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Sparse Representation Based Dielectric Loss Angle Measurement

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Abstract: Precise measurement of dielectric loss angle is very important for electric capacity equipment in recent power systems. When signal-to-noise is low and fundamental frequency is fluctuating, aiming at the measuring error of dielectric loss angle based on some recent Fourier transform and wavelet transform harmonics analysis method, we propose a novel algorithm based on sparse representation, and improved it to be more flexible for signal sampling. Comparison experiments describe the advantages of our method.

Keywords: Dielectric loss angle measurement, sparse representation, wavelet transform.

1. INTRODUCTION

In distributed monitor of the recent power systems, dielectric loss angle (DLA) plays a very important role in reflecting the insulating ability of high voltage electrical equipment, and on-line methods for measuring the electric capacity equipment mainly depend on DLA. Measuring the tangent value of DLA, $\tan\delta=I_R/I_C$, with software method is suitable with the field data sampled with hardware. Because frequency is fluctuating in power system (often in the scope of 50±0.2Hz) and the entire cyclical sampling condition is difficult to satisfy in digital sampling, "stockade effect" and "frequency spectrum divulges" are arouse, which cause large errors when measuring the phase between the waves of voltage and current during the course of real measurement.

The measurement of DLA is a problem with high noise, tiny signal and small angle. In order to suppress the high-ordered harmonic, direct current and noise components, a high accuracy method is essential. Three state-of-the-art categroies of algorithms in DLA measurements with software methods are wave matching, filtering and harmonic analysising [1-4]. Computational cost and accrucay are two major concerns for the first two methods in realtime applications, and the last one, calculates $\tan\delta$ with harmonic analysis [1-3] (*e.g.*, Fourier transform, wavelet transform), is much more efficiency and not affected by high-ordered harmonic wave and zero-drift.

How to measure DLA of electrical equipment accurately is an important research topic in electric power system. Harmonic analysis is a representative medium measurement without direct current (DC) component and harmonic interference [1]. But the stockade effect and frequency spectrum divulges caused by frequency fluctuation influence the phase measurement seriousely with harmonic analysis. In order to resolve the measure error in non-synchronous sampling, the windowed harmonic analysis is used [3]. But when noise exists (especial SNR is lower), the real fundamental wave is covered by noise, windowed Fourier transform (FT) harmonic analysis is not suitable, and wavelet transform (WT) is one of the effective time-freqency analysis method [4], which overcomes the influence casued by periodicity factor and some other uncertainly factors. WT is a satisfactory tool used for recoverying tiny signals in clustered noisy signal, and many WT based harmonic analysis methods for the measurement of DLA are proposed in the recent years. Based on the theory of the multi-resolution analysis and the proposed method base on WT, the frequency range of the observed signal is near that of the fundamental wave, and the major power near 50Hz in the signal can be reserved. But as mentioned before, the frequency of the fundamental wave is instable in practical power system, thus the fundamental wave extracted by WT based method is not precise.

The objective of our paper is to develop a novel measurement method for DLA. The rest of the paper is organized as follows. Section 2 introduce the measurement procedure for DLA with software method; Section 3 analysis the advantages and disadvantages of DLA measurement methods based on wavelet transform; Our original and improved sparse representation based DLA measurement methods are proposed in Section 4; Experimental results are reported in section 5, and the conclusion and future work are summarized in Section 6.

2. THE FORMULATION OF DLA MEASUREMENT

Generally, besides the fundamental wave (50Hz), the observed current and voltage signals in power system contain the DC component, the high ordered odd harmonic components and noises. In recent researches, the general form of mathmatical model for DLA (the waves of current and voltage signals) can be formulated as follow [1, 2]:

$$A(t)=A_0+\sum_{k=1}^{2n-1}A_k\sin(k\omega t+\varphi_k) \tag{1}$$

where, ω is the fundamental frequency which can be set around 50Hz, A_k and ϕ_k (k=0,1,3,5,7,…) are the amplitude of each component and the initial phase of each harmonic

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signal, respectively. Once we formulate current and voltage waves with Eq.(1), the following work is extracting the fundamental components of current and voltage waves, which can be denoted as vectors i and u, where, $i,u \in \mathbb{R}^{1\times N}$. Finally, δ can be computed as follow [1]:

$$\delta = \frac{\pi}{2} - \arccos\frac{R_m(0)}{\sqrt{R_i(0)R_u(0)}} \tag{2}$$

where, $R_i(0) = \frac{1}{N}\sum_{n=0}^{N-1} i(n)i(n)$, $R_u(0) = \frac{1}{N}\sum_{n=0}^{N-1} u(n)u(n)$ and $R_m(0) = \frac{1}{N}\sum_{n=0}^{N-1} i(n)u(n)$ are self-correlation functions of i and u, and cross-correlation function of i and u, respectively.

