# Classification of Electrical Disturbances in Real Time Using Neural Networks

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***Abstract*—Power-quality (PQ) monitoring is an essential service that many utilities perform for their industrial and larger commercial customers. Detecting and classifying the different electrical disturbances which can cause PQ problems is a difficult task that requires a high level of engineering knowledge. This paper presents a novel system based on neural networks for the classification of electrical disturbances in real time. In addition, an electrical pattern generator has been developed in order to generate common disturbances which can be found in the electrical grid. The classifier obtained excellent results (for both test patterns and field tests) thanks in part to the use of this generator as a training tool for the neural networks. The neural system is integrated on a software tool for a PC with hardware connected for signal acquisition. The tool makes it possible to monitor the acquired signal and the disturbances detected by the system.**

***Index Terms*—Neural networks, power quality (PQ), wavelet transform.**

## I. Introduction

**P**OWER QUALITY (PQ) is usually defined as the study of the quality of electric power signals. In recent years, grid users have detected an increasing number of drawbacks caused by electric PQ variations [1] and PQ problems have sharpened because of the increased number of loads sensitive to PQ and have become more difficult to solve as the loads themselves have become important causes of the degradation of quality [2]. Thus, these days, customers demand higher levels of PQ to ensure the proper and continued operation of such sensitive equipment.

The PQ of electrical power is usually 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 sudden catastrophic damage. 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 on the side of their customers. The classification and identification of each disturbance are usually carried out from standards and recommendations depending on where the utilities operate (IEEE in the U.S., EN in Europe, etc.). Our own classification, which is given in Table I, is based on the UNE standard in Spain which defines the ideal signal as a single-phase or three-phase sinusoidal voltage signal of 230 $V_{\mathrm{RMS}}$ and 50 Hz. In addition, we complete from our point of view some aspects which were not completely defined in this standard.

TABLE I
Types of Disturbances

| Type of disturbance | Disturbance subtypes | | Time | Range: Min. value | Range: Max. value |
|---|---|---|---|---|---|
| Frequency | Slight deviation | | 10 s | 49.5 Hz. | 50.5 Hz |
| | Severe deviation | | | 47 Hz. | 52 Hz. |
| Voltage | Average voltage | | 10 min | 0.85 Un | 1.1 Un |
| | Flicker | | - | - | 7 % |
| | Sag | Short | 10 ms-1s | 0.1 U | 0.9 U |
| | | Long | 1s-1min | | |
| | | Long-time disturbance | > 1min | | |
| | Under-voltage | Short | < 3 min | 0.99 U | |
| | | Long | > 3 min | | |
| | Swell | Temporary Short | 10 ms – 1s | 1.1 U | 1.5 KV |
| | | Temporary Long | 1s - 1min | | |
| | | Temporary Long-time | > 1 min | | |
| | | Over-voltage | < 10 ms | | 6 KV |
| Harmonics and other information signals | Harmonics | | - | THD > 8 % | |
| | Information signals | | - | Included in other disturbances | |

## II. Artificial Intelligence Applied to PQ

Artificial intelligence (AI) may be broadly defined as the automation of activities that are associated with human thinking, such as decision-making, problem-solving, learning, perception, and reasoning [3] for the resolution of complex problems. Thus, these days, because of the important development of computers, AI tools [2] (e.g., artificial neural networks (ANNs)

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have emerged as an interesting alternative for the resolution of problems which require some kind of human reasoning.

In the classification of electrical disturbances, all of the factors that make AI (and, in particular, ANNs) a powerful tool are present. We get information which is massive—electrical signals are constantly being received—and distorted—there is an important noise component—so that a classification of the disturbances (which can sometimes be highly complex) must be carried out.

Thus, new and powerful tools for the analysis and operation of power systems, as well as for PQ diagnosis are currently available. An excellent overview of these tools is presented in this paper [3]. Thus, the main intelligent tools of interest include expert systems, fuzzy logic, and ANNs. Expert systems are expensive in their development and normally slow in their execution (therefore, they are not good for real-time applications). On the other hand, fuzzy-logic schemes are useless for the classifications of PQ disturbances due to the fact that they are not well suited for fuzzy techniques (the distinction among the various types of disturbances is discretely defined by standards or recommendations). Therefore, the schemes of most extended use are based on ANNs (besides, they have the advantage of being very recommendable for real-time use due to their low time consumption).

The detection and classification of electric disturbances requires the preprocessing of data, feature extraction, and final classification. Thus, in order to extract the signal features, ANNs are usually combined with mathematical analysis, such as Fourier and wavelet transforms for the generation of signal features which serve as inputs of the network [4]. Signal evaluation consists of both spectrum and transient analysis. The Fourier transform is most commonly used for spectrum analysis. However, transients are commonly analyzed by means of digital wavelet transform. It is hardly feasible to localize and estimate transients by means of the Fourier technique.

