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Application of Wavelet Transform Technique for Extraction of Partial Discharge Signal in a Transformer

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Abstract

Partial discharge (PD) monitoring is one of the most effective techniques for insulation condition assessment of HV power apparatus. Partial discharges inside a power transformer excite electromagnetic transients that can be detected using sensors operating in the ultra-high frequency band. However, on-line PD measurements are affected by high levels of electromagnetic interference (EMI) that makes sensitive PD detection very difficult. Use of wavelet transform (WT) technique offers many advantages over conventional signal processing techniques such as filters and is ideally suited to process transients in high voltage testing and measurements. In this paper wavelet transform technique is first applied to a simulated PD signal and its veracity is then verified by applying the technique to captured UHF PD signal from a transformer. Signal-to-noise ratio is used to compare the reconstructed signal with the original PD signal to assess pulse extraction from noise by wavelet transform analysis.

Keywords: UHF PD pulse, wavelet transform, denoising, signal-to-noise-ratio

1. INTRODUCTION

Power transformers are in service under different environmental, electrical, and mechanical conditions. The power transformer is an important link in a power system that is stressed the most.. In spite of advances in the areas of manufacturing, processing, optimal design, and quality control, these apparatus have continued to fail while in service. The insulation system is the key component of the transformer.partial discharges (PD) are recognized as the main cause of insulation deterioration process leading to failure of the apparatus. These PD's can be generated due to several mechanism e.g. presence of floating metal particle, protrusion on the conductor, internal discharges in the paper or surface of insulation. A failure in the insulation initially develops as a partial failure where the insulation can not withstand the local electrical stress leading to thermal break down and low energy discharges termed partial discharges. As the transformer ages due to normal/abnormal (overload or short circuit) operation, the deterioration occurs in its components. Irrespective of care taken during maintenance of transformers, floating/wedge particles are introduced in to the transformer. Shield material, bolted joints and end frames are potential sources of metal particles. Hence, oil has to be changed or improved by oil filtration unit. These become he potential sources for PD activity. In addition, high electric stresses exceeding local breakdown stress of oil also give rise to corona type PD. In an actual transformer all these phenomena (wedge, floating, and corona) may be occurring continuously simultaneously. PD pulses have very low amplitude and the maximum level specified according to Indian and international standards is 500pC (pico Coulombs) for power transformers. Various methods (electrical, acoustic) have been developed to detect PD pulses in power transformers. The ultra-high frequency (UHF) technique benefits from low attenuation as signals propagate from PD to sensor inside the transformer tank. Good signal-to-noise ratios can be obtained propagation time causes negligible phase shift relative to the power frequency so that phase resolved PD patterns can readily be obtained.

Power companies are increasingly resorting to diagnostic measurements to assess the status of the insulation system of HV apparatus mainly through sensor development, data acquisition/collection, and development of methods for condition measurement of the power transformers. Diagnostics contains interpretation of off-line and on-line measured data. During the monitoring interferences and disturbances affect the measurement data in noisy conditions and PD signal is buried in the noise. Noise can be defined as any unwanted signal that is not related to the input signal. The primary sources of random, unpredictable noise are from radio waves, electrostatic discharges (ESD), power utility transients, corona and lightning, and thermal noise. Extracting the PD pulse buried in such noise is the main aim of this paper.

Among signal processing methods, the wavelet and its associated transforms[1,2,3] represent a powerful signal processing tool with a wide variety of applications. The wavelet transform(WT)technique scores over the Fourier transform as information regarding both the time-domain and frequency-domain are available with WT. Wavelet transform has the ability not only to decompose a signal into its frequency components, but also to provide a non-uniform division of the frequency domain, whereby it focuses on short-time intervals for the high-frequency components and long intervals for low frequencies. This attribute to tailor the frequency resolution can greatly facilitate signal analysis and the detection of signal features.

In this paper the WT technique is applied to extract PD signals buried in noise, firstly, from a digitally simulated PD signal sufficiently corrupted by noise, and later, from a

PD signal captured through a UHF antenna connected to a power transformer [4, 5]. A mathematical model of PD signal was used to generate the PD signals digitally. An experimental was set up to simulate various types of discharges in an oil medium and the signals due to the partial discharges were captured using a UHF antenna. After decomposition and reconstruction of these signals through the WT technique, good signal-to-ratio was obtained for these signals.

