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A COMBINATORIAL TECHNIQUE USING WAVELET AND EMPIRICAL MODE DECOMPOSITION FOR DENOISING PARTIAL DISCHARGE SIGNATURE

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ABSTRACT

Insulation diagnostics has been accepted and applied as a tool for condition assessment of high voltage equipment to identify the weak spots of the insulation. Partial discharge (PD) signal features indicate insulation condition of the equipment effectively. Extracting PD signal is one of the major tasks in PD measurement system. PD signals are characterized by a high-frequency current pulse from the noisy background. Noise detection and removal pose considerable challenges due to unknown sources that cause noise distribution. A Recent literature survey indicates there are only a few methods to detect a few of noises types. Though wavelet threshold function and Empirical Mode Decomposition (EMD) technique evolved as noise detection tools not much work related to the design of robust techniques which will lead to a simultaneous reduction of types of noise has been reported to literature.This paper proposes a novel hybrid structure that combines wavelet threshold function and EMD technique, which has been applied to both numerically simulated PD pulses and later to the observed data from the laboratory. Quality metrics Signal to Noise Ratio (SNR), Cross-Correlation (CC), Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR) are used to compare the results. The obtained result indicates the superior performance of proposed hybrid technique in denoising white noise pulses from the PD signatures. The average PSNR value of proposed hybrid technique for removal of white noises has been found to be more than the PSNR values of traditional methods. By fitting statistical distribution, the noise separated from the PD has been proven to be white noise.

Keywords: partial discharge, de-noising techniques, wavelet transform, EMD, wavelet based EMD.

1. INTRODUCTION

Effective condition monitoring is a conventional measure to improve the performance, longitivity and reliability of the high voltage equipment. Specifically in transformers, as it is subjected to several stresses inclusive of thermal, electrical and mechanical stresses, the dielectric strength of its insulation deteriorates. Though there are several diagnostic methods available they are not practical all the time and they can only be performed offline. After extensive research Partial discharge (PD) signal features have widely been used as a diagnostic measurement to analyze and monitor high voltage insulation system by identifying state of the insulation properties such as voids, cracks, and cavities which reduce the life of the equipment. So, detection of PD is an important task of a high voltage engineer to evaluate the system condition.

Partial discharges are imperfect break down, which partially bridges the insulation between the electrodes which occurs when the local electric field exceeds the threshold of the surrounding medium. PD detected by measuring the apparent charge, inception voltage and rate of repetition and so on by connecting a coupling capacitor in parallel or by suitable measuring impedance (RC, RLC) [1] in series with the test object. Though the amplitudes of the discharges are small it can cause gradual deterioration which may lead to a complete breakdown.

In this context, several researchers have concluded in their studies that online monitoring is suitable than offline because of its advantages such as no interruption in operational service and it also ensures continuous monitoring. However, regardless of the advantages difficulty encountered in online measurement and unshielded laboratories, there are high-level noises that inevitably exists during measurement due to switching of power electronics, corona pulses from overhead transmission lines, power frequency noises etc. So it is evident that valuable PD information might get suppressed by these noises which result in poor diagnostics of the system.

Interferences coupled with PD during measurement are classified as (i) Discrete spectral interference (DSI), (ii) white noise and Pulse Shaped Interference (PSI) [2]. Since PD measurement and analysis is important, to ensure the reliable operation of high voltage equipment, it is imperative to ascertain suitable methodology to suppress the noise and to recover the PD signal as the delay can cause further deterioration and false interpretation. This paper proposes a novel hybrid structure that combines wavelet threshold function and EMD technique, which has been applied to both numerically simulated PD pulses and later to the observed data from the laboratory and compared with the traditional methods.

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2. LITERATURE SURVEY

PD signal de-noising is the initiatory work in signal analysis. As stated before, PD data is highly coupled with background noises such as white noise, broadcast radio noise and impulse noises during measurement. These noises have distinct characteristics; substantial work has been carried out by researchers to suppress these noises. A number of filters such as Fourier Transform based digital filters, Adaptive Filters, Mallat's Algorithm, Notch Filters, Matched Filters have been utilized either in time domain/ frequency domain for de-noising PD data [3]. The major drawback in FT based filters is that it loses the original signal if new interference enters with different center frequency, the filter becomes unusable. From the reports, it is evident that these filters perform well for removal of narrowband interferences only. Mallat algorithm used to suppress narrow band interference [4] that affects PD during online measurement. The major drawback of Adaptive Filter is, it does not consist of constant filter coefficients and previous information is also unknown. In [5], the various issues related to PD measurement and the theory of matched filters for mitigating DSI and white noise from PD data discussed [6]. Though these methods have some advantages, they can perform well for any one type of noise only and as a result of large bandwidth of PD signal, it is concluded that real-time application is not possible.

Among the various de-noising techniques, Wavelet Transform (WT) based de-noising method has been identified as the most powerful for suppressing DSI and white noise. Thresholding based WT method also has some drawbacks such as band aliasing, loss in signal energy etc. Also, this technique suffers from the difficulty of choosing of mother wavelets and decomposition levels. To circumvent these difficulties, several techniques have been introduced to choose the mother wavelet such as spatially adaptive thresholding method, trial and error choice, energy based method, fast lifting scheme and the recent one is histogram-based threshold estimation. In research work [7] and [8] Empirical Mode Decomposition (EMD) method has been proposed as an effective method to de-noise because EMD is suitable for non-linear and non-stationary signal, which is similar to PD characteristics.

3. SIMULATION OF PD AND ADDITION OF NOISE

PD signals are a small electrical pulse, characterized as non-periodic impulses with time duration of 10^{-9} to 10^{-7}s. PD shape and other parameters such as duration of the signal, magnitude, repetition rate etc depends on type and location of PD, equipment size which is going to be tested and the type of measurement. PD measurements should be taken from noise/ disturbance free atmosphere.

The high voltage laboratories are generally shielded by using faraday cage, so the influence of external interference is not possible in measured data.

Besides, internal noises resulting from electronic devices and detection circuit impedance can distort and submerge the PD pattern recorded as a result of different insulation defects. As per the IEC standard, the permissible noise level is less than 50% of PD magnitude for accurate and sensitive measurement.

Depending on the measurement circuit, insulation failure and so on PD pulse models may differ at the measuring side. So to evaluate the denoising performance, as suggested by the researchers damped exponential pulse (DEP) realized by RC circuit and damped oscillatory pulse (DOP) realized by RLC circuit are numerically modeled by the following equations [1 and 2]. The waveforms are expressed by the following mathematical equation

$$\mathrm{DEP} = A(e^{-t/t_1} - e^{-t/t_2}) \quad (1)$$

$$DOP = A \times \sin(2\pi f_c t)\,(e^{-t/t_1} - e^{-t/t_2}) \quad (2)$$

In the equation, A corresponds to pulse peak value, t_1, t_2 are the pulse time constants and FC are the oscillatory frequency of the DOP pulse. In signal processing techniques, white noise is considered as a random signal with flat power spectral density, which has a normal distribution with zero mean and finite variance. In particular white noise (SNR=25db; mean=0; STD=2) is added to the simulated signal, to resemble actual PD signal corrupted with noise. The simulated PD corrupted with white noise is shown in the Figures (1-4).

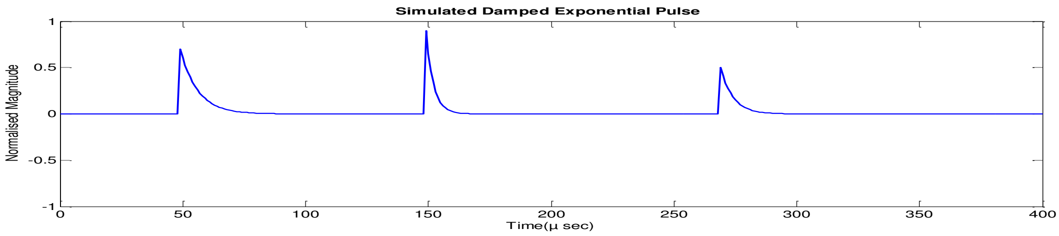

Figure-1. Simulated damped exponential pulse.

