

# Pattern Recognition Techniques Applied to Electric Power Signal Processing

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**Abstract:** We propose in this paper an approach whose main objective is to detect disturbances that affect an electric power signal. The method allows us to locate the time occurrence of these disturbances. The signal processing consists of determining two distributions that are based on the energy of the wavelet signal decomposition: the deviation distribution and the deformation distribution. These distributions are a "signature" of the disturbance and are able to provide an identification of the type of the problem. The method has been developed using the analysis by the Discrete Wavelet Transform (DWT). The electrical signal is decomposed into several levels by DWT. The different waveforms resolution levels allows us to detect any deviations from the sane signal. Then we present a study to develop a machine learning algorithms for the recognition of power quality disturbances (PQD). The machine learning algorithms identifying the (PQD) is based on artificial neural network (ANN) and support vector machines (SVMs). These methods offer effective solutions through their included multilayer perceptrons (MLPs) and support vector machines (SVMs) with Gaussian radial basis kernel. The energy distributions data obtained in the first step will be used as feature vectors for training (MLPs) and (SVMs) to classify (PQD). The simulation results show that the proposed method has a high recognition value, making it effective for monitoring and classifying (PQD).

**Keywords:** Power Quality Disturbance, Form factor, Discrete Wavelet Transform, signals processing, Artificial Neural Network, Support Vector Machines, Power Line Transmission, Electromagnetic Compatibility (EMC).

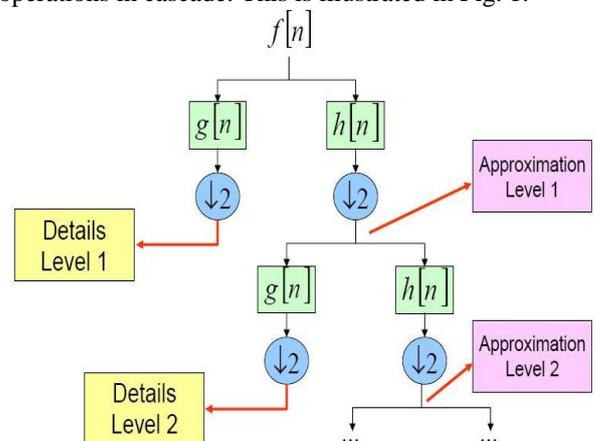
## I. INTRODUCTION

The quality of power supplied by the network of electric energy is affected by disturbances. The nature and origin of these defects are numerous. We cite, for example, short circuits, harmonic distortions, cuts, the sudden drop of voltage, amplitude ripple and transients phenomena caused by switching loads. We cannot prevent the formation of these defects nor predict the timing of their occurrence. So to avoid the adverse effects of these defects, we must be able to detect and identify them. However, whenever the disturbance lasts for few cycles, a simple observation of the waveform does not allow us to recognize the presence of the defect nor to identify the kind of disruptive failure. The wavelet transform (WT) [1], [3] has been adopted in several areas, such as telecommunications, electromagnetic compatibility, acoustics, biomedical etc... The WT analysis allows multiple simultaneous resolutions in time and frequency. Its main advantage is the nature of multi resolution

analysis by zooming into the signal discontinuities. The WT is suitable for the analysis of small waves, non stationary, transient, or highly variable in time phenomena. In this paper, we propose a method whose main purpose is not only to detect problems but also to classify them. The proposed method uses the multi wavelet transform techniques working with multiple neural networks or support vector machines. We use a learning vector quantized as a powerful classifier that can detect and classify different power quality signal disturbances. We have adopted Matlab (The Math works Inc., South Natic, MA, and USA). The application of wavelet toolbox and the LS-SVM 1.5 toolbox provides a complete implementation of this approach.

## II. DISCRETE WAVELET TRANSFORM

The wavelet transform first appeared in the 1980s in the work of J. Morlet on seismic signals. Yves Meyers and Ingrid Daubechies proved later the presence of orthonormal wavelet bases that would open new perspectives in wide areas and applications (coding, reconstruction...). The discrete wavelet transform (DWT) can be thought of as a filtering process. It decomposes a discretized signal in the time domain, in several signals spread over several levels of resolution. The wavelet is chosen as a filter for the signal decomposition. The decomposition process called "sub-band codification" is conducted according to a pyramid algorithm by filtering operations in cascade. This is illustrated in Fig. 1.



