A Real-Time System for the Generation and Detection of Electrical Disturbances

Iñigo Monedero, Carlos León, Member, IEEE, Antonio García, José Manuel Elena, Member, IEEE, Juan C. Montaño, Senior Member, IEEE and Jorge Ropero

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 Electronic Technology Department at the University of Seville and the Institute for Natural Resources and Agrobiology at the Scientific Research Council (CSIC) for the generation and detection by means of neural networks of electrical disturbances.**

Index Terms-- **Electrical disturbance, neural network, power quality, wavelet transforms.**

I. INTRODUCTION

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	-

Fig 1.- Standard IEEE 1159

II. ARTIFICIAL INTELLIGENCE ON POWER QUALITY

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].

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].

The aim of the pre-processing of the signal is to get a feature extraction by means of wavelet transform and other mathematical techniques which provides an unique characteristic which can represent every single PQ disturbance. It is carried out by means of a different resolutions analysis using the technique called multi-resolution signal decomposition or multi-resolution analysis.

The work described in this paper has been supported by the Spanish Ministry of Science and Technology (MCYT: Ministerio de Ciencia y Tecnología) through project reference number DPI2002-04420-C03-03.

In multi-resolution analysis the signal is discomposed in a set of approximation wavelet coefficients and another set of detail wavelet coefficients. The obtained approximation coefficients are in turn decomposed in order to increase the level of resolution.

The detail coefficients of the lowest levels store the information from the fastest changes of the signal while the highest ones store the low-frequency information. Thus, with the help of these new mathematic tools the detection of the electrical disturbances has tended to be easy but their classification is still a difficult task in which ANNs play an important role [6-13].

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 apparently optimal design of the ANN is found but the low and limited number of train patterns does not give good results. In particular, in PQ a great numbers of these 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 irregular apparition of these disturbances in the time.

III. 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 (figure 2). The objective of this generator is to create an unlimited number of patterns to be used by a classification system. On the other hand, the possibility of generating these patterns as real signals has been added in order to test detection equipments as well as ours.

The Electrical Pattern Generator makes 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 is simple and consists of a header with the file information (name, number of sample cycles and sampling period) and 3 data columns corresponding to the three-phase voltages of each one of the samples.

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.