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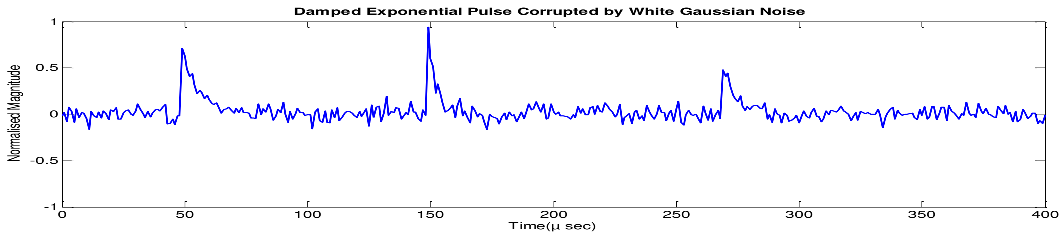

Figure-2. Damped exponential pulse corrupted by white Gaussian Noise.

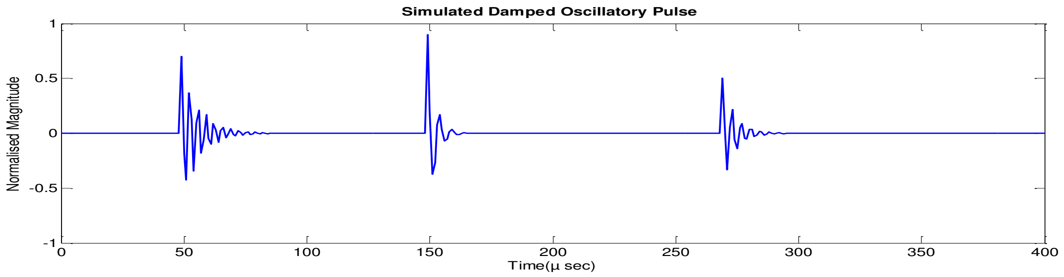

Figure-3. Simulated damped oscillatory pulse.

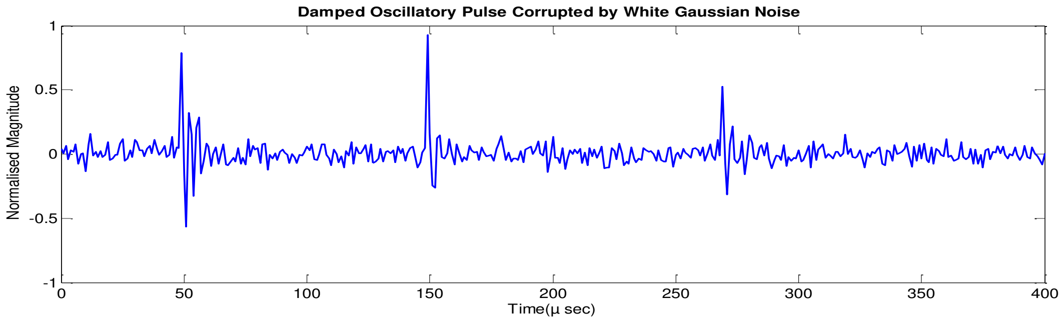

Figure-4. Damped oscillatory pulse corrupted by white Gaussian Noise.

4. DENOISING METHODS

4.1 Wavelet Transform

The wavelet transform is described as a small wave tends to be asymmetric and irregular in a wave shape. Wavelet Transform (WT) is preferred being a better tool for analysis of non-stationary signals. Like Fourier analysis, wavelet splits the signal into shifted and scaled version of the mother wavelet. An effective method applicable for discrete type signals like PD, as reported in the previous study, is Discrete Wavelet Transform (DWT). Another type of WT is Continuous Wavelet Transform (CWT), which is not suitable because it is computationally expensive and creates a lot of redundant data [13].

DWT consists of a pair of filters such as low-pass and high-pass filters known as Quadrature Mirror Filter (QMF). Decomposition is done in DWT by passing the signal through QMF and the signal is downsampled; as a result, the signal is split into low-frequency components (approximations) and high-frequency components (details) [14]. The approximation is again fed through the filters for further decomposition. The signal is reconstructed using Inverse Discrete Wavelet Transform (IDWT). Whenever the signal is down-sampled, the signal length is halved every time like ½, ¼ of the original signal, i.e. odd numbered elements are moved from the data and even numbers are preserved for generating a new set of coefficients.

Though the proposed technique has been accepted as a better one, since it has low processing time and better reconstruction, there are still some issues which are considered as the main problem to be sorted out. The algorithm of the wavelet transform is given in Figure-5 as a flowchart.

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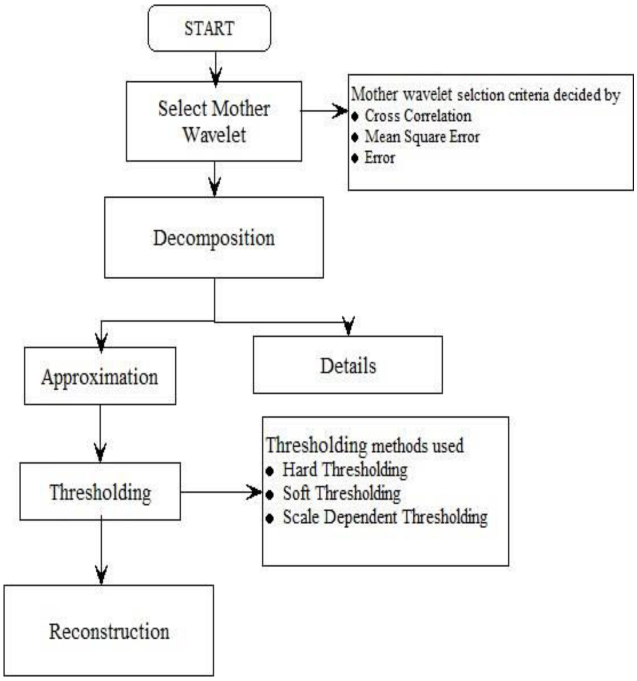

Figure-5. Wavelet transform algorithm flowchart.

4.1.1 Selection of mother wavelet

During the implementation of DWT, the main challenge is in selecting the optimum wavelet for decomposition. Till now a standard or general procedure is not available to select a mother wavelet [15]. As more than one mother wavelet with the same properties is often feasible, researchers have developed quantitative approaches to find the correlation between signal and mother wavelet. Wavelet families such as Haar, Daubechies (DB), Symlet (Sym), Biorthogonal (Bior) are so far used as basic functions in PD signal de-noising[16]. However, standard procedure or defined rules for selecting mother wavelet is yet to be developed. Researchers so far used any of the following metrics such as subband energy[15] or signal to noise ratio or cross correlation as the metrics to select the mother wavelet. Considering the above, the quality metrics Mean Square Error (MSE), Cross-Correlation (CC) and Error are calculated for the mother wavelets and the results are tabulated as below. By considering all the three metrics, based on the results, Db7 with level 5 is chosen as the best wavelet for denoising as it has high CC value and less error.

Table-1. Mother wavelet selection rules.

Wave name and level	CC value	Error	MSE
db5 (level 5)	0.9308	5.654×10^{-12}	6.5206×10^{-4}
Sym5 (level 5)	0.9214	2.8964×10^{-13}	1.2935×10^{-4}
db7 (level 5)	0.9333	3.77×10^{-12}	8.907×10^{-5}
db7 (level 4)	0.9308	2.293×10^{-12}	8.75×10^{-5}
Dmeyer (level 6)	0.9290	1.3592×10^{-5}	1.298×10^{-4}
Dmeyer (level 5)	1.0000	1.1796×10^{-5}	1.2365×10^{-4}

4.1.2 Selection of threshold

Thresholding of certain decomposition level coefficient is done by eliminating the coefficient less than the threshold value, which may create distortion in the reconstructed signal. So, choosing of threshold also takes an important role in de-noising [17]. Threshold techniques are mainly classified into local and global thresholding. In this, the local thresholding chooses single value as a threshold to be applied to all the coefficients, whereas the latter one chooses different values corresponding to each wavelet level. The common threshold functions are namely Hard Thresholding and Soft Thresholding [18].

