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Comparative Analysis of Segmented Correlation Trimmed Mean Algorithm for Locating Random and Static Partial Discharges in Power Cables

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ABSTRACT

Power cable monitoring for partial discharge (PD) source is a crucial act to identify the cable's insulation weakness before the cable breakdown. Recently segmented correlation trimmed mean (SCTM) algorithm had been applied to double-end PD measurement method. The algorithm showed significant improvement in performance when applied to PD source localization on power cables. However, the previous research study only focuses on the performance of the SCTM algorithm for static PD localization. This paper employs a random PD model to evaluate the accuracy of the SCTM algorithm in detecting PD sources. MATLAB simulations compared SCTM algorithm's performance for random PD generation and static PD sources in double-end PD measurements. Results showed signal-to-noise (SNR) significantly influenced localization accuracy. Maximum PD estimation error ranged from 0.0539 to 0.0891 for random PD scenarios, while for static PD, it remained consistently at 0.0102 across all SNRs. The average PD estimation error was consistently lower for SCTM with static PD locations. As SNR improved, average errors converged to 0.0102 for both scenarios, indicating increased accuracy with lower noise levels. In conclusion, the SCTM algorithm is more effective when used with static PD locations for power cable monitoring, leading to more accurate PD estimations. This research enhances the reliability and efficiency of PD source localization, vital for preserving power cable integrity and preventing breakdowns.

1. Introduction

Observing the condition of cables is necessary to ensure stable and reliable operation, as mentioned by Gugulothu *et al.,* [1]. According to several authors [2-4], over time, PD has been recognized as an important indicator of cable damage and insulation degradation. These issues can arise due to factors such as long-term operation, insufficient grounding distance, electrical insulation

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failure, poor contact, exposure to an extended period of stress, inadequate insulation, aging, and harsh environmental conditions. As described by Ma *et al.,* [5] PD is a complex physical phenomenon caused by a localized concentration of electrical stress in an insulator. Although partial discharge generally does not cause a breakdown of the insulation, it will cause the performance of the dielectric insulation to decrease and eventually lead to the failure of the power equipment. The presence of PD is an important issue because it can cause insulation failure and affect the safety and reliability of the electrical system. Partial discharge activity can gradually erode the insulating material, resulting in reduced dielectric strength and an increased risk of electrical damage. Damage to underground cables results in significant economic losses, especially for the sector involved. These sectors are highly dependent on uninterrupted power supply to maintain their operations.

According to the Performance & Statistical Information on the Malaysian Electricity Supply Industry 2019, report published by Energy Commission [6], the industrial sector accounted for 45.4% and the commercial sector accounted for 30.6% of the highest electricity consumption in 2019. Therefore, quick recovery and identification and location of faults can reduce customer complaints, downtime, lost revenue, and employee repair costs, as indicated by R. Tariq *et al.,* [7].

From the findings presented by Rao *et al.,* [8], power cables in today's industrial conditions require better mechanical protection to ensure an uninterrupted power supply. The rising demands faced by the power sector encourage manufacturers to produce innovative cable designs (e.g., cross-linked polyethylene insulation, PVC insulation) in order to meet critical technical and reliability issues, as discussed by Wang *et al.,* [9]. Consequently, Chai Chang Yii *et al.*, [10] have concluded that the most effective early warning indicators for electrical insulation deterioration in power cable networks are the detection and measurement of partial discharge sources.

In recent years, remarkable progress in the advancement of localization algorithms is achieved by several researchers [11-18]. A noteworthy statistical algorithm that has gained prominence is the SCTM algorithm, which is based on the multi-end PD location algorithm by C. C. Yii *et al.,* [19]. This algorithm effectively employs segmented correlation (SC) techniques and trimmed mean data filtering (TMDF) techniques to enhance the accuracy of partial discharge algorithms. Its performance has been rigorously tested by Abu Bakar *et al.,* [20] in the context of double-end PD location. Although most of these authors [10,19] primarily cater the localization algorithms to static PD source models, it is important to note that static PD source models pose certain challenges when compared to random PD generators due to their limited representativeness and lack of variability.

