

Neural Networks and HOS for Power Quality Evaluation

Juan J. González De la Rosa

Universities of Cádiz-Córdoba, Spain

Carlos G. Puntonet

University of Granada, Spain

A. Moreno-Muñoz

Universities of Cádiz-Córdoba, Spain

INTRODUCTION

Power quality (PQ) *event* detection and classification is gaining importance due to worldwide use of delicate electronic devices. Things like lightning, large switching loads, non-linear load stresses, inadequate or incorrect wiring and grounding or accidents involving electric lines, can create problems to sensitive equipment, if it is designed to operate within narrow voltage limits, or if it does not incorporate the capability of filtering fluctuations in the electrical supply (Gerek et. al., 2006; Moreno et. al., 2006).

The solution for a PQ problem implies the acquisition and *monitoring* of long data records from the energy distribution system, along with an automated detection and classification strategy which allows identify the cause of these voltage anomalies. Signal processing tools have been widely used for this purpose, and are mainly based in spectral analysis and wavelet transforms. These *second-order* methods, the most familiar to the scientific community, are based on the independence of the spectral components and evolution of the spectrum in the time domain. Other tools are threshold-based algorithms, linear classifiers and Bayesian networks. The goal of the signal processing analysis is to get a feature vector from the data record under study, which constitute the input to the computational intelligence modulus, which has the task of classification. Some recent works bring a different strategy, based in higher-order *statistics* (HOS), in dealing with the analysis of *transients* within PQ analysis (Gerek et. al., 2006; Moreno et. al., 2006) and other fields of Science (De la Rosa et. al., 2004, 2005, 2007).

Without perturbation, the 50-Hz of the voltage *waveform* exhibits a *Gaussian* behaviour. Deviations from Gaussianity can be detected and characterized via HOS. Non-Gaussian processes need third and fourth order statistical characterization in order to be recognized. In order words, *second-order* moments and *cumulants* could be not capable of differentiate non-*Gaussian events*. The situation described matches the problem of differentiating between a transient of long duration named fault (within a signal period), and a short duration transient (25 per cent of a cycle). This one could also bring the 50-Hz voltage to zero instantly and, generally affects the sinusoid dramatically. By the contrary, the long-duration transient could be considered as a modulating signal (the 50-Hz signal is the carrier). These *transients* are intrinsically non-stationary, so it is necessary a battery of observations (sample registers) to obtain a reliable characterization.

The main contribution of this work consists of the application of higher-order central cumulants to characterize PQ *events*, along with the use of a competitive layer as the classification tool. Results reveal that two different clusters, associated to both types of *transients*, can be recognized in the 2D graph. The successful results convey the idea that the physical underlying processes associated to the analyzed *transients*, generate different types of deviations from the typical effects that the noise cause in the 50-Hz sinusoid voltage *waveform*.

The paper is organized as follows: Section on higher-order cumulants summarizes the main equations of the cumulants used in the paper. Then, we recall the competitive layer's foundations, along with the *Kohonen* learning rule. The experience is described then, and the conclusions are drawn.

HIGHER-ORDER CUMULANTS

High-order *statistics*, known as *cumulants*, are used to infer new properties about the data of *non-Gaussian* processes (Mendel, 1991; Nikias & Mendel, 2003). The relationship among the cumulants of r stochastic signals, $\{x_{i \in [1,r]}\}$ and their moments of order p , $p \leq r$, can be calculated by using the *Leonov-Shiryayev* formula (Nandi, 1999; Nikias & Mendel, 2003). For an r th-order stationary random process $\{x(t)\}$, the r th-order cumulant is defined as the joint r th-order cumulant of the random variables $x(t), x(t+\tau_1), \dots, x(t+\tau_{r-1})$,

$$C_{r,x}(\tau_1, \tau_2, \dots, \tau_r) = \text{Cum}[x(t), x(t+\tau_1), \dots, x(t+\tau_r)]. \quad (1)$$

Considering $\tau_1 = \tau_2 = \tau_3 = 0$ in Eq. (1), we have some particular cases:

$$\tau_{2,x} = E\{x^2(t)\} - C_{2,x}(0), \quad (2a)$$

$$\tau_{3,x} = E\{x^3(t)\} - C_{3,x}(0,0), \quad (2b)$$

$$\tau_{4,x} = E\{x^4(t)\} - 3(\tau_{2,x})^2 = C_{4,x}(0,0,0). \quad (2c)$$

Eqs. (2) are measurements of the variance, skewness and kurtosis of the statistical distribution, in terms of the *cumulants* at zero lags. We will use and refer to normalized quantities because they are shift and scale invariant.

COMPETITIVE LAYERS

The neurons in a competitive layer distribute themselves to recognize frequently presented input vectors. The competitive transfer function accepts a net input vector \mathbf{p} for a layer (each neuron competes to respond to \mathbf{p}) and returns outputs of 0 for all neurons except for the winner, which is associated with the most positive element of the net input. For zero bias, the neuron whose weight vector is closest to the input vector has the least negative net input and, therefore, wins the competition to output a 1.

The winning neuron will move closer to the input, after this has been presented. The weights of the winning neuron are adjusted with the *Kohonen* learning rule. If for example the i th-neuron wins, the elements of the i th-row of the input weight matrix (\mathbf{IW}) are adjusted as shown in Eq. (3):

$$\mathbf{IW}_i^{l+1}(q) = \mathbf{IW}_i^{l+1}(q-1) + \alpha [p(q) - \mathbf{IW}_i^{l+1}(q-1)], \quad (3)$$

where \mathbf{p} is the input vector, q is the time instant, and α is the learning rate. The *Kohonen* rule allows the weights of a neuron to learn an input vector, so it is useful in recognition applications. The winning neuron is more likely to win the competition the next time a similar vector is presented. As more and more inputs are presented, each neuron in the layer closest to a group of input vectors soon adjusts its weight vector toward those inputs. Eventually, if there are enough neurons, every cluster of similar input vectors will have a neuron that outputs “1” when a vector in the cluster is presented.

EXPERIMENTAL RESULTS

The aim is to differentiate between two classes of PQ *events*, named long-duration and short-duration. The experiment comprises two stages. The feature extraction stage is based on the computation of cumulants. Each vector’s coordinate corresponds to the local maximum and minimum of the 4th-order central *cumulant*. Secondly, the classification stage is based on the application of the competitive layer to the feature vectors. We use a two-neuron competitive layer, which receives two-dimensional input feature vectors during the network training.

We analyze a number of 16 1000-point real-life registers during the feature extraction stage. Before the computation of the cumulants, two pre-processing actions have been performed over the sample signals. First, they have been normalized because they exhibit very different-in-magnitude voltage levels. Secondly, a high-pass digital filter (5th-order Butterworth model with a characteristic frequency of 150 Hz) eliminates the low frequency components which are not the targets of the experiment. This by the way increases the *non-Gaussian* characteristics of the signals, which in fact are reflected in the higher-order cumulants. Fig. 1 shows the comparison of the two types of *events*.

After pre-processing, a battery of sliding central cumulants (2nd, 3rd and 4th-order) is calculated. Each cumulant is computed over 50 points; this window’s length (50 points) has been selected neither to be so long to cover the whole signal nor to be very short. The algorithm calculates the 3 central cumulants over 50 points, and then it jumps to the following starting

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