DE-NOISING TECHNIQUE

The general wavelet de-noising procedure involves three steps as detailed below [9]:

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.

4.4 BASIS FUNCTION AND DECOMPOSITION LEVEL SELECTION

For any PDs measurements, WT de-noising involves decomposing polluted PD signals into certain N levels to acquire decomposition coefficients with a selected wavelet basis function. Coefficients associated with interference are discarded and those coefficients associated with PDs are retained, using the preset threshold value. PDs signals can be reconstructed using modified coefficients.

Selection of a basis function is crucial to this WT technique. For on-line PD measurement excessive interference causes very low SNR, which means most of the WT coefficients have to be discarded, as they are noise associated. To DWT signal and IDWT coefficients directly can be used to reconstruct the original signal as a perfect reconstruction without any loss. However using modified coefficients, especially for on-line PDs measurement where most of the coefficients have to be modified, the IDWT is no longer a perfect reconstruction. Under such circumstance a Biorthogonal wavelet basis function family is recommended because of its linear phase characteristic.

QMFs are used in DWT and IDWT progress; the most common wavelet filters (low-pass and high-pass complementary filters) are finite impulse response (FIR) filters, e.g. Daubechies (dbN), coiflet (coifN), SymletsA (symN) filters. However the FIR filter is not required to be a linear phase. Only those FIR filters with symmetrical coefficients are linear phase filters. Biorthogonal wavelet filters are linear phase filters. Its decomposition and reconstruction filter coefficients are symmetrical as illustrated in Figure 3, which is produced by MATLAB wavelet toolbox. When a signal passes through a filter, the filter will modify the signal in amplitude and/or phase. The nature and extent of the modification of the signal is dependent on the amplitude and phase characteristics of the filter. Filters with nonlinear phase characteristics will cause signal distortion in the time domain when the signal is filtered. Linear phase characteristic is necessary as the phase delay and group delay of linear phase FIR filters are equal and constant over the frequency band. This characteristic ensures adjacent signals will not be overlapped together after reconstruction.

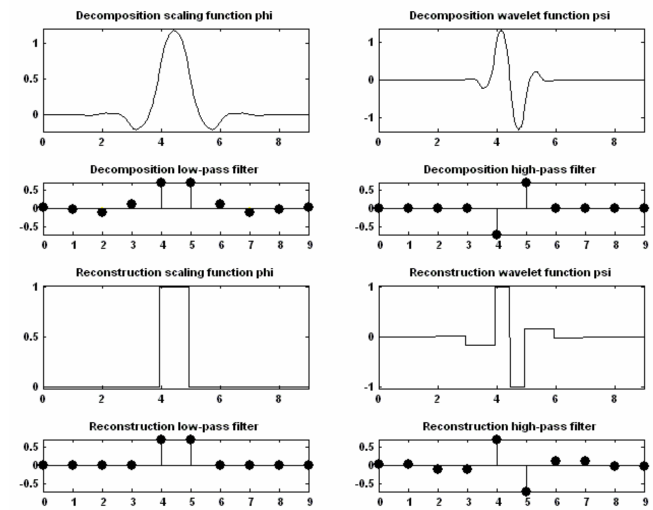

Figure 3. Wavelet Decomposition. The second row is the decomposition filter; the fourth is the reconstruction filter.

It was suggested by Ma et al [15] that use of the correlation coefficient γ be made to provide a criterion for identifying an appropriate wavelet choice for PD pulse detection. The Daubechies-2 wavelet basis function was adopted by Ma et al in [15] and Shim et al. in [18] since the damped exponential decay shape of this wavelet was thought to best represent the PD signature. Daubechies wavelet families were also suggested by Satish et al [13] based on comparison among many practical examples. In his simulation, better results were obtained with Daubechies-30. To some extent, the wavelet transform is a measure of similarity. The more similar between the original signal and wavelet basic function, the higher the coefficients produce [22]. For de-noising and reconstruction considerations, the optimal wavelet suitable for a given signal is the one that is capable of generating as many coefficients with maximal values as possible throughout the time scale domain [25]. In practical applications, the PD pulse shape characteristic is determined by the sensor in conjunction with the test object, defect type , location, signal propagation and attenuation. Therefore field testing is desirable before the wavelet basis function is chosen. Based on the above analysis Bior1.5 was selected from the Biorthogonal family for use in the work described here, as it is the most similar one to the PD pulse observed in authors' on site on-line PD measurement.

The number N of decomposition levels was selected based on trial and error until PD-associated coefficients can be distinguished from noise at a certain WT scale [7]. Then, coefficients associated with PDs are retained and coefficients corresponding to noise are discarded. The number N of decomposition levels is also dependent on sampling frequency: the number of levels N should be selected to ensure that the DWR decomposition has high enough frequency resolution to discriminate the different frequency components between noise and PD. In order to balance computation complexity and frequency resolution we have selected N to be between 10 and 20 when the sampling rate is 100 Mega samples/second.

4.5 THRESHOLD DETERMINATION

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. For an untrained operator instead of an expert, automation of threshold value determination is desirable. A 'trial and error' process to determine threshold value is not practical for routine maintenance. A successful threshold value determination algorithm must have both wide applicability and strong noise reduction capability for the normal operator.

Satish et al [13] 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 [18] applied a universal threshold rule developed by Donoho and Johnston [23], whereby the universal threshold level is set to be:

$$\lambda = \sigma * [(2 * \log nj)1/2] \quad (2)$$

where σ is an estimate of the noise level and nj is the number of wavelet coefficients in the current level.

