An Alternative Pre-processing Technique Applied to Power Quality Disturbances Identification

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***Abstract*— This research presents the development of an alternative pre-processing technique of signals based on the fractal dimension calculation, entropy and signal energy that will be applied to disturbances classification occurring in an electrical power system (EPS). With respect to the power quality disturbances, the voltage sags, voltage swells, oscillatory transients and interruptions were considered for this application. In order to test and validate the proposed technique, a representative database has been obtained through computer simulations of a real EPS using the ATP software. Through windows data and the pre-processing technique proposed, the data were directed to Artificial Neural Network (ANN) architecture to classify the power quality events. The results shown that, combining both the data pre-processing techniques and ANNs, a satisfactory performance of all the proposed methodology can be obtained.**

Keywords—Power Quality, Events Classifier, Artificial Neural Networks, Pre-Processing Techniques.

I. Introduction

In the last few years the power quality has become the target of many researches carried out either by academic or by energy supplier company researchers. Although a desired power quality, it has certain disturbances that affect both the frequency range of the power network and the voltage and/or current waveforms. The main disturbances that indicate a poor power quality are: voltage sags, voltage swells, overvoltages, subvoltages, interruptions, oscillatory transients, noise, and harmonic distortions [1].

Among the studies devoted to detection and classification of events related to power quality, many applications are based on certain mathematical tools such as Wavelet Transform (WT) [2]-[3].

In the specialized literature is possible to find a variety of methods applying WT with intelligent systems, once this combination can provide an automated classification of the events highlighted [4].

Among the intelligent systems used, artificial neural networks (ANN) [5] and fuzzy inference systems [4] are the most applied. Intelligent systems are used because they present as inherent characteristics the possibility of extracting the system dynamic and can generalize the response provided from the system, namely through the stages of training and validation. The intelligent systems are normally applied to the pattern recognition, functional approximation and processes optimization [6].

In [7] it was carried out a comparative study between Fourier Transform with different types of windows and Wavelet Transform using Daubechies filter. Later, the processed signals were submitted to a Multilayer Perceptron (MLP) neural network so that this ANN may classify the disturbances.

In [3], a wavelet neural network was proposed for the classification of certain disturbances. However, a pre-processing step based on entropy calculation was accomplished. The results presented shown the potential of the proposed method for disturbances classification even under the influence of noise.

In this context, it is proposed a new approach to classify some of the major disturbances associated with poor power quality: voltage sags, voltage swells, oscillatory transients and interruptions. This methodology was developed carrying out certain window of signs that characterize the simulated events. It should be mentioned that, for each window, the fractal dimension [8] has been estimated, as well as the Shannon entropy [9] and the signal energy [10]. After this data pre-processing stage, artificial neural networks are parameterized and the calculated variables are provided as inputs. From this procedure, a good automated classification model can be evidenced and the results will be reported in the next sections.

II. Aspects of Computer Simulation

The computer simulation has been developed using the

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ATP (Alternative Transients Program) software [11], which is properly used for modeling a real distribution system. It should be emphasized that the system has been designed using data provided by a local energy utility. The ATP software enables the configuration of all parameters needed to construct the model and the variables to extract the disturbances data. Then, it can be stated that it was modeled to have great similarity with those found in the field. For all simulated situations, the sampling rate of 7680Hz has been considered.

The power system modeled through ATP can be viewed in Fig. 1.

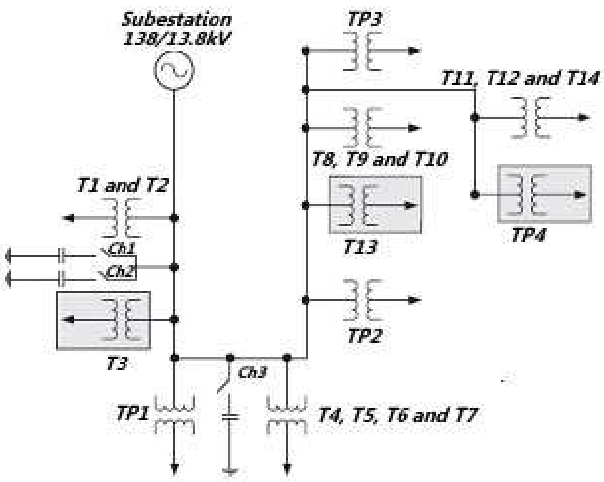

Fig. 1. Power system modeled by ATP.

