CLASSIFICATION OF POWER QUALITY DISTURBANCES VIA HIGHER-ORDER STATISTICS AND SELF-ORGANIZING NEURAL NETWORKS

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Abstract: This work renders the classification of Power Quality (PQ) disturbances using fourth-order sliding cumulants' maxima as the key feature. These estimators are calculated over high-pass filtered real-life signals, to avoid the low-frequency 50-Hz sinusoid. Four types of electrical AC supply anomalies constitute the starting grid of a competitive layer performance, which manages to classify 90 signals within a 2D-space (whose coordinates are the minima and the maxima of the sliding cumulants calculated over each register). Four clusters have been clearly identified via the competitive network, each of which corresponds to a type of anomaly. Then, a Self-Organizing Network is conceived in order to guess additional classes in the feature space. Results suggest the idea of two additional sets of signals, which are more related to the degree of signals' degeneration than to real new groups of anomalies. We collaterally conclude the need of additional features to face the problem of subclass division. The experience sets the foundations of an automatic procedure for PQ event classification.

1 INTRODUCTION

Power Quality (PQ) analysis is becoming a key factor for the economy because equipment is highly sensitive to the power line signal's imperfections (Moreno and *et al*, 2007; IE3, 1995b). As a consequence, malfunctioning not only has to be detected, but also predicted and diagnosed, to identify the cause and prevent the system from a similar shock. This is reflected a posteriori in an increase in the amount and quality of the industrial production. The solution for a PQ problem implies the acquisition and monitoring of long data records from the energy distribution system, along with a detection and classification strategy, which allows the identification of the cause of these voltage anomalies. These perturbations can be considered as non-stationary transients, so it is necessary a battery of observations to obtain a reliable characterization. The goal of the signal processing is to get a feature vector from the target data, which constitute the input to the computational intelligence modulus, with the task of classification. Traditional measurement algorithms are mainly based in spectral analysis and wavelet transforms. Complementary second-order methods are based on the independence of the spectral components and the evolution of the spectrum in the time domain. Others are threshold-based functions, linear classifiers and Bayesian networks (De la Rosa et al., 2009,).

Recent works are bringing a higher-order statistics (HOS) based strategy, dealing with PQ analysis (De la Rosa et al., 2007; Ömer Nezih Gerek and Ece, 2006,), and other fields of Technology (De la Rosa et al., 2004; De la Rosa et al., 2008,). They are based in the following argument. Without perturbation, the 50-Hz of the voltage waveform exhibits a Gaussian behavior. Deviations can be detected and characterized via HOS; non-Gaussian processes need at least 3^{rd} and 4^{th}-order statistical characterization in order to be characterized, because 2^{nd}-order moments and cumulants could be not capable of differentiate non-Gaussian events.

Concretely, the problem of differentiating between a transient of long duration named oscillatory

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(within a signal period) and a short duration transient, or impulsive transient (25 per cent of a cycle), has been outcome under controlled conditions in (De la Rosa et al., 2009,), and the idea of differentiating between healthy signals and signals with transients was pointed out and accomplished in (De la Rosa and Muñoz, 2009,). This problem was previously described in (Bollen et al., 2005) and matches HOS category, in the following sense. 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 (Bollen et al., 2005). Similarly, considering the statistical deviation from the Gaussian behavior that power disturbances add to the power line, it seems appropriate to launch the task of higher-order classification of more types of electrical anomalies, also considering the confluence of various perturbations in the same measurement register.

The contribution of this paper consists of the application of fourth-order central cumulants at zero lags to characterize PQ events in the time-domain (measuring maxima and minima values of higher-order cumulant sequences), along with the use of competitive layer and SOM as the classification tools. Four different sets of signals have been a priori established and confirmed using a competitive layer. The first set comprises *healthy* sine-waves from the power 50 Hz-line. Then, we consider signals with oscillatory mono-frequency (long duration) transients of relatively high amplitude; we also consider for the second set the signals with harmonics, which distort the shape of the sine-wave producing a not very high valued fourth-order cumulant. The third group gathers features' anomalies which appeared simultaneously in a signal, corresponding to impulsive transients (of short duration), and/or a weak sag (RMS descent), and/or oscillatory high-amplitude events. Finally, signals clearly affected by high-amplitude impulsive transients and/or deep sags are contained in the fourth set. Sets ♯3 and ♯4 may be joined in one, but signals in set ♯4 are clearly more affected and probably by only one type of perturbation. On the other hand, signals belonging to set ♯3 are generally affected by several anomalies. Consequently, four classes have been established with the possibility od upgrading the detection towards 6 clusters.