Although both mathematical analyses (Fourier and wavelet) can be used to generate good signal features, the wavelet algorithm has an important advantage when it is a necessary to quickly analyze the signal (and, therefore, for real-time systems) due less computational complexity. Thus, whereas the complexity of the wavelet algorithm is lineal, the Fourier one is O(NlogN). The advantages of this type of scheme are opposed to deterministic methods (for instance, threshold detectors) which are the possibility of classifying successful signals with more of a disturbance (by means of accurately training the ANNs) as well as better performance in the classification of those types of disturbances in which the measurement of their thresholds is highly complex (for instance, in frequency disturbances). Besides, Wavelet analysis is capable of detecting events of data that other analysis tools would miss, including trends, breakdown points, and discontinuities.

The aim of the preprocessing of the signal in wavelet-ANNs schemes is to obtain a feature extraction which provides a unique characteristic which can represent every single PQ disturbance. Thus, for instance, it can be carried out by means of a wavelet analysis in different resolutions using the technique called multiresolution signal decomposition or multiresolution analysis.

In multiresolution analysis, the signal is decomposed 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 new mathematic tools, the detection of the electrical disturbances tends to be easy but the classification is still a difficult task in which ANNs play an important role [5]–[12].

From that extraction, the problem is a question of pattern recognition by means of ANNs. Thus, one of the most important tasks is to generate an adequate number of training patterns in order to train the ANNs correctly so that they can classify future inputs appropriately. In particular, in PQ, a great number of these electrical patterns are necessary due to 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 obtaining real useful training patterns directly from the power grid due to the irregular apparition of these disturbances and the difficulty in capturing them.

## III. NN Real-Time Classifier

We have developed a prototype of a real-time system for the detection and classification of electrical disturbances. The system is a detector of power-line disturbances whose classification kernel is based on AI techniques (particularly on ANNs). The system consists of a PC application which includes an acquisition card, an environment to monitor the acquired signal, and an AI kernel to classify possible disturbances. On the other hand, an electrical pattern generator has been developed as an auxiliary tool to generate electric patterns for the ANNs.

### *A. Environment*

The environment of the application (Fig. 1) shows the information which is acquired and registered by the system. It consists of several windows in which the acquired signal is represented by means of the $V_{RMS}$ of the three phase signals, and the neutral signal. Other windows show the last detected disturbance, a bar diagram which reports the number and the type of detected disturbances and a historic window which registers the date and time of the different events.

We also have other options such as a bar diagram reporting a temporal graphic view of the disturbances, a more detailed representation of the last detected disturbance—those are shown in Fig. 2—or a three-phase diagram and representation of the signal.

The acquisition card obtains 640 samples every 100 ms. This window width and number of samples proved to be sufficient for our aim in the range of detection of disturbances. **AUTHOR: TABLE 4 AND FIGS. 3, 4, AND 8 NEED TO BE CITED IN TEXT**

The acquired samples are shown on the chart and processed by the AI kernel. When one or more disturbances are detected within these 100 ms, the corresponding registers are updated, changing the corresponding windows for the last disturbance, the bar diagrams, and the historic.

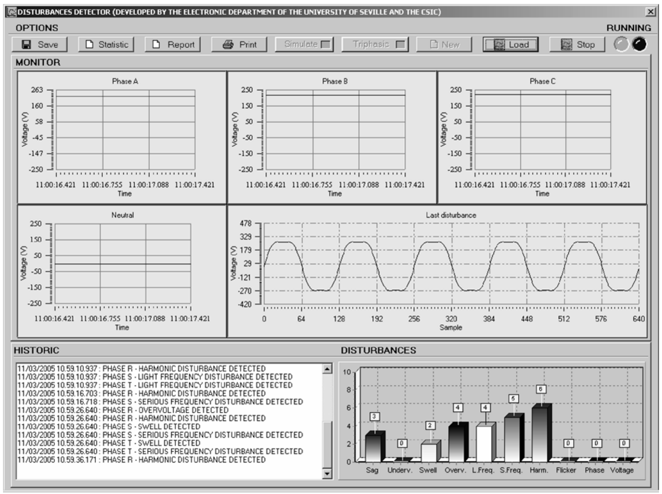


Fig 1. Classifier environment (I).

