Classification of Disturbances in Electrical Signals Using Neural Networks

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Abstract. This paper describes a currently project accomplished by the authors in the area of Power Quality (PQ) using artificial neural networks (ANN). The efforts are oriented to obtain a product (Power disturbances monitor for three-phase systems) that permits a real time detection, automatic classification, and record process of impulsive or oscillatory voltage transients, long term disturbances, and waveform distortions in electrical three-phase AC signals. To classify the electrical disturbances, we consider using a fully connected feedforward ANN with a backpropagation learning method based on Generalized Delta Rule. In order to select the best alternative more than 200 network architectures were tested. Long-term disturbances, like swells or long-duration interruptions, have been detected using a method based on the test of the RMS value of the signal. Short-term disturbances, like sags, are detected by sampling a cycle of the electrical signal, and waveform distortions are detected using the main harmonics of the signal. To train the ANN we have developed a three-phase virtual generator of electrical disturbances. In order to compress the ANN input data we use the Wavelet Transform.

1. Introduction

The term *power quality* is applied to a wide variety of electromagnetic phenomena in power systems. In recent years, the use of electronic equipment has increased the interest in power quality and several terms have been developed in order to describe

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power systems disturbances. There can be completely different definitions for power quality, depending on the point of view of utilities, manufacturer of load equipment, or customer. For instance, utilities may define power quality as reliability and show statistics demonstrating that the system is almost 100 percent reliable. The manufacturer of load equipment may define quality power as those characteristics of the power supply that enable the equipment to work properly. However, power quality is ultimately a customer-driven issue and the customer's point of reference must take precedence. Therefore, a power quality problem can be defined as *any power problem manifested in voltage, current, or frequency deviations* that results in failure or malfunctioning of customer equipment.

The subject of this paper is the analysis of the voltage quality for sensing any deviation of the voltage waveform out of certain limits. Alternating current power systems are designed to operate at a sinusoidal voltage of a given frequency (typically 50 or 60 Hz) and magnitude. Any significant deviation in the magnitude, frequency, or purity of waveform is a potential power quality problem. These deviations must be fast detected for further actions or storing for classification and statistical studies.

Software procedures have been developed, applying the FFT for analyzing these disturbances [1]; however, due to the great amount of stored data and the time of required processing, such procedure is slow and not very efficient. To minimize storage space, we need to represent signals by as few bits as possible. This is the data compression problem, and has been studied for several decades especially for image compression [2]. Likewise, the noise reduction has been dealt with from a statistical point of view [3-5].

Continuous and discrete wavelet transform (DWT) have been used in analysis of non-stationary signals and several papers [6-8] have proposed the use of wavelets for the analysis of power systems. They are able to remove noise and achieve high compression ratios because of the "concentrating" ability of the wavelet transform. If a signal has its energy concentrated in a small number of wavelet coefficients, this signal will be relatively large compared to any other signal or noise that has its energy spread over a large number of coefficients. This means that thresholding the wavelet transform will remove the low amplitude and undesired coefficients in the wavelet domain and reconstructs the signal with little loss of information. Wavelet thresholding has important applications in statistic. Donoho and Johnstone [9] propose to start with a wavelet decomposition of the data set, thresholding later the coefficients, and then use the wavelet reconstruction as an estimate function. This is the model of the fast and efficient algorithm for data-compression that we consider in this paper.

2. Power Quality Measurement for Three-Phase Systems

The power quality measurement system or power quality monitor (PQM) described in this paper has been specifically developed for the analysis of three-phase line voltages. It stores data by sampling the three phase-to-neutral voltages simultaneously. Then, an efficient measurement algorithm, based on the power-frequency data estimation obtained from three equidistant samples of a sinusoidal signal, calculates the instantaneous frequency for the synchronization of the voltage and sampling periods. It allows the estimated power frequency to be defined from the pondered mean of the estimation performed in each phase R-S-T.

Thus, the detected R-phase of the voltage signal can be processed to construct a perfect three-phase system for being used as reference. The PQM detects individual events, at the time of occurrence, by comparing the monitored signals to the reference three-phase voltages. When a threshold parameter is exceeded, a disturbance event is detected. Threshold parameters are adjustable over a specified range to accommodate different monitoring circumstances.

 Instantaneous voltage. Instantaneous voltage amplitude measured with respect to the power-frequency sine wave. Short-duration voltage variations such as impulsive and oscillatory transients, waveform distortion and voltage fluctuations can be detected. The measurement interval for short-duration voltage variation is from 500ns to 50ms.

 AC rms voltage. With rms sensing, according to the above strategy of synchronization, the measurement interval is an integral number of cycles of the fundamental power frequency. Harmonic content, swell, long-term interruptions and voltage unbalance events can be detected. The measurement interval is from 1 cycle to 1 min.

