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A novel method for power quality multiple disturbance decomposition based on Independent Component Analysis

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ABSTRACT

In this paper, a novel method for power quality signal decomposition is proposed based on Independent Component Analysis (ICA). This method aims to decompose the power system signal (voltage or current) into components that can provide more specific information about the different disturbances which are occurring simultaneously during a multiple disturbance situation. The ICA is originally a multichannel technique. However, the method proposes its use to blindly separate out disturbances existing in a single measured signal (single channel). Therefore, a preprocessing step for the ICA is proposed using a filter bank. The proposed method was applied to synthetic data, simulated data, as well as actual power system signals, showing a very good performance. A comparison with the decomposition provided by the Discrete Wavelet Transform shows that the proposed method presented better decoupling for the analyzed data.

1. Introduction

There has been widespread interest concerning Power Quality (PQ) issues over the last three decades due to various reasons pointed out in [1]. The new scenario foreseen for smart grids [2] reinforces the growing concern for PQ in decades to come and the main reasons for this are: the growth of distributed and diversified generations, the new uses predicted for power systems (e.g. electric car stations) and the increasing demand for power system self monitoring, control and operation. The proper diagnosis of PQ problems requires a high level of engineering expertise. Added to the difficulty of PQ diagnosis, the required expert knowledge is not only in any one area, but rather in many areas of electric power, e.g., electric drives, sensors, rotating machines, transformers, power electronics, power supplies, capacitor switching, protection, power system faults, harmonics, signal analysis, measuring instruments and general power system operation [3].

Various tools of signal processing and artificial intelligence have been proposed to address problems such as detecting and classifying disturbances, parameter or indices estimation, data compression and so on. Recently, authors have presented PQ disturbance detection and classification using S-transform [4], discrete wavelet transform combined with neural networks [5,6], Energy Difference of Multiresolution Analysis (EDMRA) [7], Slant transform [8] and so on. In [9], a fast Modified Recursive Gauss–Newton (MRGN) method to estimate power quality indices in distributed generating systems during both islanding and non-islanding conditions is proposed. Nevertheless, there are some unsolved PQ issues, as well as forthcoming topics concerning the smart grid scenario which favor the development of new methods and tools for PQ analysis. For example, identifying the PQ disturbance source is still an unresolved issue in a realistic power system scenario or/and when different disturbances occur in sequence or simultaneously within a same time interval of the analyzed signal. In fact, only more recent work considers the occurrence of multiple disturbance in power system signals, which leads to more complex methods when compared to methods addressed for isolated disturbances.

Among the recent methods that address the occurrence of multiple disturbances, most of them are focused on the problem of classification. In [10], a method for classifying power quality single and multiple disturbances based on S-transform feature extraction and a rule based classifier is proposed. In [11], a classifier is proposed consisting of several processing components arranged in a cascade form, including amplitude estimator (to recognize sags, swells or interruptions), Wavelet Transform, transient detector and neural networks to recognize other multiple disturbances (harmonics and flickers, in this case). In [12], a novel analysis of PQ events is presented using amplitude and frequency demodulation concepts to separate various single/multiple event patterns to be classified using Fuzzy classifiers. All methods cited above have a preprocessing step in common which extracts some representative parameters that can distinguish information from multiple disturbances in some way, and a classification step that uses an intelligent method to make this distinction. However, none of

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them is specialized in decomposing or recovering the waveforms of individual disturbances which occur in multiplicity.

The Wavelet Transform (WT) has been widely used to assess and analyze PQ due to its time–frequency representation capacity. The Discrete Wavelet Transform (DWT) is based on the Multiresolution Analysis (MRA), which decomposes the original signal into approximated and detailed versions by scaling functions and wavelet functions, respectively [13]. Despite the great capacity of the DWT for PQ analysis, when different disturbances that present spectral compositions within the same frequency band occur simultaneously at the time, this technique does not work well when the aim is to decompose the power signal into its individual disturbances. In order to find an alternative solution to this problem, a new approach for PQ multiple disturbance decomposition is proposed in this paper, based on the statistical properties of each individual disturbance, which is the Independent Component Analysis (ICA) [14]. Therefore, instead of searching for differences in time and/or frequency, the ICA attempts to find statistical independence among the components that occur simultaneously.

The ICA is a blind source separation technique which estimates components that are as independent as possible [14]. In the context of PQ, the ICA has recently been investigated. In [15], a new method based on the ICA and Empirical Mode Decomposition (EMD) arithmetic to monitor and analyze power quality disturbance is proposed. The ICA is applied aiming to enhance the system's performance in the presence of noise and interference. In [16], a new method of power quality comprehensive evaluation is proposed based on the use of improved-ICA to find out the weight of various indicators in the feature space, solving the ambiguous coupling problem in these indicators. In [17], an ICA-based method for harmonic source identification and estimation is proposed. If the harmonic currents are statistically independent, the ICA is able to estimate the currents using a limited number of harmonic voltage measurements without any knowledge of the system topology.

This paper proposes the novel use of ICA for PQ analysis aiming to identify the independent disturbances in a multiple disturbance scenario from a given mixture model of single disturbances. This method recovers the waveforms of single disturbances without prior knowledge of what disturbances are involved and how they are mixed. As the ICA is a technique that is originally applied to multivariate data, a preprocessing step using a filter bank that generates multiple mixtures from a single measured power signal, allowing the use of only one monitor of PQ, is proposed in this work. In addition, the proposed method presents a simple procedure based on the LMS (Least Mean Square) algorithm to recover the magnitude and sign of the estimated independent disturbances, overcoming an indeterminacy inherent in the ICA model [14]. The proposed method is tested using synthetic data, simulated data, as well as actual power system signals, and its performance concerning the decomposition is compared to that performed by the DWT.