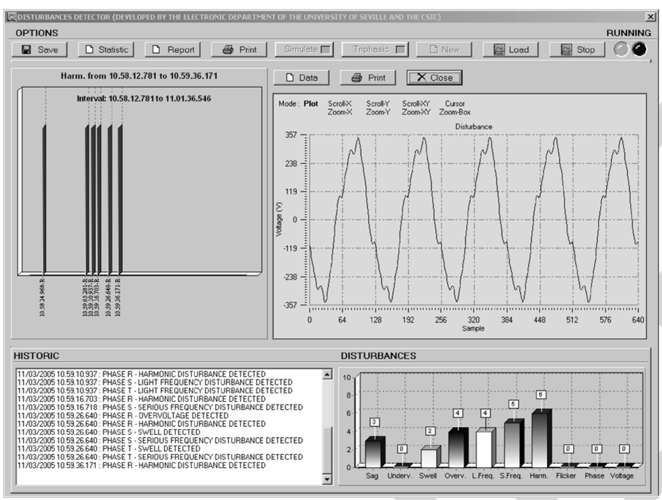


Fig 2. Classifier environment (II).

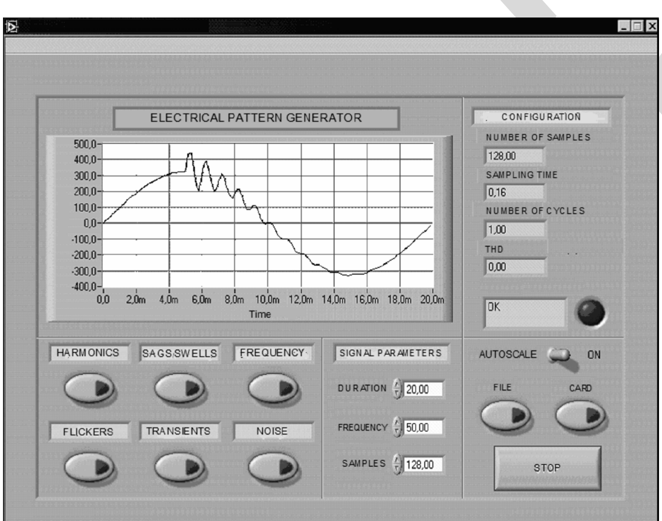


Fig 3. Electrical pattern generator.

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

## B. Electrical Pattern Generator

An aforementioned important problem with ANNs applied to PQ is the impossibility of getting real patterns directly from the power grid due to the irregularity in the apparition of disturbances and the problems in their identification. In turn, it is very difficult to obtain access to databases of electrical disturbances and, once achieved, to adjust the features of the obtained electrical patterns to the requirements of the system to be designed (in parameters such as sample time and voltage range defined for each type of disturbance).

Thus, for the task of training ANNs for the detection and classification of electrical disturbances, we developed an electrical pattern generator (EPG) which is patent pending. An unlimited number of patterns to be used by a classification system can be generated. This EPG is based on a PC environment which has been programmed on LabView. The EPG 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 (50 Hz or 60 Hz) and to add one or more disturbances on the display window. 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 three data columns corresponding to the samples of the three-phase voltages.

On the other hand, the possibility of generating these patterns as real signals has been added in order to be able to simulate other detection equipments. Thus, the signal is generated by a digital-to-analog converter (DAC) card connected to the PC and then amplified from the output voltage level of the card to a high-voltage level ($V\mathrm{pp} = 1500$ volts) able for testing actual loads.

The types of disturbances include impulse, oscillation, sag, swell, interruption, undervoltage, overvoltage, harmonics, and frequency variations. Parameters of the amplitude disturbances (impulses, sags, swells, interruptions, undervoltages, and overvoltages), such as amplitude, start time, final time, and rising and falling slope can be configured by the EPG. The edition of harmonics allows for the configuration of amplitude and phases as far as 40 harmonic order including the possibility of adding an offset.

We have generated over 27 000 signal files including one-disturbance signals and two-disturbance signals, and tried to sweep all types of disturbances.

## C. Detection and Classification Kernel

The classification process carried out by the kernel involves two steps: a feature extraction of the acquired signal and the ANNs analysis and detection of signal disturbances.

For the feature extraction, the kernel uses a wavelet multiresolution analysis of the acquired signal for the generation of signal features [5]–[11]. The aim of feature extraction by