The paper is structured as follows. The following Section 2 explains the fundamentals of power quality monitoring. Higher-Order Statistics are outlined then in Section 3, to be followed by a summary on competitive layers and self-organizing networks in Section . Finally, results are presented in Section 5 and conclusions are drawn in Section 6.

2 POWER-QUALITY CHARACTERIZATION

As more and more electronic equipments enter the residential areas and business environment, the subjects related to PQ and its relationship to vulnerability of installations is becoming an increasing concern to the users. Particularly has arisen and increased the need to protect sensitive electronic equipment from damaging over-voltages. 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 (Bollen et al., 2005; Moreno and *et al*, 2007; Paul, 2001).

The two main regulated aspects of PQ are the following:

- Technical PQ, which includes: Continuity of supply or reliability (long interruptions) and Voltage quality (voltage level variations and voltage disturbances).
- Commercial services associated to the wires (such as the delay to get connected to the grid, etc.) as well as commercial services for energy retail to regulated customers.

Assessment of voltage quality and power disturbances involves looking at electromagnetic deviations of the voltage or current from the ideal single-frequency sine wave of constant amplitude and frequency. A consistent set of definitions can be found in (IE3, 1995b). Regulation in European countries proposes to use the standard EN-50160 to define the voltage quality ranges. This norm actually describes the electricity through the technical characteristics that it has to fulfill to be considered as a compliant product. But there are a lot of undefined aspects; besides the fact that most of the regulator has yet to publish the technical criteria to measure and control all the voltage quality characteristics and decide what would be the penalization. The fact is that the only voltage quality aspect that is now enforced is the maximum voltage level variation settled to ±7 % (which is actually different to the ±10 % fixed on the EN-50160). But even this aspect is not yet controlled and there is not any defined procedure to determine if the limit has been reached.

On the other hand, the presence of disturbances on power distribution also affect the energy efficiency of the system. As far as energy efficiency is concerned in a power distribution system, the two dominant factors in PQ are its unbalanced and harmonic distortion. In an electrical installation when single-phase loads (especially those with non-linear characteristics), are not evenly and reasonably distributed among the three-phases of the supply, we are in the presence of unbalance. Voltage unbalance in a three-phase system causes three-phase motors to draw unbalanced current. This phenomenon causes additional power losses in conductors and motors and can cause the rotor of a motor to overheat.

Among all categories of electrical disturbances, the voltage sag (dip) and momentary interruption are the nemeses of the automated industrial processes. Voltage sag is commonly defined as any low voltage event between 10 and 90% of the nominal RMS voltage lasting between 0.5 and 60 cycles. Momentary voltage interruption is any low-voltage event of less than 10% of the nominal RMS voltage lasting between 0.5 cycles and 3 seconds. In medium voltage distribution networks, voltage sags are mainly caused by power system faults. Fault occurrences elsewhere can generate voltage sags affecting consumers differently according to their location in the electrical network. Even though the load current is small compared to the fault current, the changes in load current during and after the fault strongly influence the voltage at the equipment terminals. It has been discovered that the 85% of power supply malfunctions attributed to poor PQ are caused by voltage sag or interruptions of fewer than one second duration. Starting large motors can also generate voltage sags, although usually not so severe. In comparison with interruptions, voltage sags affect a larger number of customers and for some customers voltage sags may cause extremely serious problems. These can create problems to sensitive equipment if it is designed to operate within narrow voltage limits, or it does not have adequate ride-through capabilities to filter out fluctuations in the electrical supply.

Over-voltage is an RMS increase in the AC voltage, at the power frequency, for durations greater than a few seconds, and can be the result of a programmed utility operation, or the effect of an external eventuality (IE3, 1995a). 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 (Moreno et al., 2007).

