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SURVEY OF DE-NOISING TECHNIQUES FOR PARTIAL DISCHARGE INTERFERENCES

G. Suganya[1], S. Jayalalitha[2], K. Kannan[3] and S.Venkatesh[4]
[1]Shanmugha Arts, Science, Technology & Research Academy University, Tirumalaisamudram, Thanjavur, India
[2]School of Electrical and Electronics Engineering, SASTRA University, Tirumalaisamudram, Thanjavur, India
[3]Humanities & Science, SASTRA University, Tirumalaisamudram, Thanjavur, India
[4]Vellore Engineering College University, Chennai, India
E-Mail: suganyasaravanan46@gmail.com

ABSTRACT

Partial Discharges (PD) are recognized as one of the main causes of degradation of internal insulation of power equipment and its subsequent failure in high voltage equipment. In most real-time applications such as extruded cables, Gas Insulated Substations (GIS) etc., polymeric insulation systems which invariably used. It is necessary and demand to detect even very low levels of PD pulse discharge and it becomes imperative that improved PD measurement systems capable of accurately detecting and acquiring pulse are utilized for diagnosis. Hence, from the perspective of practical on-site PD measurement and analysis, several non-conventional PD detections and measurement techniques are increasing being utilized. It necessitates meaningful measures to ensure appropriate noise detection and its removal. Detection and analysis of PD signals are significantly influenced by a variety of sources of noise during on-site measurement. Different types of noise interferences affect the measurement of PD signals which includes discrete spectral interference, repetitive pulses from power electronics components, amplifier noises etc. This research survey presents an overview of the state of the art of various PD detection and de-noising in detailed perspective and insight into the various PD detection and measurement techniques. Also, this paper presents the appropriate methods to extract the PD pulses from various types of noises. In addition, a substantially exhaustive compendium of findings reported by several researchers has been carried out and a comprehensive summary of various types of noises and interference signals during measurement of PD including specific benefits and limitations of various de-noising methods to extract PD pulses from noisy data are discussed in this research survey.

Keywords: partial discharge, PD detection, PD measurement, PD interferences, De-noising techniques.

INTRODUCTION-PARTIAL DISCHARGE AND CHARACTERISTICS

Partial Discharge (PD) phenomena and measurement serve as a vital non-intrusive technique for carrying out an assessment of the condition of the healthiness of insulation system of power equipment. PDs [1] are discharges which occur due to the enhancement of electric stress in a localized region of an insulation system placed between electrodes (conductors). PD is a complex stochastic and non-Markovian process [2] which exhibits considerable statistical variability in its pulse patterns. These complexities during the discharge process may be attributed to various factors which include the appearance of the initiatory electron that leads to the discharge of pulses, memory propagation effect, pressure and temperature in the defect source etc. PDs are characterized by pulses of very short duration which may range from a few tens of nano-seconds to a few tens of µsecs in the case of solid dielectrics. While in the case of liquids, discharges may be range in the order of few tens of µsec to a few hundreds of µsec.

In this context, several researchers have indicated in their studies that various types of noise influence during real-time PD measurement present considerable challenges during analysis and monitoring of insulation system of power system. PD measurement methods are broadly classified into two categories namely off-line and on-line. Regardless of the advantages, online measurements present more complexities and challenges because of the divergent and random nature of high order noises which appear during real-time on-site measurement. It is worth mentioning that without noise elimination it is possible that the valuable PD information which may provide vital inferences on the nature of the source of defect in the insulation system may get overlapped and superposed by disturbance. The major classification of noises experienced during online measurements is discrete spectral interference, periodic pulse shaped interference and random interference. These categories of noise greatly reduce the sensitivity of measurement of PD pulses. It is observed by [3] that pulse shaped interferences occurs in the bandwidth of 50 kHz to 200 kHz while studies by [4] indicate a typical bandwidth of discrete spectral interference between 100KHz to 200MHz which in turn falls within the framework of PD measurement of pulse time response characteristics [5].

Hence, it becomes imperative that in order to reduce noise and to simultaneously increase the bandwidth of the signal, flexible noise reduction techniques have to be adopted by several researchers to a considerable degree of success. Various digital signal processing techniques used so far for the significant reduction of noise in PD is discussed in this research study. This research survey aims at providing a comprehensive understanding of a wide variety of PD detection techniques both off-line and on-line, measurement aspects including specific issues related to bandwidth requirements and a detailed analysis of

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Table-1. Survey and summary of various PD detection techniques.

Detection methodology	Types	Unique/Salient characteristics	Merits	Limitations	Applications
Conventional Method(as per standard IEC 60270)	Straight Detection Method Balanced Bridge Detection Method Pulse Discrimination Method	Based on the measurement of apparent charge	• Allows PD level detection • Double sensor allows the auto calibration	• Detection equipment is expensive and difficult to install in the field • Electromagnetic shield not present	Cables, GIS, Transformers [4], [6]
Electrical Detection	Ultra high-Frequency method	No electrical connection between sensor and transformer so reliability and safety.	• Low noise level due to shielding effect of transformer • Protected from external noises	Incapable of locating exact location of PD	GIS, Transformers, Rotating machines, Cables (Off-line testing)[5]
	Pulse Capacitive Coupler method	Collects and measures the PD induced current at the detection coil	• Good sensitivity and great implementation simplicity	Not suitable for long term monitoring of transformer	
Acoustic Method	Based on pressure variations in the insulation (Sensor available from 30KHz- 1MHz)	Detects and locates the position of the PD by studying the amplitude attenuation or phase delay of the acoustic waves propagating from the PD	• Provides better noise immunity in real time online applications	Difficulty to know the origin of PD due to interference/degradation of the signal from the environment.	Transformers and Gas insulated substations (GIS) [7]
Optical Method	Uses optical fiber sensor	Based on light produced as the result of ionization during the discharge.	• Highly sensitive • Reduces electromagnetic interference present in the signal.	•Absorbs total light emitted by liquid and solid insulations and no detection is possible •PD cannot be calibrated	Power transformer, Cables, GIS[8]