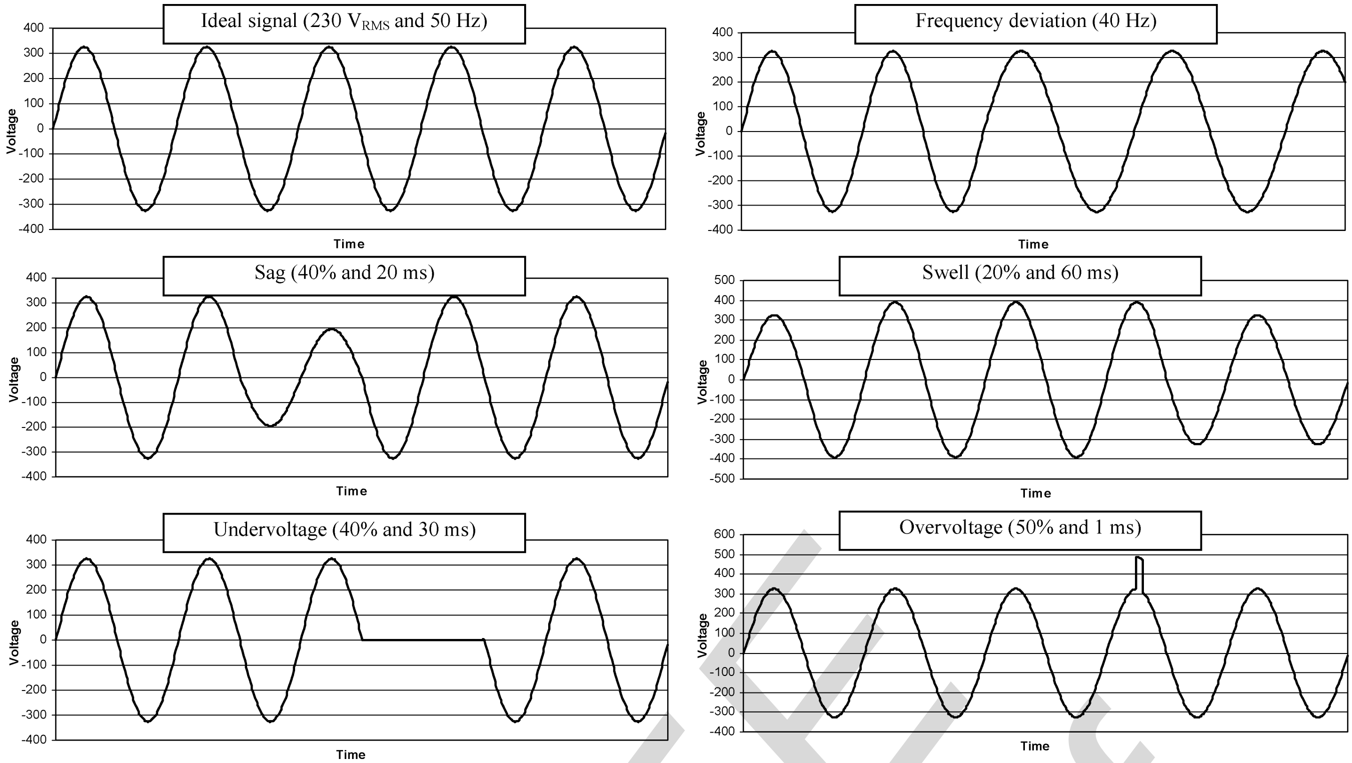


Fig 4. Some examples of disturbances generated from the EPG.

wavelet transforms is to provide a unique characteristic which can represent every single PQ disturbance.

For the design of several feature vectors, we have carried out a study of the variation of the detail coefficients of a wavelet transform (which stores each level of decomposition the detail information of the analyzed signal) for the different kinds of disturbances as well as the variation of these coefficients to possible noises found in the signal. The aim of this study was to characterize the signal reaching one or various feature vectors which, in turn, required a low calculus level in order to fulfil the real-time specification of the tool.

The study was divided into four parts relating to the three main types of disturbances to be characterized (voltage disturbances, frequency deviation, and harmonic components)—see Table I—and to noisy signals. The procedure of the studies involved the comparison of the wavelet detail coefficients of the disturbances with the wavelet detail coefficients of an ideal voltage signal from the standard (sinusoidal signal of 230 V and 50 Hz). Thus, we start with the Haar mother wavelet because it is the fastest of the Daubechie's family (speed was very important for real-time applications). Level seven was chosen to be convenient for the wavelet analysis of the voltage signal.

Through a study of the variations of the different detail coefficients in each level, we proved that the most adequate levels for characterizing the harmonics and frequency deviations were levels 4, 5, 6, and 7. It made sense because these last wavelet levels are more adequate for detecting low-frequency signal variations.

For the voltage disturbances, we chose levels 1, 2, 6, and 7 in order to capture both the amplitude components and the frequency variations. In this case, we selected high and low analysis levels because of the wide variety in the duration of these kinds of disturbances (trying to capture slow variations with high levels and fast ones with low levels).

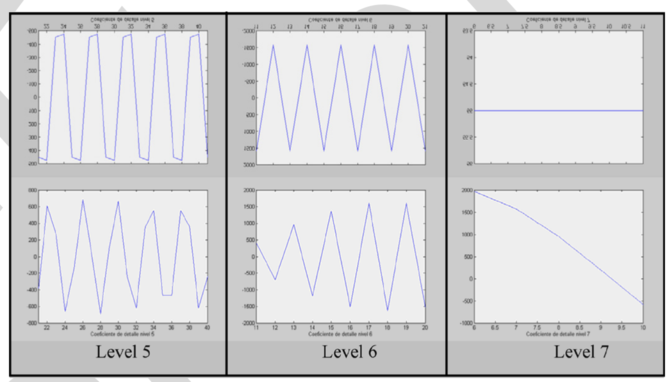


Fig 5. Comparison of wavelet detail levels 5, 6, and 7 in a 50-Hz signal (upper row) and a 53-Hz signal frequency deviation (lower row).

