Measurement 42 (2009) 478–484

Contents lists available at ScienceDirect

Measurement

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

Higher-order characterization of power quality transients and their classification using competitive layers ☆

Juan José González de la Rosa [a,b,*], Antonio Moreno Muñoz [a,c], Antolino Gallego [d], Rosa Piotrkowski [d,e], Enrique Castro [d]

[a] Research Group PAIDI-TIC-168: Computational Instrumentation and Industrial Electronics
[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, Ed. Leonardo da Vinci, E-14.071, Córdoba, Spain
[d] University of Granada, Department of Applied Physics, Research Group, PAIDI-TEP-232, Numerical Methods and Signal Processing in Dynamical Systems
[e] School of Science and Technology, San Martin University, M. de Irigoyen 3100 (1650) San Martin, Buenos Aires, Argentina

ARTICLE INFO

Article history:
Received 27 July 2008
Received in revised form 12 September 2008
Accepted 15 September 2008
Available online 22 September 2008

Keywords:
Higher-order statistics (HOS)
Neural classifiers
Power-quality analysis
Transient categorization

ABSTRACT

This paper deals with power-quality (PQ) event detection, classification and characterization using higher-order sliding cumulants (which are calculated over high-pass filtered signals to avoid the low-frequency 50-Hz sinusoid), whose maxima and minima are the coordinates of two-dimensional feature vectors. The classification strategy is based in competitive layers. We focus on the problem of differentiating two types of transients: short-duration (impulsive transients) and long-duration (oscillatory transients). The results show that the measured vectors are classified into clearly differentiated clusters in the feature space. The experience aims to set the foundations of an automatic procedure for PQ event detection.

1. Introduction

Power Quality (PQ) or power disturbances are concerned with deviations of the voltage or current from the ideal single-frequency sine wave of constant amplitude and frequency. PQ problems commonly faced by facilities operations include transients, sags, swells, surges, outages, harmonics, and flickers that vary in quantity or magnitude of the voltage. A consistent set of definitions can be found in [1].

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 [2,3].

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 the identification of the cause of these voltage anomalies. 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, with the task of classification. Signal processing for this purpose are mainly based in spectral analysis and wavelet transforms. Second-order methods are based on the independence of the spectral

☆ This work is funded and supported by the Spanish Ministry of Science and Education (projects DPI2003-00878, PTR95-0824-OP and DPI2006-02970) and by the Andalusian Government (excellency project PAI2005-TIC00155).

* Corresponding author. Address: University of Cádiz, Area of Electronics, EPSA, Av. Ramón Puyol S/N, E-11202, Algeciras-Cádiz, Spain. Tel.: +34 956028020; fax: +34 956028020/01.
E-mail address: juanjose.delarosa@uca.es (J.J. González de la Rosa).

0263-2241/$ - see front matter © 2008 Elsevier Ltd. All rights reserved.
doi:10.1016/j.measurement.2008.09.006

components and the evolution of the spectrum in the time domain. Other tools are threshold-based functions, linear classifiers and Bayesian networks.

Some recent works bring a different strategy, based in higher-order statistics (HOS), in dealing with the analysis of transients within PQ analysis [4,5], and other fields of Science [6–8]. Without perturbation, the 50-Hz of the voltage waveform exhibits a Gaussian behavior. 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 (completely characterized), because 2nd-order moments and cumulants could be not capable of differentiate non-Gaussian events.

The problem of differentiating between a transient of long duration named oscillatory (within a signal period) and a short duration transient, or impulsive transient (25% of a cycle), falls into the set of HOS applicability. The short transient 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), and is associated to load charges [2]. These transients are intrinsically non-stationary, so it is necessary a battery of observations (sample registers) to obtain a reliable characterization.

The contribution of this paper consists of the application of higher-order central cumulants to characterize PQ events in the time-domain (measuring maxima and minima values of higher-order cumulant sequences), 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, attending to third and fourth-order characterization. The successful results convey the idea that the physical underlying processes associated to the transients, generate different types of deviations from the typical effects that the noise cause in the 50-Hz sinusoid voltage waveform.

The paper is structured as follows. The following Section 2 explains the fundamentals of the importance for power quality monitoring. Higher-order statistics are outlined in Section 3. Competitive layers are summarized in Section 4. Results are presented in Section 5. Finally, conclusions are drawn in Section 6.