3. WAVELET TRANSFORM BASED DLA MEASUREMENT

Wavelet transform (WT) is one of a widely used time-frequency analysis tool [4-7]. It produces a variable time-frequency window by flex and shift of wavelet function, so it has unique advantages in transient and non-stationary signal analysis aspect, especially set off transient signal of the frequency spectrum to extract the characteristics of components. The multi-resolution analysis of WT is used to extract the DLA in the online monitor system. According to the theorem of Nyquist sampling, when we select the number of sampling points as 128 (*i.e.*, the sampling frequency is 6.4kHz), the cut-off frequency is 3.2kHz. So, we can decompose the original signal with 7 layers wavelet transform as shown in Table **1**.

The observed signal can be reconstructed with scaling coefficient 'c7' and wavelet coefficients 'd7'~'d1'. In the measurement of DLA, we need to reconstruct the fundamental wave (50Hz), therefore, the coefficient 'd7' which corresponding to the detail information of 25~50Hz should be remained, and the other ones ('d1'~'d6') and 'c7' should be set to be zeros for wave reconstruction.

With the finite layers of wavelet composing, we cannot obtain the exact wave frequency but only a domain of frequency (see 'd7' in Table **1**). When the frequency is fluctuating in a real power system, the reconstruction result of the fundamental wave with wavelet transform is not very accuracy; Otherwise, the whole cycle of the waves of voltage and current is needed, and the starting and ending points of a while cycle in original waves is hard to determined.

4. SPARSE REPRESENTATION BASED DLA MEASUREMENT

4.1. Original Sparse Representation based DLA Measurement

Sparse representation (abbreviated as SR, also named as sparse sensing or compressive sensing) [8, 9] is an attractive signal reconstruction method proposed by Candes *et al.*, which has become one of the most important analysis tools in signal processing. The main purpose of SR is to reconstruct a signal $s \in \mathbb{R}^{m\times 1}$ with an over-completed dictionary $D \in \mathbb{R}^{m\times n}$ with sparse coefficient vector $c \in \mathbb{R}^{n\times 1}$. The atoms (column vectors) in dictionary D are non-orthogonal, while the basis with wavelet transform are orthogonal. The formulation of SR can be written as the following l_1-norm constrained optimization problem:

$$\min_c \|s - Dc\|_F^2 + \alpha\|c\|_1 \tag{3}$$

where, α describes the sparsity of the sparse coefficients c. Once we get an over-completed dictionary with the odd ordered harmonic components (1,3,5,7 ordered components are used in our simulation experiments, just as that in most current paper), sparse representation can be used for decomposing the measured current and voltage signals with fundamental component and other high ordered odd harmonic components, as shown in Fig.(**1**).

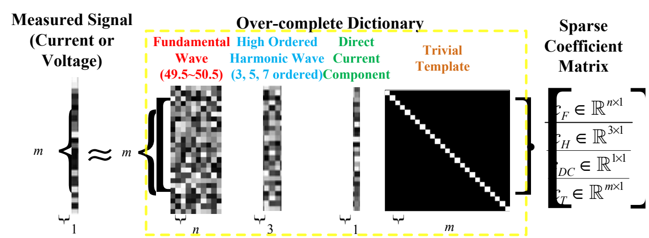


Fig. (1). SR based dielectric loss measurement.

Obviously, fundamental wave, high ordered harmonic waves and direct current component must be included in the over-completed dictionary D. Here, we take 3, 5, 7 ordered harmonic waves into account (blue part in Fig. **1**), and the higher ordered ones are very tiny in real power system; In

Table 1. The decompose procedure of wavelet transform for signal with 6.4kHz sampling frequency.

Scaling Coefficient (Approximate Component)	Signal Component/Hz	Wavelet Coefficient (Detail Component)	Signal Component/Hz
c1	0~1.6k	d1	1.6k-3.2k
c2	0~800	d2	800-1.6k
c3	0~400	d3	400-800
c4	0~200	d4	200-400
c5	0~100	d5	100-200
c6	0~50	d6	50-100
c7	0~25	d7	25-50

order to reduce the influence of frequency fluctuate for accuracy measurements, we use a number of columns of fundamental waves and the fundamental frequency are 49.5, 49.6, …, 50.5 (red part in Fig. **1**) instead of only one column of 50Hz fundamental wave and the range from 25 to 50 in WT based method; For the sake of denoising, we add a column of DC component (green part in Fig. **1**) and an additional unit matrix (brown part in Fig. **1**) in D. m is the product of the number of the sampling points in each cycle and the number of cycles; n=11 is the number of fundamental frequency.

