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Level dependent partial discharge signal de-noising using stationary wavelet transform

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PD monitoring is an effective tool to evaluate the insulation condition of power electrical equipment. However, the major challenge during PD measurement at site is that PD signals are severely affected by external noises and disturbances like white noise, random noise, Discrete Spectral Interferences (DSI), which are generated due to broadcasting stations, stochastic noise and pulses from power electronics at site conditions. Extracting PD signals from these noises is a challenging task.This paper proposes a new method for selecting the mother wavelet based on the energy of the approximation coefficients. The coefficients are obtained using SWT by decomposing the extracted noisy signal to the maximum decomposition level which depends only on the length of the noisy signal. Hard thresholding is used as the threshold function and range dependent threshold estimator is used for obtaining the threshold value. For reconstruction of de-noised signal, the last level approximation coefficient and the thresholded 'details coefficient' are used. As most of the lower level details coefficients comprise of noises it can be discarded during reconstruction. A method for discarding noises during reconstruction is also proposed in this paper.

Keywords: *SWT, partial discharge, DWT, noisy signal, signal to noise ratio.*

1.0 INTRODUCTION

PD monitoring is an effective tool to assess insulation condition of high voltage equipment. However, during on-site measurements the PD signals are highly affected due to interferences like DSIs caused by radio transmission and power line carrier communication systems, periodic pulse shaped interferences caused by power electronics or other periodic switching, stochastic pulse shaped interferences caused by infrequent switching operations, random pulses due to harmonics from mains and white noise caused by thermal noise due to detection system itself poses a greater difficulty in determination and meaningful analysis [1].

Different de-noising techniques like, Fast Fourier Transform, Low- pass filters, Winger-Ville Distribution, Short-Time Fourier Transform, Least Mean Squares, Frequency-Domain Adaptive Filtering using DFT, Recursive Least Squares, Exponentially-Weighted Recursive Least Squares, Matched Filtering, Notch Filtering, Wavelet-based Thresholding (Discrete Wavelet Transform, Stationary Wavelet Transform, Wavelet Packet Transform, Second Generation Wavelet Transform and Dual Tree Discrete Wavelet Transform) have been proposed by researchers for de-noising PD signals. Discrete Wavelet Transform (DWT) and Stationary Wavelet Transform (SWT) have been frequently used to de-noise PD signals affected by high noise. But Stationary Wavelet Transform (SWT) has an advantage of being a time-invariant

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transform whereas classical DWT is not, which means that, even with periodic signal extension, DWT of a translated version of a signal is not the translated version of DWT of that signal, this is known as Pseudo-Gibbs phenomenon. Time invariance is achieved by eliminating the down-sampling and up-sampling process in DWT and up-sampling the filter coefficients by a factor of $2^{(j-1)}$ in the j^{th} level of the algorithm. SWT is a highly redundant scheme as the output of each level contains the same number of samples as the input, therefore for an N level decomposition there will be a redundancy of N in the wavelet coefficients. Figure 1 represents a 3 level decomposition structure of SWT.

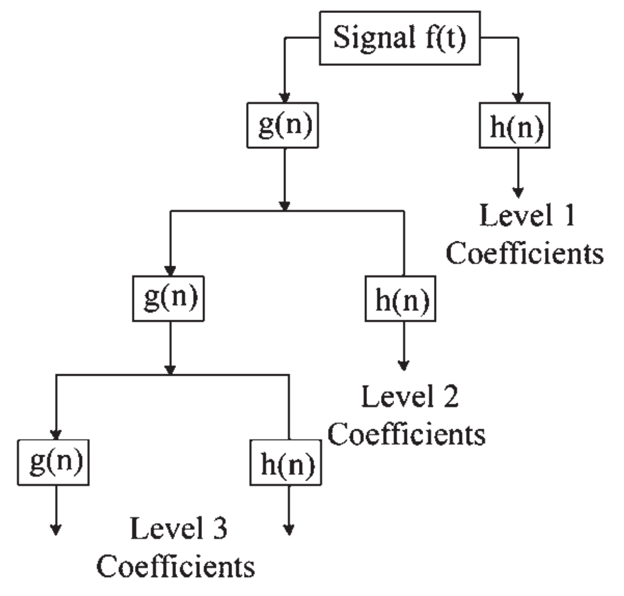

FIG 1: SWT DECOMPOSITION STRUCTURE

2.0 SIMULATION STUDIES

Using mathematical model, simulation studies were carried out to de-noise PD signals by both SWT and DWT methods. The parameters considered for evaluation are: Signal to Noise Ratio (SNR), Cross Correlation Coefficient (R_{xy}), Peak Amplitude Distortion (PAD) and Mean Square Error (MSE). The simulated results, and the results of comparison with DWT and de-noising results of field signals are discussed in the paper.