Static PD sources exhibit consistent discharge patterns and magnitudes at fixed locations, which makes it challenging to simulate real-world PD scenarios accurately. Conversely, the variability introduced in random PD generators better mimics the complexity of PD phenomena observed in practical applications, enabling a comprehensive assessment of localization algorithms, and enhancing their reliability in diverse operational conditions. In this paper, the application of SCTM algorithms specifically for random PD sources, acknowledging the benefits it offers in addressing the limitations of static PD source models is presented.

2. Methodology

2.1 Modelling PD Signals and Environmental Noise

Figure 1 depicts a diagram of the online PD estimation system developed in this study for power cables. The proposed system uses the double-end PD measurement method for PD localization estimation. Two PD sensors are strategically positioned at locations A and B, with a separation distance of 2 km, to capture PD arrival signals emitted by an underground cable PD source.

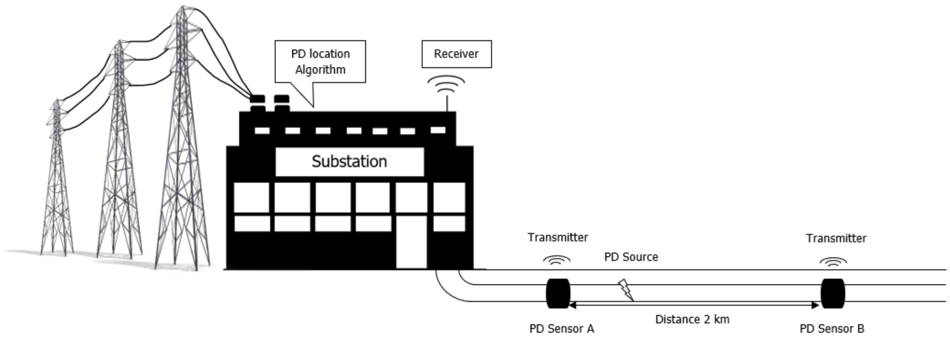

Fig. 1. Online PD localization estimation system diagram for underground cables

For the purpose of PD localization analysis, a mathematical model of the PD pulse was utilized to simulate high-frequency PD signals. The model employed is described by Li *et al.,* [21], as shown in Eq. (1).

$$s(t) = A[e^{-a_1 t}\, cos(w_d t - \varphi) - e^{-a_2 t}\, cos(\varphi)] \tag{1}$$

where:
A – The magnitude coefficient, assumed to be 0.01;
$\mathrm{a_1} - 1\ \mathrm{Ms^{-1}}$;
$\mathrm{a_2} - 10\ \mathrm{Ms^{-1}}$;
$\varphi - \tan^{-1}(\mathrm{w_d}/\mathrm{a_2})$;
$\mathrm{w_d} - 2\pi \mathrm{f_d}$;
$\mathrm{f_d} - 1\ \mathrm{MHz}$.

The simulative sampling frequency, f_s, is set at 100 MHz. The propagation velocity of the PD pulse along the power cable, v_f, is determined by Khan *et al.,* [22], as shown in Eq. (2).

$$v_f = {v_s}/{\sqrt{\varepsilon}} \tag{2}$$

where:
$\mathrm{v_s} -$ Propagation velocity in free space (300 m/μs);
E – Effective relative permittivity of the cable dielectric and semiconducting screen layers.
For a specific medium-voltage three-core cable (50 mm^2 Cu/XLPE/PVC, 8.7/15 kV) the propagation velocity is 156 m/μs from the laboratory experiment conducted by Khan *et al.,* [22]. The simulated PD pulse is then adjusted according to the propagation velocity. In real environments, PD signals captured by PD sensors are corrupted by white Gaussian noise (WGN). To model WGN, the MATLAB function 'wgn(m,n,p)' was employed to generate WGN with a normal distribution probability density.

2.2 Segmented Correlation Trimmed Mean (SCTM)

The SCTM algorithm enhances the precision of PD localization estimation. It employs the SC techniques to estimate 200 PD localization samples, followed by the application of TMDF technique for data refinement. This algorithm represents a novel approach in the realm of double-end PD measurement by Abu Bakar *et al.,* [20], previously pioneered in the multi-end PD measurement method described by C. C. Yii *et al.,* [19]. TMDF is a statistical analysis technique that eliminates inaccurate PD localization samples and computes the average of high-precision samples to derive a refined estimate of PD location. Figure 2 illustrates the process flow of the SCTM algorithm.