2. SIMULATION OF PD SIGNAL

2.1 Experimental Setup

A 120 MVA, 132/33 kV transformer filled with oil was used for the experimental set up. A system consisting of a UHF antenna suitable for a partial insulation structure known as radome, along with an RF amplifier, signal cables and measurement system was developed for simulation. The UHF antenna used is a dual arm Archimedean spiral type antenna with an active frequency range of 0.3 -3 GHz. The nominal gain is 3 dB. A two stage RF amplifier with an active frequency range 0.1 to 3 GHz with a single stage gain is used to amplify the signals. The measurement system consisted of a 1 GHz band width, 8 bit, 4 G samples/sec maximum sampling rate digital storage oscilloscope (DSO).Various types of discharges were simulated and the signals due to the partial discharges were captured using the UHF antenna. These signals were analyzed and characterized for different types of discharges. A wedge type of PD signal was used for analysis purpose and is shown in fig.1. The signal was found to consist of a few low frequencies of the order 7 to 14 MHz and a few very high frequencies above 400 MHz. The remaining frequencies contribute very little to the main signal.

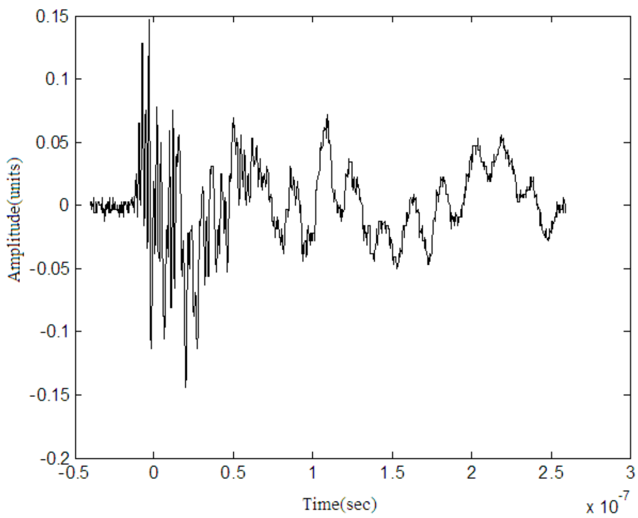

Fig.1. Typical wedge type UHF PD signal

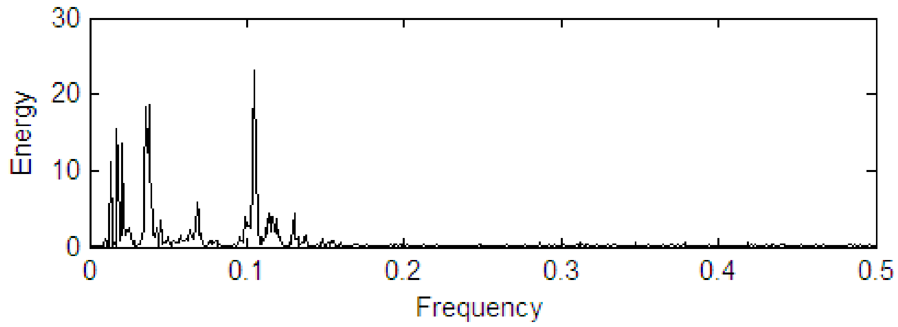

Fig.2. Frequency spectrum of wedge type UHF PD signal

Spectral analysis, shown in fig.2, has shown that only the part of UHF signals with large amplitude coefficients is crucial and as such it is redundant to use the whole length of signal for analysis. Truncated signals with 1200 data points containing all the large amplitude coefficients will be sufficient for analysis.

2.2 Digital simulation

The PD is an exponentially decaying pulse of very short duration. The mathematical model of PD for UHF measurement [5, 6] is given by the following equation.

$$V(t) = Ae^{-\frac{(t-t_o)}{\tau}} \tag{1}$$

Here A is the amplitude of PD pulse, τ is time constant of the pulse discharge. The wave front of the PD pulse is very steep and about 0.1μs and decays exponentially, and the width of the pulse is about 10μs .The time constant of pulse decay T is taken as 10ns.Sampling frequency is 10MHz. Amplitude of the PD pulse is taken as A=1 and several pulses were generated for t0 = 0.5μs, 0.75 μs etc.