2.1 PD Signal Simulation

High frequency PD signals can be simulated mathematically using Damped Oscillatory Pulse (DOP) as proposed by Hao Zhang and et. al[2]. The DOP signal is expressed as.

$$S(t) = A(e^{-\alpha_1 t}\cos(\omega_d t - \varphi) - \cos\varphi) \quad ...(1)$$

Where A is the amplitude of the pulse, α_1 and $\alpha_2$are the decaying exponential functions which determine the different PD parameters like rise time, pulse width and pulse decay time, $\varphi=\tan^{-1}(\omega_d/\alpha_2)$ is the phase difference and $\omega_d=2\pi f_d$, $f_d$is the oscillation frequency of the DOP signal. In the present study the parameters chosen were $A=1\times10^{-5}$V, $\alpha_1= 3.07\times10^5 s^{-1}$, $\alpha_2=1\times10^4\ s^{-1}$and f_d is 250kHz. The simulation was carried out with MATLAB, where white Gaussian noise is simulated using 'wgn' function with a power of -70dBW and discrete spectral interference is simulated using a series of amplitude modulated signals as shown in the following equation.

$$DSI = \sum_{c=1}^{8}\left(1 + m\sin(2\pi f_m t)\right) \times A\sin(2\pi f_c t) \quad ...(2)$$

Where, A is the amplitude of the carrier wave, m is the modulation index, $f_m$is the frequency of modulation and f_c is the frequency of the carrier wave. The values of these parameters are assumed to be A = 3mV, m = 0.4, f_m= 100kHz, f_c = 10MHz to 80MHz.Random noise is simulated using 'rand' function by generating random numbers between 1×10^{-7}Vand 5×10^{-6}V.Periodic pulses are simulated using the 'pulstran' function by generating Gaussian periodic pulses at a frequency of 2MHzwith 50% bandwidth and a pulse repetition rate of7.8125µs. Stochastic pulse is simulated using the following equation.

$$S(t) = A(e^{-\alpha_1 t} + e^{-\alpha_2 t}) \times \sin(\omega t - \varphi) \quad ...(3)$$

Where A,α_1, α_2,φ and ω have the same sense as in equation (1), whereas their values are $A=1\times10^{-7}$V, $\alpha_1=5\times10^5\ s^{-1}$,$\alpha_2=1\times10^4\ s^{-1}$, $\omega=2\pi f$, f=650kHz is the oscillatory frequency of the stochastic pulse and $\varphi=\tan^{-1}(\omega/\alpha_2)$.The sampling frequency of the simulated signals is fixed at 64MHz. DSI, random noise, white Gaussian noise, periodic pulse type noise and stochastic pulse type noise are added to DOP signal to simulate the noisy PD signal.

2.2 Pd De-Noising Using Swt

SWT implementation requires addressing some important issues like mother wavelet selection, decomposition level estimation, threshold function selection and threshold value estimation. In this study mother wavelet is selected on the basis of an energy criterion given by the following equation

$$E = \sum_{i=1}^{k} cA_i^2 \qquad \text{...(4)}$$

Where, E is the energy and cA is the approximation coefficient. Using this criterion, the mother wavelet having highest energy at the highest decomposition level is chosen as the optimum mother wavelet for de-noising the PD signal.

The highest decomposition level to which a signal can be decomposed depends on the length of the signal and is expressed mathematically as follows.

$$DL = fix(\log_2 N) \qquad \text{...(5)}$$

Where, DL is the decomposition level, N is the length of the signal and fix indicates rounding of to the nearest integer towards zero.Hard threshold function defined by the following expression is used to threshold the details coefficient obtained by decomposing the signal.

$$f_h(x) = \begin{Bmatrix} x; & |x| > t \\ 0; & |x| \leq t \end{Bmatrix} \qquad \text{...(6)}$$

This threshold function retains those wavelet coefficients whose absolute values are greater than the threshold and discards those that are less than or equal to the threshold by setting them to zero. Modified range dependent threshold estimator is employed for evaluating the threshold value [3], which is obtained from the following equation.