With respect to Fig. 1, the substation transformer (138/13.8kV, 25MVA), the distribution transformers T3 and T13 (45kVA) and the particular transformer TP4 (45kVA), they had been modeled according to their saturation curve. The loads connected to these transformers represent a similar approach to that found in practice. The other transformers have been modeled without considering their saturation curves.

It should be noticed that both the distribution transformers and the particular ones have $\Delta - Y$ connections with the grounding resistance of zero ohm. It can also be verified that in the EPS previously mentioned, there are three banks of capacitors, two of them been modeled for 600kVAr and the other for 1,200kVAr.

With respect to cabling, the main feeder consists of a CA-477 MCM bare cable in a conventional overhead structure represented by coupled RL elements.

III. Data Acquisition

As the power system analyzed has been simulated, the extraction of data is given by the ATP software at a sampling rate of 7680 Hz.

In order to test the proposed technique, 89 cases have been generated to form a representative database: 34 cases of voltage sags, 28 of voltage swells, 15 of oscillatory transients and 12 cases of interruptions.

Considering these events, data windows have been necessary to create a homogeneous database, and to better prepare the data to the pre-processing stage, according the fractal dimension calculation, entropy and energy of each data window. Thus, a window containing 32 samples, which corresponds to a quarter of the cycle of the analyzed voltage signal has been used. The relevant displacement of this data window has been characterized in a step of 8 samples. An example of this window is showed in Fig. 2.

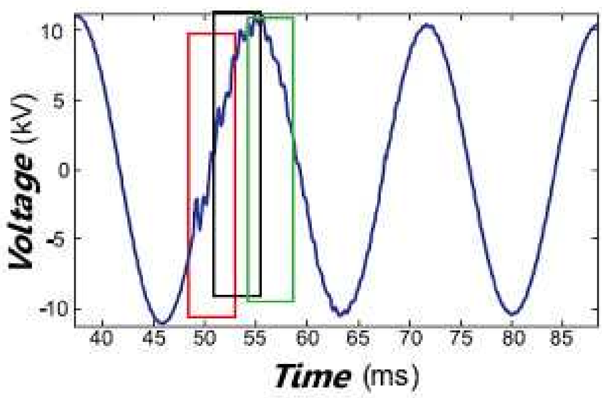

Fig. 2. Example of the voltage data window.

Just after the windowing and the pre-processed stage, the data set will be considered and divided into a set for training and another set for validation of the associated ANNs.

IV. Data Pre-processing

In the data pre-processing stage, three variables were calculated: fractal dimension, Shannon entropy and signal energy from each window that comprise the database.

A. Calculation of the Fractal Dimension

The fractal dimension has been calculated by using the Direct Wavelet Transform (DWT), and applied to the maximum level of the signal. Therefore, as in this case 32-point-windows have been used, the maximum that can be achieved is obtained by the following equation:

$$level_{\max} = \frac{\log(n)}{\log(2)} \tag{1}$$

where n is the number of points of each considered window.

However, it is important to emphasize that for a better response of the fractal dimension, the filter used by DWT must usually have a lot of factors (over 15), because this ensures a more symmetrical response to the impulse [8]. In this case, the filter Symmlet with support 16 has been applied.

The DWT being applied, two vectors, $x[.]$ and $y[.]$ were generated, containing the details length of each wavelet subband and the energy of each of these subbands respectively. The procedure for the creation of vectors $x[.]$ and $y[.]$ can be viewed in Fig.3.

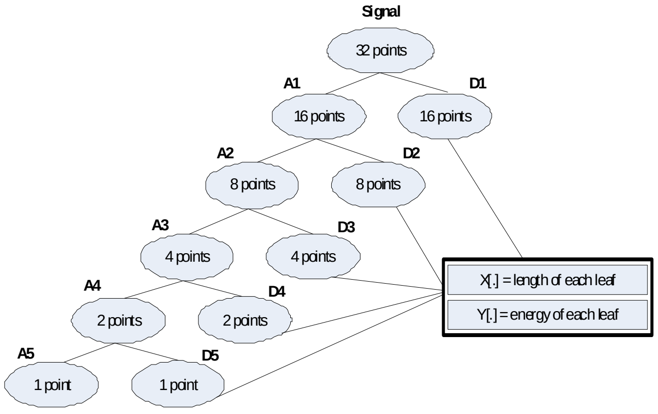

Fig. 3. Direct Wavelet Transform for calculation of the fractal dimension.