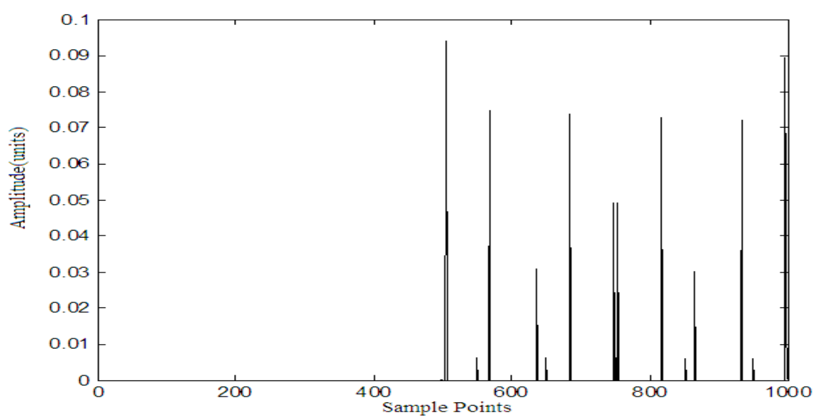

Fig.3. Simulated PD signals

Fig.3 shows a set of digitally simulated PD pulses generated using (1). Only the positive pulses have been shown. White noise, representing the telecommunication noise and corona, was randomly generated and added to produce the corrupted PD signal.

3. THE WAVELET TRANSFORM

Signal processing methods such as Fourier transform, Wavelet transform are usually used in the detection of break points, incipient frequencies in the signals and detecting the edges in the images, removal of noise etc. Traditionally, techniques used for signal processing have been realized in either time or frequency domain to analyze and extract PD events. In the case frequency domain the Fourier transform assumes that any signal could be decomposed into a series of sine and cosine waveforms with the signal under analysis localized arbitrarily throughout the frequency domain but the information in time however is lost. With regard to the PD pulse structure, there always exist non-periodic and fast transient features in the PD signals detected, which tend to be ignored and cannot be revealed efficiently and explicitly by this kind conventional transform. For these reasons, the Fourier transform applied to partial discharge analysis has serious limitations. On the other hand, the wavelet transform is a linear operation that decomposes a signal into components that appear with different scales. The wavelet transform maps a time-domain signal into a two dimensional array of coefficients, thus localizing the signal in both time and frequency domain simultaneously. The wavelet transform is useful in analyzing transient, irregular and non-periodic signals in phase-space i.e. time-scale or time-frequency domains as against the Fourier transform which considers phenomena in an infinite interval

Wavelet analysis employs a prototype function called the mother wavelet. This function has a mean zero and sharply decays in an oscillatory fashion, i.e., it sharply falls to zero on either side of its path. The wavelet transform can be accomplished in two different ways depending on what information is required out of this transformation process. The first method is a continuous wavelet transform (CWT), where one obtains a surface of wavelet Coefficients, CWT (b, a), for different values of scaling 'a' and translation 'b', and the second is a Discrete Wavelet Transform (DWT), where the scale and translation are discretized, but not are independent variables of the original signal.

3.1 Continuous Wavelet Transform

The continuous wavelet transform (CWT) was developed as an alternative approach to short time Fourier transforms (STFT) to overcome the resolution problem. The continuous wavelet transform is defined as follows:

$$CWT(b,a) = \int f(t)\psi^{*}_{b,a}(t)dt \qquad (2)$$

Where * denotes complex conjugation. This equation shows how a function f(t) is decomposed into a set of basis functions ψb,a(t), called the wavelet, and the variables 'a' and 'b', scale and translation, are the new dimensions after the wavelet transform.

The inverse wavelet transform of the above is given as

$$f(t) = \iint CWT(b,a)\psi_{b,a}(t)dbda \qquad (3)$$

The wavelets are generated from a single basic wavelet ψ(t), so-called mother wavelet, by scaling and translation:

$$\psi_{b,a}(t) = 1/\sqrt{a}\psi(t - b/a) \qquad (4)$$

In equation (5.6.1.3), 'a' is the scale factor, 'b' is the translation factor and the factor 1/√a is for energy normalization across the different scales.

3.2 Discrete Wavelet Transform

In the CWT the variables 'a' and 'b' are continuous. DWT results in a finite number of wavelet coefficients depending upon the integer number of discretization step in scale and translation, denoted by 'm' and 'n'. If a0 and b0 are the segmentation step sizes for the scale and translation respectively, the scale and translation in terms of these parameters will be a=a0m and b=b0a0m

$$\psi_{b,a}(t) = 1/\sqrt{a}\psi(t - b/a) \qquad (5)$$

Equation (5) is the mother wavelet of continuous time wavelet series.