In hard thresholding, the coefficients, whose absolute values are greater than the threshold are kept and those less than or equal are set to zero.

In soft thresholding, it sets the coefficients whose absolute values lower than the threshold to zero and shrink the other elements towards zero

4.1.3 Empirical mode decomposition

Empirical Mode Decomposition (EMD) is a method for analyzing non-linear and non-stationary signal in a time-frequency representation. It smoothens the non-smooth signal, i.e. the noisy signal in time domain is broken into a set of signals, from high frequency to low frequency which is known as Intrinsic Mode Functions (IMF). This decomposition process is known as a sifting process. Two conditions which define IMF Functions are i) Having the same number of zero-crossings and extrema, ii) Having symmetric envelopes defined by local maxima and minima [21].

From the IMF results, it is evident that the frequency content is more in the first IMF and less in the n^{th} IMF. Like wavelet thresholding, EMD eliminates the noise content from the data and only a few works are devoted to the processing of PD data. In this work, results are reported for noise corrupted PD signal based on the technique EMD incorporating wavelet thresholding procedures [8]. And the results are compared with other de-noising techniques for validation. The algorithm of EMD is explained in Fig. 6 as a Flowchart.

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4.1.4 Limitations of EMD and WT schemes

The main drawback in wavelet scheme is it that relies on the fact that, the signal energy is concentrated on only a few coefficients and noise energy is concentrated on only a few coefficients. So to access this, the basis function should be fixed, which does not match all type of real signals. Recently, Huang introduced the empirical mode decomposition (EMD) method as a new tool for analyzing non-stationary and nonlinear data. The main advantage of EMD is that the basis function is derived from the signal itself. The main drawback of EMD is the mode mixing which is defined as single IMF which may contain signals of widely disparate scales/ signal of similar scales residing in different IMF [22]. This mode mixing causes aliasing in time-frequency distribution and also makes the signal unclear [23].

4.1.5 EMD based wavelet denoising

By studying the filtering characteristics of EMD, it is clear that EMD and Wavelet transform have similar filtering techniques [24]. Like in wavelet transform the energy of the signal concentrates more likely in finer temporal scales and reduces towards the coarser ones. Here in this method, a trip point is calculated based on the energy distribution of the signal to separate the finer modes which are noise dominated. After selecting the IMF, as the filtering characteristics are similar wavelet thresholding rules are incorporated to remove noise from the IMF [25]. Figure-7 explains the algorithm of EMD based Wavelet denoising.

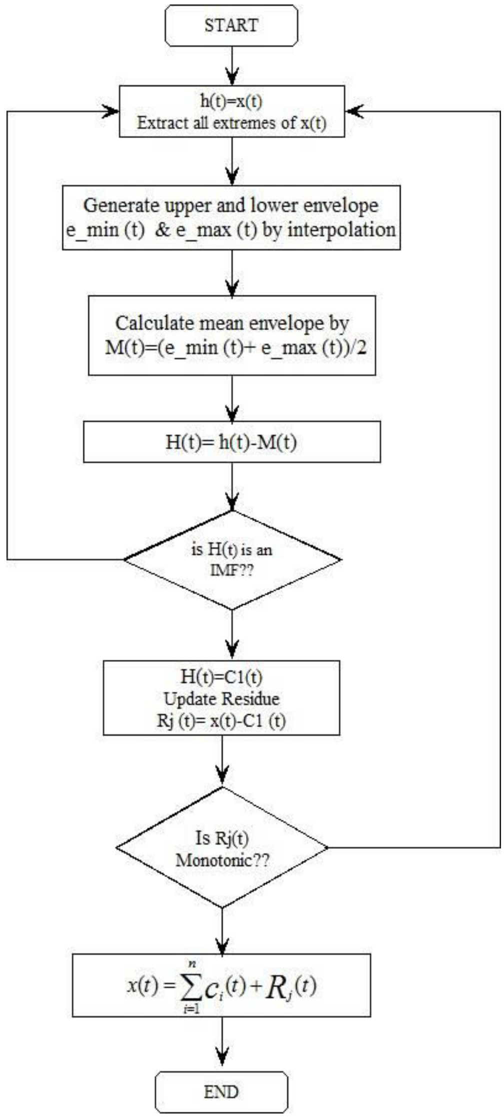

Figure-6. Empirical mode decomposition algorithm flowchart.

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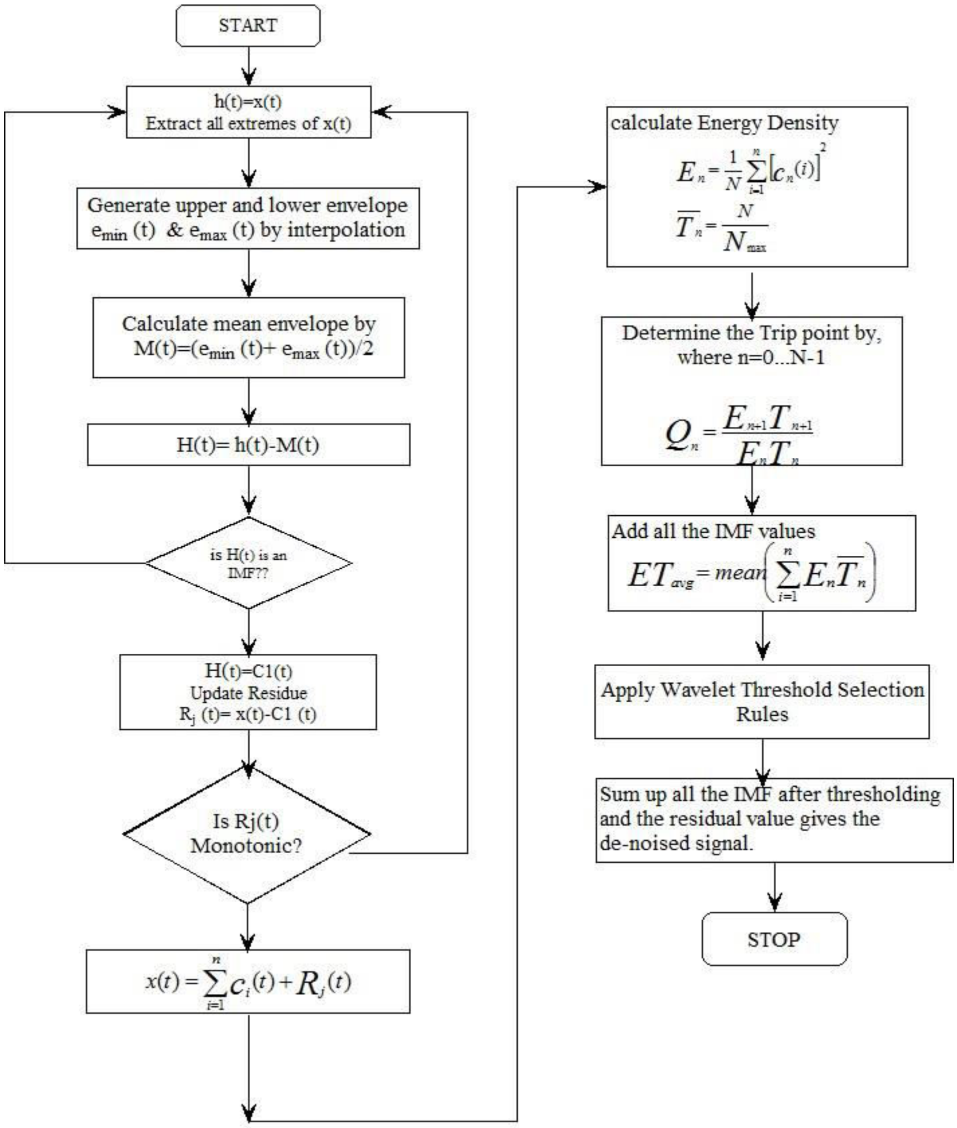

Figure-7. Wavelet transform based empirical mode decomposition algorithm flowchart.

