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Partial Discharge Localization in Transformers Using UHF Sensors

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Abstract—**The location of the partial discharge (PD) source inside a transformer can be determined by using the time differences between signals that are captured by an array of three UHF sensors. However, other unwanted signals are also picked up by the sensors and may result in a false PD location. This paper discusses the application of multivariate denoising to the PD signals. Three methods are compared to determine the time difference between the received signals and locate the PD source. With the first peak method, the time difference is calculated by taking the first peak of the signal as the arrival instant. In the second method, the arrival time is determined from the knee point of the cumulative energy curve. For the third method, the time difference is determined by applying the similarity function to the plot of the cumulative energy of the PD signals. The last method is fully automated. However, experimental results show the first peak method tends to be the most accurate.**

Keywords: Partial discharge location, Ultra High Frequency (UHF), cumulative energy.

I. Introduction

The ultra high frequency (UHF) partial discharge (PD) detection has proven effective in verifying the insulation condition of GIS. This technique is now being developed and applied to transformer diagnostics [1, 2]. The UHF detection method offers better sensitivity and is able to capture the fast electromagnetic transients emitted by PD events. However, the PD pulse signals are very weak even for a well-designed UHF sensor (antenna). This situation is further exacerbated by the interference from unwanted signals or noise. Typical interferences in the UHF range consist of digital radio, television and telecommunication signals, thermal noise in the detection system and periodic pulses from switching operations [3, 4, 5].

To determine the PDs location, a minimum of three sensors must be used to record the PD signals and enable triangulation. The signals can be processed to determine the arrival time difference between them. The signals captured by the sensors, as aforementioned, are corrupted by the interference. This can affect the accuracy of the time difference measurement and lead to a false location result.

To remove the unwanted interference and noise, the PD signals need to be denoised before further analysis can be carried out. One of available techniques to denoise multiple signals is the multivariate denoising method. This technique is an improvement of the direct univariate denoising, achieved through a final principal component analysis (PCA). It has been shown to perform well when applied to denoise multi-channel recording signals [6].

Localization of the PD source can be done by comparing the time difference between the sensors arrival times. There are three methods. In one approach, the time reference can be determined from the first peak of the signals [7, 8]. The second method examines the cumulative energy of the signal [7, 9, 10]. From the energy curve, the time difference between signals is determined by finding the knee point where the change is sudden. The drawback is that human judgment is required to decide on the knee point [7].

To overcome the above-mentioned problem, a third method is proposed in this paper. Here, the cumulative energy curves of two signals are compared and checked for their similarity. The similarity is calculated as the difference of two cumulative curves. One curve is shifted toward others until the difference between them is minimum. The time that is needed to achieve the minimum value is taken as the time difference between the two signals.

In this paper, the captured PD signals were first denoised by applying a Matlab multivariate denoising tool and subsequently the three aforementioned methods were applied to locate the PD source.

II. Experiment Set-up

The experiments were conducted using a small transformer tank with dimension 71.5 cm width, 118 cm length and 95 cm height. The tank is filled with mineral oil up to 50 cm of depth.

Three UHF sensors were used to capture the PD signals. Their outputs were connected to a 4-channel digital oscilloscope via coaxial cables of identical length. The sensors and the PD source are immersed in oil and their coordinates are shown in Table 1.

The PD source is a needle-plate electrode. To generate the PD, the voltage was raised to 19 kV. An oscilloscope was used to record the PD signals. It has 5 Gs/s resolution for each channel and has a built-in computer system to record the data. With sampling rate of 5 Gs/s, the time resolution is 0.2 ns.

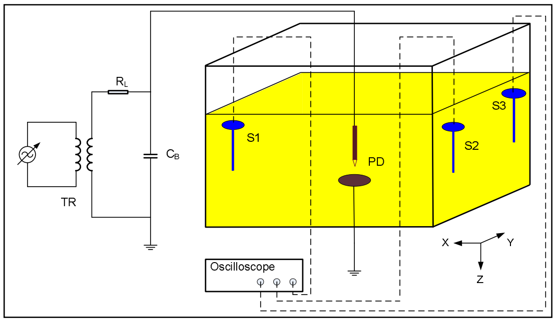


Figure 1. Experiment arrangement

TABLE I. UHF SENSORS AND PD SOURCE POSITION

	x (cm)	y (cm)	z (cm)	Δ*(cm)
Sensor 1	103	10	46	74.7
Sensor 2	10	10	48	40.8
Sensor 3	10	50	44	44.2
PD Source	36	29	73	0