After discretization in terms of the parameters, ao, bo, 'm' and 'n', the mother wavelet can be written as :

$$\psi'_{b,a}(m,n) = 1/\sqrt{a_0}\Psi(t - nb_0 a_0^m / a_0^m \qquad (6)$$

$$\psi'_{b,a}(m,n) = a_0^{m/2}\psi(ta_0^{-m} - nb_0) \qquad (7)$$

Further, after discretization, the wavelet domain coefficients are no longer represented by a simple 'a' and 'b'. Instead they are represented in terms of ‘m’ and ‘n’. The discrete wavelet coefficients DWT (m, n) are given by equation:

$$DWT(m,n) = a_0^{m/2}\int_{-\infty}^{+\infty} f(t)\psi(ta_0^{-m} - nb_0)dt \qquad (8)$$

The transformation is over continuous time but the wavelets are represented in a discrete fashion. Like the CWT, these discrete wavelet coefficients represent the correlation between the original signal and wavelet for different combinations of ‘m’ and ‘n’.

3.3 PD De noising with Wavelet Transforms

PD signals are transient, irregular and non-periodic in nature. When PD pulses are extracted from the slow-changing disturbance of the telecommunication carrier signals through wavelet transform, the characteristics of the high frequency components must reflect the pulse signals and the low frequency components that of the disturbance. Ideally if a wavelet is selected to match the PD pulse shape, the PD pulse could be extracted from any noisy environment irrespective of the type of disturbance. If one only considers the high frequency components and the others are neglected, restraining the slow changing disturbances can effectively extract the PD pulse signals. In reality, telecommunication carrier signals are slowly changing disturbance the amplitude of the signal being much higher than the PD pulse. The frequency of the carrier signal generally is about 100 kHz, largest signal-to-noise ratio (SNR) being 20 times, and sampling frequency is 10MHz.

Wavelet analysis of the simulated PD signal is then carried out. With the mother wavelet chosen, input signal is decomposed in to approximate and detail components on which a soft or hard thresholding can be applied and then the signal is reconstructed, to the required number of levels, scaling and dilating the of mother wavelet[6]. Reconstruction of the signal results in a denoised version of the original signal. The number of decomposition-reconstruction of levels can be chosen either by trial and error method, or by computation using (9).The maximum number of levels J to which a signal can be decomposed [6] using the wavelet transform is given by (9) given below.

$$J = fix(\frac{\log n/(n_w - 1)}{\log 2} \qquad (9)$$

In the above equation n is the length of the signal, n w gives the length of a decomposition filter associated with the chosen wavelet, fix is to round the value in the bracket of (4) to its nearest integer. For example, if a =4, J=9, for record length is 2300 and DB2 is used, n w =12, as a result, J=7. DB6, n w =12 and J=7.However, the best decomposition level is usually below the maximum possible number J.

4. RESULTS & DISCUSSION

The main frequency components of the damped exponential PD signal between 7MHz-4 GHz with a central frequency of 300MHz. Accordingly the required number of levels has been calculated as 5. When more levels are decomposed, the PD pulse would be broken and mixed with noise causing the loss of accuracy of the reconstructed pulse [6]. Beyond this level, little energy of PD signal and mostly noise would be introduced. For analysis, the recorded voltage signals were normalized and processed with the denoising tool. The salient features of data processing and results obtained for each signal are discussed below. The parameters used for the optimum results of the respective signals are given in Table 1.

Table 1. Optimum values of denoising parameters

Wavelet	Threshold type	Level	Threshold selection rule
Haar	Soft	5	sqtwolog
Db 3	Soft	5	sqtwolog

Three criterion are normally used to evaluate the performance of a denoise tool. In practice more than one criterion is to be used in order to have an idea of full impact of varying the parameters [7-9]. Among the three criteria of Signal-to-noise ratio (SNR), crossed correlation and amplitude reduction, only SNR has been used as a preliminary study to evaluate the performance of WT.

A comparative study of the captured signal and the digitally simulated signal was done using Haar and Daubechies wavelets. The SNR of the PD signal with and without white noise was then computed for the original and the de-noised signal. In general, a de-noising method is considered acceptable, when SNR is high, the percentage reduction in amplitude is low, and the distortion in pulse shape is minimum.