With the over-completed dictionary D, we can solve the ℓ_1-optimization problem with different numerical algorithms, such as BP, MP, OMP etc., and the sparse coefficients can be obtained. Here, we are only concerned with the coefficients c_F corresponding to the fundamental wave, while ignoring c_H, c_{DC} and c_T corresponding to high ordered harmonic wave, DC component and trivial template, respectively. The fundamental component in the measured voltage or current signal can be reconstructed with the sparse fundamental wave coefficient c_F and the fundamental component in D (red part in Fig. **1**).

4.2. Selection of Sampling Frequency

According to the Nyquist sampling theorem, if sampling frequency is greater than or equal to 2 times of the greatest frequency in original signal, we can uniquely determine and reconstruct the signal with ideal low-pass filters. But in practical, in order to ensure the reconstruction accuracy, the sampling frequency is often set to be 7-10 times of the greatest frequency of original signal. But with the increasing of the sampling frequency, the storage space and computation time are increasing.

Sparse representation challenges the traditional Nyquist sampling theorem, which can reconstruct the original signal with much lower sampling frequency. Fig. (**2**) shows the values and the relative errors of DLA with the sampling times changing from 1~1000 in each cycle (*i.e.*, the sampling frequency is changing from 50~50kHz) based on sparse representation.

In Fig. (**2**), it is clear to see that, with the increasing of the number of the sampling points in each cycle, the absolute errors of δ are decreasing, but the reduction becomes very slow when the sampling points are larger than 100 (the absolute errors of δ is very close to 0). The similar results can be obtained when we change the frequency of the original signal (49.5~50.5Hz) and the real dielectric loss angle δ (0~0.02rad). As described previously, taking measurement accuracy, storage space and computation time into account, we select 128 as the number of sampling points in each cycle (*i.e.*, the sampling frequency is 6.4kHz) in this paper.

4.3. Improved Sparse Representation based DLA Measurement

When sampling the waves of voltage and current in the power system, it is scarcely possible to determine the starting points of the whole cycle of wave; moreover, under the fluctuating of frequency in power system, even we get the starting ones, it is still very hard to determine the ending points under the instable sampling frequency. Here, when constructing the over-completing dictionary D, we improve the original SR based DLA measurement method in 4.1, and take S sampling points in each cycle (S is less than the number of sampling points in the whole cycle, we set 128 in our experiments) with 2 incremental points, *i.e.*, we take the points from 1+s to S+s (s are even numbers from 2 to 128-S) to construct the first ((S/2+1)*n) columns of D. The subsequent columns in D are constructed similarly. When we reconstruct the fundamental wave, we only need to select S continuous sampling points in observed wave, no matter the first point is the starting point of the whole cycle or not.

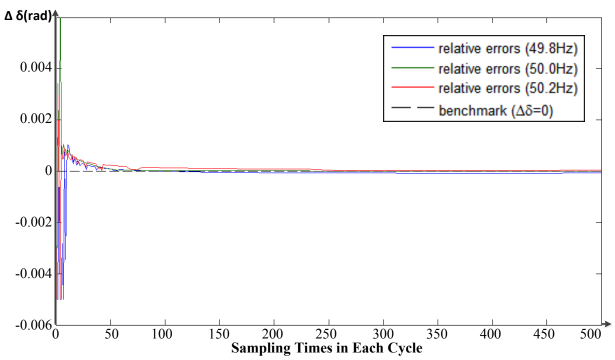


Fig. (2). Absolute errors contrast of changing sampling times in each cycle.

5. EXPERIMENTS

5.1. Experiment Settings

In order to test the performance of our algorithm, DLA is computed and compared with FT, WT, original SR and improved SR based method, respectively. In our simulation experiments, the fundamental wave component of voltage and current of sine wave analog measured is considered as basis, and it is assumed that 30% of 3th-ordered, 3% of 5-th ordered and 5% of 7th-ordered harmonic are included in the observed waves; we set the dielectric loss angle of power system equipment is range from -0.02rad to +0.02rad, the sampling frequency f_s=6.4kHz (128 sampling points in a whole cycle). Let the expression of voltage to be