Once the vectors are determined, the fractal dimension can be calculated according to:

$$D = 2 - \left| \frac{\beta - 1}{2} \right| \quad (2)$$

where β is the angle of the average line that sets the points given by the vectors $x[.]$ (length of each leaf) and, $y[.]$ (energy of each leaf), by the least squares method. The calculation of least squares can be performed according to the following equation:

$$\beta = \frac{j \sum_k \log_2(x_k) \cdot \log_2(y_k) - \sum_k \log_2(y_k) \cdot \sum_k \log_2(x_k)}{j \sum_k \log_2(x_k)^2 - \left(\sum_k \log_2(x_k)^2 \right)} \quad (3)$$

where j is the signal length, x_k corresponds to the vector $x[.]$ at its *k-th* position and y_k corresponds to the vector $y[.]$ at its *k-th* position.

Through this calculation, the data corresponding to one of the ANNs inputs have been obtained. Just to illustrate and verify how the calculation of the fractal dimension affects the signals from the disturbances, examples of the fractal dimension for voltage sags, voltage swells, interruptions and oscillatory transients, are represented by the figures 4, 5, 6 and 7, respectively.

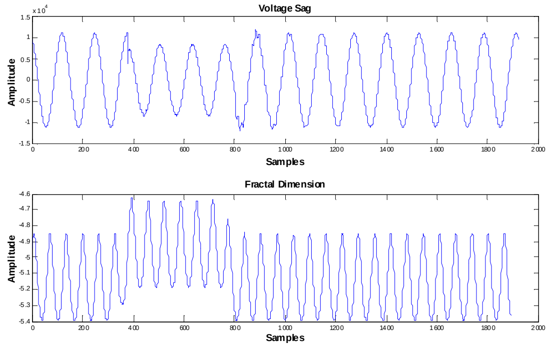

Fig. 4. Voltage sag with its respective fractal dimension.

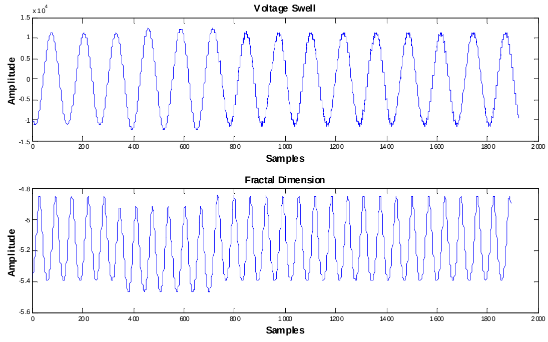

Fig. 5. Voltage swell with its respective fractal dimension.

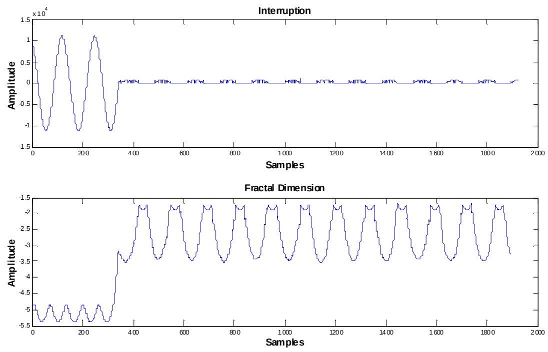

Fig. 6. Interruption with its respective fractal dimension.

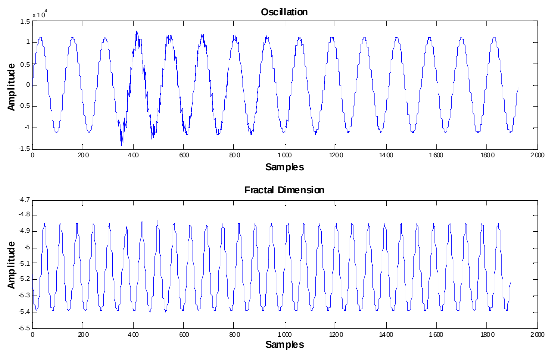

Fig. 7. Oscillatory Transient for calculation of fractal dimension.

B. Calculation of the Shannon Entropy

In the analysis of signals, the entropy is defined as a measure of knowledge lack about the information in the signal. Therefore, less noisy signals also have lower entropy [9]. The calculation of the Shannon entropy can be carried out according to the following equation:

$$S = \sum_{i=1}^{N} p_i \cdot \log(p_i) \tag{4}$$

where N corresponds to the *i-th* windows of the signal and p represents the normalized energy of the windows.