2. The importance of power-quality characterization

As more and more electronic equipment enter the residential and business environment, the subjects related to Power Quality (PQ) and its relationship to vulnerability of installations is becoming an increasing concern to the users. Particularly has increased the need to protect sensitive electronic equipment from damaging over-voltages [9,10].

Over-voltage is an RMS increase in the AC voltage, at the power frequency, for durations greater than a few seconds [11]. Over-voltage can be the result of a programmed utility operation, or the effect of an external eventuality. Under normal operating conditions, the steady-state voltage is regulated by the utility within a limits band accepted by the EN-50160. Deviations from these limits are rare, and the utility can actuate readily to correct them, if known their occurrence, by acting on conventional distribution technologies, such as tap-changing transformers [12].

However, under the typical operating conditions of a power system it is always possible the presence of damaging momentary excess of voltage. Although by themselves they would be described as "abnormal", it is possible to distinguish between surge and swell. A surge is an over-voltage that can reach thousands of volts, lasting less than one cycle of the power frequency, that is, less than 16 ms. A swell is longer, up to a few seconds, but does not exceed about twice the normal line voltage.

Power system surges, based on waveform shapes, can be classified into "oscillatory transients" and "impulsive transients" [1,3] and they are the goal of this research work. Oscillatory transient surges show a damped oscillation with a frequency range from 400 Hz to 5 kHz or more. Impulsive transient surges present a fast rise time in the order of 1 ns–10 μs over the steady-state condition of voltage, current or both, that is unidirectional in polarity (primarily either positive or negative), reaching hardly twice the peak amplitude of the signal. They are damped quickly, presenting a frequency range from 4 kHz to 5 MHz, occasionally reaching 30 MHz.

Categorization of electrical transients based on waveform shapes and their underlying causes (or events) has been studied in [2], and a few previous studies [4,5] using HOS for feature extraction of electrical signals have shown the possibility of distinguish transients based on details beyond the second-order.

In the following Section 3 we present higher-order statistics in the time-domain in order to present the signal processing tool, along with a basic example which shows the performance of the statistical estimators which have been used in the computation of the cumulants. This example also motivates the use of HOS in time-series characterization.

3. Higher-order statistics

3.1. Mathematical foundations

Higher-order cumulants are used to infer new properties about the data of non-Gaussian processes [6,13]. In multiple-signal processing it is very common to define the combinational relationship among the cumulants of r stochastic signals, $\{x_i\}_{i\in[1,r]}$, and their moments of order p, $p \leqslant r$, given by using the *Leonov-Shiryaev* formula [14,15]

$$Cum(x_1, \cdots, x_r) = \sum(-1)^{p-1} \cdot (p-1)! \cdot E\{\prod_{i\in s_1} x_i\} \cdot E\{\prod_{i\in s_2} x_j\} \cdots E\{\prod_{i\in s_p} x_k\}, \tag{1}$$

where the addition operator is extended over all the partitions, like one of the form $(s_1, s_2, \ldots, s_p)$, $p = 1, 2, \cdots, r$; and

($1 \leqslant i \leqslant p \leqslant r$); being s_i a set belonging to a partition of order p, of the set of integers $1,\ldots,r$.

Let $\{x(t)\}$ be an rth-order stationary random real-valued process. The rth-order cumulant is defined as the joint rth-order cumulant of the random variables $x(t)$, $x(t+\tau_1),\ldots$, $x(t+\tau_{r-1})$,

$$\begin{aligned} &C_{r,x}(\tau_1,\tau_2,\ldots,\tau_{r-1}) \\ &\quad = Cum[x(t),x(t+\tau_1),\ldots,x(t+\tau_{r-1})] \end{aligned} \tag{2}$$

The second-, third- and fourth-order cumulants of zero-mean $x(t)$ can be expressed via [16]:

$$C_{2,x}(\tau) = E\{x(t)\cdot x(t+\tau)\} \tag{3a}$$

$$C_{3,x}(\tau_1,\tau_2) = E\{x(t)\cdot x(t+\tau_1)\cdot x(t+\tau_2)\} \tag{3b}$$

$$\begin{aligned} &C_{4,x}(\tau_1,\tau_2,\tau_3) \\ &= E\{x(t)\cdot x(t+\tau_1)\cdot x(t+\tau_2)\cdot x(t+\tau_3)\} \\ &-C_{2,x}(\tau_1)C_{2,x}(\tau_2-\tau_3) - C_{2,x}(\tau_2)C_{2,x}(\tau_3-\tau_1) \\ &-C_{2,x}(\tau_3)C_{2,x}(\tau_1-\tau_2) \end{aligned} \tag{3c}$$