For generating the simulated digital PD signal, shown in figure 4, equation (1) was used. The signal was truncated with 1200 data sample points being chosen. Noise was randomly generated and convoluted with the PD signal to simulate a corrupted PD signal as accurately as possible. The corrupted signal was then processed using the Haar 5 and db 3, level J=5 wavelets. The results are shown in figure 5.A physical inspection shows that denoising is better with the db3 wavelet. SNR with the Haar 5 wavelet was calculated as 1.4706 dB while dB3 wavelet had a SNR of 1.5272dB. Comparing the SNR of the two signals, SNR of Daubechies turns out to be higher validating the resemblance of the reconstructed denoised signal.

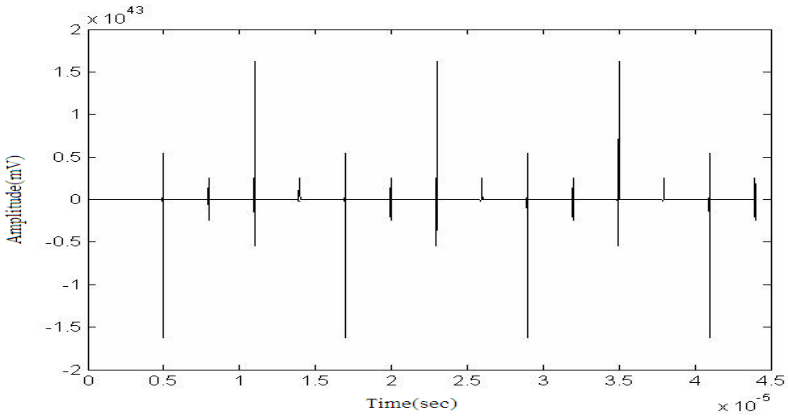

Fig.4. Digitally simulated PD

Figure 6 shows the original UHF PD signal with noise truncated to 1200 sample data points where the energy of the PD signal is the most. Figure 7 shows the reconstructed denoised UHF PD captured signal obtained with the Haar 5 wavelet and figure 8 shows the Daubechies wavelet transform specifically dB3 wavelet with level J=5.A physical inspection of the denoised signal obtained using db3 with the original signal reveals it to be closer to the original PD signal than the one obtained with Haar. To truly ascertain this, correlation coefficient has to be calculated which is not covered in this work.