C. Calculation of the Signal Energy

The signal energy is calculated to achieve the full potential of a signal [10]. However, some signals have negative sides and therefore a quadratic sum of the sampled points must be made as shown in the following equation:

$$E = \sum_{i=1}^{N} \sum_{\mathrm{j}=1}^{\mathrm{M}} \mathrm{sinal}_{\mathrm{i,\,j}}^{2} \tag{5}$$

where N corresponds to the *i-th* windows and M represents the *j-th* point of the windows (32 points for each window).

V. Artificial Neural Network

Artificial Neural Networks are computational models inspired in human brain, which may acquire and maintain the knowledge. In this work, ANN has been employed with MLP architecture. This architecture is generally applied in pattern recognition, functional approximation, identification and control [6]. Hence, considering the pattern recognition task this architecture might be applied to disturbance classification.

In order to perform the disturbance identification process, ANNs have been developed and applied. All of the ANNs have been configured with 15 neurons in the first hidden layer, 20 neurons in the second and only one neuron in the output one. In hidden layers, hyperbolical tangent functions such as activation functions have been used, and in the output layer, a linear function with limits set between 1 and -1 has been used. Thus, the activation function of the output layer may represent if one disturbance exists in determined window of the signal under analysis.

The ANNs architecture previously commented is shown in Figure 8.

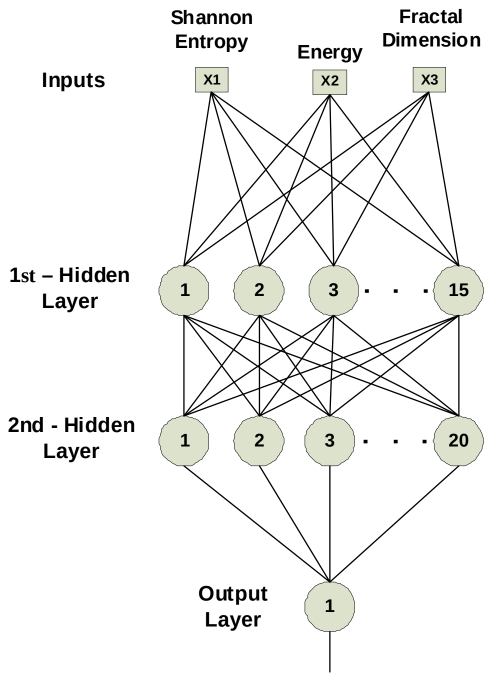

Fig. 8. MLP architecture of the ANNs.

All of the ANNs have been developed using the toolbox available in Matlab® software [12]. It should be highlighted that after pre-process step one database containing 1160 samples was generated.

Its important to mention that this methodology has used one ANN to classify each power quality disturbance.

A. ANN Training

During the training process, three algorithms, such as, Levenberg-Marquardt, Resilient Backpropagation and Backpropagation were evaluated. This experiment was done to verify the performance of the pre-process methodology proposed in this work.

Application of Levenberg-Marquardt was necessary due to its capacity in accelerating the convergence process. This training algorithm consists in one approximation of the Newton method to non-linear systems [13]. On the other hand, the Resilient Backpropagation was employed due to its capacity for eliminating the harmful effect. This effect is caused by the partial derivates in the training process. Thus, only the signal of partial derivates is used to update the synaptic weights [12].

Backpropagation training algorithm was employed because it is commonly used to train MLP neural networks.

The dataset used to train the ANNs was formed by 70% of the samples contained in the database which correspond to 812 samples.

Besides the training algorithm, the maximum number of epochs was evaluated too. So, for the Levenberg-Marquardt algorithm as many as 300 epochs were used, whereas for the

Resilient Backpropagation and conventional Backpropagation as many as of 3000 epochs were used.

B. *ANN Validation*

In the validation step, the neural networks received an input dataset containing 30% of the remaining data (348 samples). The objective of this step is to verify the integrity and generalization of the training step.

VI. Results

After ANNs parameterization, they were submitted to the training and validation process. In Fig. 9, 10 and 11 are presented the graphics of root mean squares versus number of epochs of each algorithm.