By putting $\tau_1=\tau_2=\tau_3=0$ in Eq. (3a), we obtain

$$\gamma_{2,x} = E\{x^2(t)\} = C_{2,x}(0) \tag{4a}$$

$$\gamma_{3,x} = E\{x^3(t)\} = C_{3,x}(0,0) \tag{4b}$$

$$\gamma_{4,x} = E\{x^4(t)\} - 3(\gamma_{2,x})^2 = C_{4,x}(0,0,0) \tag{4c}$$

The expressions in Eq. (4c) are measurements of the variance, skewness and kurtosis of the distribution in terms of cumulants at zero lags (the central cumulants).

Normalized kurtosis and skewness are defined as $\gamma_{4,x}/(\gamma_{2,x})^2$ and $\gamma_{3,x}/(\gamma_{2,x})^{3/2}$, respectively. We will use and refer to normalized quantities because they are shift and scale invariant. If $x(t)$ is symmetrically distributed, its skewness is necessarily zero (but not *vice versa*); if $x(t)$ is Gaussian distributed, its kurtosis is necessarily zero (but not *vice versa*). In the experimental section, results are obtained by using sliding cumulants, i.d. a moving window in the time domain over which to compute the each cumulant.

In practice, the computation of the cumulants and the poly-spectra is based in estimates. For example, given an N-sample signal vector $x(n),\ n=0,\cdots,N-1$, the following expressions, Eq. (5)[1], Eq. (6) and Eq. (7) describe three estimates for the second, third and fourth-order cumulants, respectively.

$$\hat{C}_{2,x}(\tau) = R_{x,\text{unbiased}}(\tau) = \frac{1}{N-\tau}\sum_{i=1}^{N-\tau}[x(i)-\bar{x}][x(i+\tau)-\bar{x}], \tag{5}$$

$$\begin{aligned} \hat{C}_{3,x}(k,l) &= C\hat{u}m[x(n),x(n+k),x(n+l)] \\ &= \frac{1}{N}\sum_{n=0}^{N-1}x(n)x(n+k)x(n+l), \end{aligned} \tag{6}$$

[1] Unbiased autocorrelation.

$$\begin{aligned} &\hat{C}_{4,x}(k,l,m) = C\hat{u}m[x(n),x(n+k),x(n+l),x(n+m)] \\ &= \frac{1}{N}\sum_{n=0}^{N-1}x(n)\cdot x(n+k)^*\cdot x(n+l)^*\cdot x(n+m)^* \\ &-\frac{1}{N^2}\left[\sum_{n=0}^{N-1}x(n)\cdot x(n+k)^*\right]\left[\sum_{n=0}^{N-1}x(n+l)^*\cdot x(n+m)^*\right] \\ &-\frac{1}{N^2}\left[\sum_{n=0}^{N-1}x(n)\cdot x(n+l)^*\right]\left[\sum_{n=0}^{N-1}x(n+k)^*\cdot x(n+m)^*\right] \\ &-\frac{1}{N^2}\left[\sum_{n=0}^{N-1}x(n)\cdot x(n+m)^*\right]\left[\sum_{n=0}^{N-1}x(n+k)^*\cdot x(n+l)^*\right]; \end{aligned} \tag{7}$$

where τ is a generic time-lag, $k,l,m \in [-\chi,\ldots,-1,0,1,\ldots,+\chi]$, and $n=0,1,\ldots,N-1$; χ is the index of the maximum time shift (lag) between samples of a record.

Eq. (5) represents an unbiased estimator, while Eqs. (6) and (7) represent biased estimates. If the total number of terms averaged are considered in the denominator (e.g. $N-\tau$), the estimator is unbiased. By the contrary, if the number of sampled data (N) are considered, the estimator is biased.

If different signals are involved Eq. (6) turns into Eq. (8):

$$\hat{C}_{x,y,z}(k,l) = \frac{1}{N_3}\sum_{n=N_1}^{N_2}x(n)y(n+k)z(n+l), \tag{8}$$

where N_1 and N_2 are chosen such that the summations involve only signal components with $n \in [0, N)$-1], and N is the number of samples; unbiased estimates are obtained if N_3 is set equal to the actual number of terms which are averaged.