Fig. 5 shows the difference between detail levels 5, 6, and 7 in a 50-Hz signal and the same levels in a 53-Hz signal (high-frequency deviation). As may be observed, in these last levels, we can distinguish the frequency disturbance as much in its waveforms as in the range of their amplitude. In level 6, the detection in the frequency change of the waveform of the signal is clearly observed.

The next step consisted of the characterization of the above mentioned waveforms by means of an adequate feature vector (with the least possible number of inputs) detecting the amplitude variations of the selected detail coefficients relative to the waveform of that same detail coefficient from a signal without disturbances. It is important that the detection was independent of the location of the disturbance within the window (i.e,, the feature vector corresponding to a selected sag must be the same), independent of its starting time within the window. Thus, the complexity in the classification process was simplified to a large extent.

In order to achieve the above mentioned objectives, the feature vectors (which would be used as inputs for the ANNs) were generated carrying out a number of operations on the different wavelet levels. In particular, we used the following values for each level of the detail wavelet coefficients.

- The integral of the waveform of the coefficients.
- The maximum of the absolute values of the coefficients.
- The $V_{RMS}$ of the waveform of the coefficients.

These values were used as an abstract of the different waveforms of the detail levels; in other words, a limited and convenient set of values which were able to identify a wavelet waveform in a unique way. Thus, the integral of the waveform gives the energy amount of the signal. The maximum absolute value of the coefficients identifies possible peaks of the waveform and the $V_{RMS}$ carries out a calculus of both amplitude and frequency. On the other hand, these values were selected due to the fact that they are time-independent. In other words, they do not vary in function of as to which localization of the analyzed waveform extracted was found to be the disturbance per second. In this way, many patterns were saved for training and the process was optimized.

Therefore, three values were used by each level. In addition to the previously mentioned parameters, for each level of wavelet detail coefficients, we used the $V_{RMS}$ of the sampled signal as an input for every ANN.

In particular, for the previously mentioned second step in the classification process, we first designed three ANNs: one for amplitude disturbances, another for frequency deviation, and a third one for harmonics. The main reason for using several ANNs is the different architecture of the three main types of disturbances: voltage, frequency, and harmonics (resulting in different wavelet levels used for the classification of each disturbance type). Besides, a unique ANN with seven outputs—one for each type of disturbance—requires too many neurons to work properly and, consequently, more memory resources.

Later, we noticed the advantage of designing one new ANN (besides those designed for classification) which was able to detect, with a very high success rate, the appearance or absence of any type of disturbance in a signal section. Thus, as shown in Fig. 6, the classification system would use this new ANN (called disturbance ANN) as a filter to detect signals with disturbances and three parallel ANNs to classify the different disturbances existing in the signal. The advantages of this filter network (which should have a high degree of reliability in the filtering process as a basic condition) were that it avoids unnecessary analyses in the rest of the classification networks, saving analysis time and possible errors in the other three networks (whose success rate would be doubtlessly lower because of their higher number of outputs).

Therefore, the classification process, which is represented in Fig. 6, carries out the following steps: first of all, the inputs are given to the disturbance ANN, whose output is either 0—no disturbance—or 1—disturbance—. If there is a disturbance, the ANN inputs are given to three other ANNs, each one specializing in the detection of a class of disturbances. In the same way, the outputs of these ANNs are 0 or 1, depending on whether there is or not that kind of disturbance. These classes are, according to Fig. 1, voltage disturbances—sags, swells, undervoltages and overvoltages, frequency disturbances—slight and severe deviations, and harmonics disturbances.

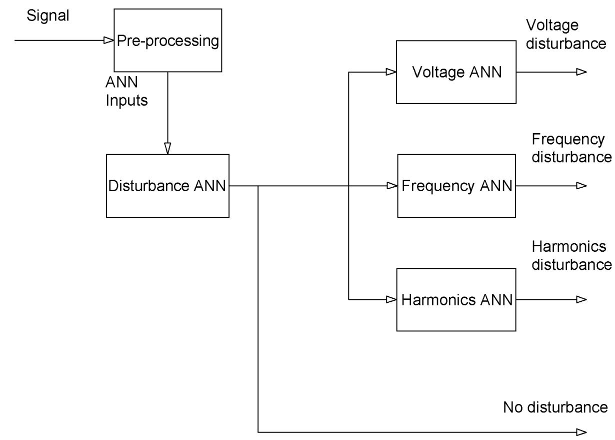


Fig 6. Block diagram.