*Δ = distance to the PD source

III. PD SIGNALS

A. *Signals propagation and waveform patterns*

According to the well-known Maxwell's theory, the propagation velocity of electromagnetic waves in a given medium is $v = 1/\sqrt{\mu\varepsilon}$ where μ is the permeability and ε is the permittivity of the medium. In air, the propagation velocity is the speed of light (i.e. 3×10^8 m/s). In oil, it would be slower because of its higher permittivity as compared to air, the latter has a relative permittivity of 1. Without exact manufacturer data on the relative permittivity of mineral oil, experiments were conducted to determine the speed of the electromagnetic waves emitted by the PD source and propagating in oil. This was found to be $2\text{x}10^8$ m/s (i.e. two thirds the speed of light).

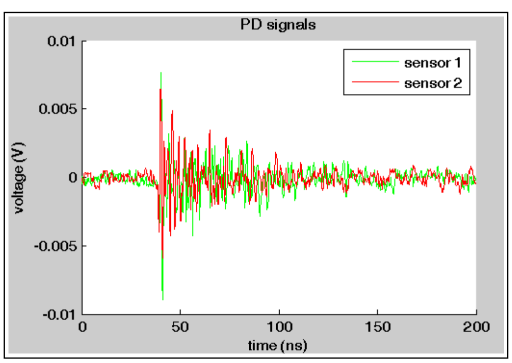


Figure 2. Time domain of the PD signals captured by two sensors at different positions

The electromagnetic signals generated by the PD source inside the transformer tank will travel in all directions. During the course of propagation, the signals may encounter internal barriers or the transformer tank and thus reflection and/or refraction may occur. This can cause distortion to the signal waveform. Figure 2 shows the PD signals captured by two sensors that were placed at different positions. The signal wavefronts show a similar pattern but after a few cycles the waveforms show different shape and magnitude.

The PD signal patterns are also very much affected by the sensors location. Different locations may produce different patterns. This might be because the initial wavefront of the field radiated by the PD source may not be uniform in all directions. Also the PD signals may be attenuated along its path, and the density of the oil could be non-uniform and thus the velocity of the signals changes [9].

Another factor affecting the PD waveform pattern is the sensor type in use in detecting the PD signals. In the experiment three monopole sensors were employed to capture the EM signal emitted by the PD source. This monopole sensor has lower sensitivity and bandwidth as compared to disk-type sensors [11]. However, it has faster signals response [12] and less oscillation. Consequently, the monopole sensor type was chosen to detect the PD signals in the experiment. Figure 3 shows the step-pulse response of the monopole sensor and log-spiral disk type sensor.

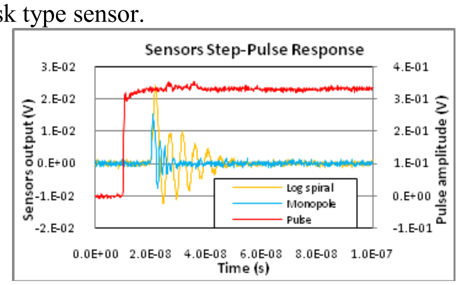


Figure 3. Step-pulse responses of the monopole and log-spiral sensors.

B. *Denoising the PD Signals*

In practical environment situations, the noise or interference mainly consists of continuous sinusoidal carrier signals from communication systems, thermal noise in the detection system, and periodic pulse-shaped noise from thyristor operation [3, 4]. To denoise the PD signals, multivariate denoising tool is applied.

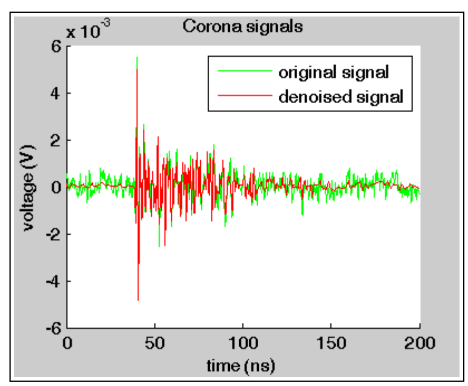


Figure 4. Denoising of corona discharge signals.

