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Efficient signal processing technique for information extraction and its applications in power systems

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ABSTRACT

This paper describes a novel mathematical method for decomposing power system signals obtained from measurements and monitoring of power systems. The technique is characterized as a self-based decomposition since the own system signals generate the basis used in the analysis. The resulting decomposition is sensitive to the system operation and is strongly related to the system operating parameters and power consumption, even when signals are non-purely sinusoidal. Mathematical theory is carefully exposed and three potential applications in power systems are presented to prove the efficiency of the signal processing method: high-impedance fault detection in three-phase distribution systems, single-phase VAR and harmonic compensator and three-phase voltage filtering. The investigation demonstrates that the technique is an effective signal-processing tool for power system applications, such as signal filtering and nonlinear process detection.

1. Introduction

Advanced techniques for monitoring and control of power systems have been continuously proposed; and in the rapidly evolving scenario of smart grids, new concepts of information extraction based on measurements and signal processing have also emerged. Fault location and parameter identification of transmission systems are only a few examples of sophisticated applications of signal processing in the frequency and time domain. These signals are measurements obtained from Phasor Measurement Units (PMUs) and digital protective relays (fault records) [1–3]. The sampling rate and accuracy of new measurements have increased enormously in the last 10 years and, therefore, new techniques are required for processing such data. Regardless of the type of study conducted on power systems, signal processing techniques are required and must be capable of extracting highly relevant information from monitored variables [4–7].

Signal processing methods range from the time domain and frequency domain to the time-frequency domain, such as the Fast Fourier Transform (FFT), the Short-Time Fourier Transform (STFT), the Wavelet Transform (WT), the S-Transform and hybrid methods combining the previous ones. The techniques above are widely employed in power system problems, mainly in power quality disturbance recognition [6–11], fault detection and classification [12–15], and waveform filtering and compensation [16]. However, as stated in [17], by observing that signal processing techniques are mainly designed for speech and image signals, it is certain that a beginning challenge on the development of signal processing in power systems has emerged since new techniques and paradigms can impact measurements and analysis and also enhance quality requirements [18].

In non-stationary signals, where disturbance and abnormal events take place, the use of the FFT becomes inadequate [19]. The STFT divides the signal into time segments, in which the signal is considered stationary. Although the STFT can be used to overcome some limitations of the FFT, the frequency resolution is fixed for the whole spectrum. The WT, as well as the STFT, also represents the signal in the time-frequency domain, with different frequency resolutions. However, the selection of an adequate mother wavelet function for the problem being analyzed is imperative. Moreover, hybrid methods are also applied to solve frequency resolution problems [20].

The tools mentioned above and other well-established signal transforms are derived from different orthogonal bases. For example, the FFT uses orthonormal complex-sinusoids of different frequencies as basis vectors for the signal decomposition. On

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the other hand, the Cosine transform uses real sinusoids of different frequencies as basis vectors for the signal decomposition. These decompositions show that a decomposed signal can be synthesized with the superposition of such sinusoidal basis. However, the decomposition products do not translate system parameters or a notion of the system power consumption. Phase information in the FFT, for example, could be useful to indicate the nature of the power consumption in a particular frequency; nevertheless, it does not translate a global notion of power consumption, especially in non-purely sinusoidal systems [21–23].

Several analyses for abnormal or nonlinear process detection may not be properly represented in pre-established bases, e.g, parameter extraction from frequency content during a high-impedance fault represents an extremely difficult process, as discussed in the technical literature [3,24]. In fact, some frequencies are not adequately identified from signals obtained during high-impedance faults, which leads to inaccuracies in such fault detection and location task.

In this paper, a novel signal processing tool for power system applications, namely the Orthogonal Component Decomposition (OCD) technique is presented in details. The OCD technique was successfully used in [3] for detection of high-impedance faults in distribution systems, where a brief presentation of the OCD was made. Here, the theoretical and mathematical concepts of the technique are presented and discussed in depth. Differently from the FFT and other well-known tools, the OCD technique does not decompose signals in pre-established basis but uses the signals being analyzed as a basis for the decomposition. Accordingly, the decomposition products are highly sensitive to the system operation and are strongly related to the system operating parameters and power consumption, even when signals are non-stationary and non-purely sinusoidal.

The products of the OCD are extremely sensitive to variations in the system parameters, which means that the proposed signal processing detects many events that are not commonly detected when using other decompositions. Also, the results from the decomposition are time-domain functions, i.e., the proposed signal processing tool can be used as a feature extractor for different system conditions, providing some useful visualizations of time-varying signals. As the decomposition products are calculated in each instant of time, nonlinear phenomena can also be perceived using this technique.