### D. *Structure of the NNs*

Important features in the design of ANNs are the study of the necessary input pattern, the ANN structures, transfer functions, and learning algorithms.

As mentioned in the previous section, we have used the following values as input vector of the disturbance and voltage ANNs: the $V_{RMS}$ of the signal, the integral, the maximum of the absolute values, and the $V_{RMS}$ of the detail wavelet coefficients of level 1, 2, 6, and 7. On the other hand, as inputs for frequency and harmonics networks, we used the $V_{RMS}$ of the voltage signal, the integral, the maximum of the absolute values, and the $V_{RMS}$ of the detail wavelet coefficients of level 4, 5, 6, and 7. In order to obtain faster convergence and better results, these data were scaled so that the minimum was $-1$ and the maximum was 1.

Moreover, the kind of ANN chosen is a multilayer perceptron with three hidden layers with a different number of neurons, depending on the ANN and its number of outputs. A typical three-layer ANN used for the classification process is shown in Fig. 7. The output functions of the layers have been chosen with a logarithmic sigmoid transfer function for all of the layers.

All of the inputs, structures, functions, and training algorithms have been obtained after testing the different ones. The best results until now have been obtained for the ANNs shown in Table II.

We designed two sets of training and test patterns: the first set had 11501 training patterns and 2914 test patterns whereas the second one had 20 254 training patterns and 5088 test signals. The first set included a higher number of signals without disturbance than the second set (which included a high number of signals with one or more disturbances). Thus, the disturbance ANN (designed to distinguish between a disturbed signal and a

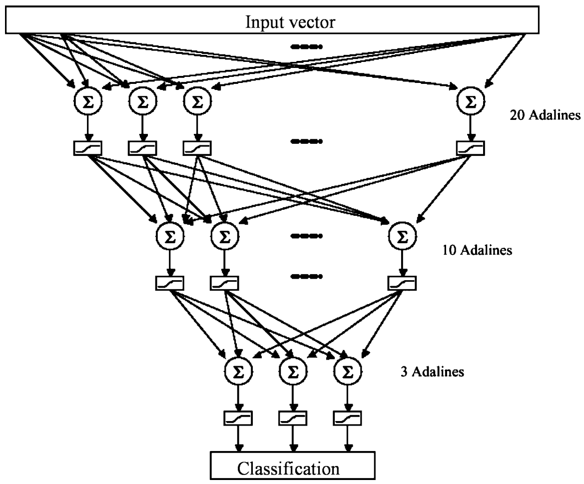


Fig 7. Three-hidden layers perceptron.

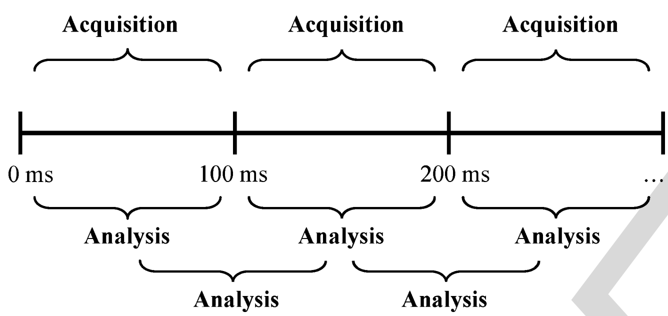


Fig 8. Time analysis process of the samples.

TABLE II
NEURAL-NETWORK STRUCTURE

| *ANN type* | *Number of hidden neurons* | *Number of outputs* |
|---|---|---|
| Disturbance | 20, 14 & 8 | 1 |
| Voltage | 25, 16 & 10 | 4 |
| Frequency | 16, 12 & 7 | 2 |
| Harmonics | 20, 14 & 8 | 1 |

nondisturbed one and, therefore, requiring a greater balance between both types) was trained using the first set and the rest of the ANNs using the second set (designed to classify the kinds of disturbance in an *a priori* disturbed signal extract).

### E. Time Analysis

A last step in the design of the detection and classification neural system involved its integration into a real-time environment. First, we had to optimize the different calculus carried out in the detection and classification process and then we had to make sure that the time consumed met the time requirements of our system.

Thus for programming tasks, we have used the MATLAB tool to test the different possibilities in the preprocessing of the signal and in the structure of the kernel. We used this tool due to the powerful toolboxes it contains with specialized functions, utilizing the signal and the wavelet toolboxes for the preprocessing task and the ANNs toolbox for the design of the kernel [12].

Once we carried out the test and found a good code for the preprocessing and the AI kernel, we reprogrammed their algorithms in C++ to optimize the execution time (taking care with the programmed wavelet transform algorithms which were the most complex algorithms in the kernel).