Multivariate wavelet denoising deals with regression models of the form :

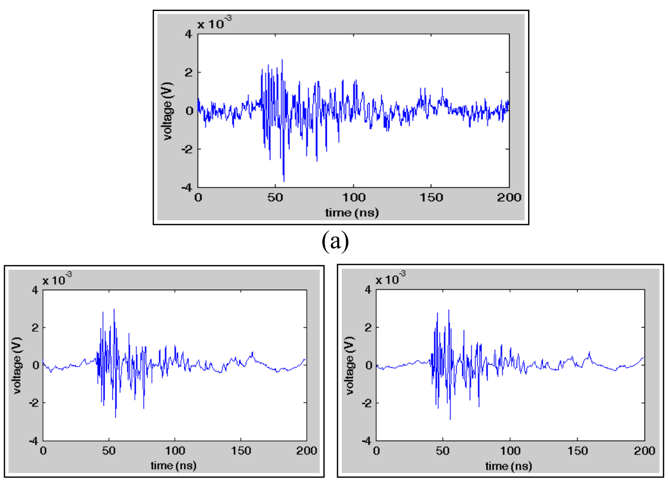
$$X(t) = f(t) + \varepsilon(t),\ t = 1, \ldots, n. \quad (1)$$

where :

$(X(t))_{1\le t\le n}$ = observed signals
$\varepsilon(t)_{1\le t\le n}$ = centered Gaussian white noise of unknown variance σ^2
f = unknown function to be recovered

The multivariate denoising procedure can be carried out in four steps as follows [6]:

1. Perform wavelet transform at level J for all columns of X.
2. Remove noise by a simple multivariate thresholding after a change of basis. The noise covariance estimator is defined as $\hat{\Sigma}_\varepsilon = MCD(D_1)$ and is used to compute V such that $\hat{\Sigma}_\varepsilon = V \wedge V^T$ where $\wedge = diag(\lambda_i, 1 \le i \le p)$. Apply to each detail after a change of basis, the p univariate thresholding using threshold $t_i = \sqrt{2\lambda_i \log(n)}$ for each ith column. Figure 5.b shows the typical result of this step. The denoised signal using a simple multivariate thresholding shows satisfactory result but this result still can be improved.
3. Improve the obtained result by retaining fewer principal components. Perform PCA of the matrix A_J and select the appropriate number p_{J+1} of useful principal components.
4. Reconstruct the denoised matrix $\breve{X}$ from the simplified detail by inverting the wavelet transform. Figure 5.c shows the further denoising by performing PCA to the signal of step 2. The result shows improvement where the signal is clearer and smoother.



(a)

(b) (c)

Figure 5. (a) original signal, (b) denosing using multivariate thresholding, and (c) result after retaining PCA component

IV. SIGNALS TIME DIFFERENCE CALCULATION

The PD location in a transformer tank can be estimated by using the time difference between signals captured by sensors.

A. First Peak Method

The time difference is defined as the difference between the first peaks of two PD signals. The procedure is as follows:

1. Denoise the original signal by applying multivariate denoising tool. The denoising is done to the PD signals captured by three sensors at the same time.
2. Squaring the signals to make the signals unipolar.
3. Normalize the signals so that they have similar magnitude.
4. Use the same threshold value which is 10% of the signals magnitude.
5. Pick the first peak point above the threshold value which is then used to determine the arrival time.
6. Calculate the time difference between the two first peaks of the PD signals.

The first peak of a PD signal is determined manually from the signals waveform (Fig.6). It is defined as the point where the waveform achieves the first highest local magnitude which is above the threshold value.

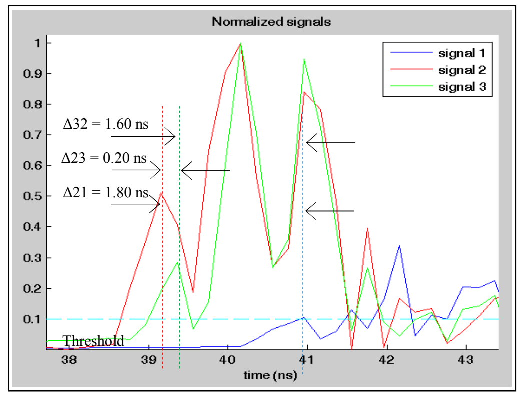


Figure 6. Zooming of PD signal waveforms to determine the first peak of the signals

This method has good accuracy with a mean error of 0.34 ns or 6.8 cm. Also the determination of the point of the peak time is simple and easy although it has to be done manually. The threshold value chosen is somewhat arbitrary. There is no strict rule. Here, 10% of the normalized PD signals was chosen as the threshold value in order to adequately remove the noise.