However, under the typical operating conditions of a power system there is risk of damaging due to a momentary excess of voltage. Although by themselves they would be described as ”abnormal”, it is possible to distinguish between surges and swells. 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 milliseconds. 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” (IE3, 1995b; Paul, 2001) and they are the goal of the present 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 (Bollen et al., 2005), and a few previous studies (De la Rosa et al., 2007; Ömer Nezih Gerek and Ece, 2006,) using HOS for feature extraction of electrical signals have shown the possibility of distinguish transients based on details beyond the second-order. In a real-life 50-Hz power line signal, it is very common to find these transients. In Fig. 1 we show an example of anomalous signal, including transients which are not classified between short-duration and long-duration. We show the computation of three higher-order time-domain statistics in order to introduce them qualitatively. The second-order estimator operates as an increase-of-power detector, showing the bumps associated to the increase of power, which in turn are associated to the anomalies of the power-line sine wave, but the third and fourth-order sliding cumulants have to be interpreted further. The most intuitive procedure is to calculate their maxima and minima.

Once the foundations of PQ have been settled down, in the following Section 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.

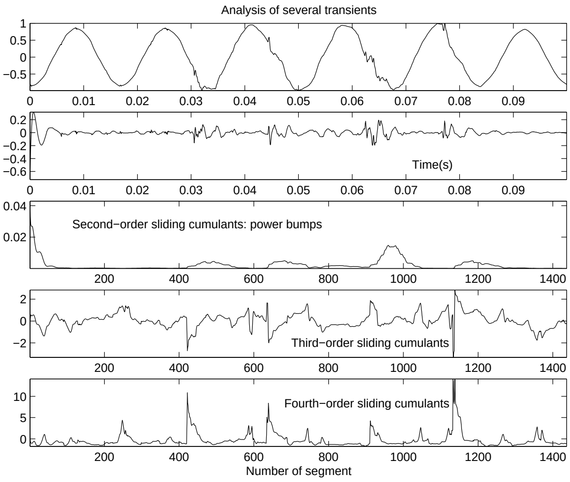

Figure 1: Several transients in the power line 50-Hz sine wave, and the computation of time-domain statistics. The signal has been previously normalized and high-pass filtered in order to remain with the transients.

3 HIGHER-ORDER STATISTICS

Higher-order cumulants are used to infer new properties about the data of non-Gaussian processes (De la Rosa et al., 2004,). 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 $p, p \le r$, given by using the *Leonov-Shiryaev* formula (Nikias and Mendel, 1993; Mendel, 1991)

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

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

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

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

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

By putting $\tau_1 = \tau_2 = \tau_3 = 0$ in Eq. (3), 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. (4) 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.

To show the relevance of HOS an illustrative example is prepared. Four noise processes: Gaussian; uniform; exponential and Laplacian, previously catalogued in, and indistinguishable from the second-order perspective, are presented in this subsection in order to illustrate the importance of introducing higher-order cumulants. The *4*th-order cumulants are computed according to the estimate given in (De la Rosa et al., 2009,). We consider a 2048-point sample register for each random set of data. The four identical autocorrelation sequences contrast to the fourth-order ones, where substantial differences are observed, specially those corresponding to zero time lags. This can be seen in Fig. 2, where the *4*th-order cumulant sequences are depicted. The theoretical values of the cumulants at zero time-lag are: 0 (Gaussian), -1 (uniform), 6 (Exponential), 12 (Laplacian). 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.

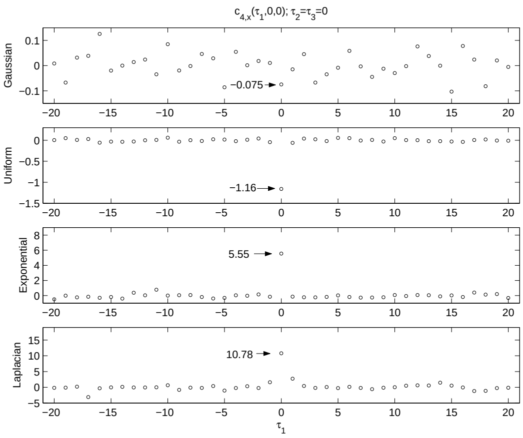

Figure 2: *4*th-order cumulant sequences for the four noise processes. Sample values at zero time lag are included in each sub-figure.