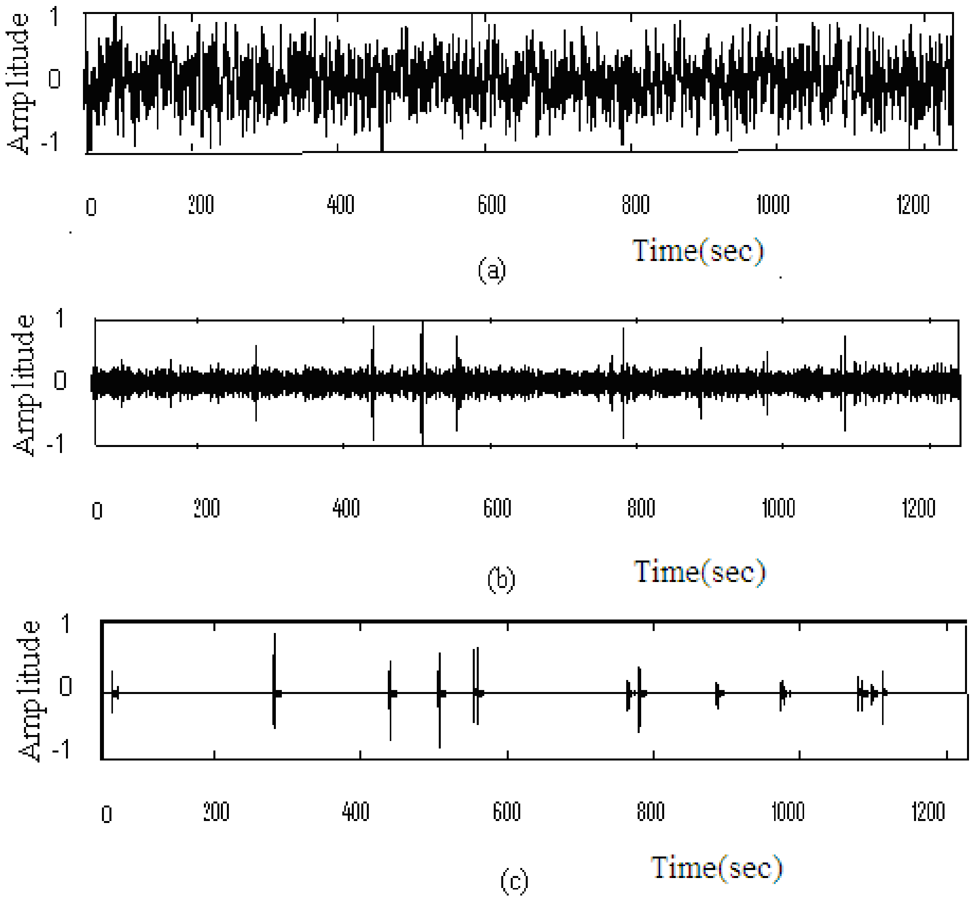

Fig.5. (a) Original signal buried in noise, (b) de-noised signal using Haar 5 wavelet, (c) de-noised signal using db3 wavelet

It can be seen that the pulse signal could be clearly extracted from the disturbance with this wavelet transform. SNR with the Haar 5 wavelet was calculated as 1.3487dB while dB3 wavelet had a SNR of 1.4912dB. Comparing the SNR of the two signals, SNR of Daubechies turns out to be higher validating the resemblance of the reconstructed denoised signal.