various sources of noise and interference signals with PD pulses[5]. In addition, a detailed summary of various types of de-noising methodologies utilized by researchers has been deliberated in this research study.

OVERVIEW OF VARIOUS PD DETECTION TECHNIQUES

Detection of PD is closely related to the sensitivity and calibration of the detection system since the primary objective of measurement is to utilize an appropriate detection system which has its sensitivity adequate enough for carrying out measurements in the presence of inevitable noise. This aspect is of considerable importance since such pulses are associated with the extremely small quantum of energy. Detection techniques used in PD are classified as electrical, chemical, acoustic and optical methods based on the physical characteristics such as electromagnetic radiation in the form of light, heat and radio wave, acoustic emission, ozone formation and the release of nitrous oxide gasses [6]. Major classification of PD detection schemes is indicated in Figure-1.

Based on detailed studies of research literature the various unique and salient characteristics, merits and limitations including possible applications in the real-time analysis are summarized in Table-1.

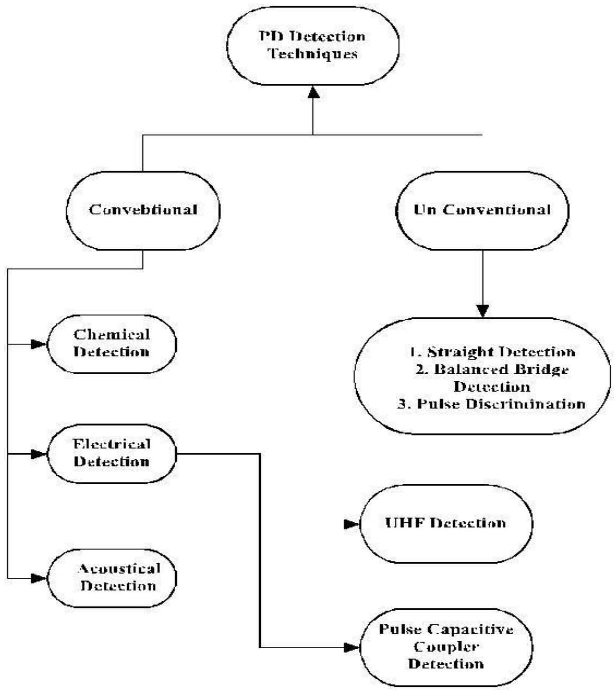

Figure-1. Representation of various types of PD detection methods.

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PD MEASUREMENT

Several sophisticated PD measurement and detection techniques are available such as optical, acoustic and electrical or conventional method, which emits energy in the form of light, heat and radio frequency energy. According to the guidelines of IEC 60270, the conventional method of PD measuring technique proposes measurement of PD based on three standardized types of strategies namely direct (straight) detection, balanced bridge detection and pulse discrimination methods. The direct detection comprises two possible variants of circuit arrangements. In the first circuit arrangement the PD current pulses are transferred to the measuring circuit by utilizing a coupling capacitor connected in parallel to the series combination of the object under test with the measuring impedance (also sometimes familiarly referred to as coupling quadrupole), while in the second setup the test object is connected in parallel to the combination of coupling capacitor in series with measuring impedance. The electromagnetic noise that leads to a poor sensitivity of PD measurement can be eliminated to a reasonable extent by utilizing the balanced bridge method which is based on the strategy of removal of noise by Common Mode Rejection Ratio (CMRR) of the ratio arms of the bridge detector circuit. However, the measurements are considerably affected by interferences during onsite PD testing. For this reason, pulse polarity discrimination system with adjustable filters is designed. The electrical measurement technique especially uses two types of measuring impedances as filters such as narrow-band which comprises an R-L-C combination and wide-band which usually involves R-C detectors/ filters [9].

The main disadvantage is that pulse magnitude information may be lost during measurement with narrow-band filter when two successive pulses overlap. Since detection and measurement of PD activity during on-site and on-line testing invariably comprises low-frequency components up to 1 MHz, researchers and utilities have indicated through studies that neither narrow-band nor wide-band filters have the ability to completely suppress the interferences [10]. Hence, researchers and power utilities have begun utilizing Ultra Wide Band (UWB) with the advantages of providing greater sensitivity, the possibility of observation of pulses lesser than equal to 1ns and recording of the true shape of the original signal. Details on the comparison of PD detector type with regard to the bandwidth and center frequency values [11-13] are indicated in Table-2.