Having detected the disturbance event, the digitized samples are stored in memory. As subsequent processing, measurement, and reporting of the disturbance event will be based entirely upon the stored samples, the PQM retain two-cycles data from before and after the detection point to accurately reconstruct the entire disturbance event.

Furthermore, the digitized data is formatted to provide a compressed and detailed graphic representation of the disturbance waveform. Therefore, the PQM includes two algorithms: one for calculating the harmonic spectrum of the incoming voltage data, using the discrete fourier transform (DFT), and other algorithm for filtering and compressing the collected disturbance data using the discrete wavelet transform (DWT). The two algorithms are applied concurrently.

The conventional DFT is applied to the original digitized samples, $f(n)$, getting the set of fourier coefficients and the first 50 harmonics in phasor form. The second algorithm consists of the following steps.

A. Wavelet decomposition. $f(n)$ samples are transformed in order to generate a set of signal coefficients. The DWT used (Daubechies family Db4) is applied to $f(n)$, getting signals $a_j(n)$ and $d_1(n)$, where j is the index level. Family Db4 is particularly appropriate for detecting disturbances of high frequency (transients), as it is more localized in time than other members of the same family are.

B. Threshold wavelet estimators and reconstructed signal A process of comparison between the input signal and the reconstructed signal $a_j(n)$ begins. This process stops when the difference between the two signals is less than the set threshold. One of the goals of the present work is to reach a high compression ratio. This expresses the minimum amount of data necessary for recovering the original signal.

In a first phase, the algorithm of coefficient filtering performs a comparison of signals a_j with the original signal *f(n)* to obtain the error signal $\square_j$. In a second phase, the absolute maximum value of $\square_j$ is compared with a fixed threshold $\square$. If the magnitude of the error signal is less than $\square$, then the signal resulting (reconstructed signal) is the new reconstructed signal $f(n)^*$. In both phases, the *optimal relative error* between the original *f(n)* and the reconstructed $f(n)^*$ signal is used for measuring the quality of the estimator.

These recording mechanisms make the PQM most suitable for automatic classifying of disturbance waveforms and analyzing complex power-quality problems when properly applied by the expert user.

2.1. Three-Phase Arbitrary-Function Generator

We are developing a three-phase arbitrary-function generator (Fig. 1) that simulates all kinds of electrical disturbances in line voltages such as oscillatory transients, waveform distortion, voltage fluctuations, sag, swell, interruptions and voltage unbalance. Generated signals simulate those obtained at low-voltage level by line voltage transducers.

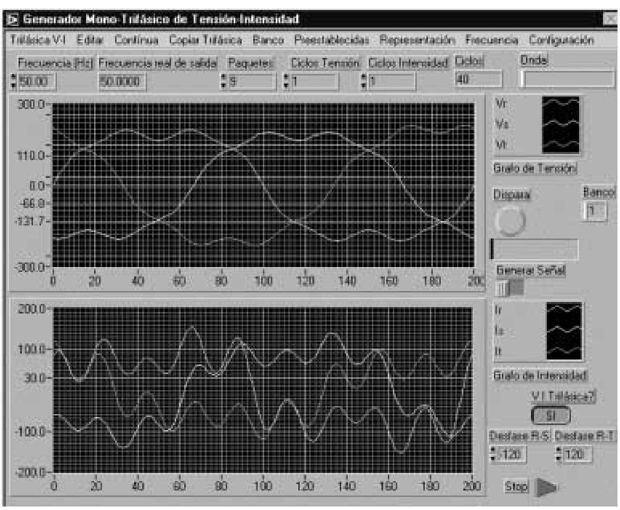

Fig. 1. Three phase arbitrary-function generator

A wide range of parameter settings and combination possibilities make the instrument an appropriate tool for training artificial neural networks in the classification process of electrical disturbances. Local operation via PC-control, using the LabView program running under Windows, makes the unit user-friendly during test parameter set-up.

The instrument enables tests to be performed in accordance with EN-50160 and the other common standards of the European Union (EU). Tests can be pre-programmed and stored for being recalled at any arbitrary time at the touch of a button. Continuously varying values for three-phase voltages and dropout time can be defined to occur autonomously. These tests can also be programmed to run in an endless loop.

At present, three arbitrary functions are generated after completion of the parameter settings using the initial program. It superimposes three sinusoidal signals with combined harmonic content (up to the 50th harmonic). Power frequency variations, total harmonic distortion and voltage imbalance of the three-phase voltage signals can be initially selected too. Fig. 2 shows the screen for parameter settings in case of the voltage waveforms of Fig. 1.