Her method has been used to process data from an in-service cable PD measurement [18]. The signal is decomposed in to nine levels using Daubechies-2 wavelet basis function since the shape of this wavelet best represents the PD signature. By visual inspection some scales are omitted as they contain mostly noise. Thresholding by equation (2) 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. 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 [15] proposed a automated level-dependent threshold selection method, which is given by equation (3):

$$\lambda j = \sigma j / 0.6745 * [(2 * \log n j)1/2] \quad (3)$$

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:

$$\delta_{\lambda}^{H}(x) = \begin{cases} x & if\ |x| > \lambda \\ 0 & if\ |x| \le \lambda \end{cases} \quad (4)$$

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

$$\delta_{\lambda}^{S}(x) = \begin{cases} x - \lambda & if\ x > \lambda \\ 0 & if\ |x| \le \lambda \\ x + \lambda & if\ x > -\lambda \end{cases} \quad (5)$$

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 [15]. More information on the thresholding rules can be found in [25].

5 A NEW TECHNIQUE OF WAVELET NOISE REDUCTION

The three wavelet de-noising techniques described above have greatly increased our capability to extract PDs from a high EMI environment. However those techniques are mainly aimed at single PD pulse recovery. A whole ac cycle with multiple PDs has not been considered. Details of data acquisition and processing progress of the first method have not been mentioned in [13]. Data acquisition and processing for the last two methods [15, 18] is based on using triggering signals above the noise level: the PD peak must be able to be identified by a skilled operator to ensure accurate triggering. Since they are based on the single signal triggering, it is inevitable that the rest of PD activities in the same ac cycle, which are also higher than noise level, cannot be triggered and recorded. Therefore the q-Φ and n-Φ phase characteristics will not be available.

Also, because the first two methods are not fully automatic, experience and prior knowledge are needed to determine threshold values. While the last method has a threshold selection algorithm which is fully automatic, however its triggering process is not. These limitations require a new technique for on-line PD measurement de-noising.

A new automated wavelet noise reduction method has been developed by the authors in laboratory tests in an attempt to increase PD measurement sensitivity and to extract PDs from a high level noise environment. It is well known that PDs occur only if the applied voltage is higher than the PD inception voltage (PDIV). When the applied voltage is lower than the inception level there is no PD activity: under such conditions every signal recorded is noise.

Based on the above analysis, voltage is raised to just below PD inception level to record noise, including power supply, amplifier, digital oscilloscope and ambient noise. The signal is recorded and triggered with a line-triggering mode to record a whole ac cycle. Then this noise record is decomposed by selected wavelet basis function “bior1.5” to certain level, e.g. 10 levels. Coefficients at each level are compared within this level and the absolute maximum coefficient will be stored to be the threshold value at this level. The maximum coefficient is selected as it represents the maximum noise characteristic. Any coefficients higher than this value are totally noise unrelated, and are thus only possibly associated with PD activities. After computation, ten detailed threshold values and one approximate threshold value will be stored for future signal de-noising. Then voltage is raised to a level higher than the PD inception voltage to acquire PD activity. The signal causes triggering and is recorded as before. This potential PD record then is decomposed by the same wavelet basis function to the same level to generate WT coefficients. All coefficients at each level will be thresholded by the corresponding threshold value that is determined by the previous step. As those threshold values represent the maximum noise characteristics any coefficients after thresholding are PD coefficients.

The above algorithm covers the case where noise is stationary with the applied voltage. If noise varies with the applied voltage after connecting to the grid or if there is no separate voltage source available, the threshold values can be obtained by the method introduced in part 2 of this paper series [23].

It should be noted that PD inception level is closely related to PD detection sensitivity. The proposed method will provide better result if PDIV can be determined by an experienced operator. The proposed method also could be conducted if the PDIV is not known. Usually in the off-line measurement, the test supply is PD free or with negligible PD and most noise sources are external, except system white noise. Those external noises are PDIV independent. The amplifier and oscilloscope noises are also unrelated to PDIV. Thus a signal recorded when the applied voltage is much lower than PDIV also could be used as a noise record. Such a noise record can be processed to produce wavelet threshold values as mentioned previously. However if the test supply emits noise as well, the measurement sensitivity will be affected. The limitation of this method is that it has to be carried out off-line.

A hard threshold method is preferred in our application. All coefficients below preset threshold values, which are noise level related, are set to be zero. The reconstructed PD yields a better result than the soft threshold method.

5.1 SIGNAL EXTRACTION WITH SIMULATED PD PULSES

After thresholding, the PD signal can be extracted by reconstructing those modified coefficients through the IDWT. Using this technique simulations have been done to examine the performance of this new wavelet noise reduction technique and to compare it with the other three techniques described above.

As suggested by Ma et al [15] the damped exponential pulse (DEP) and the damped oscillatory pulse (DOP) have been numerically simulated as the mathematical models used for the PD simulation tests. These waveforms are expressed by equations (6) and (7), respectively, and further displayed in Figure 4a and 4b.

$$DEP(t)=A(e-t/t1-e-t/t2) \qquad (6)$$

$$DOP(t)=A\sin(2\pi fct)(e-t/t1-e-t/t2) \qquad (7)$$

where A is the pulse peak value, t1, t2 are the time constants that determine typical PD parameters such as pulse risetime, pulse width and pulse decay time. fc is the oscillatory frequency of the DOP type pulse. DEP PD is with peak magnitude of 8.14 units and DOP is with 8.04 units.