3.2. An introductory example

To show the relevance of HOS a previous example is prepared. Four noise processes: Gaussian; uniform; exponential and Laplacian, previously catalogued in [13], and indistinguishable from the second-order perspective (autocorrelation sequence), are presented in this subsection in order to illustrate the importance of introducing higher-order cumulants. The 4th-order cumulants are computed according to the estimate given in Eq. (7). We consider a 2048-point sample register for each random set of data. The four identical autocorrelation sequences are drawn in Fig. 1.

If we look into the fourth-order sequences, substantial differences are observed, specially those corresponding to zero time lags. This can be seen in Fig. 2, where the fourth-order cumulant sequences are depicted. The theoretical values of the cumulants at zero time-lag are: 0 (Gaussian), -1 (uniform), 6 (Exponential), 12 (Laplacian), according to [13]. The difference between the theoretical and the experimental value is due to the lack of averaging (only one sample register is consider). The convergency of the estimate is assured.

4. Competitive layers

The neurons in a competitive layer distribute themselves to recognize frequently presented input vectors. The competitive transfer function accepts a net input

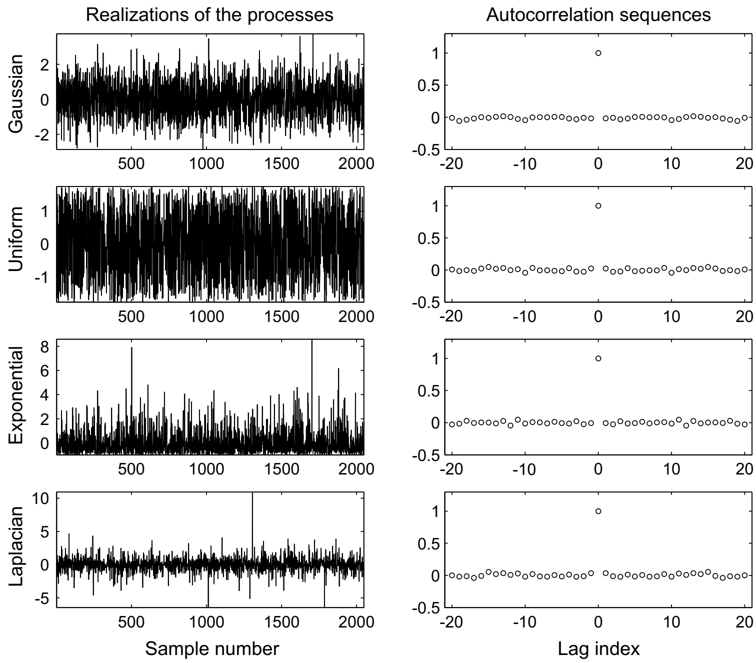

Fig. 1. The four second-order cumulants corresponding to four sample registers, each of which is a realization of a different noise process (left column of sub-figures). They exhibit the same autocorrelation sequence (sub-graphs in the right column).

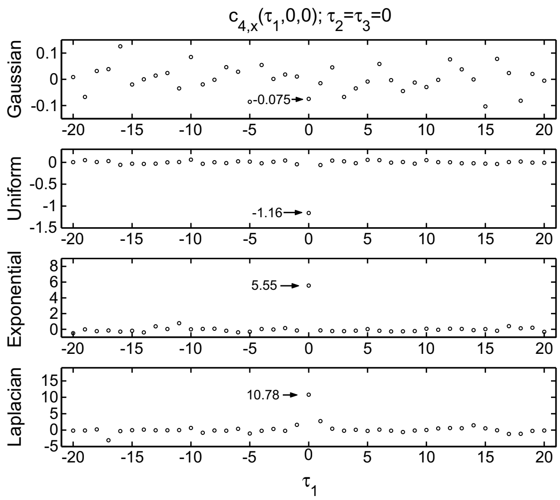

Fig. 2. Fourth-order cumulant sequences for the four noise processes. Sample values at zero time lag are included in each sub-figure.