5. SIMULATION RESULTS

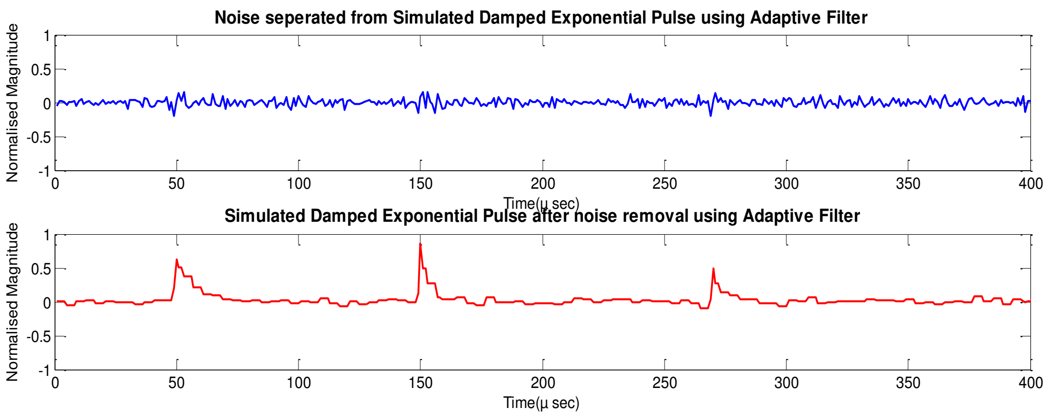

Figure-8(a) & 8(b). Separated noise and reconstructed data for simulated DEP using adaptive filter.

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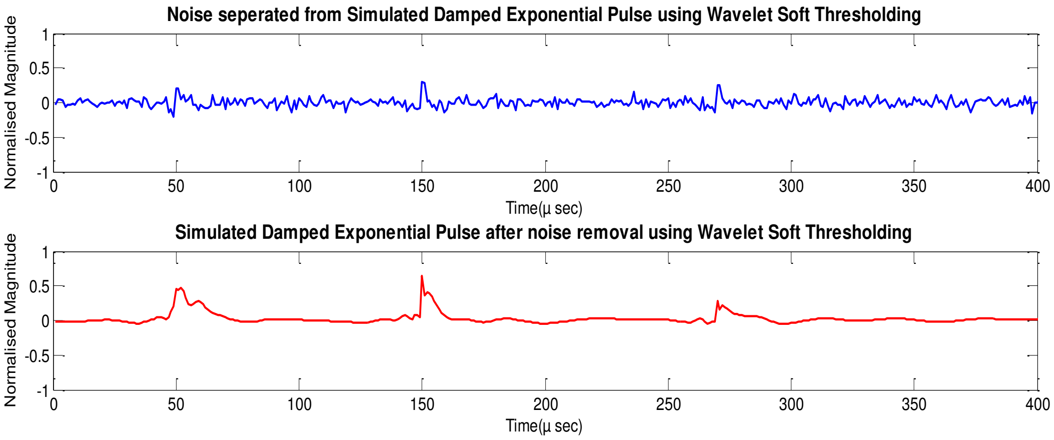

Figure-9(a) & 9(b). Separated noise and reconstructed data for simulated DEP using wavelet soft thresholding.

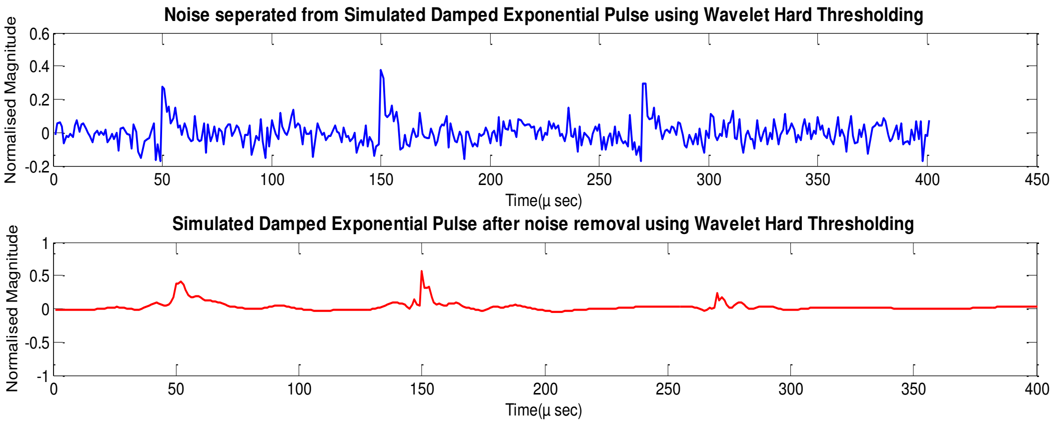

Figure-10(a) & 10(b). Separated noise and reconstructed data for simulated DEP using wavelet hard thresholding.

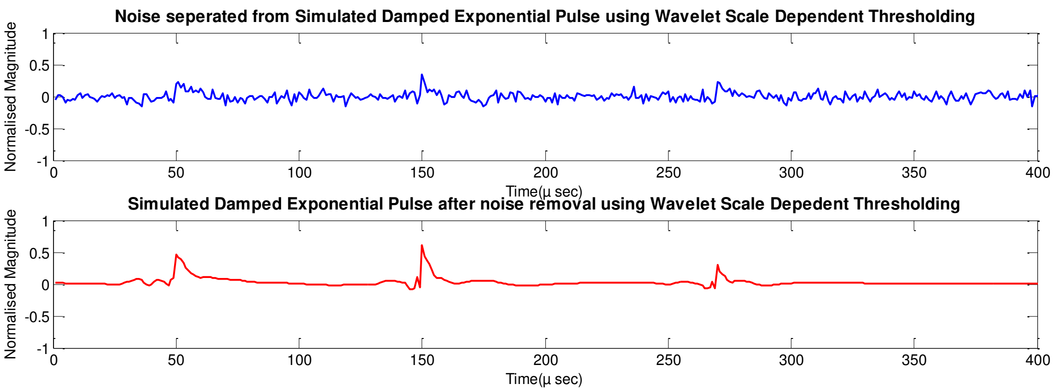

Figure-11(a) & 11(b). Separated noise and reconstructed data for simulated DEP using wavelet scale dependent.

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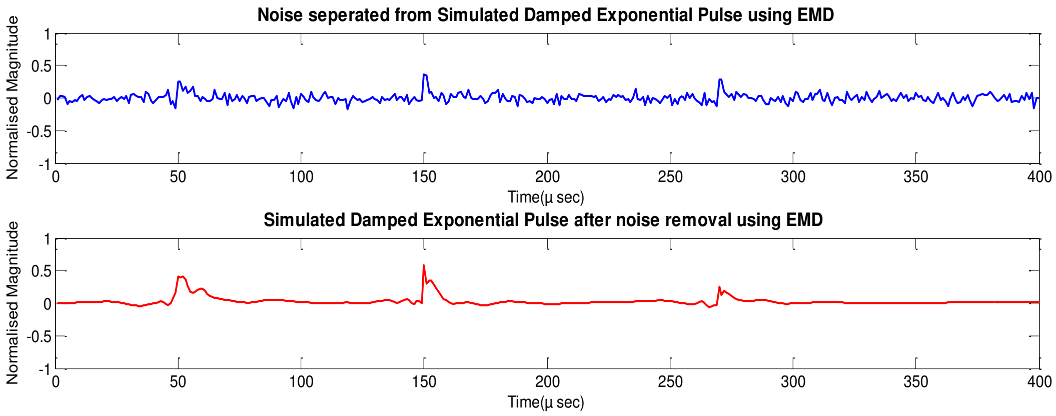

Figure-12(a) & 12(b). Separated noise and reconstructed data for simulated DEP using EMD thresholding.