4 COMPETITIVE LAYERS AND SELF-ORGANIZING MAPS

In a competitive layer neurons distribute themselves to recognize frequently presented input vectors. The competitive transfer function accepts a net input 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. (5):

$$\mathbf{IW}_i^{1,1}(q) = \mathbf{IW}_i^{1,1}(q-1) + \alpha\left[\mathbf{p}(q) - \mathbf{IW}_i^{1,1}(q-1)\right], \quad (5)$$

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 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.

Self-Organizing Maps (SOM) learn to classify feature input vectors according to how they are grouped in the input space. SOM differ from competitive layers in that neighbor-neurons learn to recognize neighboring sections of the input space. Thus, SOM learn both the distribution (as do competitive layers) and topology of the input vectors they are trained on. Consequently, instead of updating only the winning neuron, all neurons in its neighborhood are updated using the *Kohonen* rule. The neurons in the layer of a SOM are arranged originally in physical positions according to a topology function. A distance function allows the calculation of the distances between neurons. Thus, for the i*th* neighboring neuron, in the q*th* instant, we have the weight vector **w**, in Eq. (6):

$$\mathbf{w}_i(q) = \mathbf{w}_i(q-1) + \alpha\left[\mathbf{p}(q) - \mathbf{w}_i(q-1)\right]. \quad (6)$$

Thus, when a vector is presented, the weights of the winning neuron and its closest neighbors move toward. Consequently, after many presentations, neighboring neurons will have learned vectors similar to each other.

5 EXPERIMENTAL RESULTS

As conveyed in previous sections, the experiment comprises two phases. The feature extraction, and first stage, is based on the calculation of the maxima and minima of the 4*th*-order central cumulants at zero lags for each data recording; i.d., each signal is characterized in a 2-D space by a vector, whose coordinates correspond to the local maxima and minima of the 4^{th}-order central cumulants. A number of 90 different measured power-line signals were selected, containing different PQ anomalies. Secondly, the classification stage (on the 90 feature vectors) is based on the application of ANN as classification tools in a twofold frame. The mission of the competitive layer consists of confirming the existence of four different sets of signals' classes (a priori established in the research). Additionally, the SOM network is conceived to guess additional possible classes and, in case of finding out more, determine their nature and relationship with the firstly proposed four groups of features.

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 to loose information. The algorithm calculates the cumulant over 50 points, and then it jumps to the following starting point (next 50-point overlapped group); as a consequence we have 98 per cent overlapping sliding windows (49/50=0.98). Then each computation over a window (called a segment) outputs a 4^{th}-order cumulant.

Besides, each 4th-order cumulant, $Cum_{n,x}[i]$, associated to the ith computation segment has been normalized by $(Cum_{2,x}[i])^2$, 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 absolute value of the cumulants. The higher-order (n>2) normalized cumulants are the skewness and the kurtosis.

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 (5th-order Butterworth model with a characteristic frequency of 150 Hz) eliminates the low frequency components which are not the targets of the experiment.

Once filtered, each signal contains one or more types of PQ events. Four different sets of signals have been a priori settled down empirically, based on the qualitative human knowledge, and then confirmed using a competitive layer. The first set comprises *healthy* sine-waves from the power 50 Hz-line. Then, we consider signals with oscillatory mono-frequency (long duration) transients of relatively high amplitude; we also consider for the second set signals with harmonics, which distort the shape of the sine-wave producing a not very high valued fourth-order cumulant. The third group gathers features' anomalies which appeared simultaneously in a signal, corresponding to impulsive transients (of short duration), and/or a weak sag (RMS descent), and/or oscillatory high-amplitude events. Finally, signals clearly affected by high-amplitude impulsive transients and/or deep sags are contained in the fourth set. Sets ♯3 and ♯4 may be joined in one, but signals in set ♯4 are clearly more affected and probably by only one type of perturbation. On the other hand, signals belonging to set ♯3 are generally affected by several anomalies. Consequently, four classes have been established with the possibility of upgrading the detection towards 6 clusters. The limits for the four classes' intervals, in units of cumulants maxima are: [0,7], [7,12], [12,20], [20,40]. These classes can be appreciated in Fig. 3, in the upper sub-graph, for the competitive layer training results. The lower subgraph in Fig. 3, shows the results of applying the SOM network and can be seen the shifting phenomenon that occurs for the final weights vector after the training stage of the NNT over 50 epochs. This result conveys the idea of the SOM network used to refine the classification, more than performing the coarse sub-division in anomalies' subclasses.