PD DETECTION AND MEASUREMENT BASED ON EQUIPMENT

Equipment installed in power generation, transmission and distribution systems are put to service and operate continuously thus necessitating a credible and internationally acceptable measurement, condition monitoring and diagnostic system to enable assess the ageing of apparatus. Such assessments, in turn, provide a viable index on the life span of the insulation system. As deliberated in the previous section, since PD detection and measurement is based on the nature of testing and diagnostics which may be either off-line or on-line study, major advantages and limitations of such methods for three

Table-2. Characteristics of PD filter detectors.

PD detector type	Bandwidth	Centre frequency
Narrow Band	9 kHz $\leq \Delta f \leq$ 30 kHz	50 KHz $\leq f_m \leq$ 1 MHz
Wide Band	100 kHz $\leq \Delta f \leq$ 400 kHz	30 kHz $\leq f_1 \leq$ 100 kHz; $f_2 \leq$ 500 kHz
Ultra-Wide Band	~500 kHz	100 kHz $\leq f_1 \leq$ 1GHz

Table-3. Overview of advantages and limitations of PD off-line and on-line testing of equipment.

Equipment	Analysis based on result based during PD off-line Testing		Analysis based on result based during PD on-line Testing[14,15]	
	Advantages	Disadvantages	Advantages	Disadvantages
Rotating Machines	• Quick performance • Low interference • Visual inspection is possible	• PD free test transformer necessary • More expensive • No realistic test conditions • Winding is at high voltage	• Cost effective than offline testing • No external power source is needed	Possibility of interference is more
Transformers	• Low-cost measuring method	• No information of overvoltage and short circuit due to stress	• Increases reliability of test • Eliminates the flaw in interval based testing	Separation of PD from pulse interference is complex
Cables	• Used for acceptance test	• Cable should be taken out of service	• Economically advanced than offline	The presence of sinusoidal noise and

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	in newly installed cables • Able to measure cable's response to specific stress	• Testing limited to circuits with no T-junctions • High initial and running cost.	• Site of PD occurrence can be located	pulsive interference may lead to misinterpretations.

major equipment namely oil-filled apparatus, power cables, and rotating machines are summarized in Table-3.

SOURCES OF PD INTERFERENCE

The major aspects and issues encountered during PD measurement is the inevitable appearance of the external interferences, which are directly related and associated with the sensitivity and reliability of PD data. It is evident hence that when the amplifier gain has to be increased to measure small PD signal the noise in the PD signal also gets amplified. This, in turn, affects the sensitivity and reliability of the PD data [16]. Interference during PD detection and measurement are broadly classified into three major types namely discrete spectral interference, stochastic pulse shaped interference and white noise [17]

DISCRETE SPECTRAL INTERFERENCE

Discrete Spectral Interferences (DSI) is narrow-band noise signals which are sinusoidal in nature. DSI has a narrow-band spectrum, centered at its dominant Frequency [18] while PD signals are a relatively broad spectrum. The frequency range of continuous sinusoidal DSI pulse is between 30 kHz to 500 MHz [19]. In the case of sub-stations, the bandwidth of the DSI is of the order of 1500 kHz [20]. Amplitude of DSI is much higher than the amplitude of PD signal. "Zhang" has reported on a detailed analysis of the signal attenuation characteristics of PD and DSI by the correlation coefficient method which indicates a recognition rate of 77.94% and 99.7% which makes evident that it is difficult to separate PD signal and DSI. Since it is observed that the signals only differs in magnitude. DSI can be suppressed by notch filtering method /software based de-noising techniques effectively.

Table-4. Comparison of various types of noises, unique characteristics and possible sources of interference.

Types of noise	Unique characteristics of noise	Sources of interferences	Effective de-noising technique
Discrete Spectral Interference	• Narrow band spectrum centered around dominant frequencies • PD and DSI differs only in magnitude	• Communication • AM/FM radio emissions	• Fast Fourier transform • LMS Algorithm
Pulse Shaped Interference	• Broad-band signal • .Spectral density is as same as PD signal. So cannot be suppressed in frequency domain	• Corona discharge • Caused by facilities that are operating synchronously with mains.	• Wavelet Transformation
White Noise	• Power spectral density is constant	• Electromagnetic from the amplifier and other hardware circuits. (i.e) generated by the equipment itself	• LMS Algorithm • Wavelet transformation • Hidden Markov Model

PULSE SHAPED INTERFERENCES

Pulse-shaped interference (PSI) occurs in power electronic devices due to periodic switching.PSI are broad band signals, which is similar to PD signals. However, it is evident from not possible to apply frequency domain methods to suppress interference and time domain methods can be used. Pulse-shaped interference can be periodic with respect to the power frequency cycle with frequency range in the order which is over 500 kHz [20]. Since it is evident that interference can also be of random pulses wherein interference cannot be detected using the same method as that of periodic pulses since the behavior of PD pulse is different from random pulse shaped interference. Parameters considered to separate PD and pulse shaped interference are phase distribution and pulse shape. Periodic pulse shape interference occurs only at the specified phase angles, which differs from PD since PD pulses occur at certain regions of power frequency cycle and they do not occur at same phase angle [21]. The wave shape of the periodic interference differs from PD which in addition can also be used to separate pulse interference.
Conventional methods used for detection of pulse-shaped interference are an analogue method and digital method [22]. The analog method uses the bridge detection method

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for suppressing periodic pulse interference. The main drawback in the analogue method is inefficiency in rejecting radio emissions. The digital method is fast and efficient in rejecting radio emissions with minimum distortions as comparable with the analogue method, which is based on digital signal processing using the phase information data. Strong periodic pulses appear at sharp peaks which are eliminated automatically by digital methods.