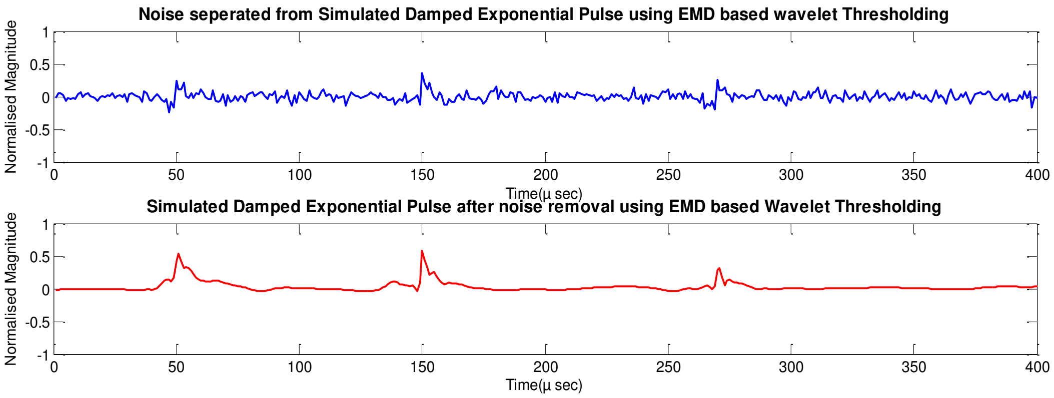

Figure-13(a) & 13(b). Separated noise and reconstructed data for simulated DEP using EMD based wavelet thresholding techniques.

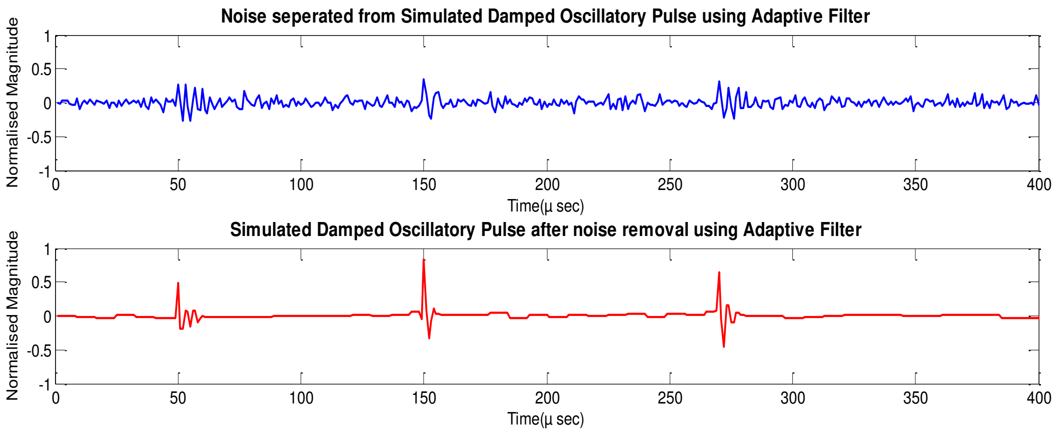

Figure-14(a) & 14(b). Separated noise and reconstructed data for simulated DOP using adaptive filter.

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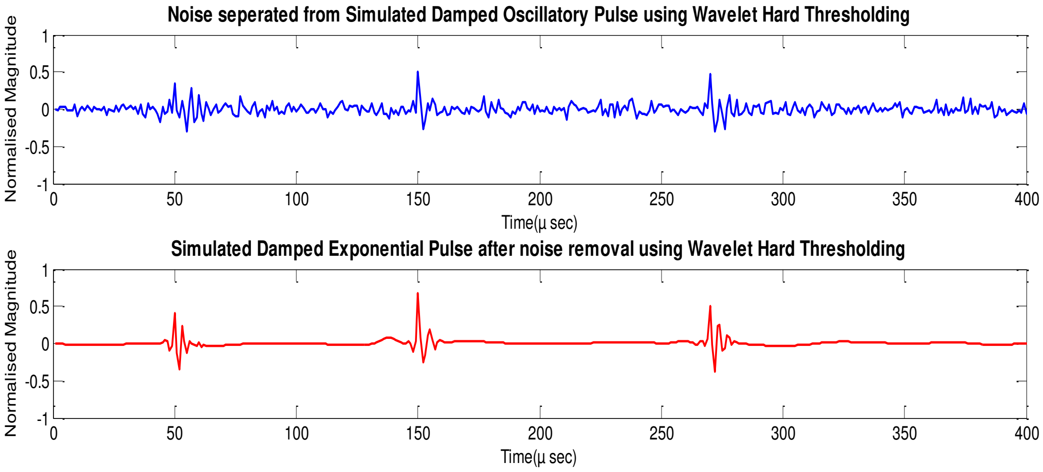

Figure-15(a) &15(b). Separated noise and reconstructed data for simulated DOP using wavelet hard thresholding.

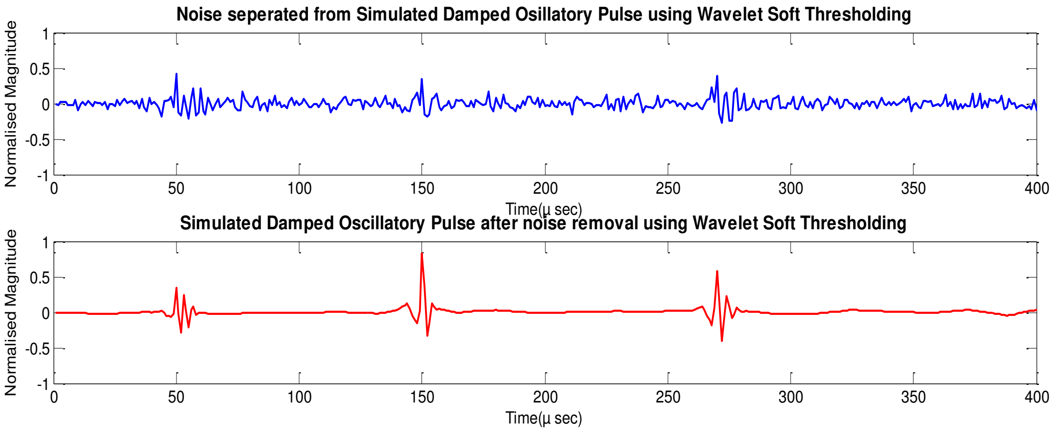

Figure-16(a)&16(b). Separated noise and reconstructed data for simulated DOP using wavelet soft thresholding.

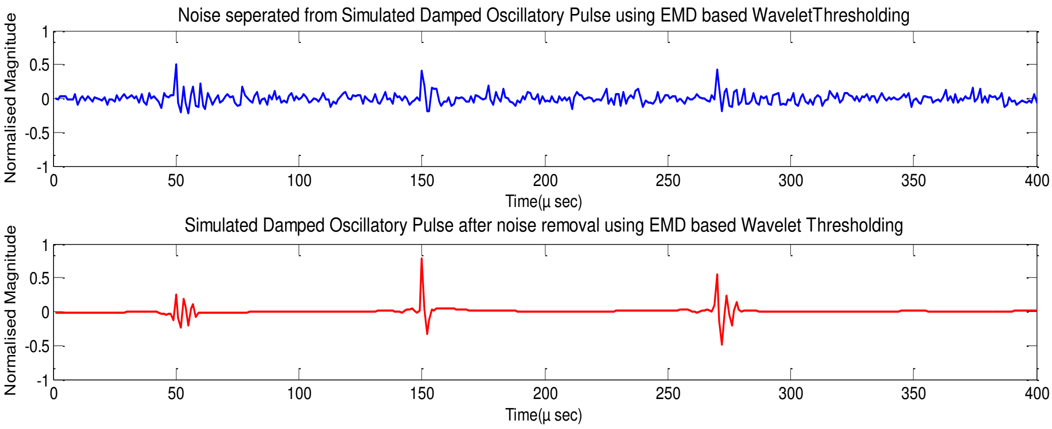

Figure-17(a)&17(b). Separated noise and reconstructed data for simulated DOP using wavelet scale dependent.

