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Procedia Environmental Sciences 11 (2011) 1302 – 1307
Procedia Environmental Sciences

De-noising of GIS UHF Partial Discharge Monitoring based on Wavelet Method

Zhao Xin[1], Quan Jiangtao[2]

[1]*State Key Laboratory of Electrical Insulation and Power Equipment, Xi'an Jiaotong University, Xi'an, China*
[2]*HuBei Electric Power Testing&Research Institute*
e-mail: zhaoxin12345@163.com

Abstract

Partial Discharge (PD) happened in GIS may induce the failure of the apparatus and endanger the safety of the grid. Detection of PD with UHF sensor can find the defect earlier. In this a paper, a de-noising method based on the wavelet method is introduced to improve the accuracy of PD detection. The general wavelet de-nosing procedures are described in the paper, after that, the proposed algorithm is demonstrated by a field test.

Keywords: Component; Partial Discharge; UHF; GIS; Wavelet

1. Introduction

PD occurs within a GIS where the electric field exceeds the local dielectric strength of the insulation. Possible causes include insulation damage caused by overvoltages and lightning strikes, incipient weakness caused by manufacturing defects, or deterioration caused by natural aging processes. Although PD may initially be quite small, it is by nature that a damaging process causes chemical decomposition and erosion of materials. Left unchecked, the damaged area can grow, eventually risking electrical breakdown[1]-[2].

Detection techniques for partial discharge are being actively studied worldwide for reliable insulation diagnosis of gas-insulated switchgear (GIS) [3]–[5], and many practical means are being applied to meet the various needs.

In this paper, a kind of UHF sensor and a kind of de-nosing method based on wavelet are introduced.

2. UHF Sensor

The reliability of electrical energy networks depends on the quality and availability of primary electrical equipment such as the power transformer. Localised internal insulation failures can, however, lead to

doi:10.1016/j.proenv.2011.12.195

catastrophic breakdowns and incur long outage and penalty costs. To reduce such risks it is normal for GIS to have passed a range of factory tests including one for partial discharge activity before acceptance and commissioning. Once installed it is costly to energise with e.g. induced test voltage or resonant sets.

A key element of our approach to UHF monitoring for transformers has been the use of dielectric windows to form a robust electrical aperture through which high frequency electromagnetic fields in the tank can be detected. This approach stems from GIS applications where it was discovered that external mounting could improve sensitivity to PD as well as simplifying sensor manufacture and reducing costs. A further advantage is that external sensors can be installed and removed while the plant is in service or with only a brief outage. Fig.1 shows some options for external mounting of UHF sensors. Note how the body of the window sensor is continuous with the tank, screening against electromagnetic interference from external sources. Maintaining the Integrity of the Specifications

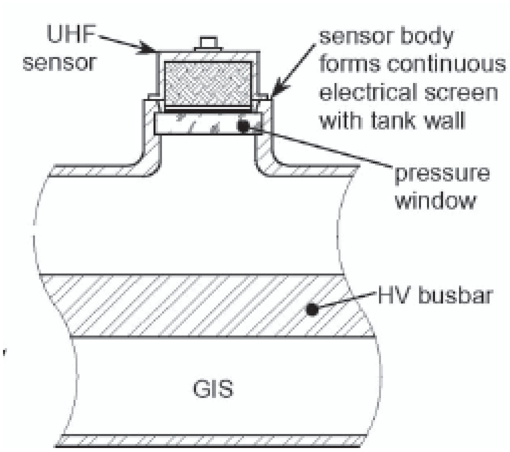


Figure 1 UHF sensor

3. De-noising with Wavelet Method

A Typical PD signal measured by UHF sensor is shown in Fig.2.

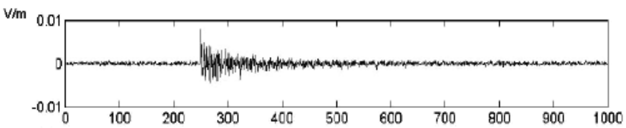


Figure 2 Typical PD signal measured by UHF sensor

The mathematical model of PD for UHF measurement is given by the following equation.

$$V(t) = Ae^{-\frac{t-t_0}{\tau}} \quad (1)$$

Here A is the amplitude of PD pulse, τ is time constant of the pulse discharge.

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 nonperiodic signals in phase-space i.e. time-scale or timefrequency domains as against the Fourier transform which considers phenomena in an infinite interval. A brief summary of the Fourier Transform, Short time Fourier Transform, and Wavelet transform are given below.

For a given unvaried function f, the Fourier transform of f and the inverse are given by

$$\hat{f}(\omega) = \int_{-\infty}^{\infty} f(t) e^{-i\omega t}$$
$$f(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \hat{f}(\omega) e^{i\omega t} d\omega \tag{2}$$

The short time Fourier transform for a given Window function g

$$g \in L^2(IR), \|g\| = 1 \tag{3}$$

g is real-valued. The short time Fourier transform f (u, τ) of a function f is defined by

$$F(u,\tau) = \int_{-\infty}^{\infty} f(t) e^{-\mathrm{iut}} g(t-\tau) dt$$
$$f(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} F(u,\tau) e^{\mathrm{iut}} g(t-\tau) d\tau du \tag{4}$$
$$g_{N,\tau}(t) = e^{iut} g(t-\tau),$$
$$F(u,\tau) = (f, g_{N,\tau})$$

The continuous wavelet transform F(a, b) of a function f is defined by

$$F(a,b) = (f, \psi_{a,b}) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t) \psi((t-b)/a) dt$$
$$(f, \psi_{a,b}) = \frac{1}{2\pi} (\hat{f}, \hat{\psi}_{a,b}) \tag{5}$$

Where

$$\hat{\psi}_{a,b}(\omega) = \sqrt{\mathrm{a}} e^{-i\omega b} \hat{\psi}(a\omega) \tag{6}$$

The general wavelet de-nosing procedure can be described as follows[6]-[9]:

• Apply wavelet transform to the noisy signal to produce the noisy wavelet coefficients to the level which we can properly distinguish the PD occurrence.