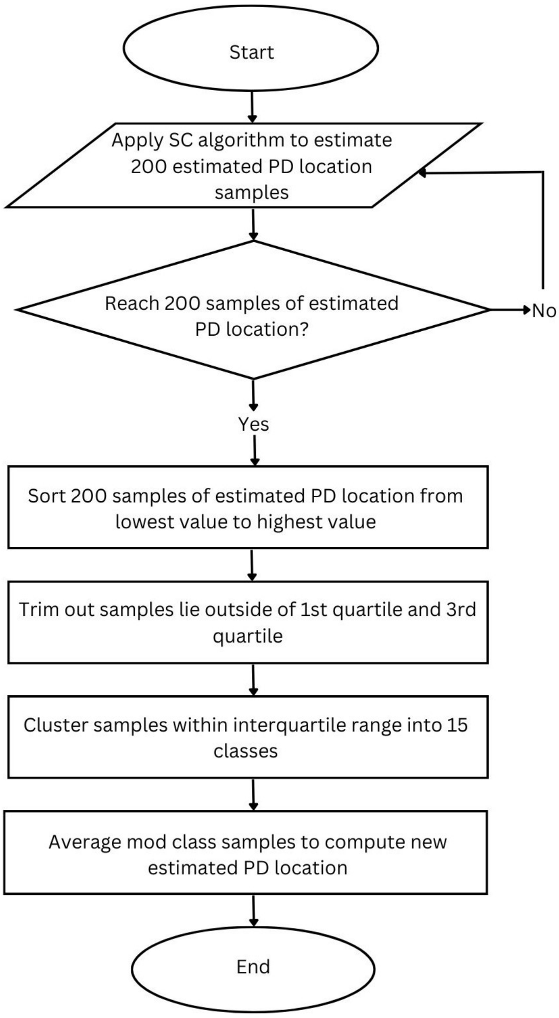

Fig. 2. Process flow of the SCTM algorithm [20]

The SCTM algorithm initially estimates 200 PD locations using the SC technique. A pre-processing step involves sorting the estimated PD localization samples in ascending order for the subsequent trimming process. The lower 25th percentile and upper 75th percentile, which represent values deviating significantly from the majority of samples, are robust indicators for the trimming process. The trimming process filters out these extreme values or outliers enabling a focus on the central portion of the data distribution for further analysis. The interquartile range (IQR) is determined by Eq. (3), which measures the spread of the data.

$$IQR = Q_3 - Q_1 \tag{3}$$

where:
Q_3 – 3rd quartile of the estimated PD samples;
Q_1 – 1st quartile of the estimated PD samples.

Following the trimming process, clustering is applied to the remaining 100 samples falling within the IQR range. The 100 samples are divided into 15 classes, and the class interval (k) is determined by Eq. (4) using the minimum (S_{min}) and maximum (S_{max}) PD localization values.

$$k = \frac{S_{max} - S_{min}}{15} \tag{4}$$

During the averaging process, the class with the highest sample count (mod class) is chosen, indicating highly precise measurements. The new estimated PD location is then derived by calculating the mean of the samples belonging to the mod class, as described by Eq. (5).

$$Mean_{PD} = \frac{\sum_{n=1}^{m} S_n}{m} \tag{5}$$

where:
n – 1, 2, 3…m;
S_n – Estimated PD localization samples that enter the mod class;
m – Total number of samples that enter the mod class.

2.3 SCTM Applied to Random PD Generator

The SCTM algorithm encompasses the comprehensive process flow of randomly generated PD, as illustrated in Figure 3. Firstly, a random PD source model is created to emulate the behaviour of PD signals. This model serves as a basis for further analysis. Subsequently, PD signals are simulated to replicate the measurements obtained from PD sensor A and PD sensor B, these signals represent the electrical activity associated with PD.

The MATLAB "randi" function is employed in this case to introduce variability when simulating or modelling scenarios that involve randomizing positions along a distance. Its purpose is to enable the analysis of the effects of variability by simulating different situations where position or location along the distance needs to be randomized. The function "randi (L,1)" selects a random integer within the range of 1 to L. This value represents the distance from the PD source to sensor A, denoted as D_A. The distance from the PD source to sensor B, denoted as D_B, is determined by Eq. (6).

$$\mathrm{D_B} = \mathrm{L} - \mathrm{D_A} \tag{6}$$

where:
D_A – Distance from PD source to sensor A;
L – Cable length.