2. Single and multiple PQ disturbance: the problem formulation

The discrete-time version of the monitored electrical signals of voltage/current can be divided into non-overlapped frames of N samples. Based on the proposed model in [18,19], the discrete sequence $\{x[n]\}$ in a frame can be shown as an additive contribution of various types of phenomena, as expressed by:

$$x[n] = x(t)|_{t=nT_S} = f[n] + h[n] + i[n] + t[n] + v[n], \tag{1}$$

where $n = 0, \ldots, N-1$, T_S is the sampling period and $x[n]$ is the discrete-time version of the continuous signal $x(t)$ sampled at the instant $n\dot{T}_S$. The sequences $\{f[n]\}$, $\{h[n]\}$, $\{i[n]\}$, $\{t[n]\}$, and $\{v[n]\}$ denote the power supply signal (fundamental component), harmonics, interharmonics, transients and background noise, respectively. Each of these signals is defined as follows:

$$f[n] = A_1[n]\sin(2\pi f_1[n]nT_S + \delta_1[n]), \tag{2}$$

$$h[n] = \sum_{k=2}^{K} A_k[n]\sin(2\pi k f_1[n]nT_S + \delta_k[n]), \tag{3}$$

$$i[n] = \sum_{j=1}^{J} A_{I,j}[n]\sin(2\pi f_{I,j}[n]nT_S + \delta_{I,j}[n]), \tag{4}$$

$$t[n] = t_{\text{imp}}[n] + t_{\text{not}}[n] + t_{\text{osc}}[n] + t_{\text{dec}}[n], \tag{5}$$

and $v[n]$ is independently and identically distributed (i.i.d.) noise as gaussian $\mathcal{N}(0, \sigma_v^2)$ and independent of $f[n]$, $h[n]$, $i[n]$, and $t[n]$.

In (2), $A_1[n]$, $f_1[n]$, and $\delta_1[n]$ refer to the magnitude, fundamental frequency, and phase of the power supply signal, respectively. From the sequence $f[n]$, several distinct disturbances that are mainly related to the fundamental component can be diagnosed. These disturbances are: sag, swell, interruption, sustained interruption, undervoltage and overvoltage [20]. In (3), $A_k[n]$ is the magnitude and $\delta_k[n]$ is the phase angle of the kth harmonic. From sequence $h[n]$, the occurrence of harmonic distortion generated by sources that are mainly nonlinear loads connected to the power system can be diagnosed. In (4), $A_{I,j}[n]$, $f_{I,j}[n]$, and $\delta_{I,j}[n]$ are the magnitude, frequency and phase of the jth interharmonic, respectively. These components appear due to the occurrence of flicker, as well as the presence of some power electronic devices. In (5), $t_{\text{imp}}[n]$ and $t_{\text{not}}[n]$ represent impulsive transients and notchings [21], respectively; $t_{\text{osc}}[n]$ refers to oscillatory transients called damped oscillations, and $t_{\text{dec}}[n]$ represents the exponential decays. These transients could be expressed by:

$$t_{\text{imp}}[n] = \sum_{i=1}^{N_{\text{imp}}} t_{\text{imp},i}[n], \tag{6}$$

$$t_{\text{not}}[n] = \sum_{i=1}^{N_{\text{not}}} t_{\text{not},i}[n], \tag{7}$$

$$t_{\text{osc}}[n] = \sum_{i=1}^{N_{\text{osc}}} A_{\text{osc},i}[n]\exp(-\alpha_{\text{osc},i}[n]T_S) \times \sin(\omega_{\text{osc},i}[n]nT_S + \delta_{\text{osc,i}}[n]), \tag{8}$$

$$t_{\text{dec}}[n] = \sum_{i=1}^{N_{\text{dec}}} A_{\text{dec},i}[n]\exp(-\alpha_{\text{dec},i}[n]T_S), \tag{9}$$

where $t_{\text{imp},i}[n]$ and $t_{\text{not},i}[n]$ are the nth samples of the ith transient called impulsive transient or notching. It should be noted that (8) refers to the capacitor switchings, as well as signals resulting from faulted waveforms. Eq. (9) defines the exponential decay, as well as the *direct current* (DC) components ($\alpha_{\text{dec}} = 0$) caused by geomagnetic disturbances or asymmetry of electronic power converters [20].

The direct use of $x[n]$ for PQ analysis normally leads to solutions with a high computational complexity. Moreover, most PQ analysis techniques developed so far (e.g., for detection and classification) consider the occurrence of an isolated disturbance in a frame [22–24]. These techniques have a high performance concerning detection and classification, sometimes very close to 100%. However, it should be noted that the occurrence of more than one disturbance in the electrical signals, at the same time interval, is a common situation due to the presence of various sources of disturbances in power systems. It is worth mentioning that disturbance analysis takes into account a non-overlap data window of a given length, normally specified in the project. Therefore, simultaneous events are hereby defined as those that occur inside the same data window.

The signal presented in Fig. 1a, obtained from the IEEE P1159.3 task force website [25], illustrates the occurrence of multiple