As mentioned in Section III, the AI kernel receives 640 samples every 100 ms. This window width and number of samples proved to be sufficient for our aim in the range of detection of disturbances. In addition, two different analyses are carried out every 100 ms in this way.

This scheme implies that the 640 samples in every 100 ms must be analyzed twice. It was applied to achieve the detection, for instance, of a 10-ms sag centered at the end of an acquisition window. If analyzed as two independent parts (two mini-sags of 5 ms) it would be not consider a sag in the UNE standard (which defines a sag as lasting at least 10 ms) and, therefore, it would be ignored.

Thus, the time requirements of our system had to achieve the following terms:

$$T_{\text{CLASSIFICATION}} + T_{\text{MONITORING}} < T_{\text{ACQUISITION}} - T_{\text{MARGIN}}.$$

In other words, the kernel time and the time for monitoring the acquired signal and the detected disturbances have to be less with a margin (thus ensuring the time requirements against possible delays of the operating system) than the time relative to the acquisition process of the 640 new samples to analyze. Moreover

$$\begin{aligned} T_{\text{CLASSIFICATION}} = (3 * T_{\text{PREPROCESSING}} & \\ + 3 * T_{\text{ANN-DETECTION}} & \\ + 3 * T_{\text{ANN-VOLTAGE}} & \\ + 3 * T_{\text{ANN-HARMONICS}} & \\ + 3 * T_{\text{ANN-FREQUENCY}}) * 2 & \end{aligned}$$

That is to say, the classification time in the worst conditions (three-phase disturbed signals) is equal to three times (for each phase) the preprocessing and the 4 ANNs delay and that result is multiplied by 2 (for each analysis window).

We carried out the measurement of the previous times in C++ code with the following results:

$$T_{\text{CLASSIFICATION}} < 30 \text{ milliseconds and}$$
$$T_{\text{MONITORING}} < 16 \text{ milliseconds}$$

The total time in the worst conditions was thus below 46 ms which involved a wide margin of 54 ms (taking into account that the window time was 100 ms).

## IV. RESULTS

### A. System Simulation

Before embedding the kernel in the classifier tool, we selected the best training method for the configuration of ANNs. Thus, for the training 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 determine whether a particular output value may be considered

TABLE III
DETECTION AND CLASSIFICATION RESULTS

| *ANN type* | *Number of outputs* | *Test signals* | *Number of errors* | *Correctly detected %* |
|---|---|---|---|---|
| Disturbance | 1 | 2914 | 52 | 98.21 |
| Voltage | 4 | 5088 | 457 | 91.01 |
| Harmonics | 1 | 5088 | 48 | 99.05 |
| Frequency | 2 | 5088 | 257 | 94.94 |

TABLE IV
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 | Sag |
| 98% and 10 ms sag | Undervoltage |
| Ideal signal with a small 4% overvoltage | Overvoltage |
| 80% Swell and 9 ms | Overvoltage |
| 97% and 10 ms sag | Ideal signal |

as a disturbance. The defined thresholds were 0.3 and 0.7 and, thus, output values above 0.7 were considered as disturbances and below 0.3 as ideal signals. Values found 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.

Two different kinds of results were considered: 1) the general results, that is to say, the percentage of success in every ANN—see Table III and 2) the particular results, which are more intuitive and consider some particular cases of failure in one of the ANNs. In addition, we have the results for only two-disturbance signals (signals with two kinds of disturbances in the same signal window).

The first conclusion we obtain is that the higher number of ANN outputs we use, the higher number of errors we get. This is due to the higher complexity introduced by the need to fix all of the outputs at the same time. In addition, the number of output combinations in the voltage ANN (which makes it possible to detect several voltage disturbances at the same time) is higher than, for instance, the frequency network (in which both outputs cannot be active at the same time). The second conclusion is related to the influence of these errors. As mentioned before, the most important ANN is the one which detects disturbances—the existence of a disturbance is more important than its type—so we have focused our efforts on its correct working. On the one hand, we must say that these percentages all refer to the testing signals but we also have to bear in mind that some of the signals that fail are filtered by the disturbance ANN. On the other hand, we have to analyze what kind of signals tend to fail. To illustrate this point in the following table, we show the results of a study of 10 samples referring to signals which fail in the voltage ANN.

Analog results were obtained for the rest of the signals and for the other ANNs. As may be observed, the signals which fail are near the limit of a disturbance, so it is not a mistake to consider them as the ANN tells us.