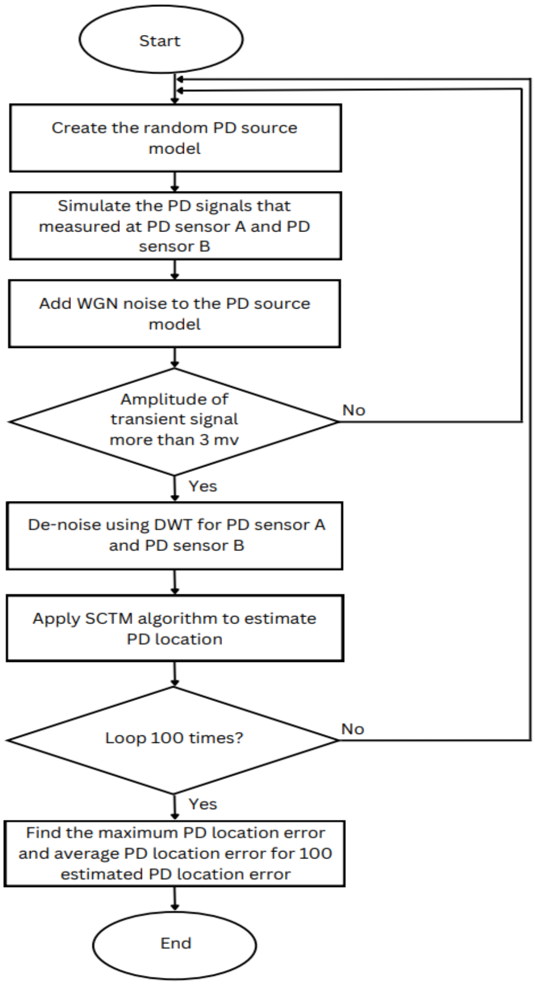

Fig. 3. Process flow of the SCTM algorithm for randomly generated PD

In order to incorporate real-world scenarios, random noise in the form of white Gaussian noise (WGN) is added to the PD source model. This noise mimics the interference and fluctuations present in practical measurements. Refer to Section 2.1 for the PD signals and environmental noise modelling.

The amplitude of PD signals is examined to determine if it surpasses the threshold of 3 mV. An amplitude exceeding this value indicates the presence of a significant transient event, triggering denoising techniques based on the Discrete Wavelet Transform (DWT) for both PD sensor A and PD sensor B. This denoising process aims to eliminate noise and enhance the clarity of the PD signals. If the amplitude does not exceed the threshold, the simulation and analysis steps are resumed with a new set of random PD source model parameters.

Once the denoising step is completed, the SCTM algorithm is used to estimate the location of the PD source. The SCTM algorithm infers the source location based on the characteristics of the PD signals. The estimation process is repeated 100 times to obtain multiple estimates of the PD location using the SCTM logarithm. This iterative loop ensures a robust evaluation of the PD source location. If the loop reaches 100 iterations, the maximum and average PD location errors are determined based on the 100 estimated PD location errors. These metrics provide information about the estimating method's accuracy and reliability. Alternatively, if the loop has not reached 100 iterations, the procedure is repeated from the beginning with a new set of parameters.

3. Results and Discussion

A series of simulations were conducted in the MATLAB environment to evaluate the precision of SCTM algorithms for both random PD generator-based scenarios and static PD locations. The outcomes are divided into two categories: the maximum PD estimation error and the average PD estimation error.