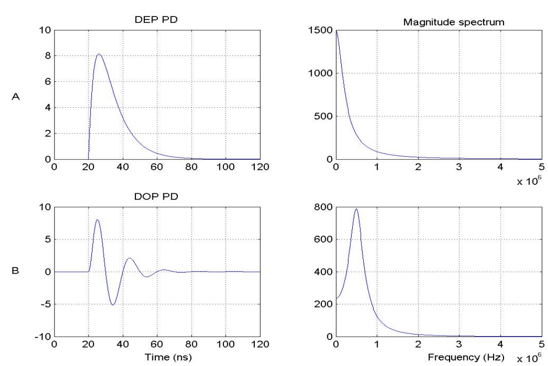

Figure 4. Figure 4a: simulated DEP pulse and its spectrum; Figure 4b: simulated DOP pulse and its spectrum

5.1.1 Damped exponential pulse (DEP)

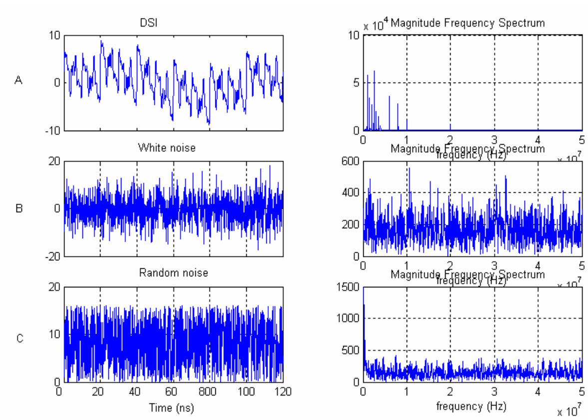

Figure 5. Simulated noises and their spectra: Figure.5a, DSI; Figure.5b, Gaussian white noise, Figure 5c, random noise.

Noises are also simulated with mathematical model. DSI is with 12 different frequencies from 0.1 MHz to 12 MHz and maximum magnitude is 16 units. White noise is standard zero mean Gaussian white noise with maximum magnitude of 18.2 units. Stochastic noise is simulated by random entries, chosen from a uniform distribution on the interval (0.0,1.0) multiplying with a gain of 16 units. The DSI, Gaussian white noise, random noise and their magnitude spectra are shown in Figures 5a, 5b and 5c respectively.

Figure 6 shows the PD extraction result obtained by the method proposed in this paper. The signal is simulated over 200 μs instead of an ac cycle to give better comparison with the other methods, as they demonstrated their capabilities of removing noise mostly in such a limited time interval. Four successive DEP-type PDs of various magnitudes, shown in Figure 6c, have been totally buried in a noisy background consisting of DSI white noise and stochastic noise. The noise is recorded separately to determine the wavelet threshold value following the method described in section 5. In this case signal to noise ratio (SNR) is –48db if defined as in equation (6), which Satish et al used in [13].

$$SNR = 10 * \log \frac{\sum_{i=1}^{N} Y^2(i)}{\sum_{i=1}^{N} [X(i) - Y(i)]^2} \tag{8}$$

where X(i) is the original reference signal, Y(i) is the de-noised signal and N is the number of samples.

More commonly SNR is defined as in equation (9), which Ma et al [15] used. In such a definition, the SNR of PD to white noise is –8.09db, to stochastic noise is -6.92 db, and to DSI is –1.01db. The overall SNR is –16.02 db.

$$SNR = 10 * \log \frac{\max(signal)}{\max(noise)} \tag{9}$$

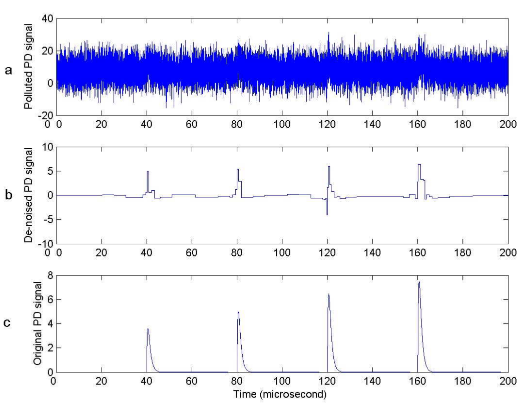

Figure 6. Simulation with DEP type PD pulses. Figure.6a polluted PD signal; Figure 6b, de-noised PD signal; Figure 6c, original PD signal.

Figure 6a is the polluted DEP-type PD signal. Figure 6c is the original PD signal with the maximum magnitude 7.02 units, and is totally immersed in noise with peak magnitude 34.85 units (Figure 6a). After adopting the de-noising method proposed in this paper, the four successive PDs are recovered as shown in Figure 6b with peak magnitude 6.35 units, i.e. a 9.45% decrease in magnitude determination.

The de-noising methods of Ma et al and Shim et al. have also been tested with the same polluted signal. Briefly, the polluted PD simulated signal has been decomposed by "db2" into 10 levels to acquire 10 levels WT coefficients. Each level WT threshold value was determined by equations (3) and (2) respectively. Then the WT coefficients were "thresholded" by those threshold values. Finally, the de-noised PD signals were recovered by reconstructing the modified WT coefficients. The de-noised signals are shown in Figure 7b and 7c respectively. Figure 7a shows the full polluted signal. The PDs cannot be extracted from the noise by those two methods. This result agrees with Ma's conclusion that his method is efficient to remove DSI but is less efficient in suppressing stochastic noise for both DEP and DOP types of PD pulses when the signal to noise ratio is less than –3db. This is due to stochastic noise having a wideband spectrum and a random occurrence [15].