**Fig 1. Pyramid Decomposition Algorithm.**

In the time domain, filtering a given signal  $f(n)$  is equivalent to convoluting this signal with the impulse response of the filter.

$$f(n) * h(n) = \sum_k f(k).h(n - k) \quad (1)$$

The signal  $f(n)$  is passed through a digital low pass filter ( $h(n)$ ) and a digital high pass filter ( $g(n)$ ). The symbol  $\downarrow 2$  in Fig. 1 represents the operation of decimation by a factor 2. This is, according to Nyquist criterion that half of the samples of the signal can be eliminated.

$$y_{high}(n) = \sum_k f(k) \cdot g(-k + 2n) \quad (2)$$

$$y_{low}(n) = \sum_k f(k) \cdot h(-k + 2n) \quad (3)$$

The wavelet decomposition is performed in two stages. The first is the determination of the wavelet coefficients. These coefficients represent the original signal in the wavelet domain. From these coefficients, the second stage is performed by calculating two versions extracted from the source signal: one version called "approximation" and one version called "detail". The operation (called decomposition) is repeated on the approximation version to obtain different levels of resolutions in the time domain.

Consider the level of resolution  $j$ , let  $a_j(n)$  and  $d_j(n)$  be the respective coefficients of the approximation version and the detail version of the signal at the  $j$ th level, and let  $h$  be the selected filter impulse response: Then

$$a_1(n) = \sum_k f(k) \cdot h(-k + 2n) \quad (4)$$

$$d_1(n) = \sum_k f(k) \cdot g(-k + 2n) \quad (5)$$

$$a_j(n) = \sum_k a_{j-1}(k) \cdot h(-k + 2n) \quad (6)$$

$$d_j(n) = \sum_k a_{j-1}(k) \cdot g(-k + 2n) \quad (7)$$

The half-band low pass filter  $h$  and the half-band high pass filter  $g$  are not independent but related by the relationship:

$$g(L - 1 - n) = -1^n \cdot h(n) \quad (8)$$

$L = \text{filter length}$

Once all the wavelet coefficients are calculated, we can reconstruct in the time domain the approximated version ( $a_j(n)$ ) and the detail version ( $d_j(n)$ ) for each resolution level  $j$  [4].

### III. GENERAL THEORETICAL APPROACH DEVELOPED FORMALISM

By applying the DWT decomposition on the perturbed signal and observing the characteristics and waveforms obtained from its decomposition on several levels, we can learn important information concerning the original signal. This information is used to detect, locate and classify the disturbance present on the signal. Software has been developed and implemented using the wavelet application of MATLAB code. Figure 2 presents an algorithm that summarizes the action:

The energy is calculated based on the Parseval theorem: "The energy contained in a signal in the time domain is equal to the sum of all the energy contained in the signals obtain by the DWT decomposition from the origin signal" [5]. This is expressed mathematically by:

$$\sum_{n=1}^N |s(n)|^2 = \sum_{n=1}^N |a_j(n)|^2 + \sum_{j=1}^J \sum_{n=1}^N |d_j(n)|^2 \quad (9)$$

Where:

$s(n)$  signal studied in the time domain

$N$ : total number of samples of signal

$J$ : total number of resolution level

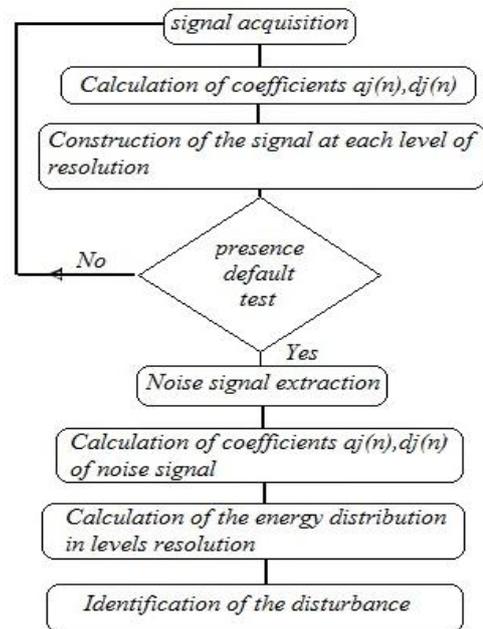


Fig 2. Algorithm of Actions Analyzes.

