Electrical Power and Energy Systems 49 (2013) 386–398

Contents lists available at SciVerse ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

An application of the spectral kurtosis to characterize power quality events ☆

Juan José González de la Rosa [a,b,*,1], José María Sierra-Fernández [a], Agustín Agüera-Pérez [a], José Carlos Palomares-Salas [a], Antonio Moreno-Muñoz [a,c]

[a] Research Group PAIDI-TIC-168: Computational Instrumentation and Industrial Electronics (ICEI), Spain
[b] University of Cádiz, Area of Electronics, EPSA, Av. Ramón Puyol S/N, E-11202 Algeciras, Cádiz, Spain
[c] University of Córdoba, Area of Electronics, Campus de Rabanales, Leonardo da Vinci Building, E-14071 Córdoba, Spain

A R T I C L E   I N F O

Article history:
Received 29 October 2012
Received in revised form 25 January 2013
Accepted 2 February 2013
Available online 15 March 2013

Keywords:
Higher-Order Statistics (HOS)
Frequency domain modeling
Power Quality (PQ)
Spectral Kurtosis (SK)

A B S T R A C T

This paper deals with a novel application of the Spectral Kurtosis (SK) in power-quality modeling and analysis. The two major advantages of this three-spectral analysis are: robustness to noise and the capability to detect nonlinearities, as impulsive-like signals. The first aim is to study some of the theoretical aspects of the SK estimation, performing a connection to the power-quality event analysis. Then, real-life situations' performances are presented to correlate results with synthetics. Despite the fact the limited resolution in the frequency domain (to gain computation speed), the method presents an accuracy of 84% over real-life registers.

1. Introduction

The higher-order statistics have been object of intensive basic and applied research during the past 10 years, due to their capability to reject noise and to complement the classical second-order characterization [1]. One of the most useful tools is the fourth-order cumulant, in which the kurtosis is inspired. The kurtosis measures the peakedness of the probability distribution associated to the instantaneous amplitudes of the time-series measurements. Its complementary version in the frequency domain, the Spectral Kurtosis (SK) can be initially defined as the kurtosis of its frequency components, and compares the variability in amplitude of the different spectral frequencies. Thus, this statistical parameter indicates how the impulsiveness of a signal varies with frequency.

The SK is a fourth order spectrum whose prior estimators were introduced in the eighties for detecting transients in sonar processing [2], enhancing non-linearities and discovering hidden processes that in turn constitute a further support for the development of technology. The scientific community uses the SK for distinguishing different types of signals [3]. Applications are biased in the field of machine diagnostics [4–6]; other works are found in the field of insect detection [7].

It has also been found that the spectral kurtosis can be used to form a filter to select out that part of the signal that is most impulsive, considerably reducing the background noise and hence improving the diagnostic capability. The identification proved to be capable to identify quadratically coupled signals when the power-spectra failed [8].

Since Power-Quality (PQ) events give rise to sudden changes in the power line signal, this higher-order statistics (in particular the SK) are potentially useful to characterize the frequency bands associated to each type of the electrical anomaly. Following this philosophy, the subjacent goal of the paper is to use an estimator of the SK to measure the variability associated to each frequency component of the electrical signal. Consequently, a constant-amplitude (zero variability) single-frequency sinusoid exhibits a minimum SK value at this frequency; where as if the amplitude varies with time, the SK increases at this concrete frequency. More precisely, if the amplitude varies according to a normal distribution, the SK is zero.

This philosophy has been brought to practice in the time-domain by several notable works. For example, Bollen et al. used advanced signal processing techniques to introduce new statistical features to PQ event detection [9]. In the same line, Gu and Bollen [10] found notable characteristics corresponding to power disturbances in the time and frequency domains. It is also remarkable the work by Ribeiro et al. [11], which uses HOS to extract new time-domain features associated to electrical anomalies. HOS

☆ This work is funded and supported by the Spanish Ministry of Science and Innovation, via the project TEC2010-19242-C03-03 (SIDER-HOSAPQ).

* Corresponding author at: University of Cádiz, Area of Electronics, EPSA, Av. Ramón Puyol S/N, E-11202 Algeciras, Cádiz, Spain. Tel./fax: +34 956028020.
E-mail address: juanjose.delarosa@uca.es (J.J. González de la Rosa).
URL: http://www.uca.es/grupos-inv/TIC168/ (J.J. González de la Rosa).
[1] Main Researcher of the Research Unit PAIDI-TIC-168.

0142-0615/$ - see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.ijepes.2013.02.002

techniques and estimators have also been implemented to specifically detect sags and swells [12].

The categorization of PQ events had been previously performed by Nezih Gerek and Ece in the work [13], where the authors used higher order cumulants and quadratic classifiers, as an alternative to second order-based methods. These same authors previously achieved good performance in second-order computing, in reference to the works using 2-D wavelet subspaces and compression techniques [14,15]; finding, despite the promising results, the limitations of the procedure and the heavy computational cost, which was a significative advance. Alienated to this work, the notable works of Poisson et al. and Santoso et al. [16,17] also reported a wavelets-based method, corroborating the potential of the technique and the limitations to implement the method in a measurement device.

Regarding the processing speed, it was notably improved in the work by Subasi et al. [18], where a Teager Energy Operator (TEO) algorithm is proposed to detect and analyze power quality events, and the method compared to others, which are second-order based. Another key evidence of improved speed processing is found in the work by Yilmaz et al. [19], where an estimator of the Lifting Based Wavelet Transform (LBWT) has been used. This work performs the analysis of voltage disturbances in the time scale, and manages to quantify PQ events. Data features are generated on a timefrequency plane, and simulations for five types of PQ events show that the proposed method is more efficient and faster in tracking signal dynamics than traditional Wavelet Transforms (WTs).