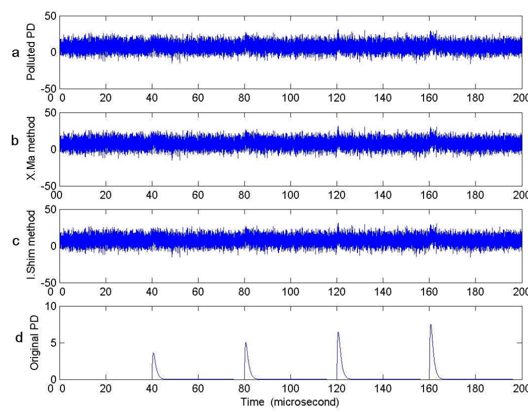

Figure 7. Results of de-noising with Ma and Shim methods. Figure 7a polluted PD signal; Figure 7b, Ma's method; Figure 7c, Shim's method; Figure 7d, original clean PD signal.

The method of Satish et al has also been tested for comparison. However, as experience and appropriate knowledge is essential to conduct that method, only the decomposition has been given in Figure 8. The choice of levels for adding to recover PDs from the noise is left to readers.

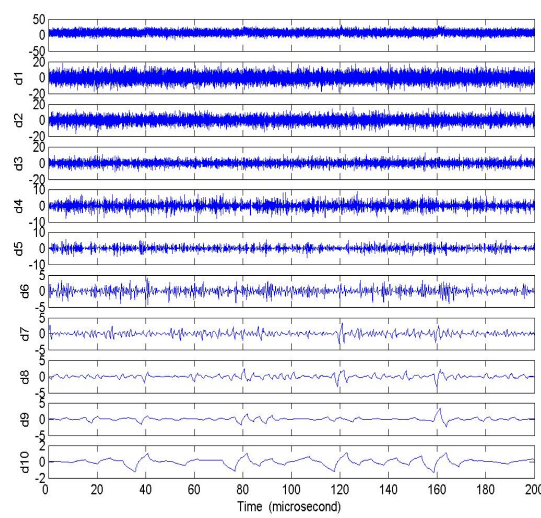

Figure 8. De-noising with Satish's method. Top trace is polluted PD signal; from second to the last trace are detail levels 1 to 10.

5.1.2 Simulation with Damped Oscillatory Pulse

Four varying magnitude and equally spaced successive DOP-type pulses were mixed with DSI, white noise and stochastic noise as before. Noise has also been recorded for threshold value calculation purposes.

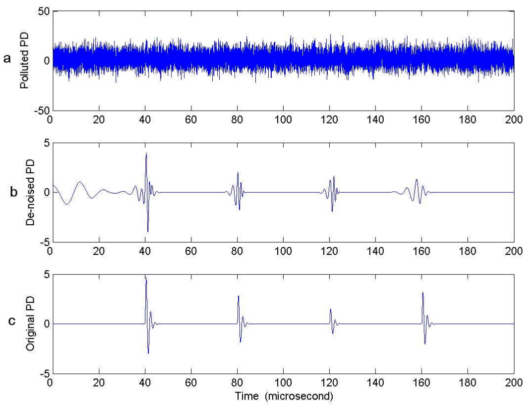

Figure 9. Simulation with DOP pulses. Figure 9a, polluted PD signal; Figure 9b, de-noised PD signal; Figure 9c, original PD signal.

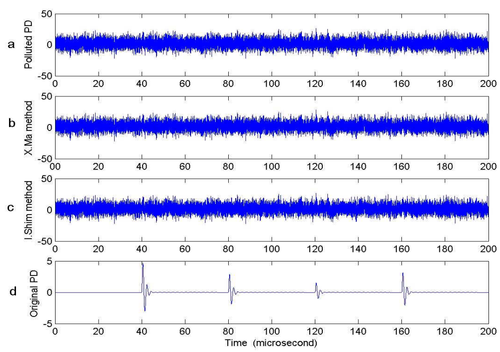

Figure 10. Simulation with Ma and Shim methods for DOP. Figure 10a, polluted PD signal; Figure 10b, Ma's method; Figure 10c, Shim's method; Figure 10d, original PD signal.

Figure 9a is the polluted DOP-type PD signal. The SNR of PD to white noise is –10.44 db, to stochastic noise is -6.96 db, and to DSI is –2.15db. The overall SNR is –19.56 db. Figure 9c is the original PD signal with the maximum magnitude 4.67 units, is totally immersed in noise with peak magnitude 26.95 units. After applying the de-noising method proposed in this paper, four successive PDs are recovered as shown in Figure 9b with peak magnitude 4.00 units, i.e. 14.35% decrease in magnitude determination.

The Ma and Shim methods have also been tested with DOP-type PD pulses when noise is present as in the above mentioned condition. The de-noising processes are the same as in part 5.1.1 with adopting threshold values determined by equation (3) and (2) respectively. Figure 10a shows the polluted signal and Figures 10b and 10c show the results of the Ma and Shim methods. They are not able to extract the PDs.

Satish's method has not been tested with a DOP-type PD simulation as it involves operator experience and knowledge.