$\sum_{n=1}^N |s(n)|^2$  : Energy of the signal  $s(n)$ .

$\sum_{n=1}^N |a_j(n)|^2$  : Energy Signal of  $j$ th level approximation.

$\sum_{n=1}^N |d_j(n)|^2$  : Energy Signal of the  $j$ th level detail.

$\sum_{j=1}^J \sum_{n=1}^N |d_j(n)|^2$  : Sum of the details energy levels.

The result of this step is to calculate the deviation rate that can be evaluated by (a) and the deformation rate estimated by (b):

$$dev(j) = \left[ \frac{ensig(j) - enref(j)}{enref} \right] \quad (a)$$

$$def(j) = \sqrt[2]{\frac{ennoise(j)}{ennoise}} \quad (b)$$

With:

$dev(j)$ : deviation between the energy distribution of the perturbed signal and the energy distribution of the sane reference signal at level  $j$  of resolution.

$ensig(j)$ : Energy concentrated at  $j$ th level resolution of the disturbs signal.

$enref(j)$ : Energy concentrated at  $j$ th resolution level of the sane signal.

$enref$ : Total energy of the sane signal.

$def(j)$ : Distribution of the energy of the noise signal at the resolution level  $j$ .

$ennoise(j)$ : Energy concentrated at  $j$ th level of resolution of the noise signal.

$ennoise$ : Total Energy of the noise signal.

We show in the next section, that  $dev(j)$  the distribution of the deviation of the energy and  $def(j)$  the energy distribution of the noise signal have unique forms specific

to each type of disturbance. This form can be used to identify the type of defect present in the signal studied.

**IV. APPLICATION IN THE CASE OF A HARMONICS PERTURBATION.**

**A. The detection and location of a disturbance, in the time domain:**

We adopted in this study Daub4 [2] as the mother wavelet. The shape of this wavelet is represented in Fig. 3.

Fig. 5 (s) shows a sinusoidal voltage of a power distribution system polluted by harmonics. The Fourier transform (Fig. 4) shows a major peak at 50 Hz which corresponds to the fundamental component. It also shows secondary peaks at 150 Hz and 250 Hz corresponding to harmonics 3 and 5. However, we have no information regarding the timing of this event. Fig. 5 (d1, d2, d3, d4, d5) shows the details versions for levels 1, 2, 3, 4 and 5 of the DWT decomposition. Fig. 5 (a5) shows the approximate version of level 5.