TABLE V
TWO-DISTURBANCE SIGNAL RESULTS

| *ANN type* | *Number of outputs* | *Test signals* | *Number of errors* | *Correctly detected %* |
|---|---|---|---|---|
| Disturbance | 1 | 1217 | 12 | 98.73 |
| Voltage | 4 | 4202 | 434 | 89.67 |
| Harmonics | 1 | 4202 | 48 | 98.85 |
| Frequency | 2 | 4202 | 257 | 93.88 |

TABLE VI
FIELD TEST RESULTS

| *Type of Signal* | *Correct classification* | *Partial classification* | *Incorrect classification* | *Correctly detected %* |
|---|---|---|---|---|
| Non-disturbance | 18 | 0 | 2 | 90% |
| Sag | 9 | 0 | 1 | 90% |
| Under-voltage | 5 | 2 | 3 | 70% |
| Temporary Swell | 9 | 0 | 1 | 90% |
| Overvoltage | 8 | 1 | 1 | 90% |
| Slight Frequency Deviation | 8 | 2 | 0 | 100% |
| Severe Frequency Deviation | 10 | 0 | 0 | 100% |
| Harmonic disturbance | 4 | 4 | 2 | 80% |
| Combined disturbance | 4 | 5 | 1 | 90% |

Table V shows the results obtained for two-disturbance signals, with approximately 27 700 signals. About 5400 (the total for both sets of patterns) were for testing and the rest were for training.

Conclusions were similar to those obtained for the case of one-disturbance signals although slightly worse. It was due to the greater complexity of the signals and to the fact that the ANNs had to correctly detect two types of disturbances simultaneously. Even so, the results remained above 89% in all of the networks, which is considered an excellent result.

## B. Connection to the Electrical Pattern Generator

For these kinds of field tests, the designed detector equipment was connected to the signal generator (digital-to-analog converter card and amplifier equipment) integrated on the electrical pattern generator.

Once each test was configured and generated, the detector equipment was programmed to perform the detection and classification of the signals and to show the results obtained for every ANN. These results are shown in Table VI.

Bearing in mind that the degree of accuracy required in the classification process due to the wide range of signal types as well as the degree of complexity of many of them, 75% of correct classifications—and 89% adding those signals classified as partially correct—appeared as a highly satisfactory result. Besides, it is necessary to consider that it is always possible to improve these results by means of new trainings of the

ANNs (adding as training patterns the previously mentioned errors and other new electrical patterns generated with the EPG). The theory of ANNs proves that the greater the number of patterns, the better the success rate of an ANN will be. For this reason, a higher success rate would be reached (which could even be 100%).

The obtained results are inside the reliability degrees reached by the professional equipment. On the other hand, there are not contractual obligations in the UNE standard for these degrees and, therefore, it guarantees the possibility of integrating the system in a first prototype of electrical disturbance detector and classifier equipment.

### C. Connection to a Low-Voltage Electric Line

These types of field tests were carried out by connecting the detection equipment to a low-voltage electric line also connected to professional equipment for the detection of electrical disturbances. The tests were made in two net points in weekly periods and were of use to refine the set of ANNs. This refinement was motivated by the existence of several high THD components, but within the standards. The process of refinement consisted, therefore, in the utilization of these signs, classified incorrectly as "out of standard" by the voltage ANN, as new patterns for our training universe.

However, none of the systems detected any disturbance in these tests, so a battery of tests was made to connect the system to a disturbance generator system.

This battery of tests was programmed for a long duration in a wind power plant which will predictably generate a high number of disturbances. It will make it possible to obtain and publish new results and, in turn, to study peculiarities in the disturbances generated by this kind of plant.

## V. Conclusion

These days, it is known that ANNs are a good choice for detecting and classifying electrical power disturbances. In the extensive literature [3]–[12] available on the detection of electrical disturbances, the problem often lies in generating a sufficient number of training patterns for the ANN to obtain good results in future inputs. With the help of the generator, it is possible to carry out a training of the ANN which is sufficiently complete to provide reliable results.

Thus, we have developed a first prototype of a real-time classifier system based on ANNs. In addition, we have developed an electrical pattern generator which is capable of generating common disturbances which can be found in the grid with the aim to make the training of ANNs easier. In turn, the generator makes it possible by means of an analog-to-digital converter and an amplifier to generate the configured signal physically.

The advantages of using the generator were the possibility of easily generating a great number of training patterns with the electrical pattern generator in order to obtain perfect training as well as the possibility to carry out the field tests of the detector and classifier.

The aim of this project, that is to say, the development of a real-time detector and classifier of electrical disturbances has been accomplished with very satisfactory results: pattern identification was validated and tested with excellent performance (fit of simulated and actual data above 89%). Moreover, results are always easily improvable through the generation of new signal patterns.

The use of signal preprocessing is quite simple; the programming and optimization in C++ of the different algorithms made it possible to achieve the objective of making our system valid in real time. This makes it possible to detect signal disturbances in time to avoid further problems.

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