3.1 Maximum PD Estimation Error

In this section, the SCTM algorithms were repeatedly executed one hundred times each for randomly generated PD locations, resulting in a total of one hundred PD location estimates for each signal-to-noise (SNR) level. The maximum PD estimate error is the largest error generated out of those one hundred estimated PD locations. The error percentage is calculated by using Eq. (7). These results were then compared to the results obtained when applying the SCTM algorithm to static PD locations, as described Abu Bakar *et al.,* [20]. The analysis encompassed a range of SNR values, as depicted in Table 1, spanned from 4 dB to -18 dB, with a decrement of 2 dB between each step. Figure 4 presents a graphical representation of the relationship between the maximum PD estimation error and SNR, based on the data extracted from Table 1.

$$\% \, Error = \frac{|Actual \, fault \, location - Estimated \, fault \, location|}{Total \, system \, length} \, x \, 100 \tag{7}$$

The results presented in Table 1 and Figure 4 demonstrate that the SCTM algorithm applied to a random PD generator exhibits slightly higher estimation errors compared to the SCTM algorithm applied to a static PD location. Specifically, at an SNR of -18 dB, the maximum PD estimation error is 0.0891 for the SCTM with a random PD generator, while it is 0.0492 for the SCTM with a static PD location. Similarly, at other SNR levels, the SCTM algorithm for static PD location consistently outperformed the SCTM algorithm for random PD generator-based scenarios, maintaining a maximum error of 0.0102 across all SNR levels. In contrast, the SCTM algorithm for random PD generator-based scenarios exhibits slightly higher errors ranging from 0.0539 to 0.0891.

Table 1
Maximum PD Estimation Error of SCTM for Random PD generator and Static PD Location

SNR (dB)	SCTM (Random PD generated)	SCTM (Static PD location) [20]
-18.0000	0.0891	0.0492
-16.0000	0.0592	0.0288
-14.0000	0.0592	0.0288
-12.0000	0.0574	0.0102
-10.0000	0.0582	0.0102
-8.0000	0.0539	0.0102
-6.0000	0.0553	0.0102
-4.0000	0.0585	0.0102
-2.0000	0.0549	0.0102
0.0000	0.0567	0.0102
2.0000	0.0553	0.0102
4.0000	0.0539	0.0102

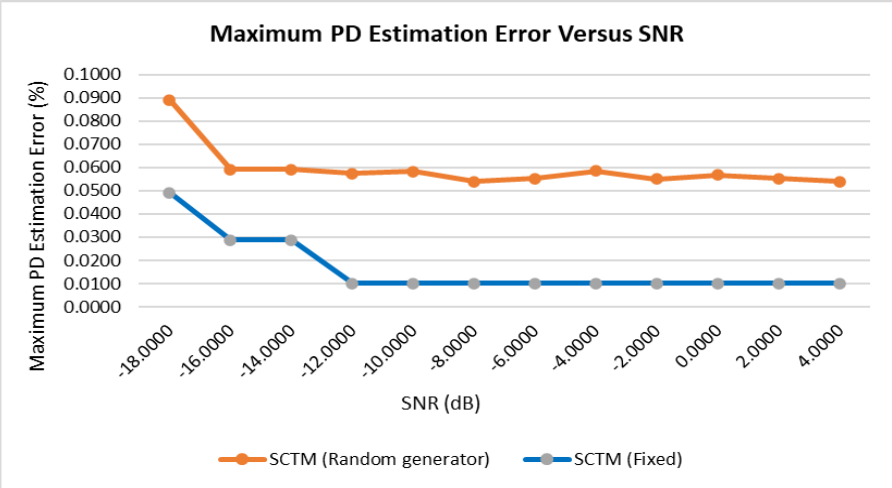

Fig. 4. Comparison of maximum PD estimation error with SNRs for the SCTM algorithm in random PD generator-based and static PD locations scenarios

3.2 Average PD Estimation Error

In this section, the SCTM algorithms were iteratively executed one hundred times to a random PD generator-based system in order to generate one hundred PD location estimates for the power cable at each SNR level. The resulting one hundred PD localization error estimates for each SNR level will be averaged to identify the average errors of the PD localization algorithm. Similar to Section 3.1, the average errors were computed across a range of SNRs (-18 dB to 4 dB). These results were then compared to the results obtained when applying the SCTM algorithm to static PD locations, as described by Abu Bakar *et al.,* [20]. A lower PD average estimate error indicates higher accuracy of the PD localization algorithm.

