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Identification of partial discharges immersed in noise in large hydro-generators based on improved wavelet selection methods

Andre T. Carvalho [a,b], Antonio C.S. Lima [b,*], Caio F.F.C. Cunha [a,b], Mariane Petraglia [b]

[a] CEPEL Eletric Research Center, Av. Horácio Macedo 354, 21941-911 Rio de Janeiro, RJ, Brazil
[b] UFRJ – Federal University of Rio de Janeiro, Av. Horácio Macedo 2030, 21945-970 Rio de Janeiro, RJ, Brazil

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ABSTRACT

Background noise is a major problem in online Partial Discharge (PD) detection. Particularly in large hidro-generator windings, PD pulses originated in locations far from the PD sensors are strongly attenuated due to the propagation characteristics of the pulses, and arrive to the sensors completely buried in the background noise. Therefore, it is of paramount importance to identify the PD signals whose power is at least around the same as that of noise, thus with a medium to high signal to noise ratio, to extend the PD predictive diagnosis to the innermost bars of the winding. The wavelet shrinkage technique provides the best results in eliminating this type of noise. For this purpose, it is essential to choose the most appropriate wavelet decomposition, defined by the topology of the decomposition tree, its number of levels and the selected wavelet functions. In this paper a new algorithm for the automatic selection of the number of decomposition levels is proposed, and two new methods for the selection of the wavelet decomposition filters applied to PD signals measured from two large hydro generators are advanced. In addition a new methodology to evaluate the performance of denoising methods, which takes into account the average results for all possible relative time shifts of the PD pulses and several noise threshold levels is described. One of the proposed methods presented much better results than do the traditional CBWS, EBWS and SNRBWS methods, with respect to both the denoising performance and the runtime.

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1. Introduction

Among all the possible failure modes, those in the insulation of high voltage equipment can cause the most severe personal and material damage, as well as huge environmental and economic losses [1]. It is therefore imperative that the degradation of insulation systems on high voltage equipment be detected, quantified and monitored since its initial state, so that the actions of convenient repair or replacement can be timely scheduled. Partial Discharge (PD) analysis has proven to be effective in predictive diagnostics of the insulation on high voltage electrical equipment [2–5]. However, PD measurements, especially when performed in the field, are extremely affected and hampered by measurement noise. The noise in PD measurements can be classified into wideband noise, narrowband interferences and pulse shaped interferences [6]. Pulse shaped noise, whether periodic or stochastic on its occurrence, inserts in the PD measurement false positives, i.e. signals with similar characteristics to the PD pulses that are however not related to the assessed insulation system.

* Corresponding author. Tel.: +55 21 39388599.
E-mail address: acsl@dee.ufrj.br (A.C.S. Lima).

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The general solution for the open loop removal of this type of noise is to use classifiers, such as artificial neural networks and support vector machines [7–12]. Narrow-band noise is usually due to interference from radio waves and telecommunication systems, and may cause distortions on PD pulses. This type of noise can be removed by properly tuned notch filters [13]. Wideband noise is the measurement background noise, stochastic in nature. The noise amplitude is directly related to the measurement sensitivity. In some cases, background noise may even completely hide the PD signals. For the elimination of wideband noise, the most successful technique is the signal processing in the wavelet domain [14]. In addition, the denoising in the wavelet domain has proven to be effective in removing narrowband interferences [15].

Particularly in large generator windings, PD pulses originated in locations far from the PD sensors are strongly attenuated due to the propagation characteristics of the pulses [16]. In the HF measurement band, PD pulses behave as traveling waves, and the stator winding can be treated as a transmission line [17]. Since the pulses traveling along a stator bar are attenuated by cross coupling with other circuits, and suffer reflections and attenuations at the end of each slot, in practice the PD pulses originated from innermost defects arrive to the sensors completely buried in the background noise [18]. For this reason, the predictive diagnosis obtained from PD measurement is usually restricted to only a small outer portion of the winding. For the same reason, the identification in the wavelet domain of those PD pulses buried in the background noise can extend the diagnosis limits and greatly improve the assessment of the winding.