It is found that this method gives a high accuracy with just 0.34 ns mean error for the time difference between sensor 2 and 1. The error decreases with the distance between sensors, as shown in Table 2.

B. Cumulative energy

The PD waveforms are converted to the cumulative energy curves using:

$$U = \sum_{i=1}^{N} V_i^2 \qquad (2)$$

Where V_i = denoised input signals
i = data i^{th}
N = number of samples in the data

The time differences between signals are acquired from the cumulative energy curves by exploiting a unique point in the curves. The most significant point that can be used to determine the arrival time of the signal and thus to determine the time differences between sensors is the knee point. The knee point is defined as the point where a sudden increase in the energy occurs [3,9].

The other method is by applying a similarity function between signals. This is done by shifting one cumulative energy curve toward the other curve. The time difference is defined as the time shifting that produces minimum similarity value.

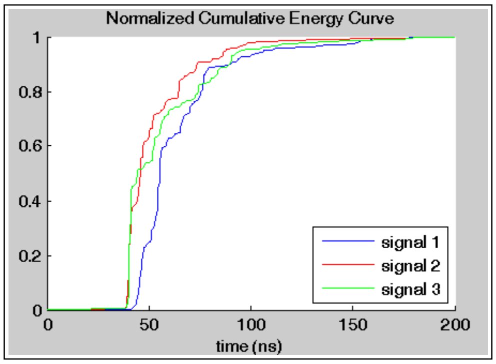


Figure 7. Normalized cumulative energy curves

1. Knee point

The knee point is the point when a sudden increase in the cumulative energy occurs [7, 10]. Fig. 6 shows cumulative energy curves simultaneously recorded by the three sensors. The point where the curves jump abruptly is related to the arrival time of the signals to the sensors and is used for determining the time difference between signals.

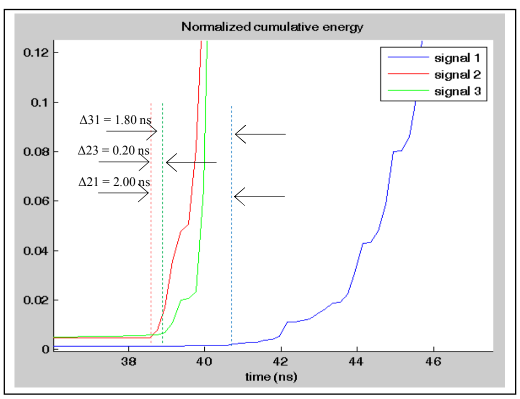


Figure 8. Zoom of the cumulative energy curves to determine time difference by picking the knee point.

To determine the knee point values, the cumulative energy curves were zoomed in as shown in Fig. 8. The knee point of signals 1 and 2 can be determined quite easily because there are clearly sudden changes in the curves. However, this is not the case for signal 3. Similar to the peak point method, the knee point method relies on human judgment in determining the knee point values.

The knee point of the cumulative energy curve method has lower accuracy than the first peak method. The highest error for the knee point method is 1.27 ns which corresponds to the case of the largest distance difference.

2. Similarity of the Cumulative Energy Curve

The time difference also can be calculated by the curve similarity method. One curve is shifted toward the others and then the difference between signals is calculated. The time difference is reached if the difference between signals is minimum or the similarity reaches the minimum value. The similarity value is calculated by:

$$\text{Similarity} = \sum_{t=1}^{n-\Delta t} S_1(t) - S_2(t-\Delta t) \tag{3}$$

where S_1 and S_2 denote the two signals, n is the number of data points and Δt is the shifting time.

The electromagnetic signal emitted by the PD source will radiate in all directions. Over its travel path, this signal can be attenuated and reflected by the transformer tank and barriers inside the tank. Thus, the sensor will capture not only the original PD signal but also the reflections.

The PD signals which are captured by sensors in different positions show similar waveform patterns but mostly at the beginning of the signals. Thus, when the signal waveform is converted to its cumulative energy curve, only 40% of the maximum value of the cumulative energy curve was used in order to reduce the error.