vector **p** for a layer (each neuron competes to respond to **p**) and returns neuron outputs of 0 for all neurons except for the winner, the one associated with the most positive element of net input. If all biases are 0, then 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 (0.9 in the present case). Supposing that the *i*th-neuron wins, the elements of the *i*th-row of the input weight matrix (**IW**) are adjusted as shown in Eq. (9):

$$\mathbf{IW}_i^{1,1}(q) = \mathbf{IW}_i^{1,1}(q-1) + \alpha[\mathbf{p}(q) - \mathbf{IW}_i^{1,1}(q-1)], \tag{9}$$

where **p** is the input vector, q is the time instant, and α is the learning rate. The neuron whose weight vector was closest to the input vector is updated to be even closer. The result is that the winning neuron is more likely to win the competition the next time a similar input is presented. As more and more inputs are presented, each neuron in the layer closest to a group of input vectors soon adjusts its weights 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, while outputting a 0 at all other times. Thus, the competitive network learns to categorize the input vectors.

5. Experimental results

The aim is to differentiate between two classes of PQ events, named long-duration (oscillatory) and short-duration (impulsive events). The experiment comprises two stages. The feature extraction stage is based on the computation of cumulants. Each vector's coordinate corresponds to the local maxima and minima of the third and fourth-order central cumulants. 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.

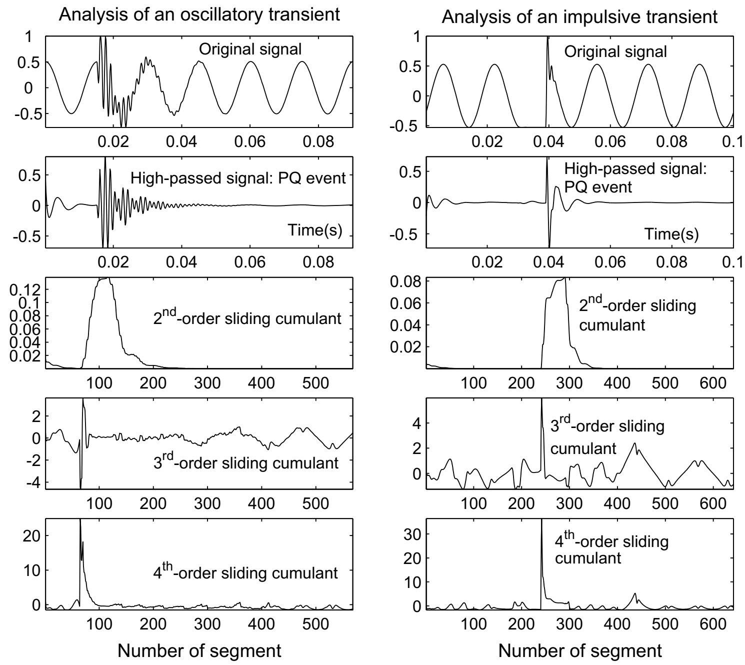

Fig. 3. Comparative higher-order analysis of an impulsive and an oscillatory electrical transients.

We analyze a number of 26,1000-point real-life registers during the feature extraction stage. Before the computation of the biased 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. This disparity of voltage levels cannot influence the results of the categorization. Secondly, a high-pass digital filter (fifth-order Butterworth model with a characteristic frequency of 150 Hz) eliminates the low frequency components which are not the targets of the experiment.

After pre-processing, a battery of sliding central biased cumulants second, third and fourth) 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 these three central cumulants over 50 points, and then it jumps to the following starting point (next 50-point overlapped group); as a consequence we have 98% overlapping sliding windows (49/50 = 0.98). Each computation over a window (called a segment) outputs three cumulants (2^{nd}, third and fourth-orders).

Besides, each nth-order cumulant, $Cum_{n,x}[i]$, associated to the ith computation segment has been normalized by $(Cum_{2,x}[i])^{n/2}$, in order to obtain categorization results associated to the shape of the sliding cumulants. This gives a real statistical characterization. If the cumulants are not normalized, the maxima and minima also gather information regarding the value of the cumulants. The higher-order ($n > 2$) normalized cumulants are the skewness and the kurtosis.

Fig. 3 shows the comparison between the analysis of an oscillatory event and an impulsive event. The second-order cumulant sequence corresponds to the variance, which clearly indicates the presence of an event, due to the excess of power. Both types of transients exhibit an increasing variance in the neighborhood of the PQ event, that presents the same shape, with only one maximum. The magnitude of this maximum is by the way the only available feature which can be used to distinguish different events from the second-order point of view. This may suggest the use of additional features in order to distinguish different types of events. Higher-order results allow to differentiate between the transients.