A comparison between the two scenarios presented in Table 2 and Figure 5 reveals a consistent trend: the average PD estimation error is consistently lower when employing the SCTM algorithm with static PD locations as opposed to using a random PD generator. For instance, at an SNR of -18 dB, the average error for SCTM with a random PD generator is 0.0289, whereas it is 0.0182 for SCTM with static PD locations. This trend persists across various SNRs, with the SCTM algorithm applied to random PD generators consistently yielding higher average estimation errors in contrast to SCTM with static PD locations.

With increasing SNR values, both scenarios exhibit a decrease in average estimation errors. At higher SNRs, approaching 0 dB, the average errors converge to a similar value of 0.0102 for both the SCTM with a random PD generator and the SCTM with a static PD location. This convergence implies that as the signal-to-noise ratio improves, reducing the noise level in the measured PD signal, the influence of the random PD generator or static PD location on PD estimation becomes less prominent. Consequently, average errors are reduced.

Overall, the obtained results indicate that applying a static PD location in the SCTM leads to more accurate PD estimations compared to using a random PD generator. The random PD generator-based localization methodology involves randomly determining the locations of PD events within the system, leading to uncertainty and variability in the measurements. It may introduce additional noise and randomness into the PD signals, which can hinder the localization process. The unpredictable nature of random PD signals can make it challenging to distinguish between genuine PD signals and noise, resulting in higher estimation errors. However, it is important to note that the magnitudes of the estimation errors are relatively small across all SNRs, indicating that both scenarios provide reasonably accurate average estimations.

Table 2
Average PD Estimation Error of SCTM for Random PD generator and Static PD Location

SNR (dB)	SCTM (Random PD generated)	SCTM (Static PD location) [20]
-18.0000	0.0289	0.0182
-16.0000	0.0217	0.0117
-14.0000	0.0231	0.0104
-12.0000	0.0210	0.0102
-10.0000	0.0182	0.0102
-8.0000	0.0168	0.0102
-6.0000	0.0160	0.0102
-4.0000	0.0146	0.0102
-2.0000	0.0160	0.0102
0.0000	0.0149	0.0102
2.0000	0.0155	0.0102
4.0000	0.0145	0.0102

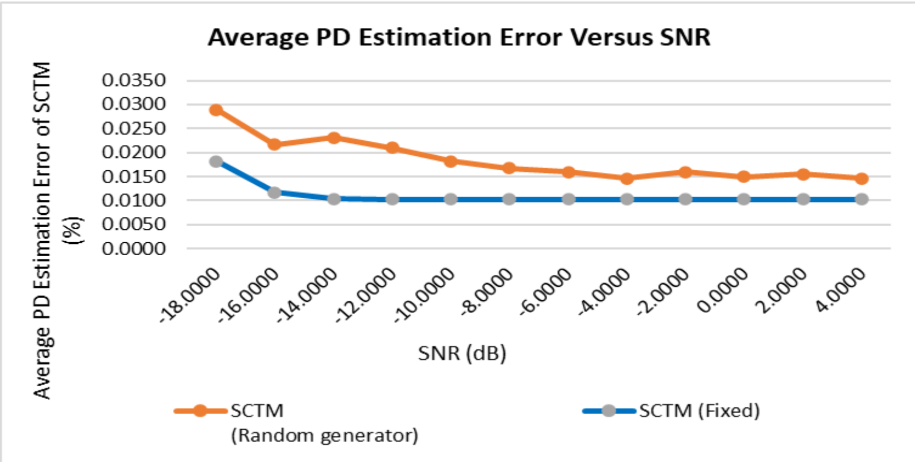

Fig. 5. Comparison of Average PD Estimation Error with SNRs for the SCTM Algorithm in Random PD Generator-based and Static PD Locations Scenarios

4. Conclusions

This study has successfully established a clear correlation between the SNRs and the accuracy of PD localization. It is evident that a decrease in SNR adversely affects the estimation of PD location, resulting in a higher error and diminished localization accuracy. The findings indicate that utilizing a random PD generator within the SCTM algorithm yields less accurate PD estimations compared to employing a static PD location approach. The discrepancy in accuracy between random PD generator-based localization and static PD location approaches can be primarily attributed to the presence of random noise interference. To address these limitations, future research endeavours should prioritize the modelling and simulation of background noise encountered in practical PD measurement environments. This approach would enable the creation of realistic scenarios, facilitating a more precise evaluation of the algorithm's performance.

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