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A SYSTEM FOR THE GENERATION AND DETECTION OF ELECTRICAL DISTURBANCES

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Abstract. Power Quality is defined as the study of the quality of electric power lines. The detection and classification of the different disturbances which cause power quality problems is a difficult task which requires a high level of engineering expertise. Thus, neural networks are usually a good choice for the detection and classification of these disturbances. This paper describes a powerful system, developed by the Institute for Natural Resources and Agrobiology at the Scientific Research Council (CSIC) and the Electronic Technology Department at the University of Seville, for the generation and detection (by means of neural networks) of electrical disturbances.

Key Words

Power quality, electrical disturbance, Wavelet transform, neural network.

1.- Introduction

Power Quality

Power Quality (PQ) is defined as the study of the quality of electric power lines. PQ has been a topic of consideration for the last two decades, and has recently acquired intensified interest due to the wide spread use of electronical devices in complicated industrial processes and the generalised power quality of commercial electric power [1]. Thus nowadays, customers demand higher levels of PQ to ensure the proper and continued operation of such sensitive equipment.

The poor quality of electrical power is normally attributed to power line disturbances such as waveshape faults, overvoltages, capacitor switching transients, harmonic distortion and impulse transients. Thus, electromagnetic transients, which are momentary voltage surges powerful enough to shatter a generator shaft, can cause catastrophic damage suddenly. Harmonics, sometimes referred to as electrical pollution, are distortions of the normal voltage waveforms found in ac transmission, which can arise at virtually any point in a power system. While harmonics can be as destructive as transients, often the greatest damage from these distortions lies in the loss of credibility of the power utilities vis-a-vis their customers. The classification and identification of each one of the disturbances is normally carried out from standards and recommendations depending on where the utilities operate (IEEE in the United States, UNE in Spain, etc).

Category			Typical Duration	Typical Amplitude
Transitory		Impulses	ns to ms	-
		Oscilation	3 μs to 5 ms	0 to 8 pu
Short-time Duration	Instantaneous	*Sag*	0.5 to 30 cycles	0.1 to 0.9
		Swell	0.5 to 30 cycles	1.1 to 1.8
	Momentaneous	Interruption	0.5 cycles to 3 s	< 0.1 pu
		Sag	30 cycles to 3 s	0.1 to 0.9
		Swell	30 cycles to 3 s	1.1 to 1.4
	Temporary	Interruption	3 s to 1 min.	< 0,1 pu
		Sag	3 s to 1 min.	0.1 to 0.9
		Swell	3 s to 1 min.	1.1 to 1.4
Long-time Duration		Interruption	> 1 min.	-
		Undervoltage	> 1 min.	0.8 to 0.9
		Overvoltage	> 1 min.	1.1 to 1.2
Voltage Unbalance			steady-state	0,5 to 2 %
Waveform Distortion		*DC Offset*	steady-state	0 to 0,1 %
		Harmonics	steady-state	0 to 20 %
		Interharmics	steady-state	0 to 2 %
		Notching	steady-state	-
		Noise	steady-state	0 to 1 %
Voltage Flutuations (flicker)			steady-state	0.1 to 7 %
Frequency Variations			< 10 s	-

Figure 1.- Standard IEEE 1159

The detection and classification of the different disturbances which cause power quality problems is a difficult task which requires a high level of engineering expertise [2]. Due to the above mentioned difficulties, artificial intelligence tools [3] emerge as an interesting alternative in the detection of electrical disturbances. The main intelligent tools of interest include expert systems, fuzzy logic and artificial neural networks (ANNs) [4].

Neural Networks on Power Quality

For the detection and classification of disturbances, ANNs can be combined with mathematical analysis such as Fourier and Wavelet transforms for the generation of signal features which serve as inputs in the network [5]. Thus, feature extraction by wavelet transforms provides an unique characteristic which can represent every single PQ disturbance at different resolutions using the technique called multi-resolution signal decomposition or multi resolution analysis. In this way, while the detection of the power quality signals has tended to be easy, their classification is still a difficult task in which ANNs play an important role [6][7][8].

Pattern recognition in ANNs generally requires preprocessing of data, feature extraction and final classification. One of the most important tasks in the design and development process of an ANN is to generate an adequate number of training patterns in order to approximate future inputs. Sometimes an optimal design of the ANN is found but the limited number of train patterns does not give good results. In particular, in PQ a great numbers of electrical patterns are necessary due to the multiple combinations of different disturbances which can coincide in one or various samples. Another additional problem with ANNs applied to PQ is the impossibility of getting real patterns directly from the power line due to the irregularity in the apparition of disturbances.

2.- Electrical Pattern Generator

For the task of training neural networks for the detection and classification of electrical disturbances we are developing an electrical pattern generator. The objective of this generator is to create an unlimited number of patterns to be used by a classification system.