The myriads or papers in this field are motivated by the fact that the worldwide interest in PQ is twofold. Equipment has become more sensitive to electrical anomalies, and at the same time the industrial electronic modules cause voltage disturbances. There is also the need for standardization and performance criteria for consumers and utilities. Consequently, and motivated by this issue a simple technique has been adopted in former works, with the goal of performing an on-site procedure, which was independent both from the device under test, as it uses normalization [12,20]. PQ events are roughly of the same frequency of the 'healthy' signal (ideal power-line sine wave). Thus, signal processing techniques benefit from this fact by measuring-detecting changes in the statistical values as the target signal is tested. The traditional analysis procedure is based in the use of a sliding window through which the statistical estimator is computed. Thereby, when the perturbed zone in the signal appears (the sliding window bumps into the anomaly), a change in the estimator is observed and automatically targeted. This working hypothesis is also present in the present research. According to this perspective, the present paper presents performance results of SK over a battery of PQ events. Results are promising since the test offers an accuracy of 84% over an ensemble of real-life signals.

The paper is structured as follows. The following Section 2, introduces the estimator for the SK and presents its performance over illustrative signals, with the goal of a further understanding. Results are presented in Section 3, where a collection of synthetics and real-life electrical faults is detailed. Finally, conclusions are drawn in Section 4.

2. The spectral kurtosis: description and illustrative examples

This section aims to introduce SK and expose the theoretical foundation of the present research through examples. In statistics, kurtosis is a measure of the "peakedness" of the probability distribution of a real-valued random variable. Higher kurtosis means more of the variance is due to infrequent extreme deviations, as opposed to frequent modestly-sized deviations. Kurtosis is more commonly defined as the fourth central cumulant divided by the square of the variance of the probability distribution, which is the so-called excess kurtosis:

$$\gamma_2 = \frac{\kappa_4}{\kappa_2^2} = \frac{\mu_4}{\sigma^4} - 3, \tag{1}$$

where $\mu_4 = \kappa_4 + 3\kappa_2^2$ is the 4th-order central moment; and κ_4 is the 4th-order central cumulant, i.e. the ideal value of $Cum_{4,x}(0,0,0)$. The "minus 3" at the end of this formula is a correction to make the kurtosis of the normal distribution equal to zero. Excess kurtosis can range from -2 to $+\infty$. This definition of the 4th-order cumulant for zero time-lags comes from a combinational relationship among the cumulants of stochastic signals and their moments, and is given by the *Leonov–Shiryaev* formula.

The sample kurtosis is calculated over a sample-register (an N-point data record), and noted by:

$$g_2 = \frac{m_4}{s^4} - 3 = \frac{m_4}{m_2^2} - 3 = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^4}{\frac{1}{N^2}\left[\sum_{i=1}^{N}(x_i - \bar{x})^2\right]^2} - 3, \tag{2}$$

where m_4 is the fourth sample moment about the mean, m_2 is the second sample moment about the mean (that is, the sample variance), and $\bar{x}$ is the sample mean; see also Appendix A.

Ideally, the spectral kurtosis is a representation of the kurtosis of each frequency component of a process (or data from a measurement instrument x_i). For estimation issues we will consider M realizations of the process; each realization containing N points; i.e. we consequently consider M measurement sweeps, each sweep with N points. The time spacing between points is the sampling period, T_s, of the data acquisition unit. The SK unbiased estimator is given by:

$$\widehat{G}_{2,X}^{N,M} = \frac{M}{M-1}\left[\frac{(M+1)\sum_{i=1}^{M}\left|X_N^i(m)\right|^4}{\left(\sum_{i=1}^{M}\left|X_N^i(m)\right|^2\right)^2} - 2\right], \tag{3}$$

where m indicates the frequency index, and $\widehat{G}_{2,X}^{N,M}$ indicates the value of the kurtosis for this Fourier frequency.

Higher-order statistics have been used in the former 7 years to detect electrical anomalies. Whilst the present works focuses in the frequency domain. Promising time domain results have been obtained in [12]; research in which frame the signal analysis was performed using the initial hypothesis that the sliding window used to extract HOS features (statistics) enclosed an exact number of cycles of the 50 Hz sine wave. The analysis is based on windows of 0.02 s width, which covers 1 cycle of a standard power signal (healthy signal). Thus, by displacing the sliding window along a healthy signal, the set of values analyzed by the HOS processing is identical, returning a specific constant value for the statistical estimator. Any electrical disturbance or anomaly over the healthy signal would produce variations from this constant value when the sliding window bumped into this distortion in the waveform, thereby revealing its presence. Furthermore, if the coupled disturbance generated another 50 Hz signal, it returned constant values, which were different from the ones associated to the healthy power-line. Consequently, we benefit from this fact, to characterize the 50 Hz disturbances coupled to a 50 Hz sinusoidal signal.

The benefit of the suggested procedure of analysis is that 50 Hz events are *tuned* by the sliding window, and the returned constant values are associated to the specific shapes of the waveforms. In order to show this working premise, an introductory example has been conceived. Nine 50-Hz signals, grouped in three sets, have been analyzed in order to observe their associated constant values. These signals and their constant HOS values are represented in Fig. 1 classified in asymmetrical, symmetrical and pure-sinusoidal signals.

These results in the time-domain are complementary to achieve satisfactory interpretation in the frequency domain. Two examples