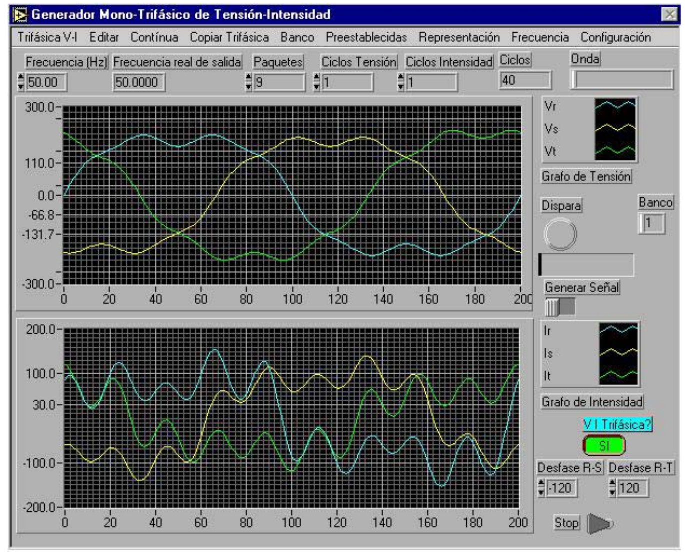

Fig 2.- Electrical Pattern Generator

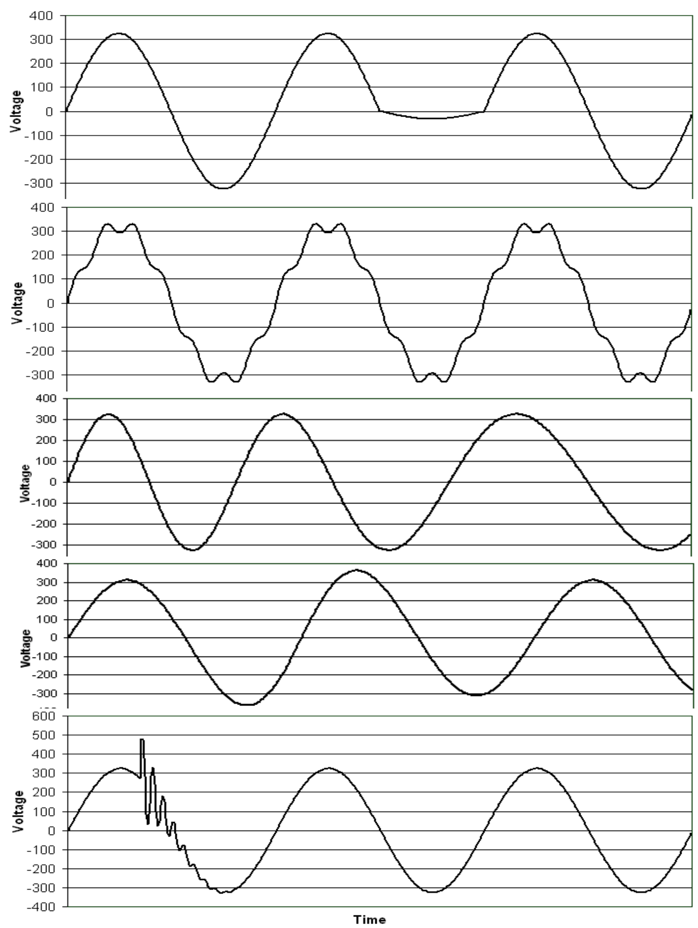

Fig 3.- Some disturbances generated by the Electrical Pattern Generator (sag, harmonic distortion, frequency deviation, overvoltage and transient)

IV. Real-time classifier based on neural networks.

In addition to the generation system, we have developed a first prototype of a real-time system for the detection and classification of electrical disturbances. The system is a detector of power line disturbances whose detection kernel is based on artificial intelligence techniques (in particular, a first version based on ANNs). The system consists of a PC application which includes the AI kernel and an acquisition card.

A. Environment

The environment of the application (figure 4) shows the information which is acquired and registered by the system. It consists of a windows in where is shown the acquired signal by means of a chart, a group of leds that informs of the detected disturbances and a window with a historic which registers the date and time of the different events.

The acquisition card obtains 640 samples every 100 milliseconds. These samples are shown on the chart and processes by the AI kernel. When one and more disturbances are detected in the 100 milliseconds, the corresponding led is turned on and the historic is updated. At the same time, a new window, dedicated to the detected disturbance, is superposed. This window consists of a chart which shows the whole disturbance and is scaled in accordance with its duration.

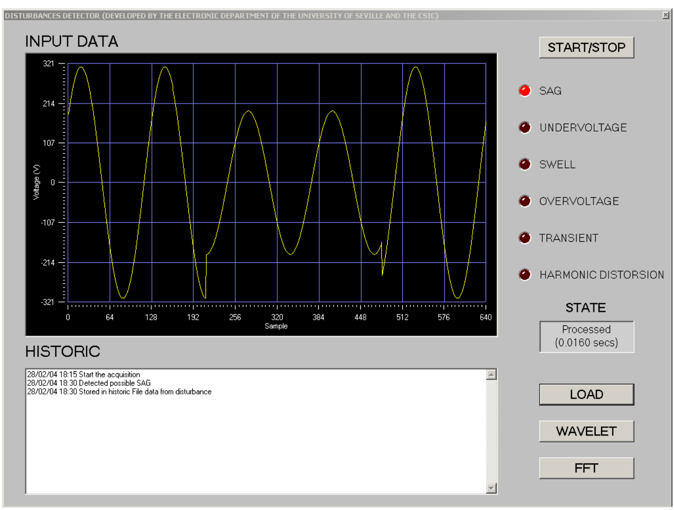

Fig 4.- Classifier environment

B. Kernel

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 [5-13]. The aim of feature extraction by Wavelet transforms was to provide an unique characteristic which can represent every single PQ disturbance.

The input vectors of the ANN are generated carrying out a number of operations on the Wavelet transform. It is known that the Wavelet transform detects better the low-frequency components in the last detail levels and fast variations in first levels. Thus, 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 disturbances would be better detected in the last levels. Therefore, we decided to use two parallel neural networks. One of them 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. In order to get a faster convergence and better results these data were scaled so that minimum is -1 and maximum is 1.