Unlike a natural environment, however, where disturbance events are unpredictable, the instrument allows the user to develop controlled, repeatable simulations. Results from simulation testing can be used to validate in real time a complete system of power disturbance analysis, including data capture, recording, classification, and reporting the results. These waveforms can be used to train an ANN too. The system can also generate three analogue sinusoidal signals to be utilized as AC threshold or, for example, as reference in the disturbance classification training processes of the ANN.

Fig. 2. Parameter settings showing the harmonic content of the voltage waveform

3. PQ Disturbances Classification Using Neural Networks

In power engineering, the analysis of PQ problems is not focused only to the detection of electrical disturbances. Far more important is the ability to classify various types of disturbances as well. As an alternative to classify the PQ disturbances, we consider using an artificial neural network (ANN). This technology has been widely used in Power Systems management [10-14]. After to evaluate several alternatives (ART2, LVQ, Counterpropagation, etc), authors selected a fully connected feedforward ANN with a backpropagation learning method [15,16] based on Generalized Delta Rule. This type of network can resolve the function approximation problem (to find the unknown function that relates a set of training patterns) [17,18]. To simulate ANNs we used simultaneously a set of five Intel PIII 450Mhz computers.

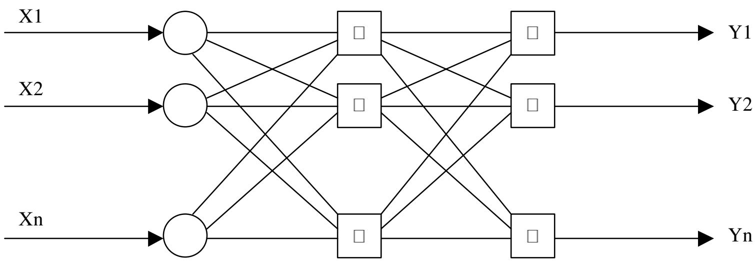

Fig. 3. Feedfordward Neural Network

The feedforward neural network type has an input layer, one or more hidden layers, and an output layer, as shown in Fig. 3.

The neurons in different layers are connected by means of weights. When a training pattern p is presented, the input for a neuron j is the sum of the weighted input signal i_{pi} :

$$net_{pj} = \sum_{i} w_{ij} i_{pi} \quad (1)$$

where w_{ji} is the weight of i^{th} input at j^{th} node. The output o_{pj} from the neuron is given by

$$o_{pj} = f_j(net_{pj}) = \frac{1}{1+e^{-net_{pj}}} \quad (2)$$

when a sigmoid activation function is used.

Training process is carried out using the backpropagation algorithm. This learning method updates the interconnection weights using the Generalized Delta Rule. In this method, the error at a given output node o_{pj}, when a training pattern p is presented, is:

$$\delta_{pj} = (t_{pj} - o_{pj}) f_j' net_{pj} \quad (3)$$

where t_{pj} = target value for j^{th} output node produced by input pattern p; and f'= first derivative of activation function used by node j. The error at a given non-output node j, when training pattern p is presented, is:

$$\delta_{pj} = f' net_{pj} \sum_{k} (\delta_{pk} w_{kj}) \quad (4)$$

in which k = number of neurons in next layer; and δ_{pk} = already computed for the k^{th} neuron in the next layer. Weights may be modified after each training pattern is presented. So, the weight change applied to weight w_{ji} , after pattern p has been presented, is:

$$\Delta_p w_{ji} = \eta(\delta_{pj} o_{pi}) + \alpha \Delta_{p-1} w_{ji} \qquad \textbf{(5)}$$

where η = learning rate; and α = momentum factor. Effectiveness and convergence of the learning algorithm depend on the value of and. If the selected learning rate is too high, the network tends to oscillate avoiding the learning process of the correct mapping from the input to the target. If the value of is very small, the network can take a very long time to learn. Momentum factor is used to speed network training. Proper selection of a momentum factorcan prevent network from oscillating.

Mean Square Error (MSE) is the measure of how well the network output matches target output. MSE is calculated at the end of each training cycle. MSE is summed over each output node for each pattern. The MSE at the end of a given cycle is:

$$MSE = \frac{1}{NT} \sum_{p=1}^{N} \sum_{j=1}^{T} (t_{pj} - o_{pj})^2 \qquad \textbf{(6)}$$

in which N = number of patterns; and T = number of outputs nodes.

There are not specific rules to select an optimal ANN architecture [19]. In the PQ problem the number of input neurons is 113, clustering in three groups:

- 48 time inputs, sampling an electrical signal period of 20 ms, in order to detect impulsive or oscillatory voltage-transients.
- 50 RMS inputs, one for each electrical signal cycle during 2 second, in order to detect long-duration disturbances like overvoltages or undervoltages.
- 15 main harmonics of the signal inputs, to detect waveform distortions.