5.2 EXPERIMENTAL TESTS OF THE DE-NOISING SYSTEMS

From the above simulation results this new wavelet de-noising technique can provide better results and greatly increase the capability of recovering PDs from a high level EMI environment. Apart from the simulations, laboratory high voltage tests have also been conducted to compare this method with the other methods under experimental conditions of noise.

The laboratory test was arranged as described in Section 2. For comparison, the PD was also measured by the conventional capacitor coupling method. Signal was firstly recorded when the applied voltage is below the PDIV. This record was used to calculate wavelet de-noising threshold values. Then the PD signal with noise, mainly measurement system white noise, was recorded as described in Section 5 over an ac cycle of 20 ms. This noisy PD record was then de-noised by the corresponding threshold values. A better result with higher sensitivity was presented. Conventional system also recorded PD activities after PDIV. This result is used to cross check against the proposed method.

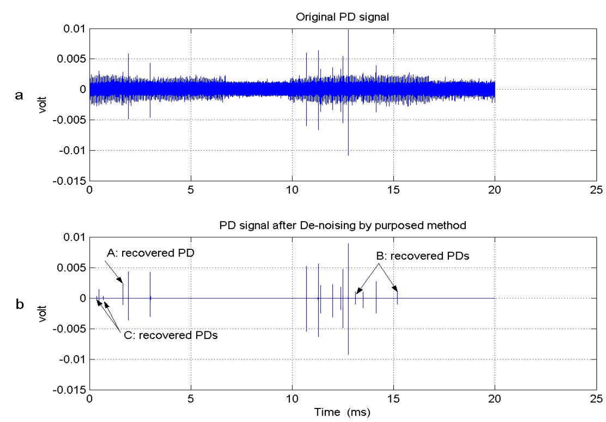

Figure 11. De-noising result with the new method. Figure 11a, Original PD signal with maximum 1500pC. Figure 11b, De-noised PD signal.

Figure 11 shows the result produced by the new WT de-noising method. The top trace is the polluted PD signal and the bottom trace is the de-noised PDs. In this case the PD level is higher than the noise level. The PD maximum value is 1500 pC. After de-noising, all noise is removed and all PD activity is retained. Some small PDs buried in noise have also been recovered, as indicated in the Figure 11b. Without this wavelet noise reduction these small PD pulses will be very hard, if not impossible, to detect through visual inspection. There are three sets of small PDs successfully recovered (A, B and C). Set A can possibly be discriminated from interference by visual inspection as the noise level here is around 2.2 mV and the set A PDs before de-noising are also around that level (about 300 pC). However sets B and C cannot be detected by visual inspection as their magnitudes are only 1 and 0.28 mV (corresponding to 150 pC and 47 pC). In this case, after de-noising, the PD peak magnitude recorded has been reduced from 9.8 mV to 8.9 mV, a 9.2% reduction.

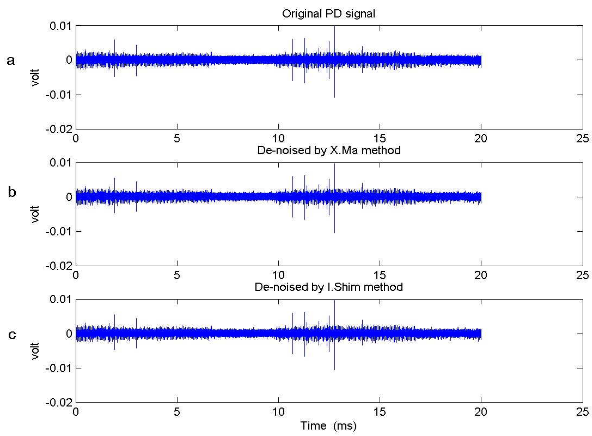

Figure 12. Results of the Ma and Shim methods. Figure 12a, original PD signal; Figure 12b, Ma's method; Figure 12c, Shim's method.

For a comparison the same original signal has been used to test the performance of the three previous WT de-noising methods. The results of Ma and Shim are shown in Figure 12. Those two WT de-nosing methods removed part of the noise from the polluted PD signal, however there is still significant noise left in the signal, which means small PD signals cannot be recovered. From Figure 12, it can be seen that some of the small PDs in sets A, B and C have been lost. In fact, 5 of 14 PD pulses are lost.

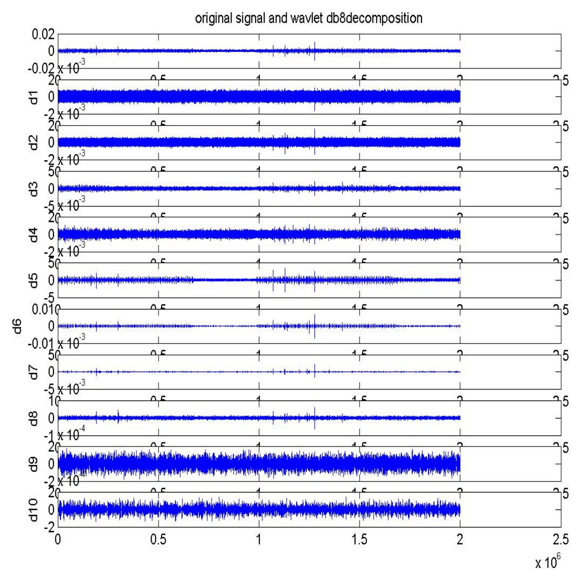

Figure 13. De-noising result with the Satish method; Top trace is PD signal with noise; from second to the last trace are detail levels 1 to 10 respectively.