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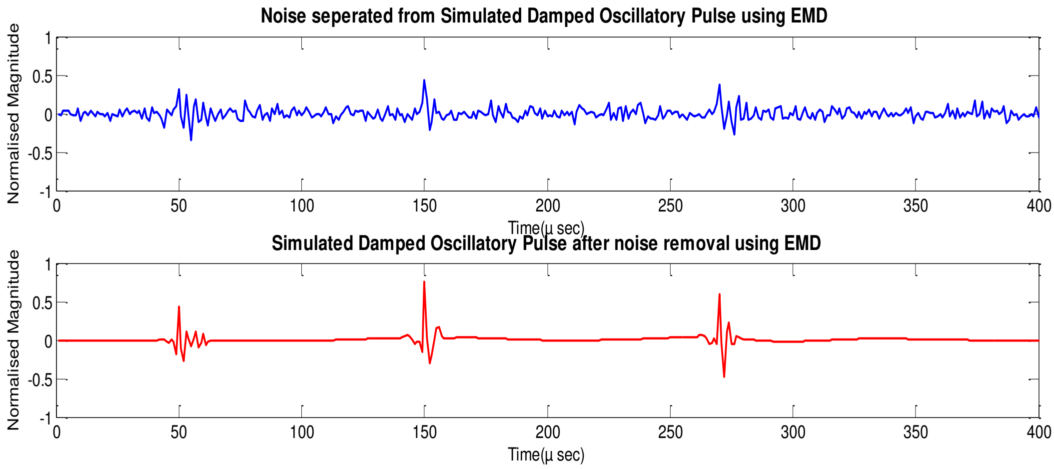

Figure-18(a)&18(b). Separated noise and reconstructed data for simulated DOP using EMD.

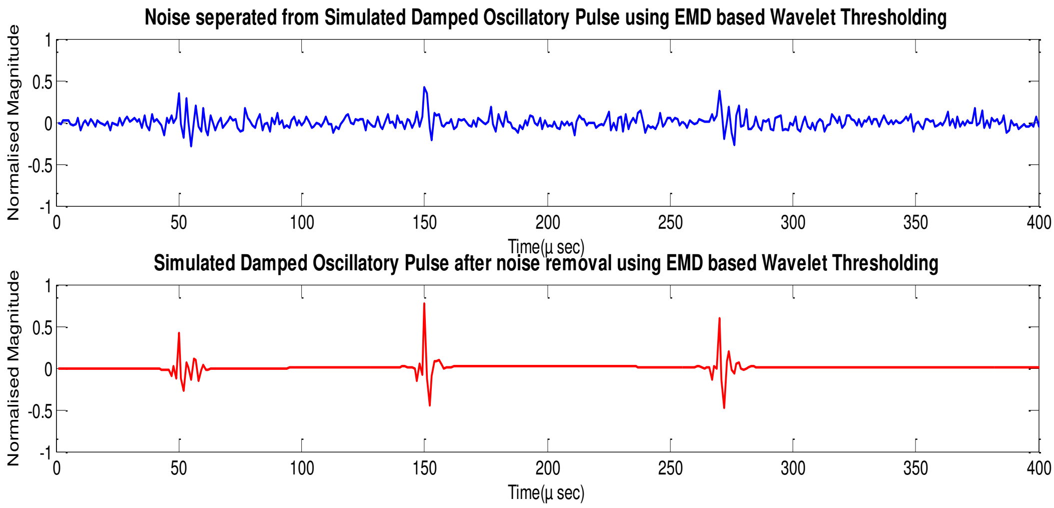

Figure-19(a) & 19(b). Separated noise and reconstructed data for simulated DOP using EMD + wavelet thresholding techniques.

6. DE-NOISING METRICS

Due to the fact that noise eminently affects the PD measurement, it is important to quantify the amount of noise present in the signal, which can be examined by different de-noising metrics. For the simulated DEP and DOP signals, to add the noise with specified range and to validate the method used to de-noise that signal, de-noise metrics is necessary[27]. The quality metrics used here reveals the amount of noise added as well as suppressed and evaluates the denoising techniques such as Signal to Noise Ratio (SNR), Cross-Correlation (CC), Mean Square Error (MSE), Pulse Amplitude Distortion (PAD), Signal to Reconstruction Error (SRR).

6.1 Signal to noise ratio

During denoising in addition to noise, sometimes frequency components near to noise frequency range are also eliminated. So to evaluate the denoising performance SNR is considered.

$$SNR(dB) = 10log_{10}\frac{\sum_{i=1}^{N} y^2(i)}{\sum_{i=1}^{N}[s(i)-y(i)]^2} \quad (3)$$

SNR implies the ratio of signal power to the noise power. After denoising, the positive value of SNR implies the greater power of signal compared to the noise and negative value SNR implies vice versa.

6.2 Cross-correlation

Cross-correlation between the signals is given by,

$$R_{xy}(r) = \sum_{n=0}^{N-r-1} x(n)y(n+r) \quad (4)$$

CC helps in depicting dependency relationship between original signal and denoised signal.

6.3 Mean square error

MSE indicates the amount of error present in the signal by measures the average of the square of the error between, original PD signal and the denoised PD signal. The equation of MSE is given by,

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(f(i) - R(i))^2 \tag{5}$$

6.4 Pulse amplitude distortion

It is determined by,

$$PAD(\%) = \frac{|x_{max} - y_{max}|}{x_{max}} \times 100 \tag{6}$$

Where X_{max} refers to the amplitude of PD pulse and Y_{max} is the amplitude of the denoised PD signal. Low PAD depicts the effectiveness of the denoising method

6.5 Signal to reconstruction error

It is calculated by,

$$SRER(dB) = 10log_{10}\frac{\sum_{i=1}^{N}s^2(i)}{\sum_{i=1}^{N}[s(i) - y(i)]^2} \tag{7}$$

Where s(i) is reference signal and y(i) is a denoised signal. For a good denoising method, it should have high SNR, SRER, and CC value. MSE and PAD value should be low.

7. COMPARISON OF METHODS

Signals generated by simulation studies and as well as observed from the lab are considered for denoising process. 200 data samples are taken into account from the measured PD data to perform the denoising process In order to assess the performance effectiveness of EMD based wavelet thresholding technique, it is compared with other techniques (FFT, AF, Wavelet) under different circumstances and the results are outlined.

Figure-8 to Figure-13 represents the denoised DEP signal and Figure-14 to Figure-19 represents the denoised DOP using different methods proposed in this study. From the figure, it is clear that FFT and AF failed to reproduce the signal effectively and give low SNR value. Table-2 shows the metrics used to compare various denoising algorithms. The third technique wavelet performed well compared to the previous methods and EMD produced slightly better results compared to DWT based filtering method. As the conclusion from the results, EMD based wavelet thresholding shows the strength in denoising as compared with other traditional techniques, which eliminates noise effectively and highlighted in Table-2. Since the technique performed well for simulated study, it is used for the laboratory data for denoising the PD signatures.

Table-2. Denoising metrics of simulated PD data.

Damped exponential pulse de-noising metrics						
	SNR	**SRR**	**CC**	**MSE**	**PAD**	**PSNR**
FT	4.35	10.43	0.78	2.84	52.75	13.625
AF	3.16	8.65	0.75	3.46	53.54	12.62
WT-ST	11.42	11.38	0.89	1.87	47.92	18.25
WT-HT	11.34	11.47	0.88	1.65	53.12	19.19
WT-SD	12.63	11.85	0.89	1.43	32.12	19.19
EMD	14.02	14.06	0.92	0.74	37.53	22.02
EMD- WT	16.25	15.24	0.92	0.15	12.54	22.32
Damped oscillation pulse de-noising metrics						
FT	11.256	5.4	0.72	2.31	34.3	12.1258
AF	9.2568	3.23	0.67	3.42	40.5	11.6245
WT-ST	15.987	8.64	0.83	1.19	30.2	19.4231
WT-HT	16.274	9.78	0.84	1.13	22.6	19.1254
WT-SD	15.268	9.43	0.87	1.02	23.10	21.127
EMD	16.589	10.32	0.89	0.12	15.3	22.4732
EMD- WT	18.264	12.50	0.93	0.12	10.4	25.2346

8. EXPERIMENTAL RESULTS

In this research, the electrical method has been used in order to generate PD signals similar to that of insulation fault in the transformer winding occurring during online PD. Two types of electrical detection methods are direct probing and RF emission method. In direct probing capacitive coupler is connected for calibration. The calibration factor is determined by feeding a known charge pulse to the equipment under test. The pulses are in the range of kHz and last for less than one second. As the work is identification and removal of noise from PD pulse, voltage-dependent PD is not essential. So

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producing a simple partial discharge across the small portion of the insulation the following testing method is used for electrical PD generation in a transformer winding.