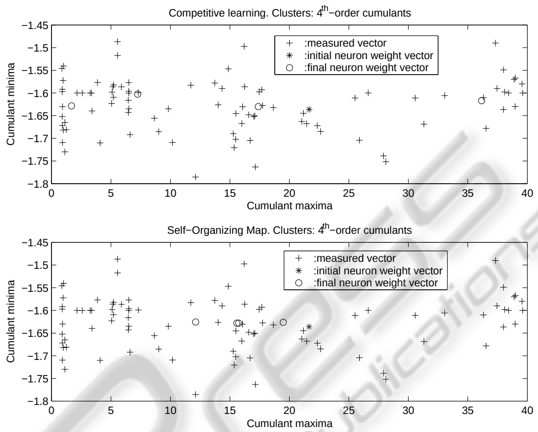

Figure 3: Four clusters for 4 types of signals. A *randtop* 2×2 topology has been selected over 50 epochs training. Upper graph: competitive layer performance. Down graph: SOM performance.

The separation between classes (inter-class distance) is well defined in the 2-D feature graph for the competitive layer. Consequently, the four 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 95 percent. 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.

An attempt to classify signals according a 6-cluster pattern has been developed. The limits for the four classes' intervals, in units of cumulants maxima are: [0,2], [2,7], [7,12], [12,20], [20,30], [30,40]. The new proposed intervals (added to the four classes proposal) are related to graded anomalies. The training results are displayed in Fig. 4, conveying the idea that, new classes are not really new anomalies.

In fact, despite the fact that the competitive layer manages to classify the signals into 6 classes (we force it), when we apply SOM networks, due to the influence of the close neighbor neurons, the final weight vectors are shifted or moved to new positions, depending on the geometry of the network (rand-to, hex-top). This clearly confirms the idea of a graded

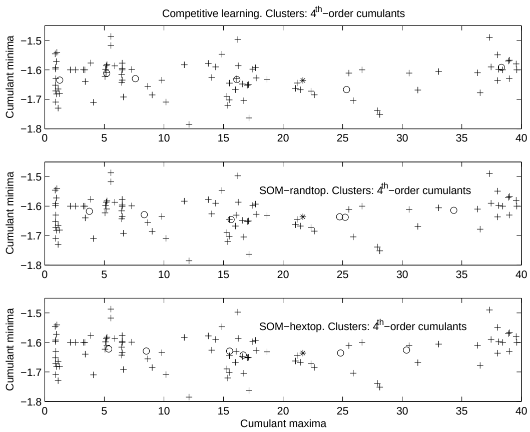

Figure 4: Six clusters for 6 possible types of signals after 50 epochs training. A 2×3 topology has been selected. Upper graph: competitive layer performance. Middle graph: SOM performance for a rand-top topology. Down graph: SOM performance for an hex-top topology.

anomaly, because the weight vectors are not located in the same position for both types of network's geometry.

6 CONCLUSIONS

In this paper an automatic procedure to classify electrical PQ anomalies has been proposed. The method comprises two stages. The first includes preprocessing (normalizing and filtering) and outputs the 2-D feature vectors, each of which coordinate corresponds to the maximum and minimum of the central *4*th-order cumulants. The second stage is based in computational intelligence and uses a competitive layer to confirm the existence of 4 classes, related to the different groups of anomalies. Then a SOM network confirms that newly added classes (proposed empirically) are not really new. New sub-divisions are related to degree of the degree of the anomaly. The geometry of the SOM network confirm this fact, moving the final weight vectors to different positions. Future work is designed to deal with a great number of signals (more than 90), trying to guess more classes with the aim of generalizing the method.

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