The kind of ANN is a multilayer perceptron with 1 hidden layer with 20 neurons. The structure of the network can be observed in figure 5. The output functions of the layers were a logarithmic sigmoid transfer function in the hidden layer and a linear transfer function for the output layer. We have reached this structure after testing a great number of different numbers of neurons and layers as well as parameters of the network. Although we have tested (and we go on testing) other kinds of structures like LVQ and RBF at these moment the best results have been reached by means of the perceptron.

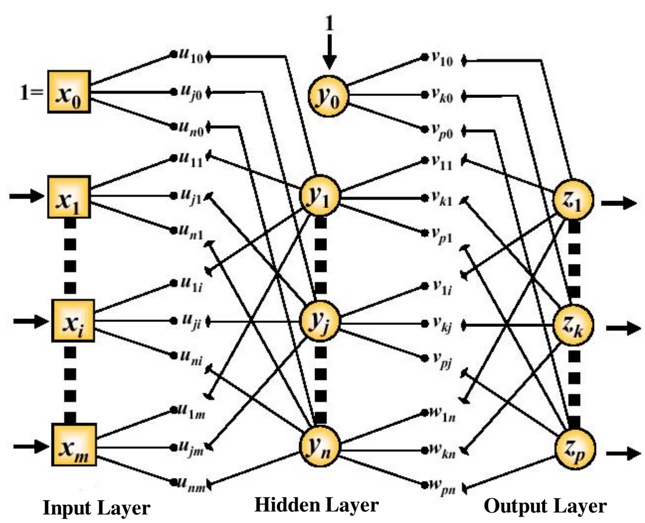

Fig 5.- One-hidden layer perceptron

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 layers with 4, 3 and 2 neurons respectively. The transfer function used in these layers was a hyperbolic tangent sigmoid.

C. Programming tasks

For programming tasks we have used the MATLAB tool to test of the different possibilities in the pre-processing of the signal and in the structure of the kernel. We used this tool due to the powerful toolboxes with specialized functions that it has. Thus, we programmed with the signal and the wavelet toolboxes for the pre-processing and the neural networks toolbox for the design of the kernel [14].

Once we carried out the test and found a good code for the pre-processing and the AI kernel, we programmed them in C++ language in order to optimize the execution time. The tests carried out in execution time about the pre-processing time are around the 0.1 milliseconds for the wavelet transform.

For the design and programming of the tool environment the selected tool has been Borland C++ Builder 5 which is a powerful tool for the development of visual applications as well as a robust C++ compiler.

V. RESULTS

Before embedding the kernel in the classifier tool we selected the best training for the configuration of ANN. Thus, for the trainings of the networks we used 80% of the generated signals as training patterns and 20% as test patterns. On the other hand, thresholds were defined in the ANN outputs in order to consider or not as disturbance an output value. The defined thresholds were 0.3 and 0.7 and thus, output values above 0.7 were considered as disturbances and below 0.3 ideal signals. The values find between 0.3 and 0.7 were taken as errors in the detection of the input pattern. The distance between the output network and the desired value was defined as a safety coefficient in the detection.

In the first network we reached the best results by means of a training of 576 epochs getting the right classification of the 95.06% of the test signals. The kind of different amplitude disturbances as well as the percent of correctly detected disturbances in each one is shown in table I.

On the other hand, in the frequency network were correctly classified the 97.53% with a training of 261 epochs.

TABLE I
RESULTS IN AMPLITUDE DISTURBANCES

Disturbance	Test signals	Number of errors	Correctly detected %
Ideal	56	4	92.86
Sag	51	3	94.12
Swell	25	1	96.00
Undervoltage	21	1	95.24
Overvoltage	38	2	94.74
Frequency deviation	52	1	98.08
Total	243	12	95.06

Besides, after carrying out an analysis of the results we realized the most of the incorrectly detected disturbances were in the threshold with other kind of disturbance. Thus, in table 2 we can observe the detected event and the real kind of signal in each one of the errors. As we can be seen there are only two patterns (an undervoltage and a sag) which were not detected as a disturbance.