The Satish method has also been applied and results are shown in Figure 13. Even using knowledge and experience the 5 small PD pulses cannot be detected.

5.3 CONFIRMATION OF PD SIGNAL VALIDITY

To recover PDs when the PD signals are smaller than the noise level is apparently convincing. However when PD levels are small, it is very hard to prove that the recovered signal is a PD or is not a PD. Therefore an experiment with a known internal PD calibrator signal was used to replace real PDs. The output value of this internal PD calibrator can be set by the user; however its advantage is that the phase position is fixed. As the original polluted data is also triggered and recorded in line mode, no matter how high the calibrator signal is they appear in the same phase position.

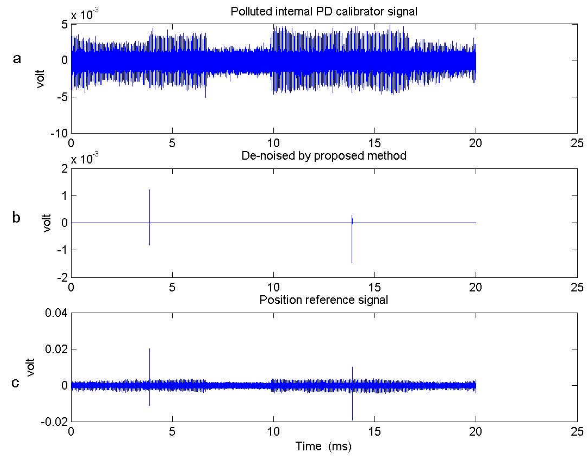

Figure 14. PD Calibrator pulse recovery. Figure 14a, polluted signal, Figure 14b, de-noised 30 pC calibrator signals, Figure 14c, 3000 pC calibrator signal as a position reference.

Figure 14 shows 30 pC internal PD calibrator signals that were successfully recovered by the WT de-noising method proposed in this paper. There are two 30 pC calibrator pulses behind excessive noise as shown in Figure 13a. Figure 13b shows the two 30 pC de-noised calibrator pulses. Figure 13c shows two 3000 pC calibrator pulses. Comparing the middle trace and bottom trace it can be found they are exactly in the same position, which proves that the de-noised signals are the original PD calibrator signals. It should be noted that PD would suffer great attenuation when it travels from the original site to the sensor and the calibrator signal used in this work might have different propagation characteristic to a real PD signal. Thus 30 pC sensitivity might not be easily achieved during the on-site measurement.

For a comparison the other three WT de-noising methods also have been tested using the same data. The results are shown in Figures 15 and 16. In Figure 15 are shown the original polluted PD signal, the de-noised signal by using Ma's and Shim's methods and the 3000 pC position reference signal.

From Figure 16, the PD pulses can be extracted by adding D7, D8 and D9 together. However the PD magnitude reduction is around 15% compared with the 10% of the new method.

By comparing Figures 14, 15 and 16 it can be seen that the new method and Satish's method are capable of recovering the 30 pC PD pulses, which has greatly increased measurement sensitivity even when high level noise is present, while the other methods cannot.

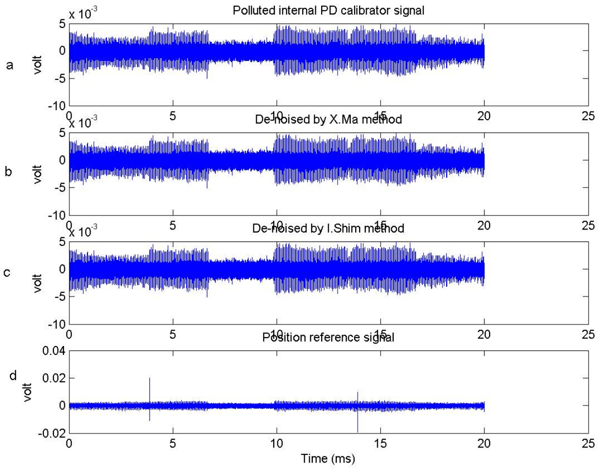

Figure 15. Calibrator pulse recovery with other methods. Fig15a, polluted signal; Fig15b, Ma method; Fig15c, Shim method; Fig15d, 3000pC position reference.

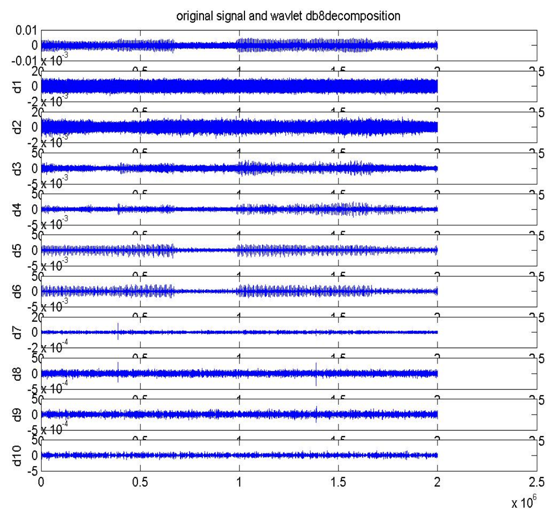

Figure 16. PD calibrator pulse recovery using the Satish method; Top trace is polluted PD signal; from second to the last trace are detail levels 1 to 10.