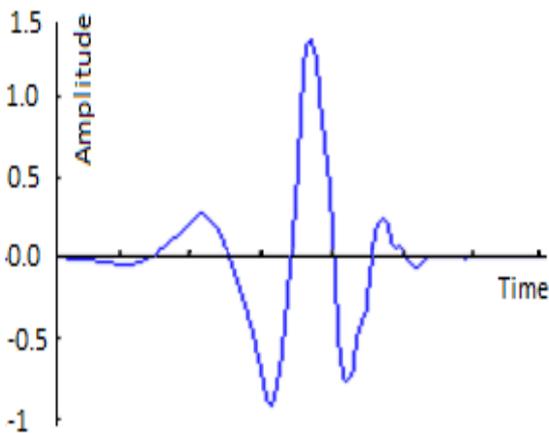


Fig 3. Wavelet Daub4

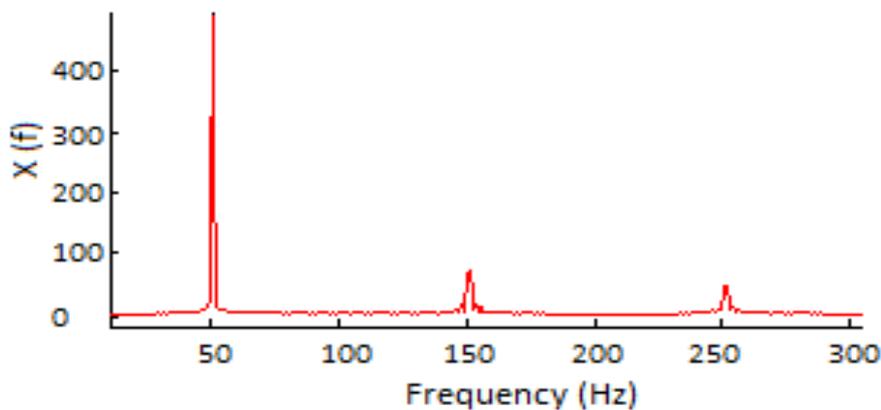


Fig 4. The Fourier Transform of the Signal Affected By Harmonics

Levels d1 and d2 of the transformed signal show clearly changes at  $t = 500$  ms. the signal of the other resolution levels of wavelets also show variations at this time. This means that switching has occurred precisely at this moment. Therefore, we can say that the disruption has been detected and localized in time [6], [4], [1]. However there is no enough information yet to specify the kind of disruption that occurred. So the noise was detected, localized but not yet identified. This point will be discussed in the following section.

**B. Identification of failure:**

In an attempt to identify the type of the present disturbance in the signal of figure 5 (s), we propose to calculate two form factors. The first is the rate of deviation that is based on the differential distribution of energy between the decomposition of the noisy signal, and the decomposition of the sane signal. The second is the rate of deformation; it is based on the energy distribution of the decomposition of the noise signal. To calculate the sane signal in case of this failure example, we remove the harmonic components in the signal spectrum by filtering and then we conduct an IFFT of the filtered spectrum. Equations a and b, allow us to quantify the distribution of energy on the resolution levels of wavelets for both the deviation between perturbed signal and the sane signal, and the energy distribution of the noise signal. The results are presented in Fig. 6 (a) for the deviation and Fig. 6 (b) for the deformation. These two distributions are representative of the defect. The approach described in this step allows us, like a magnifying glass to amplify the signal infection spreads from the sane signal and finely analyze the failure.