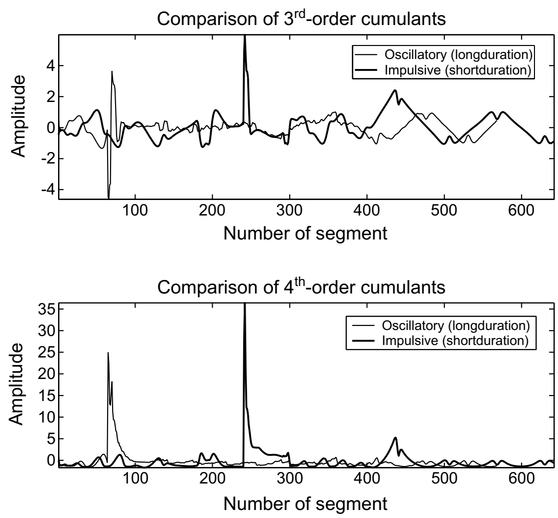

Fig. 4. Third-order vs. fourth-order analysis for the former electrical transients (zoom of the bottom sub-graphs) in Fig. 3.

Fig. 4 shows the comparison of the former events in Fig. 3 looking at the third and fourth-order cumulants. Maxima and minima of the sliding higher-order cumulants are selected as features from each sample register.

The results of the training stage (using the *Kohonen* rule) are shown in Fig. 5 and in Fig. 6, for the third and fourth-order sets of features, respectively. The horizontal (vertical) axis corresponds to the maxima (minima) values. Each cross in the diagram corresponds to an input vector and the circles indicate the final location of the weight vector (after learning) for the two neurons of the competitive layer. Before training, both weight vectors pointed to the asterisk, which is the initializing point.

The separation between classes (inter-class distance) is well defined in both 2-D feature graphs. Both types of PQ events are clustered. The correct configuration of the clusters is corroborated during the simulation of the neural network, in which we have obtained an approximate classification accuracy of 97%. During the simulation, new signals (randomly selected from our data base) were processed using this methodology. The accuracy of the classification results increases with the number of data. To evaluate the confidence of the statistics a significance test has been conducted. As a result, the number of measurements is significantly correct.

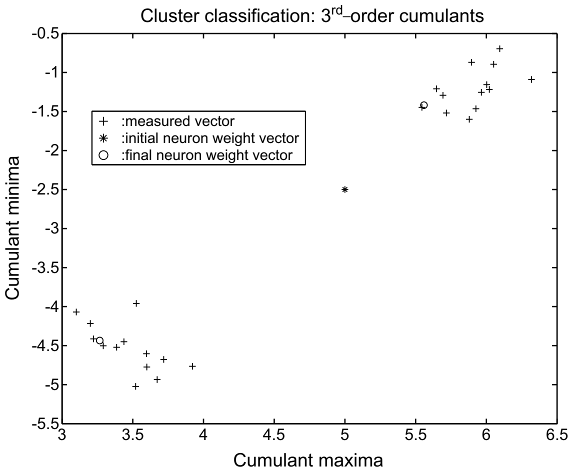

Fig. 5. Competitive layer third-order training results over 20 epochs. Upper cluster: Short-duration PQ-events. Down cluster: Long-duration event.

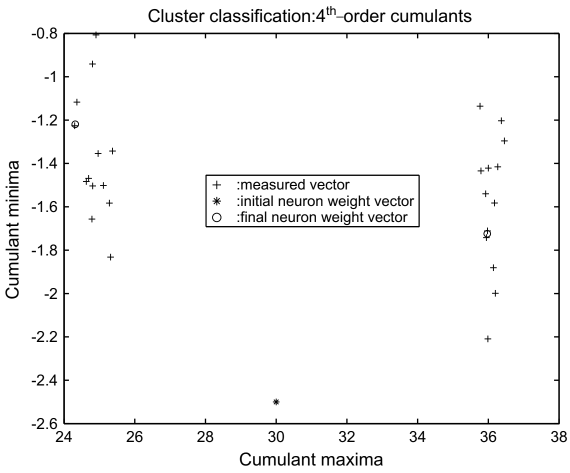

Fig. 6. Competitive layer fourth-order training results over 20 epochs. Right cluster: Short-duration PQ-events. Left cluster: Long-duration event.