WHITE NOISE INTERFERENCE

White noises are also a significant type of interference which affects the sensitivity and reliability of PD data. White noise contains frequency components ranging from zero frequency to infinite frequencies. Since theoretically, the spectrum of white noise spectrum is constant it has all frequency components

The narrow band-pass filter can also suppress white noise [23, 24]. Johnson noise and shot noise are the best examples of white noise because their power spectral density is constant [25]. Table-4 summarizes various types of noises comparing their unique characteristics, sources of interference and the various de-noising methods formulated by researchers for its effective implementation during analysis.

AN OVERVIEW OF DE-NOISING TECHNIQUES IN PD MEASUREMENT AND ANALYSIS

Since PD measurement and analysis has become a very crucial and an important measurement technique for analyzing the insulation defect and to ensure the reliable operation of the high voltage equipment it becomes evident that emphasis is laid on the role played by noise during measurement, acquisition, and diagnosis. Shielded laboratories are mostly used in off-line measurements. But during online and onsite measurements, the broadband PD detection technique is significantly influenced by the surrounding electromagnetic field interferences which in turn can cause false interpretation and reduce the sensitivity and accuracy of the measured PD signal which may subsequently lead to delay in taking up corrective remedial measures. This delay may possibly lead to further deterioration of the insulation system thus necessitating sophisticated yet reliable methods for de-noising PD signals.

HARDWARE BASED DE-NOISING TECHNIQUES

Suppression of noise during PD measurement and diagnosis using hardware based reduction methods is widely utilized in the industrial application to eliminate the interferences while online PD measurement is carried out. The basic hardware methods used are Filtering Method, Differential System, and Pulse Polarity Discrimination System.

Filtering method

Filtering Methods are mainly used to suppress DSI. It is important to note that the filter output can be changed according to interference frequency, but cannot eliminate noises with the frequency similar to PD frequency.

Differential system

Differential System can suppress periodical pulse shape interference from the transmission line effectively. Characteristics of test object and transducer characteristics should be same to achieve high rejection ratio [27].

Pulse polarity discrimination system

Pulse Polarity method is utilized to suppress external periodical interferences, which employs electronic gates to hold back the external interferences by comparing relative polarity at the two coupling devices used.

Even though hardware based techniques suppress DSI and some external interferences effectively, it is worth mentioning that this methodology may not suppress white noise effectively.

SOFTWARE BASED DE-NOISING TECHNIQUES

There have been concerted efforts recently to develop computational methods to suppress external noise and interference that contaminates on-line PD signals measurements. The majority of such techniques developed performs de-noising of DSI interferences and observed to indicate considerably satisfactory results [28]. Recent studies have indicated that the major issue is in the removal of pulse type interferences. In this context, various techniques for de-noising PD signal are analyzed in this survey.

Fast fourier transform

The Fast Fourier Transform (FFT) is a classical approach used to reveal the frequency components in the measured PD signal. This mathematical technique is used for transforming a signal from time domain to frequency domain and provides information related only to time domain based analysis. Time features of the signal are extracted by multiplying the original signal by a window function, which has zero magnitude outside the desired interval. In most of the noise suppression schemes, FFT is employed for the suppression of narrow band interference [29]. Since narrow band interference has a higher magnitude than the PD, the suppression is effective in FFT.

A method utilizing the normalized correlation coefficient (NCC) to compare the original reference signal and filtered signal after inverse FFT is applied has been proposed in [30]. NCC has a value between -1 to 1, indicates the signal shape. NCC close to 1 is preferable. From the results, it is evident that it ensures high performance and increases SNR ratio only for sinusoidal noises. "Luo X" explained FFT threshold method to suppress the narrowband interference and also to increase the Signal to Noise Ratio (SNR) of the signal. Based on Normal distribution properties the threshold value is set. Most studies in the field of de-noising of PD signal evident that FFT-based are not suitable for de-noising PD signals effectively if the noise spectrum changes.

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The other disadvantages are its cumbersome computational time and the complexities attributed to the length of FFT. A typical block diagram of the filter depicting the various processes during FFT de-noising [30] is indicated in Figure-2.

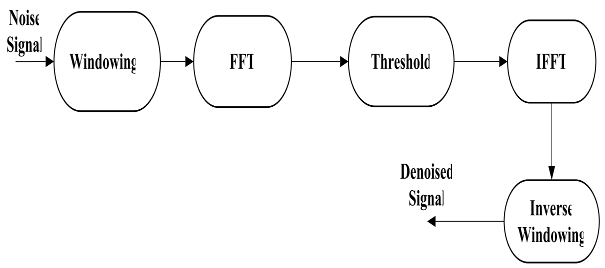

Figure-2. Block diagram of FFT De-noising.

Notch filtering

Notch filters are developed for the enrichment and removal of additive white noise in sinusoidal signal (in both time and frequency domain analysis). Initially, the notch filter had been implemented using Finite Impulse Response (FIR) filter, but from research outcomes, Infinite Impulse Response (IIR) filter have been found to be effective in removing interference signals [31], since IIR filters require less bandwidth than the FIR filters. Notch filters also known as band stop filters composed of high pass filters and low pass filters, allows frequencies above and below a particular range set by the filter. The block diagram of a basic band stop/ notch filter is shown in Figure-3.