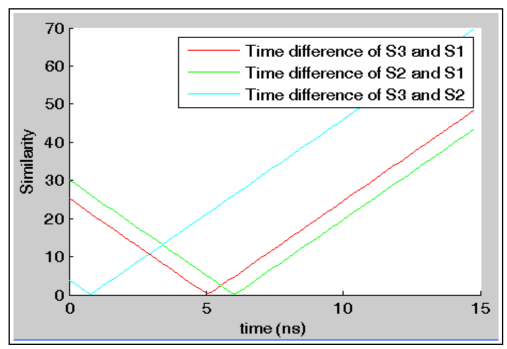


Figure 9. Time difference using similarity function

The time difference calculation in this method was done almost fully automatic. However, the result shows higher error than the other two methods. The highest by this method is 3.35 ns or 67 cm. This occurs for the signal captured by the furthest sensor (sensor 1). Note that this sensor was installed on the opposite side of the tank (Fig.1) which may explain the different cumulative energy pattern.

TABLE II. TIME DIFFERENCE BETWEEN SENSORS

	Difference between sensor-to-PD distances (cm)	**Calculated Time Difference (ns)**	**Measured Time Differences**					
			First Peak		Knee point		Similarity	
			Mean (ns)	Error (ns)	Mean (ns)	Error (ns)	Mean (ns)	Error (ns)
S31	30.4	1.52	1.74	0.22	2.64	1.12	4.71	3.19.
S21	33.9	1.70	2.04	0.34	2.97	1.27	5.05	3.35
S32	3.5	0.18	0.3	0.12	0.33	0.13	0.58	0.4

The errors of the time difference between signals captured by sensors 2 and 3 are much lower with average error of just 0.4 ns. This is because the signals of sensors 2 and 3 have similar waveform patterns and thus produce similar cumulative energy curves.

The signal waveforms from close sensors show similar patterns. If they are far apart or on different tank sides, the waveforms tend to be different. To reduce the dissimilarity, it is suggested to install sensors in a closer arrangement [9, 13]. However, this will require a higher resolution oscilloscope.

3. *The denoising effect*

Denosing is intended to remove the unwanted part of the signals that distorts the PD waveform. However, it may remove some useful part of the signals. Also, the denoising process is time consuming. Thus one needs to justify the benefits of the denoising step.

To denoise the signals, multivariate denoising was applied. In the first peak method, results from both denoised and un-denoised signals show similar results. It is easier to determine the peak point with the denoised signals. However for the cumulative energy case, there is a clearly different result between using the denoised and un-denoised ones.

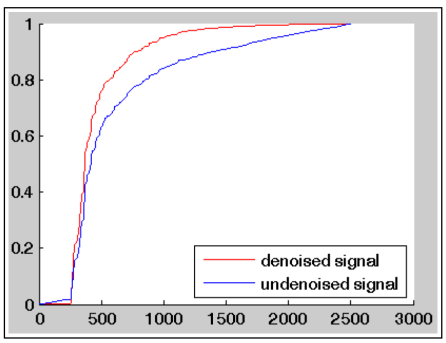


Figure 10. Cumulative energy curves of denoised and un-denoised signals

Figure 10 shows the cumulative energy curves of both denoised and un-denoised (original) signals. The patterns are similar. The difference is that after reaching the "knee point", the denoised curve increases faster to reach its maximum than the un-denoised signal. This makes the knee points in the denoised signals clearer to identify.

Using the same method with the un-denoised signals to calculate the time difference by the similarity method, the highest error of the time difference is 4.03 ns. This is higher than the denoised error of 3.35 ns.

The sensors in the experiment (Fig.1) were positioned at different distances to the PD source. With the assumption that the PD signals travel in the straight line (shortest path), the closest sensor should receive the signal first and the furthest sensor should pick up the signal last. Thus, sensor 2 should receive signal first then followed by sensor 1 and sensor 3 last. For the case where the PD signals were not denoised, 17 cumulative energy curves give incorrect sequence, i.e. sensor 1 received signals first then sensor 2 and 3. After the PD signals were denoised, the error only occurs for 9 out of 59 data.

V. Conclusion

This paper discussed the application of the first peak method and the cumulative energy curve to determine the time difference. The first peak method was done by finding the first peak above the threshold value. This method gives the most accurate result.

Also, two other methods were applied by using the cumulative energy curves. The knee point method relies on picking a point where the cumulative curve jumps abruptly. The other approach is by applying the similarity function to the plot of the cumulative energy curves.

The first two methods have better accuracy but influenced by human decisions in determining the time difference. Although the last method shows the highest error, it can be easily implemented to eliminate human involvement and thus a possibility of an automated PD locating system.

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