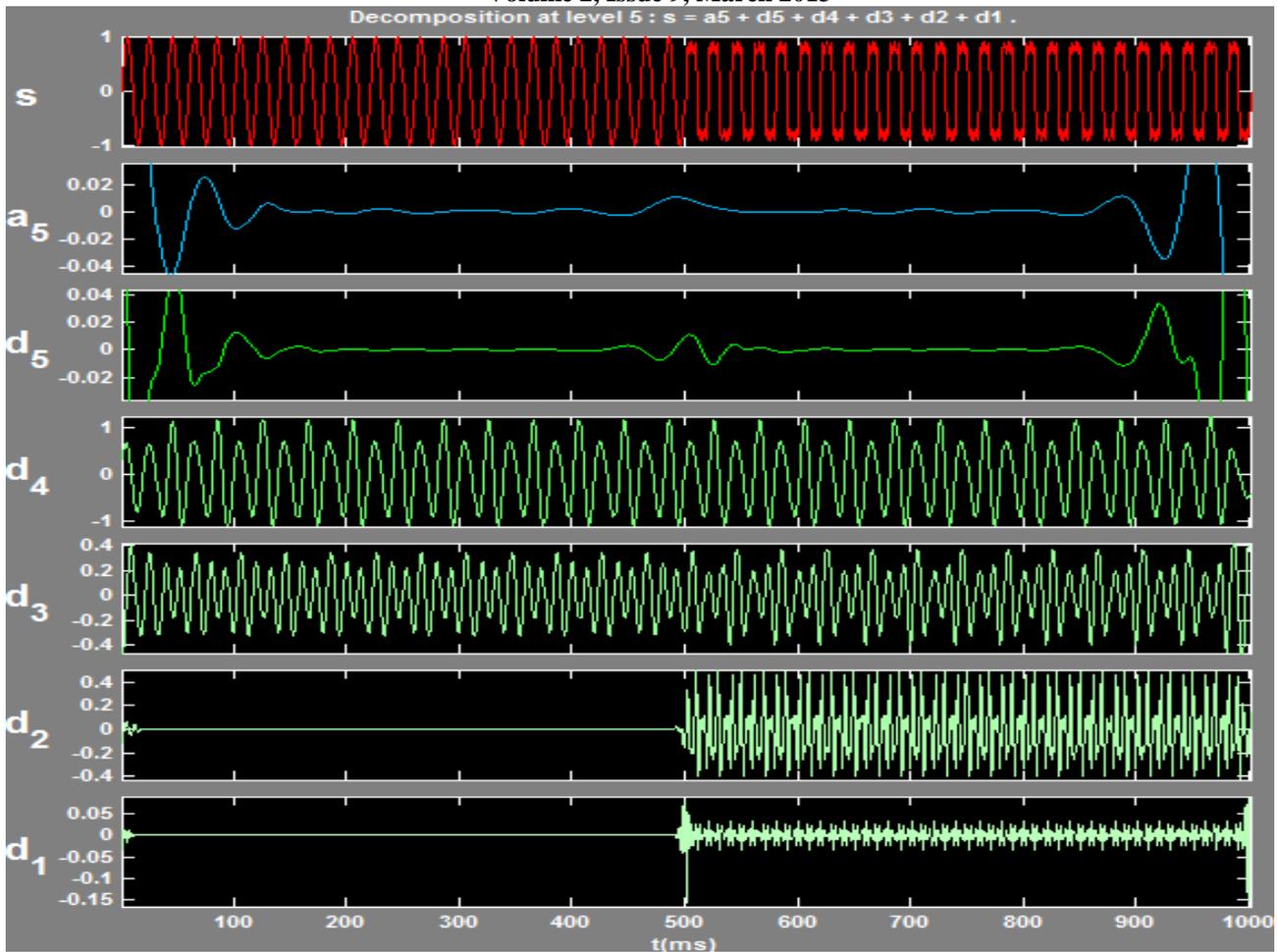


Fig 5. Wavelet Transform Signal Disturbed by Harmonics.

In the following we shall see that the shape of these curves is typical of the nature of the defect. Fig. 6 is the "signature" of the default type that is switching on the network using a harmonics pollutant load. At this stage we can say that the defect in the studied signal was clearly identified.

### V. CLASSIFICATION OF DISTURBANCES

The analysis that has been carried for a signal infected with harmonics pollution, and presented in the previous section can be extended to other types of electrical disturbances [13], [14]. Fig. 7 shows seven voltage signals analyzed by the method proposed.

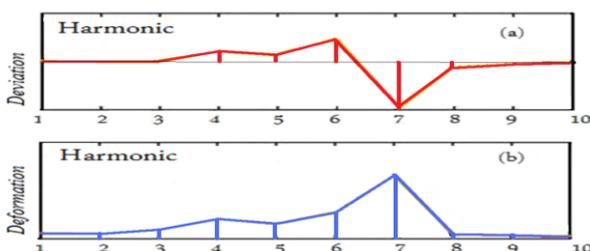


Fig 6. Distribution of Energy on the Resolution Levels of Wavelets.

