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Partial Discharge Signal Denoising based on VMD and Group-Sparse TV Denoising

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Abstract—The partial discharge signal measurement is a non-destructive diagnostics procedure to assess the status of insulation system in high voltage equipment. Due to the adverse measurement conditions, the PD signals are strongly influenced with external noise. In this paper, a new approach is presented for PD signal denoising, which combines the Variational Mode Decomposition and Group-Sparse Total Variation based denoising. The proposed method is applied to extract the simulated PD signal buried in white noise, discrete spectral interference and color noise. Simulation results show that the performance of the proposed VMD-GSTV method is superior to that of Wavelet and the recently introduced Wavelet Total Variation method, specifically when the SNR is low.

Index Terms—Denoising; Group-Sparse Total Variation; Partial Discharge; Variational Mode Decomposition

I. INTRODUCTION AND RELATED WORK

High Voltage (HV) equipment failure occurs as a result of insulation deterioration initiated by voids created in the insulation material from the combined effects of thermal, electrical, mechanical, and environmental stresses during long-term operation. Due to the high voltage stress, localized dielectric breakdown of a small portion of an insulator occurs, resulting in a Partial Discharge (PD) signal. Over the time, repetitive discharge causes permanent breakdown of insulating materials which leads to complete breakdown of the equipment[1].

The most common on-site noise reported during PD measurements are noise from corona discharge, commutator noise, white Gaussian noise, thermal noise, pink noise, and high-frequency signal interference from communication equipment, commonly referred as Discrete Spectral Interference (DSI) [2–4]. For the past few years, many researchers proposed signal decomposition based denoising algorithms for PD signals, such as Wavelet Transform (WT) [2–5], Empirical Mode Decomposition (EMD) [6, 7], Variational Mode Decomposition (VMD) [8]. Wavelet transform is considered to be one of the popular method, WT using Discrete Wavelet Transform (DWT) with hard and soft thresholding for denoising PD signal is applied in [2–4] and Adaptive Dual Tree Complex Wavelet Transform (ADTCWT) with automatic threshold by applying adaptive singular value decomposition [5]. However, the performance of Wavelet denoising relied on the type, order,

level of decomposition and threshold type - not practical for certain applications.

Apart from WT, adaptive signal decomposition techniques were used in many denoising applications [9]. EMD is an adaptive signal decomposition technique, which decomposes a signal into series of Intrinsic Mode Functions (IMFs) with the different frequency levels. EMD with Interval Thresholding (IT), Iterative IT (IIT) and Clear IIT (CIIT) were used in PD denoising [6]. Recently, a Novel Adaptive Ensemble EMD (NAEEMD) was applied to denoising PD signal [7], however, in all these EMD-based methods the IMFs are taken as mean of many trials, which results in a large amount of computation time and other issues such as error accumulation, mode mixing and end effects [10].

To overcome these issues, *Dragomiretskiy and Zosso* [11] proposed VMD, a non-recursive approach with a firm mathematical foundation. It decomposes a multi-component input signal into a set of Band Limited IMFs (BLIMFs). Hybrid of VMD and Wavelet Packet Transform (WPT) were applied to synthetic and real-time PD denoising and VMD based WT is applied in denoising UHF PD signals [8]. In spite of the noise sources considered in the literature i.e. white noise and narrow band noise, the performance of VMD need to be studied for other various noise sources.

Total Variation Denoising (TVD) is an optimization problem for removal of noise in 2-dimensional data i.e. image [12]. *Selesnick and Condat* [13, 14] developed 1-dimensional TVD algorithm, applied to an electrocardiogram (ECG) signal and vibration signal denoising [15]. Signals processed using TVD often exhibit stair-case artifacts [16], *Selesnick and Chen* proposed Group-Sparse Total Variation (GSTV) denoising which is suitable when the signal to be estimated is known to be group sparse, which is more suitable for PD signal denoising. It is an iterative algorithm derived using the Majorization-Minimization (MM) optimization method with fast solvers for banded systems of linear equations.

Usage of various decomposition methods and application of total variation denoising in PD signal is still an ongoing area of research. A new denoising approach based on VMD and GSTV techniques for PD signal corrupted with white noise, color noise and DSI is proposed in this paper.