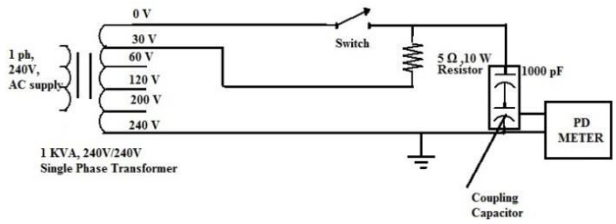

Figure-20. Test circuit used for PD generation in transformer.

In a 1KVA 240V/240V, single phase transformer is chosen as a specimen for the test. Between the tapping 0V- 30V, a 5 Ω, the 10W resistor is connected along with the switch. To limit the current flow during the closing of the switch effectively, within the current carrying capacitor of the transformer a 5 Ω, the 10W resistor is used. By closing and opening the switch suddenly for a very short duration, discharge is created between 0V and 30V tapping through the 5 Ω, 10W resistor and observed through the PD meter.1000pF capacitor is used as measuring impedance/ coupling capacitor in the circuit. The pulse shape recorded in the data acquisition unit provides information about the severity of the damage in the winding insulation. Though electrical method helps in real time monitoring of transformer, the main limitation is that PD signals are hindered by noises, which will lead to a false prediction about the insulation deterioration.

Figure-21 to Figure-23 show the PD signal observed from the laboratory which contains noise in it. As like the previous signals, the traditional techniques didn't retain the signal properly after denoising and it is also proved by the quality metrics which is highlighted and tabulated in Table-3. The other methods based on wavelet (soft, hard, scale- dependent) techniques perform more or less in the same way. (i.e. Though there are some variations in the quality metrics value, we can't find any remarkable difference in their reconstructed signal by visual inspection). By metrics and by seeing the signal after denoising, it is clear that EMD based on wavelet thresholding techniques performs well in all the three cases and gives satisfactory results.

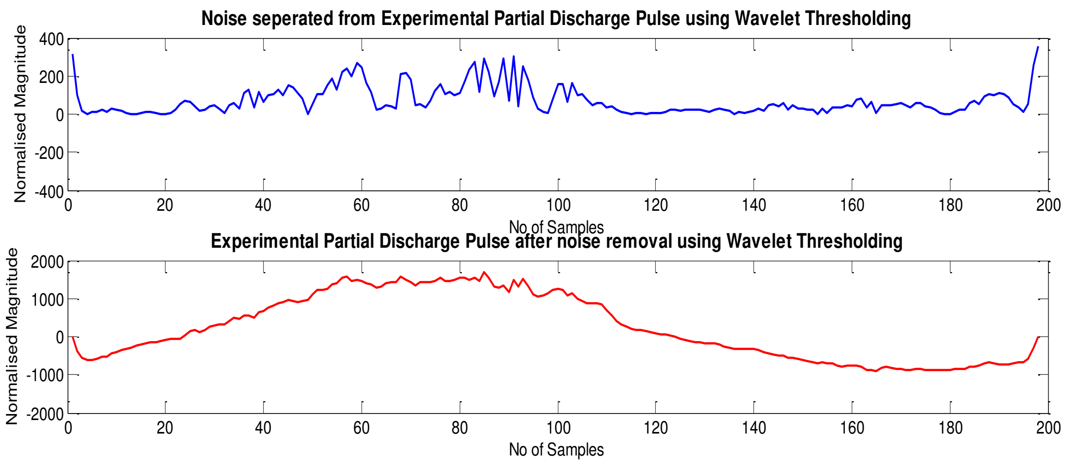

Figure-21(a)&21(b). Separated noise and reconstructed data for observed PD data using wavelet thresholding techniques.

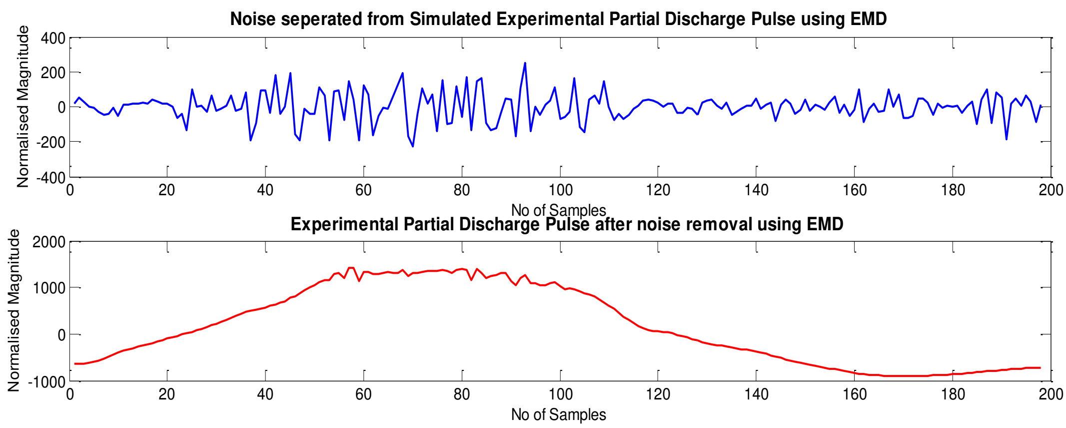

Figure-22(a)&22(b). Separated noise and reconstructed data for observed PD data using EMD.

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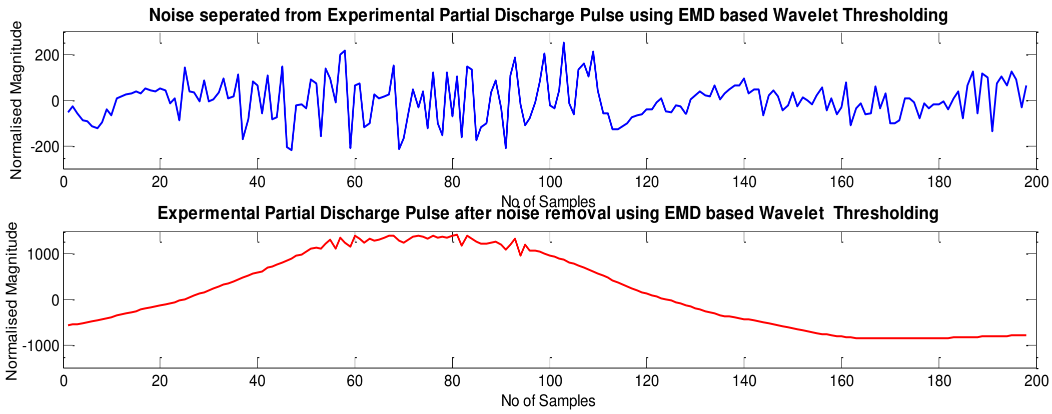

Figure-23(a)&23(b). Separated noise and reconstructed data for observed PD data using EMD.

Table-3. Denoising metrics of measured PD data.