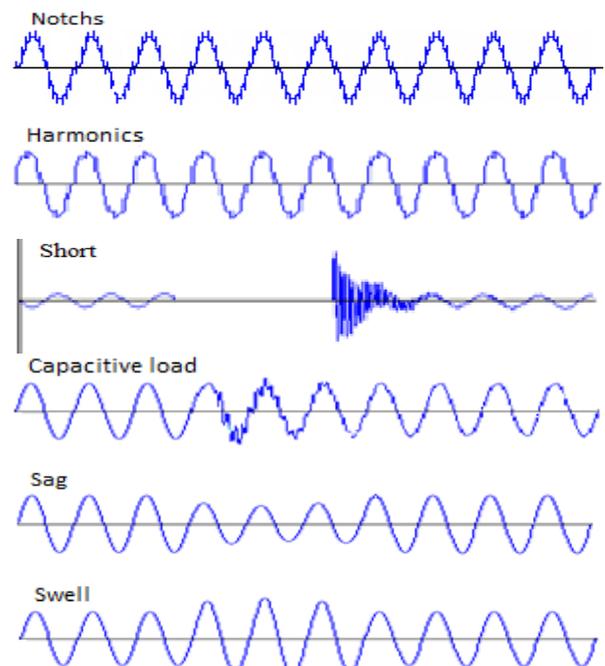




Fig 7: Signal Infected By the Most Frequent Disruption of Power Quality.

The results of the analysis are illustrated in Figure 8. For each signal infected we have presented the corresponding rate of deviation. Each graph of these families has been constructed by analyzing several cases of the same type of disturbance. However, what is important is the shape of the rate graph that is specific to each defect. This characteristic shape is unique for each type of disturbance.

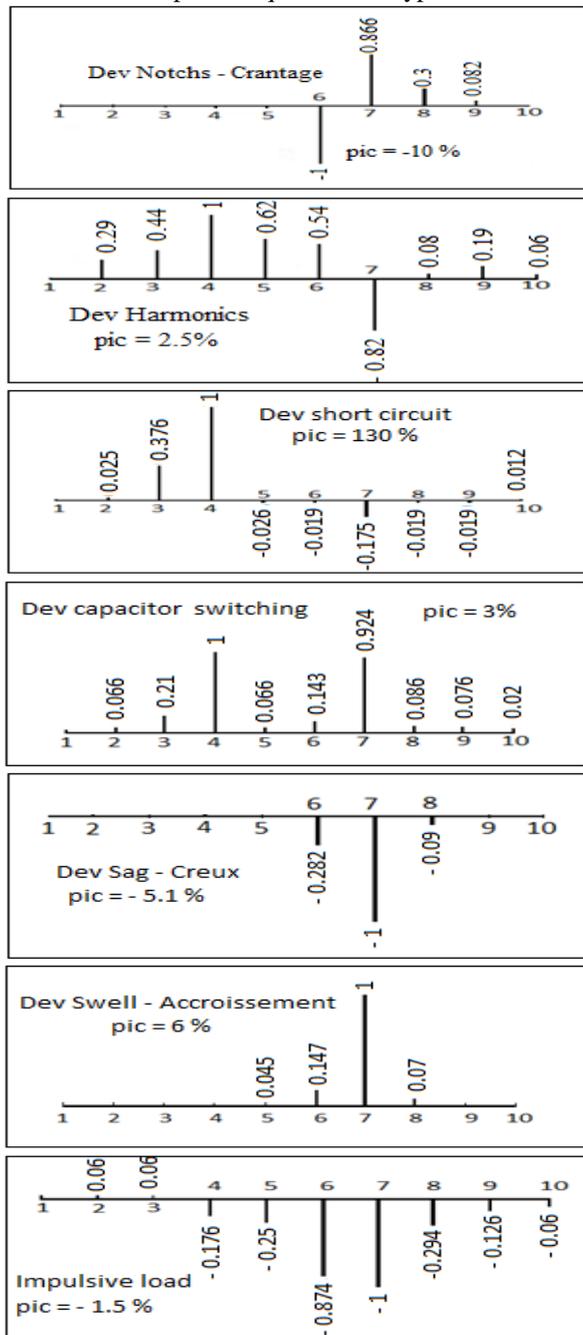


Fig 8. Average of the Deviation Distribution

Figure 9 shows seven different sets of distribution rate

of deviation and deformation which corresponds to the 7 families of power disturbances. Each family has a unique signature that can be adopted for the recognition of the type of defect. This will be useful later to find the source of disturbance and possibly correct it.