II. METHODOLOGY

The electrical detection method uses matching impedance as either RC or RLC circuit for wide and narrow band PD detection [2]. The output pulse shape is based on the type of detection circuit, which is realized as natural response of either parallel RC or RLC circuit, they are Damped Exponential Pulse (DEP) and Damped Oscillatory Pulse (DOP). In this work, DOP model along with white noise, DSI and color noise is considered for implementation. The PD signal $PD_{DOP}(t)$ is modeled using Equation (1) as given below,

$$PD_{DOP}(t) = A (e^{-\alpha t} - e^{-\beta t}) \sin(\omega t) \quad (1)$$

where A represents the amplitude of the PD signal, α and β are the damping factors and ω is the damping frequency. The PD signal with the random amplitude between 0.7V to 1.3V, α is set as 7.5×10^5 , β is set as 16×10^6 and ω as 150 kHz is considered. The sampling frequency f_s is set to 20MHz.

First noise model is a commonly-used random noise process is white noise. The built-in additive white Gaussian noise model from MATLAB[®] used with Signal-to-Noise Ratio (SNR) of -16dB, -12dB, -8dB and -4dB. The second noise model is the DSI [4], the presence of continuous sinusoidal noise from the communication systems represented in the form of combination of amplitude modulated signals given by the Equation (2).

$$n_{AM}(t) = \sum_{c=1}^9 (A_c + m * \sin(\omega_m t)) * \sin(\omega_c t) \quad (2)$$

the carrier amplitude $A_c = 1$, frequency of the carrier signal $\omega_c = 0.1 - 1.7 MHz$ in steps of 200kHz, the modulation depth $m = 0.4$ and the frequency of the modulating wave $\omega_m = 1 kHz$. A third noise model is additive pink noise simulated using MATLAB[®] function *ColoredNoise*.

The thermal noise generated by the detection system and the background noise are considered as white noise and the interference from radio transmission is considered as DSI [3, 4] and pink noise ($\frac{1}{f}$ noise) [17]. A typical on-site PD signals were simulated using Equation (1) added with the different white noise levels and the presence/absence of DSI and color noise as shown in Table I. These twelve noisy PD signals are subjected to the proposed VMD-GSTV algorithm and the obtained results are compared with wavelet denoising methods. The following section describes the proposed VMD-GSTV.

III. MATHEMATICAL BACKGROUND

A. Variational Mode Decomposition (VMD)

VMD can non-recursively decomposes a real valued input signal f into a set of K sub-signals (modes), u_k , that have specific sparsity. Each mode k is compact around a central

TABLE I: Simulated Noisy PD Signal

| PD Signal | DOP using Equation (1) | | |
|------------------|--------------------------|----------------|-------------------|
| Noise Type | AWGN | AWGN+DSI | AWGN+DSI+Color |
| AWGN Levels | -16dB, -12dB, -8dB, -4dB | | |
| Noisy PD signals | S_1 to S_4 | S_5 to S_8 | S_9 to S_{12} |

frequency ω_k , and the input signal is the sum of these components [11].

The process of signal decomposition is to solve a constrained variational problem is written as:

$$\min_{\{u_k\}, \{\omega_k\}} \left\{ \sum_{k=1}^K \left\| \frac{\partial}{\partial t} \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\} \quad (3)$$

subject to $\sum_{k=1}^K u_k = f(t)$

where $\{u_k\} = \{u_1, \dots, u_K\}$ and $\{\omega_k\} = \{\omega_1, \dots, \omega_K\}$ are the mode components and their center frequencies, K is the number of modes to be recovered, $\delta(t)$ denotes impulse function and f is the input signal.

To solve the Equation (3), constrained variational problem is transformed into unconstrained. This is achieved by introducing the Lagrangian multiplier (λ) and quadratic penalty term α . The new unconstrained problem is as follows:

$$\mathcal{L}(\{u_k\}, \{\omega_k\}, \lambda) = \alpha \sum_{k=1}^K \left\| \frac{\partial}{\partial t} \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 + \left\| f(t) - \sum_{k=1}^K u_k(t) \right\|_2^2 + \left\langle \lambda(t), f(t) - \sum_{k=1}^K u_k(t) \right\rangle \quad (4)$$

The solution of Equation (4) now can be found as the saddle point of the augmented Lagrangian in a sequence of iterative sub-optimizations referred as Alternate Direction Method of Multipliers (ADMM)[11]. The optimization procedure of VMD includes the following steps:

- 1) Initialize modes $\{\hat{u}_k^1\}$, center frequency $\{\omega_k^1\}$, and $\hat{\lambda}^1$.
Set $n = 0$
- 2) Update the modes \hat{u}_k for all $\omega \geq 0$:
$$\hat{u}_k^{n+1}(\omega) = \frac{\hat{f}(\omega) - \sum_{i < k} \hat{u}_i^{n+1}(\omega) - \sum_{i > k} \hat{u}_i^n(\omega) + \frac{\hat{\lambda}^n(\omega)}{2}}{1 + 2\alpha(\omega - \omega_k^n)^2}$$
- 3) Update the center frequencies ω_k :
$$\omega_k^{n+1} = \frac{\int_0^\infty \omega |\hat{u}_k^{n+1}(\omega)|^2 d\omega}{\int_0^\infty |\hat{u}_k^{n+1}(\omega)|^2 d\omega}$$
- 4) Update dual ascent for all $\omega \geq 0$:
$$\hat{\lambda}^{n+1}(\omega) \leftarrow \hat{\lambda}^n(\omega) + \tau \left(\hat{f}(\omega) - \sum_k \hat{u}_k^{n+1}(\omega) \right)$$
- 5) Repeat step 2 - 4, until convergence:
$$\frac{\sum_k \|\hat{u}_k^{n+1} - \hat{u}_k^n\|_2^2}{\|\hat{u}_k^n\|_2^2} < \epsilon$$

The noisy PD signal is decomposed into 5 modes ($K=5$) and their spectrum are obtained with the parameters, $\alpha = 2000$ and $\tau = 0$, tolerance level set as 1×10^{-6} as stated in [11]. The decomposed mode with the highest kurtosis value is considered as an effective component for further processing.

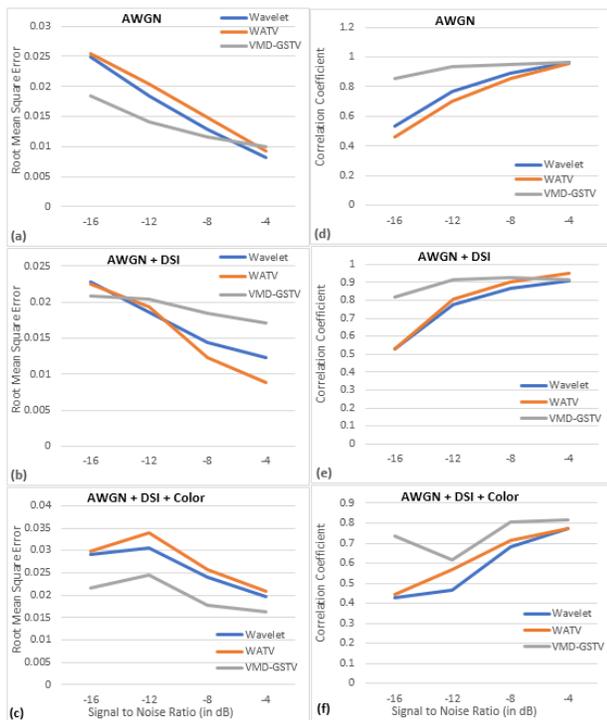


Fig. 2: Mean value of the RMSE and the correlation coefficient of denoised signal for each method: (a,d) for the white noise only; (b,e) for the white noise and discrete spectral interference; (c,f) for the white noise, discrete spectral interference and color noise.

white noise, discrete spectral interference and color noise. On the other hand, according to Table II, VMD-GSTV performs low when it is subjected to white and DSI only, however, the CC is highest as compared to other methods. The PAR value of a specific signal corrupted with three noise models are listed in Table II, wavelet denoising stands out with very low PAR values as compared to other methods. The output amplitude can be normalized to a scale for better representation as presented the results in [8].

Correlation coefficient obtained between simulated PD signal and denoised signal were plotted in Figure 2(d) - 2(f), which clearly indicates that VMD-GSTV performs better than other techniques. In spite of the promising results, the following can be considered in future work:

- Parameters such as penalty function, group size and regularization for GSTV is currently chosen based on iterative method, which can be automated / optimized
- Improved VMD method to avoid mode-mixing issue
- Selection rule for BLIMF(s) to pick the best mode with that of the PD signal

V. CONCLUSION

In this paper, a new method based on VMD-GSTV is proposed for denoising PD signals and the results are compared with wavelet and WATV denoising methods. A synthetic PD signal with white noise, DSI and color noise were considered in this study. The RMSE and CC values are in favour of VMD-GSTV based on the results obtained, and peak amplitude reduction of denoised signal is observed. With the comparative study on three denoising methods, the proposed VMD-GSTV

method achieved better results in terms of CC metric and can be potentially extended further.

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