The Electrical Pattern Generator make it possible to configure parameters such as the duration of the sample, the frequency of the signal and the number of samples in an ideal cycle (50Hz or 60Hz) and to add one or more disturbances. From the selected parameters, the generator creates a text file with the voltage values of the sample. The structure of the file consists of a header with the file information (name, number of sample cycles and sampling period) and a data column corresponding to the voltages of each of the samples. One file example from the Electrical Pattern Generator can be seen in Figure 2.

```
HEADER
Name: Impulse-01.txt
Ideal cycles: 5
Sampling period (ms): 0.156250
END HEADER
-28.171582
-12.934081
2.334579
17.597614
32.818256
47.959835
62.985875
77.860176
92.546906
107.010682
121.216659
...
```

Figure 2.- File from the Electrical Pattern Generator

The type of disturbances includes: impulse, oscillation, sag, swell, interruption, undervoltage, overvoltage, harmonics and frequency variations. In amplitude disturbances (impulses, sags, swells, interruptions, undervoltages and overvoltages), the tool allows us that parameters such as amplitude, start time, final time, rising and falling slope, be configured. The edition of harmonics allows the configuration of amplitude and phases as far as forty harmonic levels including the possibility of adding them an offset.

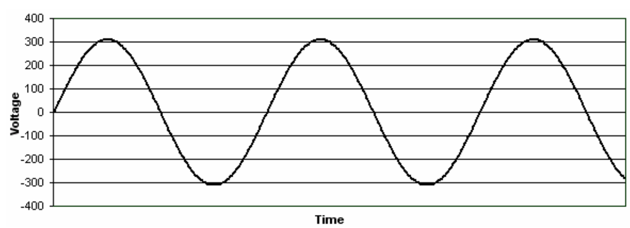

Figure 3.- Ideal signal (one-phase representation)

Models of disturbances

1.- Harmonic distortion

Harmonic distortion is defined as the phenomenon in which diverse sinusoidal signals with diverse frequencies which are multiples of the fundamental frequency are superposed on the ideal signal (Figure 4).

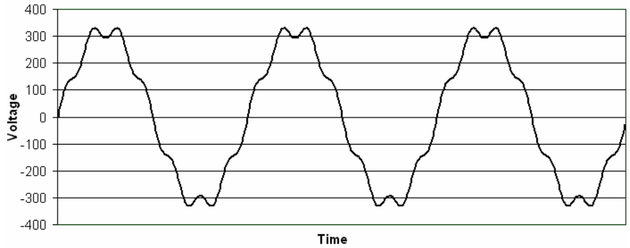

Figure 4.- Harmonic distortion

The following mathematical model was implemented in the generator:

$$C(t) = A + \sum_{i=1}^{N} A_i \sin(2\pi f_i t + \varphi_i) \qquad (1)$$

- A: DC term (V).
- A_i: Amplitude of the ith harmonic of signal (V).
- f_i: Frequency of the ith harmonic of signal (Hz)
- φ_i: Phase of the ith harmonic (Rad)
- i: Harmonic order (i= 1,.., N).

In our harmonic model *C(t)* is considered as consisting of a fundamental and 39 harmonic components.

2.- Frequency deviation

Frequency deviation is a signal disturbance added to the harmonic distortion. The model consists of the frequency modulation of the signal *C(t)* by means of the carrier signal *M(t)*, which is named modulating signal.

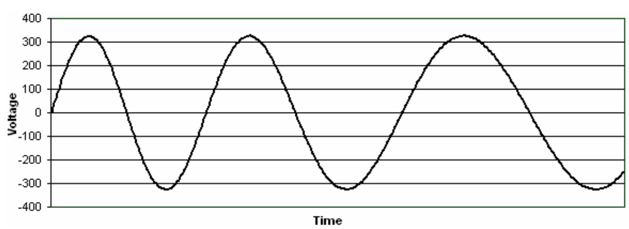

Figure 5.- Frequency deviation

The mathematical expression of this signal is:

$$M(t) = B + \sum_{j=1}^{40} B_j \, sin(2\pi j f_m t + \varphi_j) \qquad (2)$$

- B: DC term (V).
- B_j: Amplitude of the jth harmonic of signal (V)
- f_m: Fundamental frequency (Hz)
- φ_i: Phase of the ith harmonic (Rad)

Considering (1) and (2) the resultant signal would end up as:

$$X(t) = A + \sum_{i=1}^{40} A_i \, sin\left[2\pi i f_c t + \varphi_i + B + \sum_{j=1}^{40} B_j \, sin(2\pi j f_m t + \varphi_j)\right] \qquad (3)$$

which shows the harmonic content and frequency modulation.

The addition of another kind of disturbance was carried out from the previous expression X(t). Therefore, the previous expression would be the result of an ideal electrical signal or a frequency or/and harmonic disturbed signal.