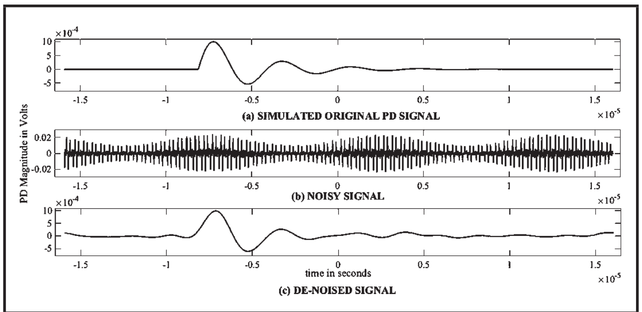

FIG 2: ILLUSTRATION OF DE-NOISING PERFORMANCE OF SWT

$$\lambda = \sigma_{mean}\sqrt{R\log(N)} \qquad \text{...(7)}$$

where, λ is the threshold value σ_{mean} is the mean absolute deviation and R is the amplitude range of the details coefficients and N is the length of the signal. Figure 2a, 2b and 2c show the simulated original PD signal, PD signal mixed with different types of noise and the de-noised signal obtained by applying SWT respectively.

After thresholding the details coefficients, the de-noised signal is obtained by reconstructing the thresholded coefficients. But all details coefficients are not required for reconstruction since most of the lower level details coefficients are components of noise. Therefore, a method for selecting the decomposition levels necessary for reconstructing the de-noised signal has to be obtained. This is achieved by including a frequency criterion which automatically selects those decomposition levels which contain the frequencies where the PD signal is concentrated. For wide-band PD detection IEC 60270 suggests a lower frequency in the range of 30 kHz to 100 kHz and an upper frequency of 500 kHz (max) [4]. This condition is employed to design the frequency criterion. The upper limit of decomposition level is obtained from equation (5). The lower limit of the decomposition level is obtained from the following equation.

$$DL_l = fix\left(\log_2\left(\frac{F_{max}}{F_{maxu}}\right)\right) + 1 \qquad \text{...(8)}$$

where, F_{max}=F_s/2 F_s is the sampling frequency of the PD detector and F_{maxu} is the upper frequency suggested in IEC 60270 which is 500 kHz.

Therefore, for reconstructing the de-noised signals details coefficients between DL_l to DL are used along with the approximation coefficient of DL.

3.0 PD DE-NOISING USING DWT

The same procedure is applied to de-noise the same PD signal using DWT. The de-noising performance of DWT is illustrated in Figure 3.Both DWT and SWT methods were capable in extracting PD signals from severe noise and their de-noising performance is evaluated using the following parameters.

$$SNR_N = 10\log\frac{\sum_{i=1}^{K} x^2(i)}{\sum_{i=1}^{K} n^2(i)} \quad ...(9)$$

$$SNR_D = 10\log\frac{\sum_{i=1}^{K} y^2(i)}{\sum_{i=1}^{K}[x(i)-y(i)]^2} \quad (10)$$

$$R_{xy} = \sum_{i=0}^{K-r-1} x\,(i)y(i+r) \quad ...(11)$$

$$PAD = \frac{x_{max}-y_{max}}{y_{max}} \times 100\%(12) \quad ...(12)$$

$$MSE = \frac{1}{K}\sum_{i=1}^{K}\left(x(i)-y(i)\right)^2 \quad ...(13)$$

Where, SNR_N is the noisy signal's signal to noise ratio, SNR_D is the de-noised signal's signal to noise ratio, R_{xy} is the cross correlation coefficient, PAD is the Pulse Amplitude Distortion, MSE is the Mean Square Error, x(i) is the original signal, n(i) is the noisy signal, y(i) is the de-noised signal, K is the number of samples, $x_{max}$is the amplitude of x(i) and y_{max} is the amplitude of y(i).

Table 1 shows the comparison between SWT and DWT methods. A third method using the automatic threshold estimator as suggested by X. Ma .et al [5] and the energy based criterion suggested in this study is also compared. It is clearly shown that SWT based method is as effective or is slightly better thanDWT based methods. The studies indicate that the performance of thresholding schemes are reduced when PD signal is mixed with periodic pulse type noise and stochastic pulse type noise.