### VI. CLASSIFICATION BY NEURAL NETWORKS.

The Among Artificial Neural Networks (ANNs), Multi-Layer Perceptrons (MLPs) [7], [8], [9], [15] are often used, particularly in pattern recognition applications. In this study, architecture of one-hidden-layer has been chosen, with activation functions of sigmoid type and with 13 neurons in the hidden layer. The MLPs are trained by the "Levenberg-Marquardt" algorithm [7], during the learning phase. We trained a neural network on the 700 signals of the learning set with early stopping: 630 signals in the learning phase and 70 to avoid over fitting. Finally, this neural network was then tested in a "blind" way on the test set composed of 160 signals. All data was analyzed off-line using software that we have developed, written in MatLab and based on the Toolbox neural networks.

### VI. CLASSIFICATION BY SUPPORT VECTOR MACHINES

In this section, we briefly sketch the ideas behind SVMs for classification and refer readers to [10] for a full description of the technique. The central idea is to separate a training set of  $l$  examples with the data vectors  $x_i$  and the corresponding class labels  $y_i$  by finding a weight vector  $w \in \mathbb{R}^n$  and an offset  $b \in \mathbb{R}$  of a hyper plane  $(w; b)$  (A) that realizes the maximal margin:

$$H: \mathbb{R}^n \rightarrow \{-1, 1\} \quad (A)$$

$$x \rightarrow \text{sign}(w \cdot x + b)$$

Solving this problem of optimization consists in mathematical terms to minimize the expression:

$$\begin{cases} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n \xi_i \quad \text{with } \xi_i > 0 \forall i \\ \text{subject to : } (w \cdot x_i + b)y_i \geq 1 - \xi_i \end{cases} \quad (B)$$

Then after rewriting this problem in terms of the positive Lagrangian multipliers, and mapping the training vectors  $x_i$  in a higher dimension space by a function  $\Phi$ , the optimization problem becomes maximizing:

$$\begin{cases} \sum_{i=1}^l \alpha_i - \frac{1}{2} \sum_{i,j=1}^l \alpha_i \alpha_j y_i y_j K(x_i, x_j) \\ \text{subject to : } 0 \leq \alpha_i \quad \text{and} \quad \sum_{i=1}^l \alpha_i y_i = 0 \end{cases} \quad (C)$$

Where K is the kernel function:

$$K(x, x_i) = \exp\left(\frac{-\|x^T - x_i\|^2}{2\sigma^2}\right)$$

$$\sigma > 0$$

For the implementations, we used the LS-SVM 1.5 toolbox Matlab that provides a complete implementation of SVMs [11]. We used the Gaussian radial basis kernel (D)

With the Minimum Output Coding (MOC) [16] technique we can realize Multi-class classification. In this study, three LS-SVM classifiers were trained to differentiate eight combinations of classes. The multi-class classifier code for a pattern is a combination of outputs of these three classifiers.

The choice of C parameter in the SVM and  $\sigma$  of the Gaussian radial basis kernel is very sensitive and capital in order to have powerful trained SVMs. The performance measure will be evaluated in terms of Receiver Operating Characteristics (ROCs) curves, and particularly the area under the ROC curves (AUCs) [12]. The optimal SVM classification that gave the highest value of the AUCs was selected. We found that the optimal values of the AUCs are obtained for  $\sigma=1$  and  $C=4$ .

**VII. PERFORMANCE MEASURE AND RESULTS.**

To evaluate the quality of the classification, the two parameters of sensitivity and specificity were used. Both characterize the percentage of good signals classification decision. For a given class i, we consider that the decision is positive (P) if the signal belongs to this class and as negative (N) if the signal does not belong to this class. Then for each class i we can build two percentage sensitivity and specificity as follow:

$$sensitivity = \frac{N_{truePositives}}{N_{truePositives} + N_{falseNegatives}}$$

$$specificity = \frac{N_{trueNegatives}}{N_{trueNegatives} + N_{falsePositives}}$$

The overall sensitivity or specificity parameter is the average of the sensitivity or specificity parameters established for all classes.