As it will be shown, the decomposition method represents a powerful tool for various applications in electric power systems concerning nonlinear process detection and signal filtering. Three distinct applications in power systems are presented to show the efficiency and real potential of the method: three-phase voltage filtering; VAR and harmonic compensation; and high-impedance fault detection in three-phase distribution systems. Furthermore, the mathematical development of the new signal decomposition technique could be useful for other signal processing methods [23,25].

2. Orthogonal component decomposition technique – mathematical concepts

The main characteristic of the OCD technique is that the resulting decomposed signals, namely, the orthogonal components, are decomposed into the system signals being analyzed, which leads to a major sensibility for detecting time-variable elements and parameters during the system operation. The technique is based on two principles derived from linear algebra concepts. The first relies on the decomposition of a function into the subspace of another function, and the second principle concerns the geometric relationship of line voltages in a three-phase power system. These two principles and their applications in power systems are introduced in the following sections.

2.1. First principle – decomposition of a function into the subspace of another function

Consider two continuous, finite and periodic functions $i(t)$ and $v(t)$, arising from an electric system. These functions are considered as vectors on the $\mathbb{R}^\infty$. It is then possible to define a derivative function $\dot{i}(t)$ and an integrative function $\tilde{i}(t)$ by Eqs. (1) and (2), respectively.

$$\dot{i}(t) = \frac{di(t)}{dt} \tag{1}$$

$$\frac{d\tilde{i}(t)}{dt} = i(t) \tag{2}$$

The purpose of the OCD is to be sensitive to the parameters of the electric system. In this way, it should be of interest to obtain decomposition products that carry out electric information. Therefore, a decomposition as formulated in (3), where signal $v(t)$ is decomposed into four parts, would indeed be very interesting for this purpose. Voltage parcel $v^p(t)$ is proportional to the current $i(t)$ and hence carries out a resistance (R) information through coefficient γ_1. Furthermore, coefficient γ_2 on $v^{q^\parallel}(t)$ carries out an inductance (L) information, since this voltage parcel is proportional to the derivative function of the current. Finally, γ_3 carries out a capacitance ($1/C$) information due to the proportionality between $v^{q^\sim}(t)$ and the integrative function of the current.

$$v(t) = \underbrace{\gamma_1 i(t)}_{v^p(t)} + \underbrace{\gamma_2 \dot{i}(t)}_{v^{q^\parallel}(t)} + \underbrace{\gamma_3 \tilde{i}(t)}_{v^{q^\sim}(t)} + v^d(t) \tag{3}$$

The last parcel in (3) is then made necessary as signal $v(t)$ in $\mathbb{R}^\infty$ cannot be spanned by just the three vectors mentioned above. Hence, the last parcel of the decomposition carries out information that are not modeled by passive electric elements.

One could consider that $i(t)$, $\dot{i}(t)$, and $\tilde{i}(t)$ are three linearly independent vectors and, therefore, are suitable for the decomposition shown above. In fact, these vectors do not form a linearly independent set as it will be shown in Theorem 1. Let $i(t)$, $\dot{i}(t)$, and $\tilde{i}(t)$ be represented by their Fourier series as follows:

$$i(t) = \sum_{k \in \Omega_i} I_k \cos(k\omega t + \delta_k) \tag{4}$$

$$\dot{i}(t) = -\omega \sum_{k \in \Omega_i} kI_k \sin(k\omega t + \delta_k) \tag{5}$$

$$\tilde{i}(t) = \frac{1}{\omega} \sum_{k \in \Omega_i} \frac{I_k}{k} \sin(k\omega t + \delta_k) \tag{6}$$

where I_k represents the kth harmonic peak value, δ_k is the kth harmonic phase angle, $\omega = 2\pi/T$ and Ω_i denotes the set of all existent harmonic indexes in the function $i(t)$, thereby $\Omega_i \in \mathbb{N}$.

The inner product describes the similarity between vectors. Signals that are as different as possible have a null inner product and are considered linearly independent and orthogonal since the angle between them is 90°. In this way, a proposition about the spatial arrangement of vectors $i(t)$, $\dot{i}(t)$, and $\tilde{i}(t)$ is made in Theorem 1:

Theorem 1 (Orthogonality). *Let $i(t)$ be a real, continuous, and finite function with periodicity T. It is proved that $i(t)$ is mutually orthogonal to its derivative $\dot{i}(t)$ and integrative $\tilde{i}(t)$ functions. Furthermore, functions $\dot{i}(t)$ and $\tilde{i}(t)$ are not orthogonal to each other, being, collinear if $i(t)$ is purely sinusoidal.*