3.- Overvoltages, swells, undervoltages and sags.

In this kind of disturbances the amplitude of the signal rises (overvoltages or swells) or falls (undervoltages and sags) a certain value along a time interval.

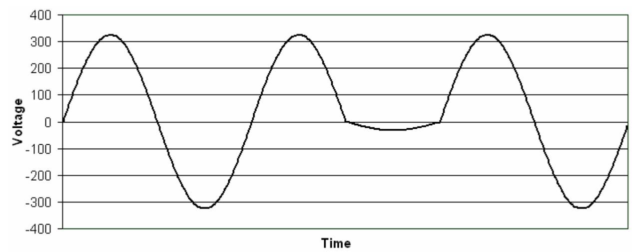

Figure 6.- Sag

In the development of the disturbance generator, a trapezoidal model for the amplitude evolution (lineal slope) was considered. The model makes it possible to approximate the amplitude disturbances most frequently encountered in power systems. Figure 7 shows a graphical of the model used for overvoltages or swells (inverse trapeze for undervoltages and sags).

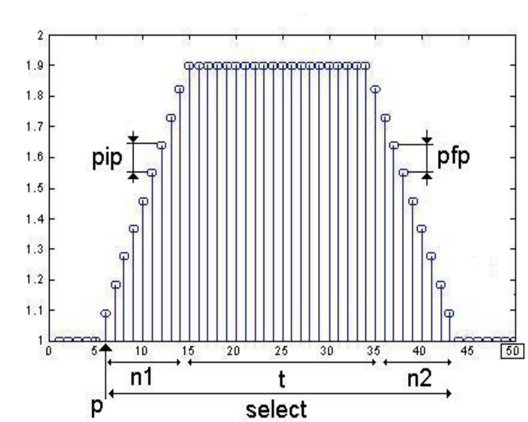

Figure 7.- Overvoltage and swell model

- p: initial sample of the trapeze
- pip: slope of the initial ramp

- pfp: slope of the final ramp
- n1: number of samples of the initial ramp
- n2: number of samples of the final ramp
- t: number of samples when the climb is reached
- select: total number of samples

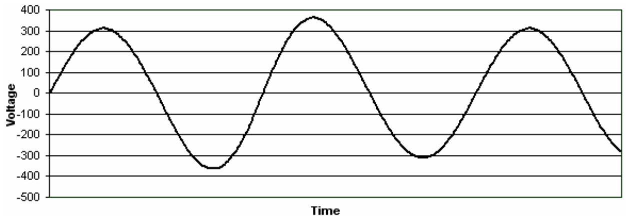

Figure 8.- Overvoltage

4.- Transients

The electrical pattern generator models transients as a damped sine through a superposed exponential function, which is added to *X(t)* at a certain point.

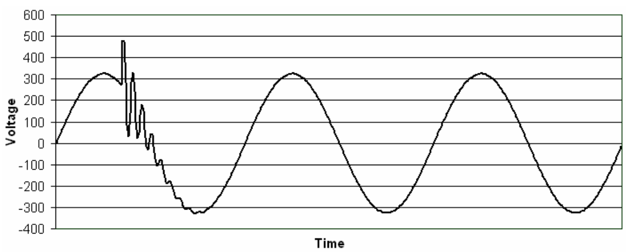

Figure 9.- Transient

The implemented mathematical model obeys to:

$$T(t) = e^{-at} A_r \sin(2\pi f_r t + \varphi_r) \qquad (4)$$

- a: transitory exponent.
- A_r: amplitude of the ripple (V)
- f_r: frequency of the ripple (Hz)
- φ_r: initial phase of the ripple (Rad)

5.- Noise

The generator makes it possible to add Additive White Gaussian Noise (AWGN) (Figure 10) in order to simulate more realistic signals of the power line.

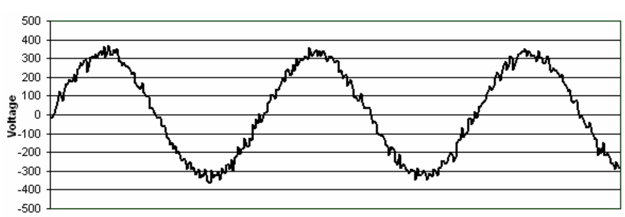

Figure 10.- A signal with AWGN

3.- Electrical disturbances classifier based on Neural Networks.

In addition to the generation system, we have developed a first version of a system for the detection and classification of electrical disturbances. The system is a detector of power line disturbances based on artificial intelligence techniques (in particular, a first version based on ANNs). We have used the previously described Electrical Pattern Generator in order to carry out the ANN training. At the moment, we have generated around one thousand patterns of electrical signals which include all the above-mentioned disturbances.