Further we used a K-fold cross validation [7] (K = 10). The learning data set (700 patterns) is randomly divided into K subsets (K-folds) of equal size. The classifier is trained on K-1 subsets, and then the validation performances are measured by testing the subset that was not used during the learning phase. This process is repeated K times by using a different subset Therefore, the ROC curves were used [12], The curves are built by plotting the sensitivity with (1 - specificity) for different cutoff values of a diagnosis test. The area under the ROC curve [12] can be interpreted as the test accuracy. The performance of the classifier is obtained by averaging the K AUCs for each ROC curve (see Table I).

**Table I: Prospective Results In The Learning Test Set.**

Classifiers	Sensitivity (%)	Specificity (%)	AUC
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SVMs RBF	93 ± 5.10	91 ± 6.67	0.92 ± 0.062
ANNs	85 ± 4.84	84 ± 6.14	0.81 ± 0.055

The 860 patterns included in this study were divided into two groups. The first group of 700 patterns, named the learning set, is used to build and determine the best feature subset: the best number of neurons in the case of a MLPs and the best kernel adjustment of variables in the case of a SVMs. The patterns in the second group, 160 patterns named test set, were only used to estimate the performance of selected subsets (see Table II).

**Table II: Prospective Results In The Final Test Set.**

Classifiers	Sensitivity (%)	Specificity (%)	AUC
SVMs RBF	95.8	95.8	0.940
ANNs	88.3	88.3	0.834

**VIII. CONCLUSION**

We have presented in this paper an approach to detect, locate in time and classify the transient disturbances on the electric grid. The proposed method is based on the decomposition of the electric signal by the wavelet transform. For each resolution level of wavelet decomposition, we calculate the energy rate of deviation and the energy rate of deformation. It was shown that these normalized distributions have a specific form related to the type of disturbance. The normalized distributions data is used as feature vectors for classifying PQD. For comparison, different classifiers the LS-SVMs and the ANNs were implemented to deal with the same classification. Therefore, the so-called cross-validation was applied to test the effectiveness and accuracy of the machine learning algorithms. The simulation results show that the SVMs with Gaussian radial basis kernel could reliably classify PQD with a high recognition value. So we reach 95.8% of sensitivity and specificity in a prospective group of 160 patterns. In addition, the presented method can identify later the nature of the charges switched on the grid of electric energy through the analysis of the disturbance caused on the network at the time of its switching

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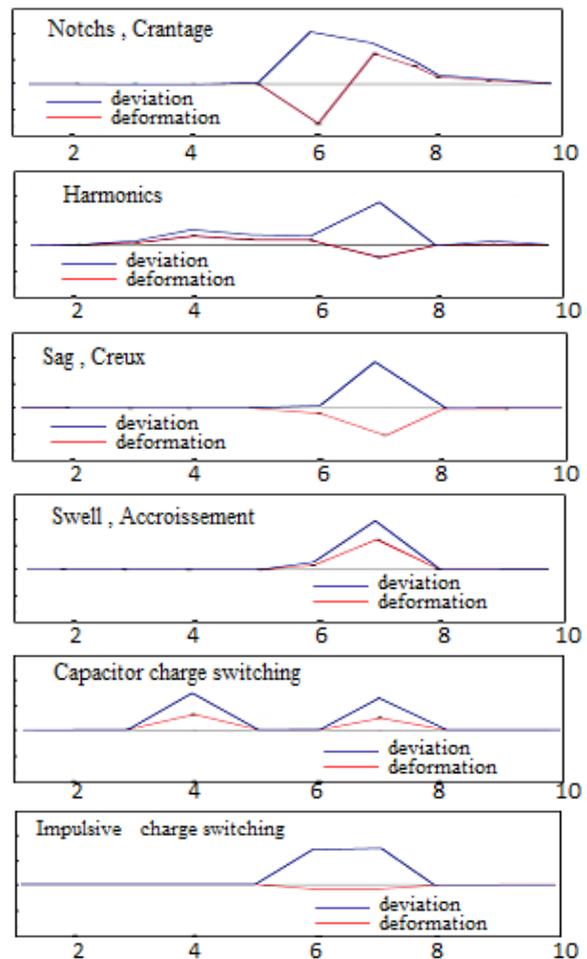


Fig 9. “Signatures” Of Disturbances.

APPENDIX