6. Conclusion

In this paper we have proposed an automatic method to detect and classify two PQ transients, named short and long-duration. The method comprises two stages. The first includes pre-processing (normalizing and filtering) and outputs the 2-D feature vectors, each of which coordinate corresponds to the maximum and minimum of the central higher-order cumulants. The second stage uses a neural network to classify the signals into two clusters. This stage is different-in-nature from the one used in [5] consisting of quadratic classifiers and was previously used in [4], without having been normalized the cumulants. The configuration of the clusters is assessed during the simulation of the network, in which we have obtained acceptable classification accuracy.

Acknowledgements

The authors thank the *Spanish Ministry of Science and Education* for funding the project DPI2003-00878, where the different noise processes have been modeled and contrasted. Thanks for supporting the PETRI project PTR95-0824-OP dealing with plague detection using higher-order statistics; and also the project DPI2006-02970, where non-destructive testing based on acoustic emission signals is performed. Our unforgettable thanks to the trust we have from the *Andalusian Government* for funding the excellency project PAI2005-TIC00155, where higher-order statistics are modeled and applied to plague detection and power quality analysis.

References

[1] IEEE Recommended practice for monitoring electric power quality, Tech. Rep. IEEE Std. 1159–1995, The Institute of Electrical and Electronics Engineers, Inc., 1995.
[2] M.H.J. Bollen, E. Styvaktakis, I.Y.-H. Gu, Categorization and analysis of power system transients, IEEE Transactions on Power Delivery 20 (3) (2005) 105–118.
[3] D. Paul, Low-voltage power system surge overvoltage protection, IEEE Transactions on Industry Applications 37 (1) (2001) 223–229.
[4] J.J.G. de la Rosa, A. Moreno, C.G. Puntonet, A practical review on higher-order statistics interpretation. Application to electrical transients characterization, Dynamics of Continuous Discrete and Impulsive Systems-Series B: Applications and Algorithms 14 (4) (2007) 1577–1582.
[5] Ömer Nezih Gerek, D.G. Ece, Power-quality event analysis using higher order cumulants and quadratic classifiers, IEEE Transactions on Power Delivery 21 (2) (2006) 883–889.
[6] J.J.G. de la Rosa, I. Lloret, C.G. Puntonet, J.M. Górriz, Higher-order statistics to detect and characterise termite emissions, Electronics Letters 40 (20) (2004) 1316–1317. Ultrasonics.
[7] J.J.G. de la Rosa, I. Lloret, C.G. Puntonet, R. Piotrkowski, A. Moreno, Higher-order spectra measurement techniques of termite emissions.

A characterization framework, Measurement (Ed. Elsevier) 41 (1) (2008) 105–118. available online 13 October 2006.
[8] J.J.G. de la Rosa, R. Piotrkowski, J. Ruzzante, Third-order spectral characterization of acoustic emission signals in ring-type samples from steel pipes for the oil industry, Mechanical Systems and Signal Processing (Ed. Elsevier) 21 (Issue 4) (2007) 1917–1926. available online 10 October 2006.
[9] A. Moreno et al, Mitigation Technologies in a Distributed Environment, first ed., Power Systems, Springer, Verlag, 2007.
[10] F. Martzloff, Protecting computer systems against power transients, IEEE Spectrum 27 (4) (1990) 37–40.
[11] IEEE Guide for service to equipment sensitive to momentary voltage disturbances, Tech. Rep. IEEE Std. 1250–1995, The Institute of Electrical and Electronics Engineers, Inc., 1995.
[12] A. Moreno, J. Flores, D. Oterino, J.J.G. de la Rosa, Power line conditioner based on ca pwm chopper, in: ISIE 2007, Proceedings of the 2007 IEEE International Symposium on Industrial Electronics.
[13] C.L. Nikias, A.P. Petropulu, Higher-order Spectra Analysis, A Non-Linear Signal Processing Framework, Prentice-Hall, Englewood Cliffs, NJ, 1993.
[14] C.L. Nikias, J.M. Mendel, Signal processing with higher-order spectra, IEEE Signal Processing Magazine (1993) 10–37.
[15] J.M. Mendel, Tutorial on higher-order statistics (spectra) in signal processing and system theory: theoretical results and some applications, Proceedings of the IEEE 79 (3) (1991) 278–305.
[16] A.K. Nandi, Blind Estimation Using Higher-order Statistics, first ed., vol. 1, Kluwer Academic Publichers, Boston, 1999.