With the help of the generator of disturbances, we are currently working in the generation of new patterns for the training of the ANN. Thus, even when the current results are very good, results will improve with the increase of the number of patterns.

TABLE II
ERRORS IN ANALYSIS

Real signal	Detected event
13% and 30 ms sag	Nearly sag
Ideal signal with a small 8% sag	Sag
Ideal signal with a small 9% sag	Sag
60% and 16 ms overvoltage	Overvoltage and swell
10.8% and 11 ms overvoltage	Swell
99.7% and 35 ms undervoltage	Ideal signal
98% and 10 ms sag	Undervoltage
Ideal signal with a small 4% overvoltage	Overvoltage
Ideal signal with a small 8% overvoltage	Overvoltage
80% Swell and 9 ms	Overvoltage
Frequency deviation	Nearly swell
97% and 10 ms sag	Ideal signal

One of the great advantages of our system because even though other detection systems of the current literature [5-13] get good results our system can be constantly improved. We are currently studying the possibility of the design of an automatic way for the generation of huge number of disturbance patterns carrying out a scan of the all possible parameters in each one of the disturbances.

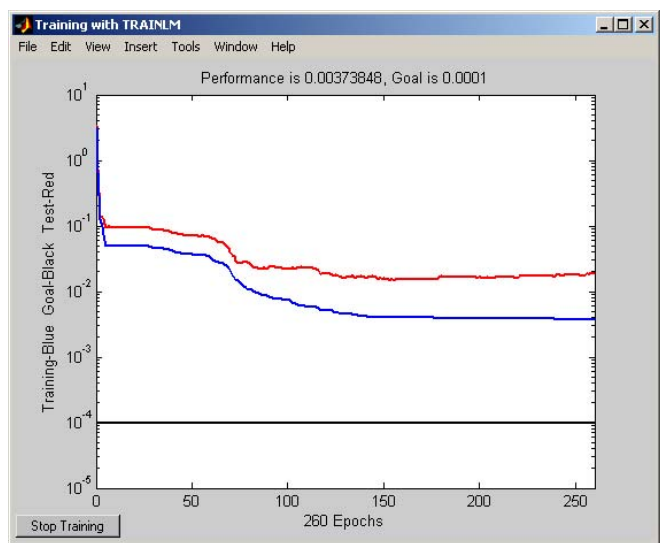

Fig 6.- Training performance of the frequency ANN

VI. CONCLUSIONS

Today it is known that neural networks are a good choice for detecting and classifying electrical power disturbances. In the huge literature [4-14] about detection of electrical disturbances which we can find, often the problem lies in generating a enough 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 prototype of a real-time classifier system based on ANNs. The advantage of our system is the possibility to generate easily a great number of training patterns with the electrical pattern generator in order to get a perfect training.

We are currently working on three lines: on the one hand we are carrying out tests with the system working in real-time using the Electrical Patter Generator and in the power line. On the second hand we are increasing the number of training patterns. Lastly we go on testing other possibilities of processing the signal and other structures of the ANN in order to improve the results as well as the execution time.

VII. References

[1] M. McGranaghan, B. Roettger, "Economic Evaluation of Power Quality", 0272-1724/02, 2002 IEEE.

[2] A.Hussain, M.H. Sukairi, A. Mohamed, R. Mohamed, "Automatic Detection Of Power Quality Disturbances and Identification of Transients Signals", International Symposium on Signal Processing and its Applications, Kuala Lumpur, Malaysia, 13-16 August 2001.

[3] R. Adapa : "Power Quality Analysis Software", 0272-1724/02, IEEE Power Engineering Review, February 2002.

[4] W.R. Anis Ibrahim and M.M. Morcos, "Artificial Intelligence and Advanced Mathematical Tools for Power Quality Applications: A Survey", 668 IEEE Transactions on Power Delivery, Vol. 17, April 2002

[5] G. Zheng, M.X. Shi, D. Liu, J. Yao, Z.M. Mao, "Power Quality Disturbance Classification Based on Rule-Based and Wavelet-Multi-Resolution Decomposition", Proceedings of the First International Conference on Machine Learning and Cybernetics, Beijing, 4-5 November 2002

[6] P. K. Dash, S. K. Panda, A. C. Liew, B. Mishra, and R. K. Jena, "New approach to monitoring electric power quality," Elect. Power Syst. Res. vol. 46, no. 1, pp. 11–20, 1998.