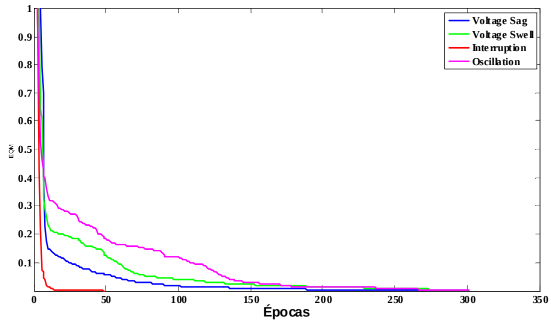

Fig. 9. ANNs training with Levenberg-Marquardt algorithm.

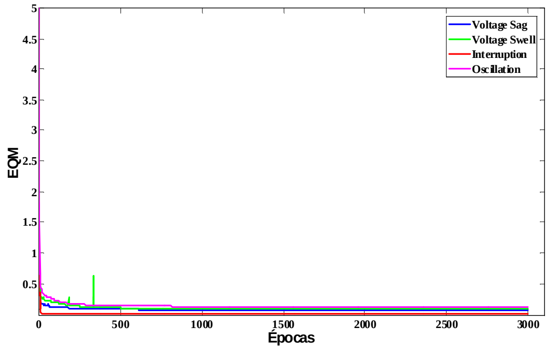

Fig. 10. ANNs training with Resilient Backpropagation algorithm.

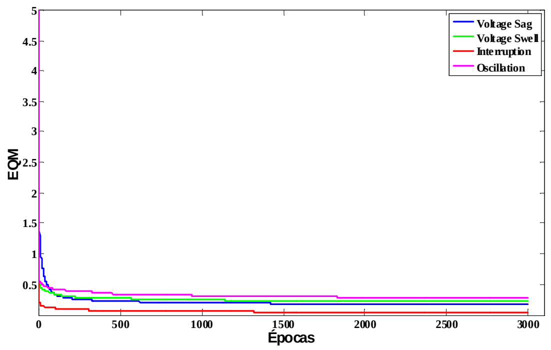

Fig. 11. ANNs training with conventional Backpropagation algorithm.

Both the results obtained in validation process and the performances of each training algorithm were evaluated. These results are presented in Tables I, II and III.

TABLE I
Performance of the ANN with Levenberg-Marquardt training algorithm.

Disturbances	**Precision (%)**
Voltage Sags	98,6
Voltage Swells	99,5
Interruptions	100
Oscillations	98,5
Mean	**99,2**

TABLE II
Performance of the ANN with Resilient Backpropagation training algorithm.

Disturbances	**Precision (%)**
Voltage Sags	98,3
Voltage Swells	98,1
Interruptions	100
Oscillations	96,8
Mean	**98,3**

TABLE III
Performance of the ANN with conventional Backpropagation training algorithm.

Disturbances	**Precision (%)**
Voltage Sags	94,2
Voltage Swells	92,2
Interruptions	99,9
Oscillations	89,9
Mean	**94,1**

From these results, it can be observed that the performances of all ANNs were satisfactory. However, the ANNs with Levenberg-Marquardt training algorithm had better precision during the identification of disturbances.

Due to the proposed objective in this research, it is possible to say that the methodology based on alternative pre-processing, helpful in classification of disturbances. It should be pointed out that even a conventional backpropagation algorithm present hit rate values about 90%.

In conclusion, the methodology can be considered robust to perform the task of identification of disturbances related to the power quality.

VII. Conclusions

This research has consisted in developing an alternative technique for the signals pre-processing based on calculations of the fractal dimension, entropy and signal energy that will enable a classification of disturbances occurring in an electrical power system.

It is possible to highlight that the proposed methodology for pre-processing has made a good data preparation for the disturbances classification stage, improving the convergence of the artificial neural networks training process, which has consequently supplied satisfactory results for identifying disturbances associated with power quality.

It is important to say that this methodology has been developed carrying out certain data window of the signals that characterize the simulated events, where, for each window, the dimension of fractal, the Shannon entropy and the energy of signal have been estimated. After this data pre-processing stage, artificial neural networks are parameterized and calculated variables are provided as inputs.

Through the results observed, one may find that the performances presented by ANNs were satisfactory. However, as expected, the ANNs with the Levenberg-Marquardt training showed better accuracy.

Thus, for future works the application of the methodology used in data pre-processing in different tasks of classification of disturbances should be expected, such as to detect the saturation of the transformers, and other problems related to electrical power systems.

VIII. References

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