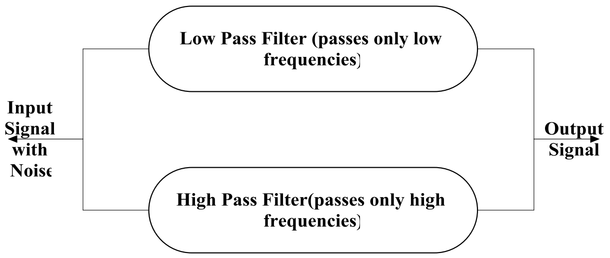

Figure-3. Typical basic block diagram of notch filtering.

The transfer function of the notch filter as deliberated by [32] is indicated in (1)

$$H(z) = \frac{\prod_{i=1}^{p}(1+\gamma_i z^{-1}+z^{-2})}{\prod_{i=1}^{p}(1+\alpha\gamma_i z^{-1}+\alpha^2 z^{-2})} \text{ Where } 0 \le \alpha \le 1 \quad (1)$$

A signal y (t) consists of 'p' sinusoids in noise passing through H(z).

$$W(t) = H(z).y(t) = H(z)\, n(t) + H(z)\, s(t) \quad (2)$$

Where W (t) = Filter output; s (t) = signal consists of p sinusoid components; n (t) = noise component.

Adaptive algorithms which are implemented using FIR notch filters can also alternatively utilize IIR notch filters for its implementation. The main advantages of the notch filter method are its computational efficiency, faster convergence, and accuracy in results [33]. The first algorithm proposed is FIR filter with Adaptive Line Enhancer (ALE) which uses two coefficients for a signal. The Later second algorithm is implemented by using IIR Notch filters along with ALE. The result obtained using IIR notch filters is comparably better than FIR as IIR requires much smaller filter length [34]. The notch filters algorithms with lattice filter implements and direct form implementation methods are compared, to know the convergence characteristics of the filter. To compare the algorithms with the direct form implementations computer simulation is performed. The second algorithm of notch filter method performs comparatively better than the first algorithm, which separates noise comparatively faster than the first algorithm. The second algorithm can filter low-frequency high amplitude sinusoidal noise from the PD signal. The main drawback in this paper is it is less sensitive to the changes in frequency and so to the changes in input noise characteristics. In [34], it is proved in recent research that notch filter combined with wavelet transform techniques serves as the best method to suppress DSI as the amplitude of DSI is much larger than that of PD signal.

It is evident from the survey that notch filter increases the accuracy of PD detection. Research study ensured that notch filters are effective only for removal of DSI in PD signal.

Matched filtering

The basic problem of existence of noise (mostly continuous noise) in online PD monitoring is accomplished by matched filtering (MF) method [35]. Usage of matched filters boosts the detection sensitivity of PD and enriches the SNR. Impulse response of matched filter while white noise present in the signal is given by

$$H(t) = A^{*}s(-t) \quad (3)$$

Matched filters are constructed using the template, which is similar to PD pulse waveform. So in the case of absence of noise, the output is only the signal energy. In semi-automated PD measurement, the measured value should exceed the threshold level to make sure the presence of a signal. Since the MF maximizes.

The complication of PD match filtering depends on test object's physical property [36]. The increase in a number of match filters requirement increases the post processing time. In order to accept match filtering for the measurement of noise, power spectrum needs to be estimated and noise should be stationary in nature.

It is apparent from the previous research survey that MF are well suitable to suppress the narrowband interferences in PD signals since it can maximize SNR of the PD signal. However real-time application of MF is not feasible at present.

Adaptive filters

Suppressing of interference in non-stationary (PD) signals using the adaptive filter discriminates DSI and white noise effectively which can be implemented in

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both time and frequency domain [37]. Other than noise cancellation, Adaptive filters usage extended to some other signal processing techniques such as system identification, Signal Control, Echo Cancellation, Signal Prediction, spectral estimation and linear prediction filtering. Interference Cancellation by the basic adaptive filter is depicted in Figure-4.

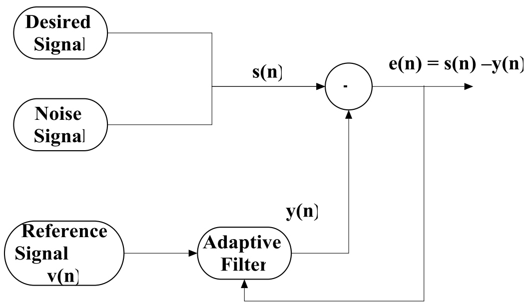

Figure-4. Block diagram of interference cancellation of adaptive filter.

In adaptive Filter algorithm, the filter changes its impulse response according to the error e (n) and produces output y(n) as close as noise signal [38, 39]. The basic two types of adaptive filters are Least Mean Square Filter (LMS) and Recursive Least Square Filter (RLS).