• Select appropriate threshold limit at each level and threshold method (hard or soft thresholding) to best remove the noises.

• Inverse wavelet transform of the thresholded wavelet coefficients to obtain a denoised signal.

3.1 Wavelet selection

To best characterize the PD spikes in a noisy signal, we should select our "mother wavelet" carefully to better approximate and capture the transient spikes of the original signal. "Mother wavelet" will not only determine how well we estimate the original signal in terms of the shape of the PD spikes, but also, it will affect the frequency spectrum of the denoised signal. The choice of mother wavelet can be based on eyeball inspection of the PD spikes, or it can be selected based on correlation γ (7) between the signal of interest and the wavelet-denoised signal, or based on the cumulative energy (8) over some interval where PD spikes occur.

$$\gamma = \frac{\sum (X-\bar{X})(Y-\bar{Y})}{\sqrt{\sum (X-\bar{X})^2 (Y-\bar{Y})^2}} \tag{7}$$

where $\bar{X}$ and $\bar{Y}$ are the mean value of set X and Y , respectively.

$$E = \sum X^2 \tag{8}$$

where E is the energy and X is the signal vector.

We choose to select the mother wavelet based on the last two methods: correlation between two signals and cumulative energy over some interval of PD spike occurrence. We found that the two methods give us a very similar outcome.

3.2 Threshold limits

Many methods for setting the threshold have been proposed. The most time-consuming way is to set the threshold limit on a case-by-case basis. The limit is selected such that satisfactory noise removal is achieved. For a Gaussian noise ; if we apply orthogonal wavelet transform to the noise signal, the transformed signal will preserve the Gaussian nature of the noise, which the histogram of the noise will be a symmetrical bell-shaped curve about its mean value. From theory, four times the standard deviation would cover 99.99% of the noise. Therefore, we could set the threshold be 4.5 times of the standard deviation of the wavelet-transformed signal to remove the Gaussian noise in the signal.

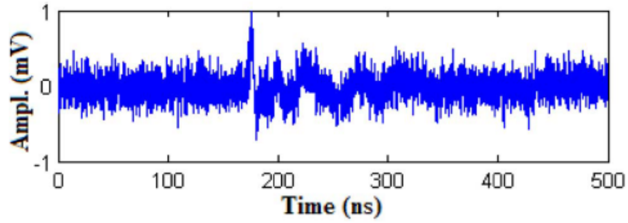
We have found that for the fiber optic signals, we could simply apply the standard deviation methods, since the signal is mostly white noises, however for the measured signals, we should set the threshold case-by-case to best denoise the signals.

Two rules are generally used for thresholding the wavelet coefficients (soft/hard thresholding). Hard thresholding sets zeros for all wavelet coefficients whose absolute value is less than the specified threshold limit. It has shown that hard thresholding provides an improved signal to noise ratio. In this study, we adopt the hard thresholding method.

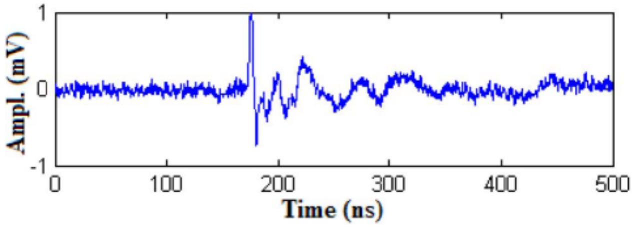
3.3 Level of Decomposition

From the previous section, we have known that the wavelet transform is constituted by different levels. The maximum level to apply the wavelet transform depends on how many data points contain in a data set, since there is a down-sampling by 2 operations from one level to the next one. In our experience, one factor that affects the number of level we can reach to achieve the satisfactory noise removal results is the signal-to-noise ratio (SNR) in the original signal. For the proposed sensor data, we could only go up to 4 or 5 level otherwise we would remove much of the PD signal, therefore the PD spikes wouldn't be captured.

Fig.2 is an example of PD signal disposed by wavelet de-nosing, the de-noised signal (fig.2(b)) has a more significant inceptive impulse than the original signal shown in fig.2(a).



(a) Original signal



(b) De-noised signal

Fig.3 Example of wavelet de-nosing of PD signal

4. Conclutions

A de-noising method based on the wavelet method is introduced to improve the accuracy of PD detection. The general wavelet de-nosing procedures are described in the paper, and the proposed algorithm is efficient demonstrated by a field test.

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ZHAO Xin, he was born in 1984. He received the M.S degree in electrical engeering form North China Electric Power University, Beijing, China in 2010.

Currently, he is a Ph.D student in Xi'an Jiaotong University, his inte

QUAN Jiangtao, he was born in Hubei province, China, in 1984. He received the M.S degree in high-voltage technique form North China Electric Power University, Beijing, China in 2010.
He is now working in HuBei Electric Power Testing&Research Institute. His interest is measuring study of overvoltage and breaker.