All of the three previous de-noising methods have been proved to be effective for off-line PDs measurement but not for on-line systems. The on-line PD measurement noise characteristics are different to those in an off-line system. For off-line PDs measurement WT de-noising methods are mainly used to remove some abrupt changes and to recover the original smooth waveform. Those methods are efficient for signals that have only a few nonzero wavelet coefficients. These signals have a sparse wavelet representation (suggested by [25]). However, in on-line measurement, the noise brings more nonzero wavelet coefficients than PDs and those coefficients are even higher than the PD coefficients.

Another reason why those methods are not suitable for on-line PDs measurement can be explained from consideration of the noise. Amplifier, oscilloscope and ambient noise are white noise, but noise from the power supply is not white noise. As a result overall noise effects and WT coefficients after WT decomposition are not Gaussian or even not close to a Gaussian model. Therefore those WT de-noising methods based on a Gaussian noise model are not suitable for on-line PD measurement. Figure 17 shows a standard zero mean Gaussian white noise distribution and on line PD measurement noise distribution (on level D1). It can be found between Figure 2 and Figure 17 that PD measurement system white noise and on-line measurement interference have completely different distributions. For on-site/on-line testing corona discharge presents large decomposition coefficients, sometimes much larger than for the actual PD coefficients. Therefore the PD and noise WT coefficients cannot be described by a standard Gaussian model, where it is assumed that, under the WT process, PD-related coefficients present a larger magnitude with a small number while the noise-related (corona) coefficients present a smaller magnitude with a large number.

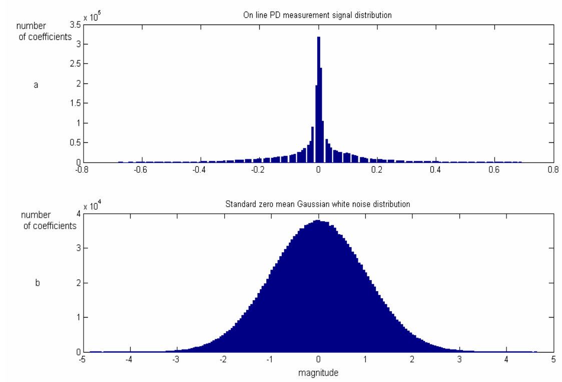

Figure 17. Noise distribution histogram. Top trace Figure 17a is the on line PD measurement noise distribution, bottom trace Figure 17b is standard zero mean Gaussian white noise model.

However with proposed method, PD could be distinguished from the excessive interference provided noise coefficients are not larger than PD coefficients at all scales or levels. The proposed method carries out a multi-level comparison. It extracts PD activities from the level where PD coefficients are larger than noise coefficients. In the levels where noise coefficients are higher than PD, those PD coefficients are set to zero for reconstruction. It is similar to Satish' visual inspection in some way. This method would not discriminate PD signal from noisy background if noise coefficients were larger than PD at all levels, which means noise components are larger than PD in any frequency band. Fortunately this is a very rare case.

6 DISCUSSION AND CONCLUSIONS

The major problem that confronts on-line monitoring of PD activity in power cables is EM noise, which can occur from a number of possible causes. While it is possible to detect high level PD signals in such situations using routine filtering techniques, the minimum PD magnitudes that are measurable with such techniques are so high that failure may be imminent. To monitor cable condition and to be able to assess insulation degradation trends requires better sensitivity in PD detection and this requires better noise rejection techniques. In the case of older XLPE cables where water trees are a problem, the transition from water trees to the detectable PDs of electrical trees is so rapid that alarm-based continuous on-line PD monitoring is needed to detect the onset of electrical trees and thus to prevent possible major cable failure.

Wavelet transform de-noising methods improve our capability to detect PDs signal in noisy environments. In this paper a new method of wavelet processing has enabled 30 pC PD signals to be detected in noise levels higher than the PD signals. This has greatly increased the PD measurement sensitivity. Two crucial issues in WT de-noising have been analyzed. Biorthogonal wavelet basis functions with linear phase characteristics have been proposed. The reason for selection of Biorthogonal and their advantages have been analyzed.

Some previous WT de-noising threshold value selection methods have been reviewed in this paper. It has been shown that those methods are not adequate for on-line application. Those methods are efficient for removing white noise and DSI, where is mainly aimed to remove some abrupt changes and to recover the original smooth waveform. In on line PD measurement interference brings more and higher WT coefficients than PD signal. Some of the existing WT de-noising methods are developed based on the assumption that noise can be described by Gaussian model. However on line PD measurement shows noise is not always to be a Gaussian distribution. Shim and Ma proposed threshold value selection rules are highly related to the numbers of data as shown in equation (2) and (3). Thus the sampling frequency and sampling period are very crucial for further de-noising processing.

A new WT de-noising threshold value selection rule has been proposed which does allow application to on-line monitoring, the details of its application for on site/on line PD measurements will be introduced in an accompanying paper [24]. The results produced by previous WT de-noising methods have been compared with the new method. The results show that this new fully automatic WT de-noising method can handle high noise levels and recover low level PD signals from noise which is of greater magnitude than the PDs. As this method can process the data which is recorded after triggering by line mode instead of being triggered by that part of the signal which is greater than the noise, it has much greater flexibility as in the latter case an experienced operator is required to ensure triggering by the right signal.

These tests demonstrate that the proposed wavelet de-noising technique will provide much better sensitivity than existing methods and will be able to be used for on-site/on-line applications, while previous methods mainly target, and are only suitable for, off-line tests. This new wavelet de-noising technique is capable of dealing with on-site/on-line PD measurement.