Least mean square

Least Mean Square adaptive filter is a more efficient method to discriminate PD signal and noise when compare to FFT [40]. LMS is a digital adaptive filter which suppresses DSI effectively but it cannot suppress stationary random noise (White Noise) perfectly. But the convergence problem exists in LMS as PD is a Non-Stationary signal. In LMS algorithm noise cancellation is done by variation in step size. But the step size increases the steady state error. So the convergence speed, step size, and convergence accuracy result in dissatisfaction in LMS method. LMS method update equation is given by

$$w(n+1) = w(n) + \mu * e(n) * v(n) \quad (4)$$

Where 'w' represents filter coefficient vector, 'e' denotes error vector, 'v' denotes reference input to the adaptive filter and 'μ'represents $7 * 10^{-8}$

A new signal processing method called the Empirical Mode Decomposition (EMD) developed and deliberated in [40] is utilized for analyzing the non-stationary signal. Suppression of DSI with multi-frequency is done by decomposing the signal into a number of Intrinsic Mode functions with different frequency bands [41, 42]. Frequency splitting characteristic is similar to the wavelet transform but it differs in the principle. IMF allows the common adaptive filter to de-noise the PD signal with multi-frequency. A few aspects related to EMD and its limitations such as end effects, sifting stop criterion, extremum interpolation, etc are deliberated in [43, 44].

Recursive least square

The adaptive algorithms are relatively quite simple but they are slow to approach optimal weight vector [45]. Convergences of such algorithms are slow due to the assumptions made related to the performance function gradient. The main objective is the coefficient of adaptive filters output signal y (t), have to match the desired signal in the least square sense [46] RLS algorithm calculates autocorrelation matrix of the input signal from the past data and the weighting factor is used to limit the influence of the very old data. Cost function of the RLS algorithm is given by

$$W(n+1) = w(n) + k(n) * e(n) \quad (5)$$

where 'w' stands for Filter coefficient vector, 'e' denotes Error vector and 'k (n)' is the weighting factor. RLS filters converge quickly compared to LMS adaptive filters, however from the statements of the researchers, it is clear that RLS filters are suitable for stationary signals and not for PD and the variance of error is high as compared to Wavelet Transform (WT). Table-5 summarizes the frequency based de-noising techniques so far used.

By theory, it is evident that the above-said methods mostly depend on either time domain or frequency domain de-noising, which is not suitable for de-noising of a PD signal because of its stochastic nature. Moreover, from the research study, it is clear that implementation these filters mostly suppress narrow band noise only. Application of Wavelets for extracting different PD pulses from noise will be very effective since its time- frequency window can automatically widen to analyze the low frequency and narrowed to investigate high-frequency component of the signal [47].

Table-5. Summary of the various frequencies based denoising techniques.

De-noising techniques	Types of noise-suppressed	Advantages	Disadvantages
Fast Fourier Transform	• Narrow band interference	• High resolution but not adaptable if the noise spectrum changes.	• Time-consuming process • Results depend on length of FFT • Location of PD pulse cannot be determined
Fast Fourier Transform	• Narrow band interference	• Simple and easy to	• Selection of threshold is

Thresholding		implement • Threshold results in better way in reducing amplitude of narrow band interference	difficult
Least Mean Square	• Discrete spectral interference • White noise (partially)	• Very short time calculation	• Convergence Speed • Step size • Convergence accuracy
Least Mean Square+EMD	• Discrete spectral interference with multi frequency	• Appropriate for both non-linear and non-stationary signal • Data – driven approach	• End effect problem • shifting stop criterion, • Extremum interpolation
Matched Filters	• Mostly Continuous noise	• Improves detection sensitivity of PD and increases SNR	• Needs estimation of power spectrum • Noise nature should be of stationary
Notch Filters	• Periodic interference • White noise	• Fast Convergence than FIR.	• Poor Stability • Computation time is long • Difficult to identify interference frequency

WAVELET TRANSFORM

In recent years, Wavelet Transform (WT) has been adopted as an alternative algorithm for the analysis of non-stationary PD signals and references showed that WT is more suitable for de-noising PD signals than frequency/ time-based filters. Wavelet analyses the signal both in time and frequency domains and the adjustable time - frequency window helps in detecting discontinuities and sharp spikes by analyzing high and low-frequency components in a signal and recovers the original signal.

Wavelet-based denoising method comprises of three steps: decomposition, thresholding, and reconstruction. In the first step, it decomposes the signal by using two filters called High Pass Filter (HPF) and Low-Pass Filters (LPF) which are commonly known as Quadrature Mirror Filters (QMF) by which the filtering and down sampling is done. HPF analyses the high-frequency component in the signal known as Details (Ds) whereas the LPF analyses the low-frequency component of the signal called Approximations (As). Defining the type and order of mother wavelet is also involved in the first step [48-51]. It seems that only trial and error method is available for the selection of suitable mother wavelet. In that, the decomposition is accomplished by inverse discrete wavelet transform. Figure-5 depicts wavelet based de-noising based on thresholding [52].

Selection procedure for suitable wavelets: Selection procedure of suitable wavelet includes following steps. Selection procedure of suitable wavelet includes following steps:

- Identification of PD pulses.
- Selection of decomposition level
- Computation performance parameters of wavelet
- Distance criterion implementation for selection of MSW
- Thresholding of wavelet coefficient.

Researchers so far used so many methods for choosing the best wavelet. In that [50] proposes cross-correlation factor as a method to choose a mother wavelet.