The number of output neurons is 8: one for a global evaluation of the voltage quality (PQ) and 7 for each disturbance: power frequency variations, transients, sags, short duration interruptions, swells, long duration interruptions and waveform distortions.

To select the other variables related with the ANN design and training is usually very complex. For example, the number of hidden neurons and the number of hidden layers to use are difficult to be determined. If the architecture is too small, the network may not have enough degrees of freedom to learn the process correctly. On the other hand, if the network is too large, the solution may not converge during training or the network may overlearn the data.

In order to select the best alternative, we have developed a three phase heuristic method. The first phase began testing the transfer functions for each neuron layer (linear, sigmoid or tanh), weight initialization (randomly or used specified values), learning rule (Generalized or Cumulative Delta Rule), and the order of training patterns presentation. A second phase sets the number of hidden neurons (10 to 140), the number of hidden layers (3 to 5), the learning rate (0.1 to 0.5) and momentum factor (0.1 to 0.5). Other objective of this design phase is to establish the utility of using partially connected networks (each ANN output only depends on a part of the inputs). In this second phase 200 network architectures were tested. The third phase objective is to test the addition of Gaussian noise to input training pattern and little variations on hidden neurons number.

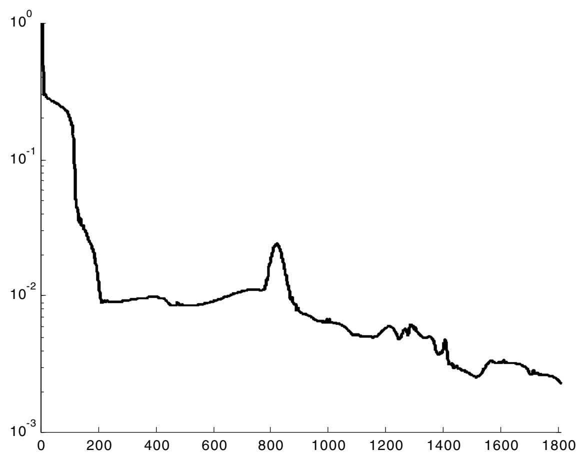

Fig. 4. Variation of MSE during the training process (1800 epochs)

Another problem is to select the training patterns. In the PQ problem we generate 1100 patterns by using the three-phase generator of electrical disturbances described above. Authors selected 900 patterns to use during training, 110 validation patterns to avoid that the ANN overlearns the training patterns, and 90 testing patterns used for evaluate the performances of the network. The training, validation and testing patterns range values are between -1 and 1 (inputs are scaled by the maximum value of the patterns). Authors employed a total of 5,000 training cycles. Fig. 4 shows the reduction of MSE during the training process for one architecture. The results obtained after training the ANN for each possibility with different architectures are shown in Table 1. The best test result is a MSE of 0.0554 (94.5% of correct PQ disturbances classification).

Table 1. Results of the ANN selection heuristic process

Phase	Parameter	Best results
Ph.1	Transfer function per layer	Linear (first layer), Sigmoid (other layers)
	Weight initialization	Randomly between -1 and 1
	Learning rule	Generalized Delta Rule
	Training patterns presentation	Randomly
Ph.2	Architecture	113 - 100 - 100 - 9 partially connected
	Learning rate	0.5
	Momentum factor	0.5
Ph.3	Gaussian input noise	Irrelevant
	Variation on hidden neurons	113 - 100 - 100 - 9 partially connected

If we analyze the error obtained for each output (Table 2) we can see that the worst figure is the output number 8 (waveforms distortions problems), but even in this case, the test MSE is minor than 8%. The only other output MSE upper 5% is the MSE for output 1 (that offers a global evaluation of the signal PQ). As conclusion, the errors obtained are satisfactory to detect and classify PQ disturbances. The next phase in our project is to integrate the ANN into the power disturbance monitor for three phase systems describes above.

Table 2. MSE for each ANN output.

ANN Output	MSE value
Unit 1: Global voltage quality (PQ)	0.051
Unit 2: Power frequency variations	0.009
Unit 3: Transients	0.026
Unit 4: Sags	0.005
Unit 5: Short duration interruption	0.001
Unit 6: Swells	0.032
Unit 7: Long duration interruption	0.001
Unit 8: Waveform distortion	0.075

4. Conclusions

This paper describes the developing of a power disturbance monitor for three-phase systems. This system classifies and stores short-term and long term disturbances, and waveform distortions in electrical three-phase AC signals, using a fully connected feedforward neural network with a backpropagation learning method. Wavelet transform is used for compress data. An arbitrary function generator has been developed for training the ANN. Preliminary tests show that the system obtains good results in the classification of electrical PQ incidences. The next project phase is to integrate the ANN into the power disturbance monitor.

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