The detection system uses Wavelet transform of the acquired signal for the generation of signal features [5][6][7][8]. The aim of feature extraction by Wavelet transforms was to provide an unique characteristic which can represent every single PQ disturbance.

For programming tasks we have used the MATLAB tool which has some powerful toolboxes (specialized functions) of signal, Wavelets and Neural Networks.

The input vectors of the ANN are generated carrying out a number of operations on the Wavelet transform. It is known the Wavelet transform detects better the slow variations in the last levels and fast variations in first levels. So, our solution is based on the concept of that the amplitude disturbances would be better detected in the first levels of Wavelet transform while the frequency ones would be better detected in the last levels. Therefore, we have used two parallel neural networks. One of them is used to detect the amplitude disturbances and the other one the frequency disturbances.

In particular, we have used the following values as input vector of the amplitude neural network: the V_{RMS} of the signal, the integral, the maximum and the V_{RMS} of the detail coefficients of 1,2 and 3 level.

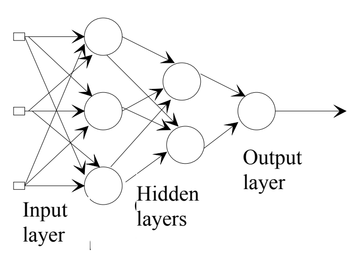

Figure 11.- Multilayer perceptron

The kind of ANN is a multilayer perceptron with 3 hidden layers with 20, 14 and 8 neurons respectively. We have reached this structure after testing a great number of different numbers of neurons and layers. Although we have tested other kinds of structures like LVQ and RBF at the moment the best results have been reached with the perceptron.

In frequency we have used the following values for the input vector of the network: the V_{RMS} of the signal, the integral, the maximum and the V_{RMS} of the detail coefficients of 6,7 and 8 level. The structure of the ANN of frequency is a multilayer perceptron with 3 hidden layer with 4,3 and 2 neurons respectively.

In the training of the networks we used 80% of the generated signals as training patterns and 20% as test patterns. In the first network we reached the best results with a training of 180 epochs getting the right classification of the 93.82% of the test signals. Besides, most of the incorrectly detected disturbances were in the threshold with other kind of disturbance. The kind of different amplitude disturbances as well as the percent of correctly detected disturbances in each one is shown in table 1.

Table 1.- Results in amplitude disturbances

Disturbance	*Test signals*	*Number of errors*	*Correctly detected %*
Sag	51	2	96.08
Ideal	56	6	89.29
Swell	25	2	92.00
Undervoltage	21	0	100
Overvoltage	38	4	89.47
Frequency deviation	52	1	98.08
Total	243	15	93.83

On the other hand, in the frequency network were correctly classified the 97.53% with a training of 261 epochs. With the help of the generator of disturbances, we are currently working in the generation of new patterns for the training of the ANN. Even when the current results are very good, we expect to get better them with the increase of the number of patterns.

4.- Conclusions

Today it is known that neural networks are a good choice for detecting and classifying electrical power disturbances. In the huge literature [4][5][6][7] about detection of electrical disturbances which we can find, often the problem lies in generating a sufficient number of training patterns to get that neural network obtains good results in future inputs. With the help of the generator is possible to carry out a training of the ANN sufficiently entire in order to get reliable results.

Thus, we have developed an electrical pattern generator which is capable of generating common disturbances which can be found in a power line with the aim of making the training of neural networks easier. Besides, we have developed a first version of a classifier system based on ANNs.

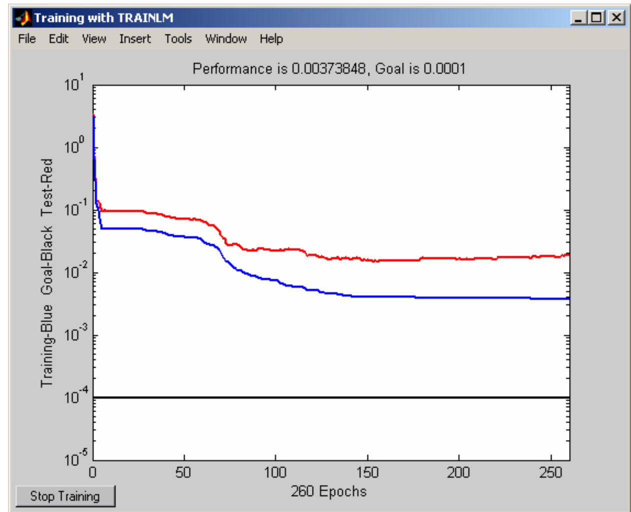

Figure 12.- Evolution of training of the frequency ANN

Our final objective is to implant this detector as a real-time system capable of classifying disturbances on line. In order to get a fast system, we are currently working in reducing and compiling the processing of the signal previous to ANN. We are testing other possibilities of processing of the signal and other structures of the ANN in order to get better the results.

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