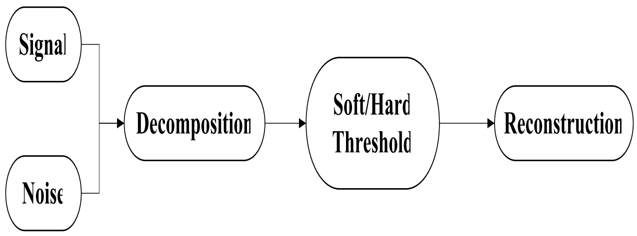

Figure-5. Wavelet denoising based on thresholding techniques.

The second step is a selection of a suitable threshold for noise cancellation. Threshold method based on standard deviation used to remove a noise component in all frequency range is proposed in [53]. In Hard thresholding the element with an absolute value greater than zero and set the element with low absolute value to zero. Hard thresholding method otherwise called as keeps or kills method.

$$\delta\lambda^{Hard}(x) = \begin{cases} x if|x| > \lambda \\ 0 \ \ if|x| \leq \lambda \end{cases} \tag{6}$$

In Soft thresholding is an extension of hard thresholding method. It sets the value lower than the threshold to zero and then shrinks other coefficient.

$$\delta\lambda^{Soft}(x) = \begin{cases} x - \lambda if x < \lambda \\ 0 \quad\ if|x| \leq \lambda \\ x + \lambda if x < -\lambda \end{cases} \tag{7}$$

During on-site measurement components with different frequency bands are present in the signal. In order to overcome the associated complexities related to

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this method, multi-resolution decomposition method (MRD) is suggested in [53] for online- onsite PD measurements. From the results, it is revealed that MRD de-noised random DSI and pulse shaped interferences more effectively. Further, this method results in minimum distortion and it denoised signals contained various interferences occurring simultaneously and noises overlapped with PD pulse effectively. In [53], WPT method is applied to de-noise and locate the PD signal in the cable. They concluded that WPT de-noised the signal based on time scales and it is well suitable for online PD monitoring. But the results are depending on the type of wavelet and standard deviation of the noise. And from previous research work, it is evident that the successful probability is 60% [54]. Investigations are going on in the wavelet based PD denoising methods, and the results showed that the thresholding based method is more adaptive than the other methods [55] After thresholding, the signal is reconstructed by upsampling in the third step is by inverse wavelet transform of the signal.

TYPES OF WAVELET TRANSFORM

Various types of wavelet transform applicable for denoising of PD signals are Continuous Wavelet Transform (CWT), Discrete Wavelet Transform (DWT), Stationary Wavelet Transform (SWT) and Wavelet Packet Transform (WPT) [56-58].

Discrete wavelet transform

In DWT a filter of different cut-off frequencies is used to decompose the signal and give the proper time and frequency information. DWT of the signal is given by,

$$DWT_x^{\varphi}(\tau, s) = \frac{1}{\sqrt{|s|}} \varphi \frac{(t-\tau)}{s} \tag{8}$$

The signal is passed through the series of high and low pass filters followed by downsampling to analyze the high and low frequencies contained in the signal. With appropriate thresholding, the coefficient estimated as noise is removed and the remaining coefficient are reconstructed by Inverse Discrete Wavelet Transform (IDWT). In DWT, after down sampling at each level, the low-frequency coefficient are decomposed to obtain next level decomposition. A typical block diagram of an implementation of decomposition of DWT is shown in Figure-6.

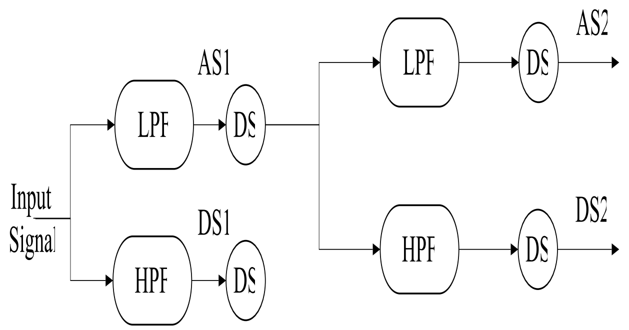

Figure-6. Wavelet decomposition of DWT.

Wavelet packet transform

WPT also follows the same procedure as that of DWT denoising method. But in WPT for next level decomposition both approximation and detail coefficient should pass through the filter for better resolution. WPT denoising technique is in Figure-7.

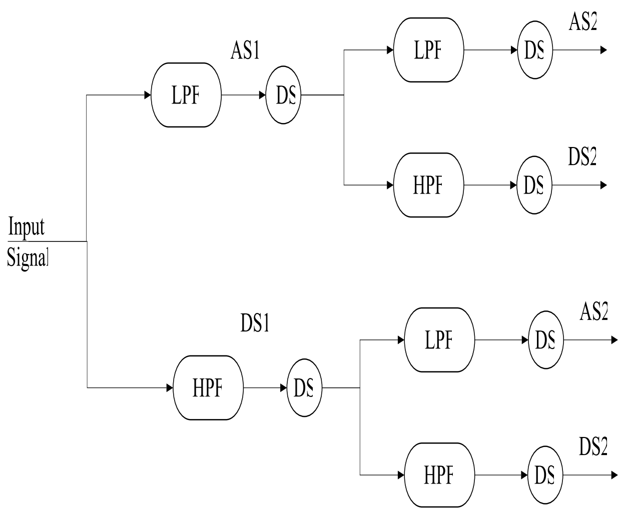

Figure-7. WPT decomposition.