The Wavelet Transform (WT) decomposes the PD signals into a sum of dilated and shifted versions of an original oscillatory function called Mother Wavelet (MW) [19]. Because different MW can be used, the problem of choosing the best MW for decomposing each type of signal arises naturally. The choice of the MW is application dependent and must be adapted to the PD signals in order to obtain good results [20]. Three main methodologies for choosing the best MW considered here are: Correlation, Energy and Signal-to-Noise-Ratio Based Wavelet Selection methods, respectively denoted as CBWS [21], EBWS [22] and SNRBWS [23].

This paper aims to denoise PD signals obtained from large hydro-generators, and two new methods for selecting the wavelets used in signal decomposition are proposed. The first one, SWTBWS, is a refinement of the CBWS, and the NewEBWS can be understood as an improvement of the EBWS and SNRBWS. This paper is organized as follows. In Section 2 *Wavelet Decomposition* is defined as the form of decomposing a discrete signal into wavelet coefficients, directly associated to the WT decomposition tree. This definition also includes, in addition to the filters used on each level, the number of levels and the topology of the decomposition tree. In Section 3 a novel algorithm, here called NWDLS, for automatically determining the number of wavelet decomposition levels is proposed. In Section 4 the previous methods for MW selection are reviewed, and in Section 5 two new methods, NewEBWS and SWTBWS, for this selection are proposed. In Section 6 a new methodology to evaluate the MW selection for PD signal denoising is justified and defined taking into account the variation of wavelet coefficients to the displacement of pulses and several noise threshold levels. Finally, in Section 7 a comparison of denoising results by applying each of the MW selection methods on a set of PD pulses measured on two large hydro generators is presented.

2. Wavelet decomposition optimization for PD denoising

The denoising process on the wavelet domain is based on the fact that the PD signals, being localized oscillations, have larger wavelet coefficients than white noise and wideband noise in general [21]. Denoising by wavelet shrinkage consists of making equal to zero the wavelet coefficients below a certain threshold value, and reconstructing the signal by the inverse wavelet transform from the modified coefficients, as shown in Fig. 1. The threshold, which can be computed globally or specifically for each decomposition subband, should be such that the coefficients associated to noise are equaled to zero, and the coefficients corresponding to PD pulses are maximally retained. For a given PD signal, the best wavelet decomposition will be the one in which the coefficients corresponding to PD pulses are mostly placed above the noise threshold.

For discrete signals, the decomposition is defined by a decomposition tree. On the Fast Wavelet Transform (FWT), this tree always has a recursive topology in which, at each decomposition level, the coefficients of the previous approximation subband $\alpha^{(j)}[n]$ are decomposed into a new approximation subband and a new detail subband, represented respectively by the coefficients $\alpha^{(j+1)}[n]$ and $\beta^{(j+1)}[n]$, as shown in Fig. 2 [24].

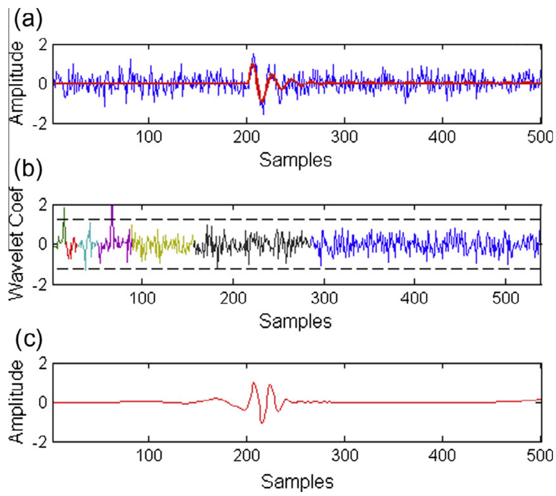

Fig. 1. (a) Simulated signal (in red), and simulated signal with added noise (in blue). (b) Wavelet Shrinkage process. The coefficients lower than the threshold (between the dashed lines) are zeroed. (c) Denoised signal. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

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