TABLE 1

DE-NOISING PERFORMANCE PARAMETERS OF DIFFERENT METHODS

	SWT	DWT	DWT (X. Ma)
SNR_N	-29.4997 dB		
SNR_D	12.2765 dB	9.2788 dB	-0.0370 dB
R_{xy}	0.9697	0.9386	0.0176
PAD	0.7299%	-12.6590%	-1.4468×10^3
MSE	2.8518×10^{-9}	5.5495×10^{-9}	7.8917×10^{-6}

It is observed that Signal to Noise Ratio of the signal de-noised by SWT methodis at 12.2765dB, whereas DWT

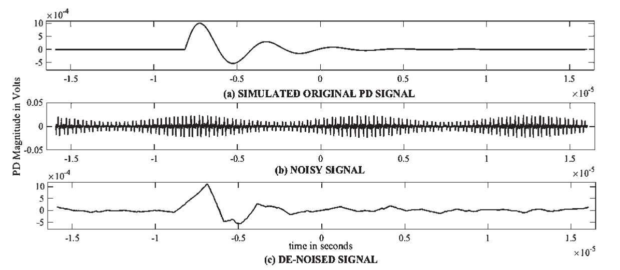

FIG 3: ILLUSTRATION OF DE-NOISING PERFORMANCE OF DWT

based method produced an SNR of 9.2788dB. The cross correlation coefficient of the signal de-noised using SWT is 0.9697 whereas that of DWT de-noised signal is 0.9386 which indicates improved similarity between SWT de-noised signal and the simulated PD signal. The Peak Amplitude Distortion value of the signal de-noised using SWT is at 0.7299%, and that of DWT de-noised signal is at -12.6580% which suggest there is an increase in amplitude of 12.658% in the DWT de-noised signal whereas the signal de-noised by SWT has a decrease in amplitude of just 0.7299%. The Mean Square Error of signal de-noised by SWT is at 2.8518×10^{-9}, whereas that of the signal de-noised by DWT is at 5.5495×10^{-9}, which indicates a lower error is obtained by de-noising the signal using SWT.

4.0 DE-NOISING ACTUAL PD SIGNALS

Corona discharge mixed with noise is generated by applying 3.73 kV to a Point-Plane electrode arrangement separated by an air gap of 10 mm. The noisy signal is then de-noised using the SWT and DWT methods explained above and their de-noising performance is evaluated using the Signal to Noise Reduction Ratio (SNRR) and Reduction in Noise Level (RNL) which are defined as follows.

$$SNRR = 10\log\frac{\sum_{i=1}^{K} y^2(i)}{\sum_{i=1}^{K}[n(i)-y(i)]^2} \quad ...(14)$$

$$RNL = 10\log\frac{1}{K}\sum_{i=1}^{K}\big(n(i)-y(i)\big)^2 \quad ...(15)$$

Where, n(i) is the extracted signal and y(i) is the de-noised signal. These two parameters are used for evaluating the performance of on-site signals because a reference PD signal is not available on-site. The de-noising performance of SWT and DWT on noisy corona pulses are illustrated in Figure 4.

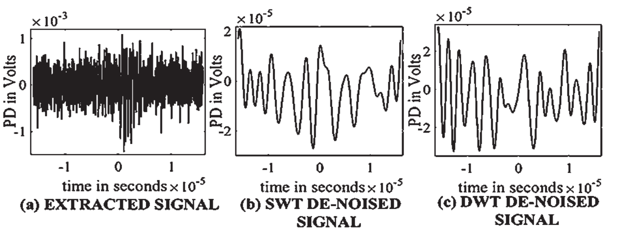

FIG 4: DE-NOISING PERFORMANCE OF SWT AND DWT ON CORONA DISCHARGES

The Signal to Noise Reduction Ratio of the signal de-noised by SWT is -30.1410 dB and that of the signal de-noised by DWT is -27.0233 dB which indicates that SWT retains the signal better and reduces noise more effectively than DWT. The Reduction in Noise Level of the signal de-noised by SWT is -160.2087 dB and that of the signal de-noised by DWT is -160.2155 dB which is almost the same indicating that both methods are capable of reducing noise. The peak values of the signals de-noised using SWT and DWT are 2.1231×10^{-5} V and 3.269×10^{-5} V respectively.

5.0 CONCLUSION

Both DWT and SWT are capable of de-noising simulated noisy PD signals. Whereas, SWT performed slightly better than DWT in de-noising simulated noisy PD signals. Both DWT and SWT performed well in de-noising corona discharges mixed with noise obtained from experimental studies.

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