Stationary wavelet transform

Down sampling process in not involved in SWT. Because of the elimination of downsampling after filtering, no of samples at each level is same as that of the original level. High and low-frequency coefficient are sampled by adding zero between each filter coefficient of the previous level as the downsampling is not considered in SWT. SWT implementation using block diagram is in Figure-8.

Continuous wavelet transform

By eliminating down sampling lack of shift invariance problem is solved by the SWT but it is a very long redundant transform. In order to overcome such redundancy instead of real filters it uses complex filters, but designing of complex filters is difficult. And the main

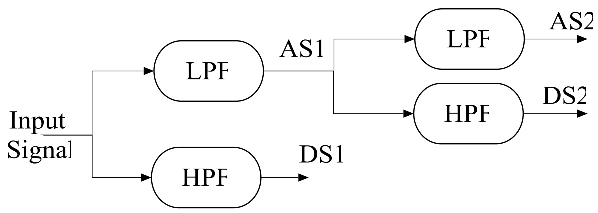

Figure-8. SWT decomposition.

the drawback of CWT is it tells when and in which frequency band the signal occurs but fails to give the time domain shape of the signal. Block diagram of decomposition of CWT is in Figure-9.

CWT of the signal is defined by,

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$$CWT_x^{\varphi}(\tau,s) = \frac{1}{\sqrt{|s|}} \int x(t)\varphi^* \frac{(t-\tau)}{s} \quad (9)$$

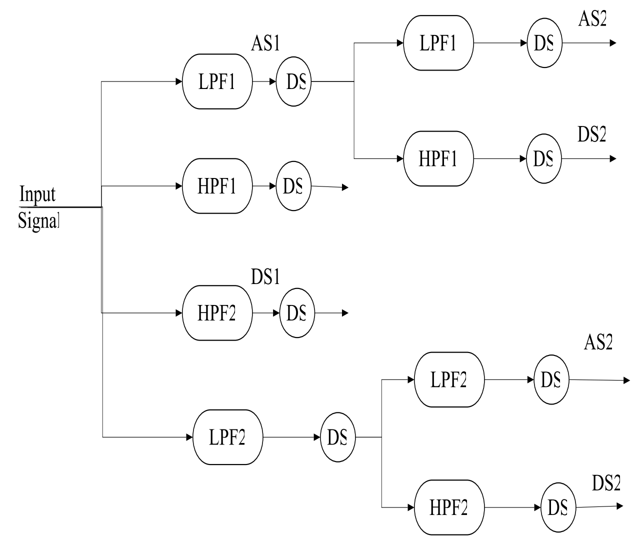

Figure-9. CWT decomposition.

Here $\varphi(t)$ is Mother Wavelet, s is scaling function and τ is shift operaror.The following table explains the various wavelet denoising methods [59, 60].

It is evident from the previous studies that wavelet transform can suppress white noise and pulse shaped interference effectively compared with other software based filters, but researchers who have applied WT encountered problems in selection of suitable mother wavelet and setting of the threshold. This issue can be overcome by using the probabilistic tool Wavelet based Hidden Markov Model (WT-HMM) [61].

Hidden Markov model

Wavelet-based Hidden Markov Model has been introduced recently for de-noising of partial discharge signals more efficiently. The main advantage of this method is it can measure the dependency between wavelet coefficient and it has no free parameters. In [62, 63], author adopts the wavelet shrinkage method for de-noising using HMM, which uses thresholding function for removing co-efficient related to noise. But threshold value is chosen only for mathematical convenience. In wavelet based HMM, clustering and persistence are considered as important properties to measure the wavelet co-efficient dependency rather than the shrinkage method .HMM methods can suppress white noise without affecting PD pulse. It has less attenuation compared with other methods. HMM method increases the signal to noise ratio (SNR).So the identification of PD signal is easy [64-66]. HMM method is adaptive, and setting of threshold value is not necessary in HMM model

Table-6. Wavelet based denoising methods and their advantages and disadvantages.

Wavelet de-noising methods	Advantages	Disadvantages
Wavelet Decomposition & Reconstruction Method	• Simple algorithm • Calculation speed is fast	• Scope of application is less
Wavelet Threshold	• Fast speed calculation • De-noising effect is good	• possible for Pseudo Gibbs Phenomenon
Translation-Invariant Wavelet De-noising Method	• Removes Pseudo Gibbs Phenomenon effect	• Speed is slow
Modulus Maxima	• Effectively retains the singularity information	• De-noising speed is slow
Wavelet Packet Transform	• Analyzes both high and low-frequency signal	• Lack of shift invariance

CONCLUSIONS

A comprehensive literature survey on the PD analysis, detection and de-noising methods has been presented here. During PD measurement noises are considered as a major problem which affects the sensitivity of the PD data, and moreover, noises sometimes lead to an improper indication of PD. To discriminate noise from PD signal de-noising methods are in need which will also increase the SNR in PD analysis. This paper presents various de-noising methods buried in interferences during online or offline measurement of PD signals. Despite all the methods used in the field of de-noising of partial discharge, WT has distinct advantages than the traditional digital signal processing or digital filtering methods, which performs well in de-noising of DSI, Sinusoidal and pulsive interferences very effectively.

But an obvious disadvantage is the setting of threshold and mother wavelet selection.

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