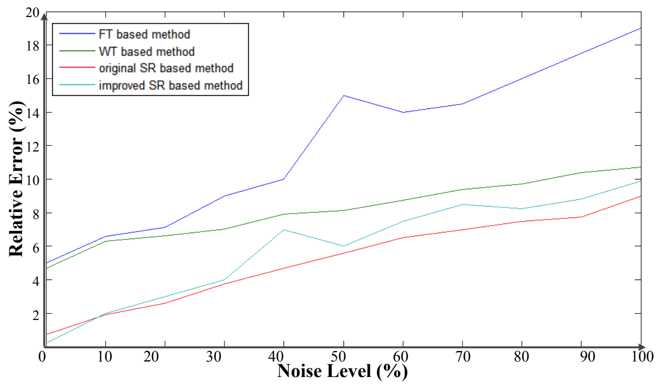
$$u(t)=e^{-3t}+\sin(wt+\varphi_{u1})+0.3\sin(3wt+\varphi_{u3}) \\ +0.3\sin(5wt+\varphi_{u5})+0.05\sin(7wt+\varphi_{u7})+\kappa n_u(t) \quad (2)$$

where, $n_u(t)$ is the noise components of voltage and κ is the noise level; $\varphi_k\left(k=0,1,3,5,7\right)$ is the initial phase of each component, and the expression of current is similar to Eq.(2).

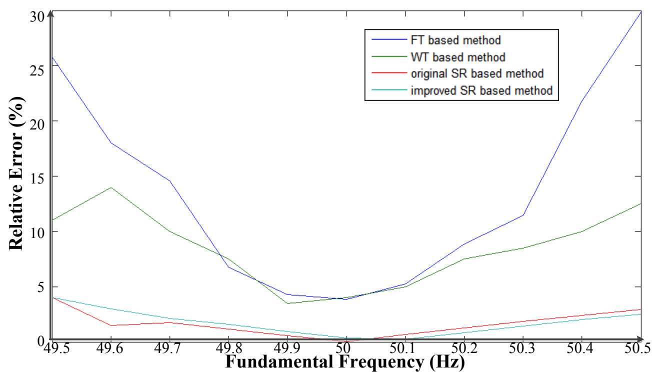
5.2. Experiment Results

Based on above experimental settings and our original and improved SR based method, we can extract the fundamental waves from the observed voltage and current signals, and compute DLA with Eq.(2). In this section, some comparison results are shown with FT [2, 3], WT [4-7], original SR (section 4.1) and improved SR (section 4.3) based methods. All the experiments are performed on computer with 2.67GHz CPU and 3GB memory, and the l_1-

optimization problem in SR based methods are solved with mexLasso in SPAMS toolbox [10].



(**a**) Comparison of relative error with noise level



(**b**) Comparison of relative error with frequency fluctuation

Fig. (3). The relative errors contrast of changing noise weight and fundamental frequency.

Fig. (**3**) is the comparison of DLA relative errors with noise level (Fig. **3a**) and the fluctuation of fundamental frequency (Fig. **3b**). As indicated in Fig. (**3**), the relative errors of these four algorithms are increased with the noise components increased, but the relative errors of our two methods (no more than 10%) are always much lower than that of other two methods (larger than 9% and up to nearly 20%). As shown in Fig. (**3b**), the frequency fluctuation of the real power system impacts all these four algorithms when computing DLA. Compared with the wavelet based method, our method suppresses the influence caused by frequency fluctuation excellently. No matter the frequency of the power system is 50Hz or far away from 50Hz (such as 49.5Hz and 50.5Hz), the relative errors for measurement of dielectric loss are under 3%, and under 1% for the most times.

Table **2** is the comparison of the computation cost of these methods with the sampling frequency 3.2KHz, 6.4KHz and 12.8KHz, respectively. It is clear to see that, our original SR based method is the most efficient, and the improved one is faster than FT based method but slower than WT and original SR based method (because of the much larger over-completing dictionary than original SR based method).

Table 2. Average computation cost of four DLA measurement methods (unit: ms).

Method / Sampling Frequency	FT	WT	Original SR	Improved SR
3.2KHz	42.13	16.85	6.34	29.78
6.4KHz	60.32	33.79	11.52	47.42
12.8KHz	105.56	55.56	23.99	89.87

CONCLUSION

In this paper, we introduce a novel sparse representation based method for dielectric loss angle measurement, which is proposed for the first time, and the improved SR based method is proposed to settle the issue that the starting points of the whole cycle is hard to obtain in the real power system. Compared with Fourier transform and wavelet transform based method, our method is much more accurate and very stability for the frequency fluctuation.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflict of interest.

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