[7] A.Elmitwally, S. Farghal, M.Kandil, S. Abdelkader and M.Elkateb, "Proposed wavelet-neurofuzzy combined system for power quality violations detection and diagnosis", IEEE Proc-Gener. Trans. Distrib. Vol. 148 No 1, pp. 15-20, January 2001.

[8] J.V. Wijayakulasooriya, G.A. Putrus and P.D. Minns, "Electric power quality disturbance classification using self-adapting artificial neural network", IEEE Proc-Gener. Trans. Distrib. Vol. 149 No. 1, pp. 98-101, January 2002.

[9] R. Daniels, "Power quality monitoring using neural networks," in Proc.1st Int. Forum Applications Neural Networks Power Syst., 1991, pp. 195–197.

[10] S. Santoso, J. P. Edward, W. M. Grady, and A. C. Parsons, "Power quality disturbance waveform recognition using wavelet-based neural classifier - Part 1: Theoretical foundation," IEEE Trans. Power Delivery, vol. 15, pp. 222–228, Feb. 2000.

[11] S. Santoso, J. P. Edward, W. M. Grady, and A. C. Parsons, "Power quality disturbance waveform recognition using wavelet-based neural classifier—Part 2: Application," IEEE Trans. Power Delivery, vol. 15, pp. 229–235, Feb. 2000.

[12] A.K. Ghosh and D. L. Lubkeman, "The classification of power system disturbance waveforms using a neural network approach", IEEE Trans. Power Delivery. Vol. 10. pp. 671-683, July 1990 .

[13] D. Borrás, M. Castilla, N. Moreno and J.C. Montaño, "Wavelet and neural structure: a new tool for diagnostic of power system disturbances", IEEE Trans. on Industry Applications, Vol. 37, No. 1, pp. 184-190, 2001.

[14] M. Mallini and B. Perunicic, "Neural network based power quality analysis using MATLAB," in Proc. Large Eng. Syst. Conf. Power Eng., Halifax, NS, Canada, 1998, pp. 177–183.

VIII. Biographies

Iñigo Monedero is an assistant professor from the Electronic Technology Department of the University of Seville. He studied Computer Science in the School of Computer Science and Engineering. Afterwards, he was working two years in the Automatics and Robotics. Currently, in the Electronic Technology Department he's doing research into Artificial Intelligence field.

Carlos León received his Physical Electronics degree in 1991 and the Computer Science Doctoral Degree in 1995, both from the University of Seville (Spain). He has been a Professor of Electronic Engineering at the University of Seville since 1991. His areas of research are expert systems, neural networks, data mining and fuzzy logic focus on Utilities System Management. Dr. León is a Member of the IEEE Power Engineering Society.

Antonio García, was born in Seville in 1960. He received his Physical Electronics degree in 1982 from the University of Seville. He has been a Professor of Electronic Engineering in the Electronic Technology Department since 1984. His areas of research are instrumentation, hardware design and digital signal processing.

Jose Manuel Elena received his Physical Electronics degree in 1977 and the Computer Science Doctoral Degree in 1999, both from the University of Seville (Spain). He has been a Professor of Electronic Engineering at the University of Seville since 1991. His areas of research are expert systems, neural networks and fuzzy logic focus on Digital Communications System Management. Dr. Elena is a Member of the IEEE.

Juan Carlos Montaño (M'80, SM'00) was born in Sanlúcar (Cádiz), Spain. He received the Ph.D. degree in physics from the University of Seville, Spain, in 1972. From 1973 to 1978 he was a Researcher at the Instituto de Automática Industrial (CSIC- Spanish Research Council), Madrid, Spain, working on analog signal processing, electrical measurements, and control of industrial processes. Since 1978, has been responsible for various projects in connection with research in power theory of nonsinusoidal systems, reactive power control, and power quality at the IRNAS (CSIC).

Jorge Ropero was born in Spain in 1976. He graduated as a Telecomunications Engineer at the University of Seville. He started to work at the University of Seville in February of 2003 for the Department of Electrical Technology, where his special interests have included neural networks and fuzzy logic.