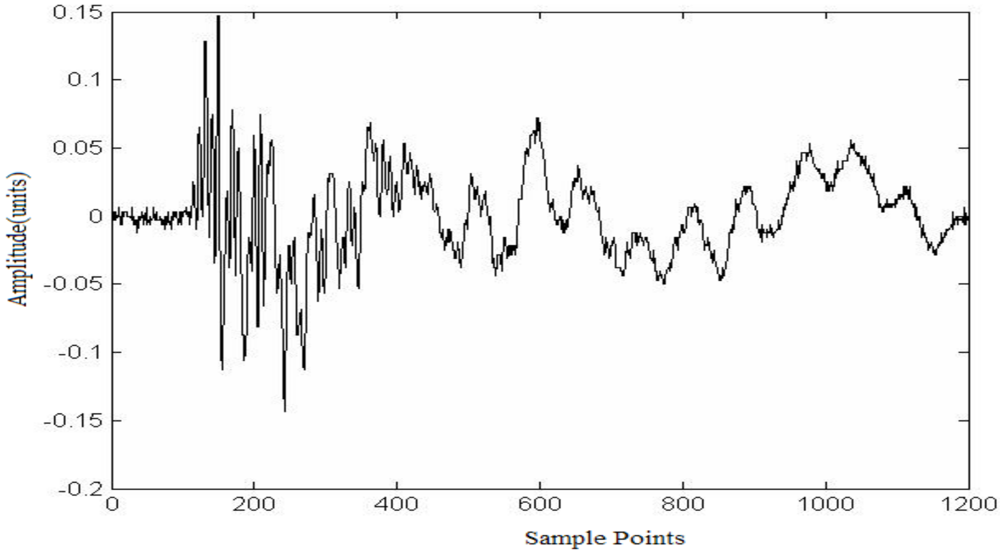

Fig.6. Original UHF PD signal truncated to 1200 data points

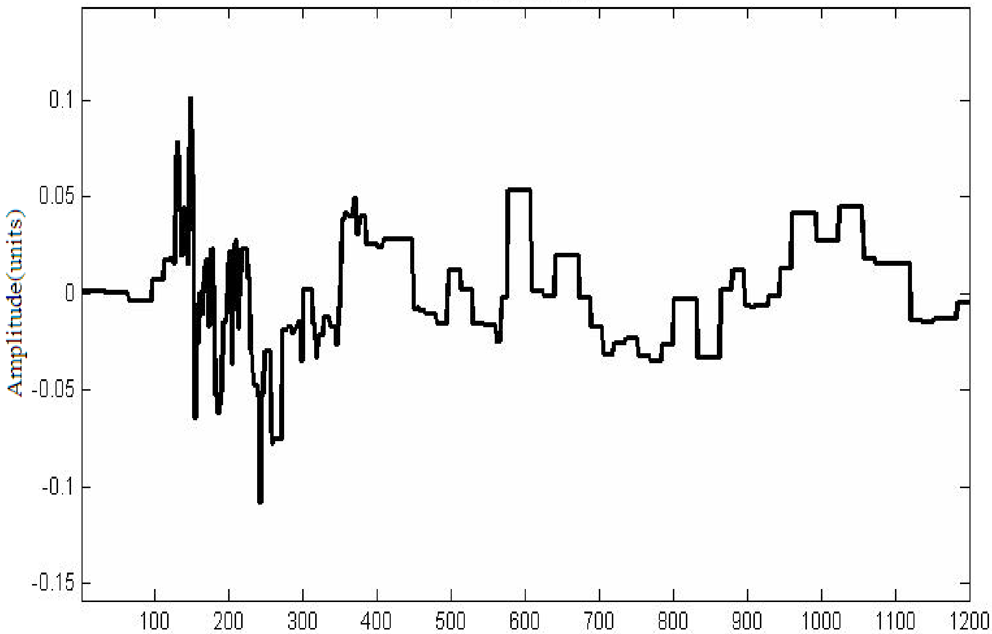

Fig.7. Wavelet de-noising of UHF PD signal with Haar 5 wavelet

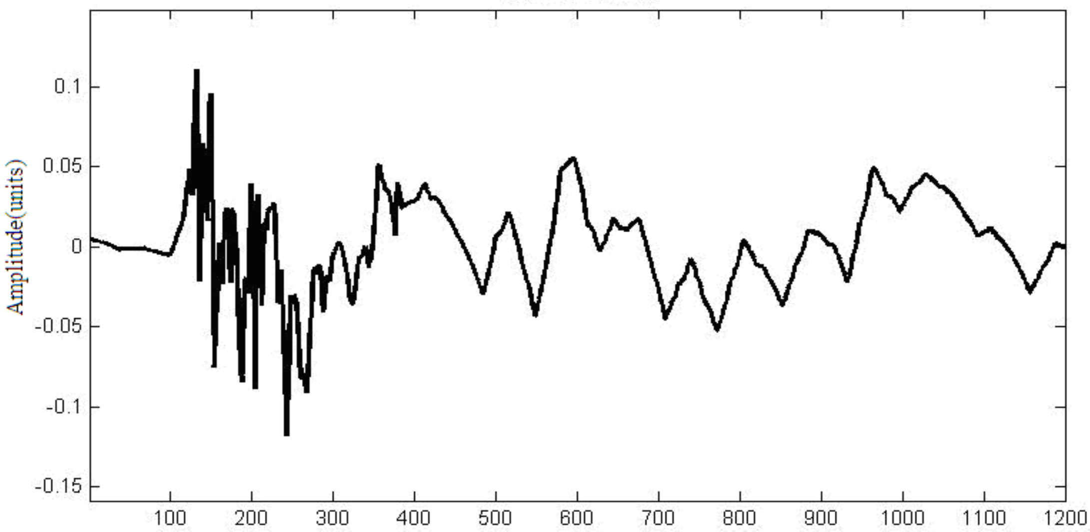

Fig.8. Wavelet de-noising of UHF PD signal with db3,J 5 wavelet

Comparison of SNR calculated for the captured UHF PD signal and the digitally simulated PD signal are shown in Table 2.

Table 2. SNR of PD signal

Signal Type	Wavelet name	Threshold type	Signal-to-noise ratio
Digital PD Signal	Haar	Soft	1.4706
Digital PD Signal	Db 3	Soft	1.5272
UHF PD Signal	Haar	Soft	1.3487
UHF PD Signal	Db 3	Soft	1.4912

5. CONCLUSIONS

Wavelet transform signal analysis approach is presented in this paper for analyzing noisy PD signals from a transformer. Signal can be de-noised based on wavelet decomposition through following steps- decomposition, threshold detail coefficient and reconstruction. Wavelet de-noising boosts the SNR of the noisy signal. Denoised results of digitally simulated PD signal and captured UHF PD signal is compared for Daubechies and Haar members of the wavelet family. Daubechies wavelet is found to be suitable as it has better SNR and the extracted signal resembles the original signal better. Though wavelet transform can extract more information than Fourier transform, the WT is inherently more complex because of dependency on the shape of signals to be extracted from noisy data, the record length and the sampling rate. However, other than mere inspection, choosing the appropriate wavelet based on the correlation coefficient calculation along with amplitude reduction can used to quantify denoising effectiveness which is the future scope of this work.

7. ACKNOWLEDGEMENTS

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