Recorded PD signal de-noising metrics						
	SNR	**SRR**	**CC**	**MSE**	**PAD**	**PSNR**
FT	12.34	9.23	0.842	2.78	30.81	11.1387
AF	10.56	5.06	0.631	3.26	50.53	10.9265
WT-ST	19.27	12.84	0.930	2.20	20.69	18.9325
WT-HT	18.23	12.68	0.932	1.95	20.18	19.2786
WT-SD	19.72	12.75	0.933	1.92	15.63	19.2718
EMD	22.05	18.96	0.92	1.42	3.42	22.7417
EMD-WT	23.24	20	0.95	0.90	1.12	27.7418

9. CONCLUSIONS

Noise elimination from the obtained PD data is the most challenging work. In this study, the real-time and simulated PD signals are denoised by using four different methods such as FFT, AF, WT, and EMD. Wavelet-based denoising is widely used, but some limitations are there in implementing wavelet. The main problem to be resolved is the selection of mother wavelet and thresholding. Most of the studies conceded that the selection is based on CC value and trial and error method. As we don't know the characteristics of the PD signal, the CC value might not give the best result every time; so other metrics such as MSE and energy values are also considered in this study to choose the mother wavelet. In wavelet thresholding, predetermined value is used as the threshold, to set the coefficients below the threshold values to zero. The obstruction in using wavelet is the basis function needs to be destined, so it may not match all the real signals. But EMD is data driven and adaptive, so no need for prior knowledge of the signal. A hybrid denoising method, presented here is based on EMD and wavelet thresholding. The adaptive nature of EMD is combined with wavelet thresholding in detecting white gaussian noise. The technique proposed here exhibits favorable results compared with traditional wavelet methods. The results of this work prove statistically that the available noise follows Gaussian distribution and hence it is considered as white noise. So from the results, it is evident that EMD-WT is considered as a promising method for removing white noise from the PD signal effectively.

REFERENCES

[1] X. Ma, C. Zhou, and I. Kemp. 2002. Interpretation of wavelet analysis and its application in partial discharge detection. IEEE Trans. Dielectr. Electr. Insul. 9: 446-457.

[2] H. Zhang, T. R. Blackburn, B. T. Phung, and D. Sen. 2007. A novel wavelet transform technique for on-line partial discharge measurements part 1: WT de-noising algorithm. IEEE Trans. Dielectric. Electr. Insul. 14(1): 3-14.

[3] S. Sriram, S. Nitin, K. M. M. Prabhu, and M. J. Bastiaans. 2009. Signal denoising techniques for partial discharge measurements. IEEE Trans. Dielectric. Electr. Insul. 12(6): 1182-1191.

[4] H. Wang, K. Tan, Z. Deheng and 1997. Properties and Applications of Dielectric Materials. Extraction of partial discharge signals using wavelet transform. Proc. 5th Int. Conf. Prop. Appl. Dielectric. Mater. 1: 322-325.

[5] J. Veen and P.C.J.M. van der Wielen. 2003. The Application ofMatched Filters to PD Detection and Localization. IEEE Electr. Insul. Mag. 19(September/October): 20-26.

[6] a. Zargari and T. R. Blackburn. 1996. Detection of partial discharge signals in unknown noisy environment. Proc. Conf. Electr. Insul. Dielectric. Phenom. - CEIDP ’96. 2: 472-475.

[7] M. A. Kashiha, D. Z. Tootaghaj and D. Djamshidi. 2009. Partial Discharge Source Classification and De-noising in Rotating Machines Using Discrete Wavelet Transform and Directional Coupling Capacitors. Energy. 2009(June): 2-5.

[8] A. Hill, B. G. Stewart, S. G. McMeekin, and G. Morison. 2013. Partial Discharge Signal Denoising Using the Empirical Mode Decomposition. Int. J. Signal Process. Syst. 1(2): 268-272.

[9] N. Li, J. Zhou, Y. Wang and X. Zhang. 2012. Suppression of UHF partial discharge signals buried in white-noise interference based on block thresholding spatial correlation combinative de-noising method. IET Gener. Transm. Distrib. 6(5): 353-362.

[10] L. X. Li, C. J. Huang, Y. Zeng, and X. C. Jiang. 2008. Partial discharge diagnosis on GIS based on envelope detection. WSEAS Trans. Syst. 7(11): 1238-1247.

[11] U. Koepf and K. Feser. 1995. Rejection of narrow-band noise and repetitive pulses in on-site PD measurements. IEEE Trans. Dielectr. Electr. Insul. 2(6): 1180-1191.

[12] R. V. Maheswari, P. Subburaj, B. Vigneshwaran, and M. Willjuice Iruthayarajan. 2014. Partial discharge signal denoising using adaptive translation invariant wavelet transform-online measurement. J. Electr. Eng. Technol. 9(2): 695-706.

[13] Y. Wang, C. Zhu, Q. Wang, Z. Wang, and Y. Yin. 2013. Processing of partial discharge ultra-high frequency signals from a true size transformer. Proc. IEEE Int. Conf. Solid Dielectr. ICSD, no. c, pp. 1012-1015.

[14] Z. S. Zhang and D. M. Xiao. 2008. Noise-based wavelet denoising technique for partial discharge measurement. WSEAS Trans. Circuits Syst. 7(6): 535-546.

[15] Ö. Altay and Ö. Kalenderli. 2015. Wavelet base selection for de-noising and extraction of partial discharge pulses in noisy environment. IET Sci. Meas. Technol. 9(3): 276-284.

[16] A. M. Gaouda, A. El-Hag, T. K. Abdel-Galil, M. M. A. Salama and R. Bartnikas. 2008. On-line detection and measurement of partial discharge signals in a noisy environment. IEEE Trans. Dielectr. Electr. Insul. 15(4): 1162-1173.

[17] S. Madhu, H. B. Bhavani and S. Sumathi. 2015. Performance analysis of thresholding techniques for denoising of simulated partial discharge signals corrupted by Gaussian white noise. Proc. 2015 IEEE Int. Conf. Power Adv. Control Eng. ICPACE 2015. pp. 399-404.

[18] D. L. Donoho. 1995. De-Noising by Soft-Thresholding. IEEE Trans. Inf. Theory. 41(3): 613-627.

[19] K. Mallikarjunappa. 2011. Removal of Interferences from Partial Discharge Pulses using Wavelet Transform. 9(1): 107-114.

[20] C. F. F. C. Cunha, A. T. Carvalho, M. R. Petraglia and A. C. S. Lima. 2015. A new wavelet selection method for partial discharge denoising. Electr. Power Syst. Res. 125: 184-195.

[21] Y.-W. Tang, C.-C. Tai, C.-C. Su, C.-Y. Chen and J.-F. Chen. 2010. A correlated empirical mode decomposition method for partial discharge signal denoising. Meas. Sci. Technol. 21(8): 085106.

[22] B. Sharma and S. Kaur. 2014. Distinction between EMD & EEMD Algorithm for Pitch Detection in Speech Processing. Int. J. Eng. Trends Technol. 7(3): 119-125.

[23] Y. Kopsinis and S. McLaughlin. 2009. Development of EMD-based denoising methods inspired by wavelet thresholding. IEEE Trans. Signal Process. 57(4): 1351-1362.

[24] Ž. B. Jakovljević. 2013. Comparative analysis of hilbert huang and discrete wavelet transform in processing of signals obtained from the cutting process: An intermittent turning example. FME Trans. 41(4): 342-348.

[25] M. A. Colominas, G. Schlotthauer and M. E. Torres. 2014. Improved complete ensemble EMD: A suitable

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tool for biomedical signal processing. Biomed. Signal Process. Control. 14(1): 19-29.

[26] Y. Pei, Y. Wu and D. Jia. 2012. Research on PD Signals Denoising Based on EMD Method. PRZEGLĄD ELEKTROTECHNICZNY (Electrical Rev. ISSN 0033-2097, R. 88 NR 1b/2012, (1): 137-140.

[27] A. T. Carvalho, A. C. S. Lima, C. F. F. C. Cunha and M. Petraglia. 2015. Identification of partial discharges immersed in noise in large hydro-generators based on improved wavelet selection methods. Measurement. 75: 122-133.

[28] R. Hussein, K. B. Shaban and A. H. El-Hag. 2015. Histogram-based thresholding in discrete wavelet transform for partial discharge signal denoising. 2015 Int. Conf. Commun. Signal Process. Their Appl. ICCSPA 2015.