In this paper (Part 1), a novel WT de-noising algorithm was introduced based on continuously modeling noise performance. It focuses on the method of how to determine the WT threshold value and selection of the basis function. It also provides a comparison, using laboratory simulation data, between the proposed method and other published methods. The following paper (Part 2) will outline the methods of practical application of the proposed technique to on-line and on-site situations. In particular, results of the application of the proposed method to on-line tests on 11 kV cables will be demonstrated [24].

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REFERENCES

[1] IEC 60270-2000, "High voltage test techniques-partial discharge measurements".

[2] S. Boggs and J. Densley, "Fundamentals of Partial discharge in the Context of Field Cable Testing", IEEE Electr. Insul. Mag., Vol. 16, No.5, pp.13-18, 2000.

[3] I. Shim, J.J. Soraghan, and W. H.Siew, "A noise reduction techniques for on-line detection and location of partial discharges in high voltage cable networks", IEE Meas. Sci. Technol., Vol. 11, pp. 1708-1713, 2000.

[4] B.T. Phung, Z.Liu, T.R. Blackburn and R.E. James, "On-line partial discharge measurement on high voltage power cables", Int. Symp. High Volt. Eng.(ISH): IEE publ. No.467, Vol. 4, pp.328-332, 1999.

[5] I. Shim, J.J. Soraghan, and W.H. Siew, "Digital signal processing applied to the detection of partial discharge: an overview", IEEE Electr. Insul. Mag., Vol.16, No. 3, pp 6-12, 2000.

[6] V. Nagesh and B.I. Gururaj, "Evaluation of Digital Filters for Rejecting Discrete Spectral Interference in On site PD Measurement", IEEE Trans. Elect. Insul. Vol.28, pp.73-85, 1993.

[7] H. Zhang, T.R. Blackburn, B.T. Phung and Z. Liu, "Signal processing of on-line partial discharges measurements in HV power cables", Australasian Universities Power Engineering Conf., Brisbane, Australia, Paper ID 161, 2004.

[8] A.K. Peters, *The World According to Wavelets,* Wellesley, 1996.

[9] Y. Meyer, *Matlab help file*, The Mathwork Inc., Release 13, 2002.

[10] O.Rioul and M.Vetterli, "Wavelet and signal processing", IEEE signal processing Mag.Vol..8, Issue 4, pp. 14-38, 1991.

[11] Y. Meyer, and S. Roques, Eds., *Progress in Wavelet Analysis and Applications*, Frontières Ed., 1993.

[12] Kaiser, G. *A friendly guide to Wavelets*, Birkhauser, 1994.

[13] L.Satish and B.Nazneen, "Wavelet-based de-noising of partial discharge signals buried in excessive noise and interference", IEEE Trans Diel. Elect. Insul., Vol.10, pp.354-367, 2003.

[14] X.D. Ma, C. Zhou and I.J. Kemp, "DSP based partial discharge characterization by wavelet analysis", IEEE 19th Int. Symp. On Discharge and Electrical Insultaion in Vacuum, Xi'an, China, pp. 780-783, 2000.

[15] X. Ma, C. Zhou and I.J. Kemp, "Interpretation of wavelet analysis and its application in partial discharge detection", IEEE Trans. Diel. Elect. Insul., Vol.9, pp.446-457, 2002.

[16] W. Hang, T. Kexiong and Z. Deheng, "Extraction of partial discharge signals using wavelet transform", Proc. 5th Intern. Conf. Properties and Applications of Dielectric Materials, Seoul, Korea, Vol.1, pp. 322-325, 1997.

[17] Y. Ming and S. Birlasekaran, "Characterization of Partial Discharge Signals Using wavelet transform and statistical techniques", IEEE Intern. Sympos. Electr. Insul., Boston, MA, USA, pp. 9-13, 2002.

[18] I. Shim, J.J. Soraghan, and W.H. Siew, "Detection of PD utilizing digital signal processing methods, part 3: open-loop noise reduction", IEEE Electr. Insul. Mag., Vol, 17, No.1, pp.6-13 , 2001.

[19] Y.Tian, P.L. Lewin and A.E. Davies, “Comparison of on-line partial discharge detection methods for HV cable joints”, IEEE Trans. Dielectr. Electr. Insul., Vol.9, pp.604-615, 2002.

[20] S. Mallat, “*A Wavelet Tour of Signal Processing*”, Academic Press. 1998.

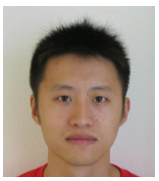
[21] S. Mallat, "A theory for multi-resolution signal decomposition: the wavelet representation", IEEE Patt. Anal. Mach. Intell., Vol. 11, pp. 674-693, 1989.

[22] H. Zhang, T.R. Blackburn, B.T. Phung and Z.Liu, “Application of signal processing techniques to on-line partial discharge detection in cables”, Intern. Conf. Power System Technology, Paper No. MB7.2D.L, 2004.

[23] D.L. Donoho, “De-noising by soft-thresholding”, IEEE Trans. Information Theory, Vol. 41, pp. 613-627, 1995.

[24] H. Zhang, T.R. Blackburn, B.T. Phung and D. Sen, “A Novel Wavelet Transform Technique for On-line Partial Discharge Measurements, Part 2: On-site noise rejection application”, submitted to TDEI, 2006.

[25] M. Misiti, Y. Misiti, G. Oppenheim and J. Poggi, W*avelet Toolbox Manual-User’s Guide*”, the Math Works Inc., USA, 1996



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