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Power Disturbance Classifier Using Wavelet-Based Neural Network

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ABSTRACT

This paper presents a wavelet and neural network based technology for the monitoring and classification of various types of power quality (PQ) disturbances. Simultaneous and automatic detection and classification of PQ transients, is recommended, however these processes have not been thoroughly investigated so far. In this paper, the hardware and software of a power quality data acquisition system (PQDAS) is described. In this system, an auto-classifying system combines the properties of the wavelet transform with the advantages of a neural network. Additionally, to improve recognition rate, extraction technology is considered.

Keywords: Power quality, Wavelet-based neural network, Power disturbance classifier

1. Introduction

This paper proposes a real time power quality (PQ) monitoring and classification system using a wavelet and neural network. Automatic disturbance recognition can be carried out by the wavelet transform and by additional data which effectively removes existing redundancy in time-domain data. Therefore, memory size for classification can be reduced [1-3]. This recognition method is carried out by back propagation (BP) in the wavelet domain. The outcomes of the networks are then integrated using a decision-making simple voting scheme. This wavelet-based neural network is an advanced mathematical tool for analyzing waveforms and images. It has the capacity to reveal various data aspects including breakdown points, discontinuities, etc., that may be missed by any other analysis tool. And it can identify and classify power quality problems through training.

Power quality disturbances are various with short-time problems. It is recommended that methods of detection and classification of the PQ transient signals be done in a simultaneous and automatic process. Therefore, the proposed wavelet network, which combines the properties of the wavelet transform with the advantages of neural networks, will be effective in power quality analysis in real time. The hardware of the power quality data acquisition system (PQDAS) and some case studies are described in this paper.

2. Wavelet Transform

The wavelet transform is the mathematical theory associated with building a model for non-stationary signals using a family of wavelets, which are scaled and shifted versions of the mother wavelet. A discontinuous

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wavelet transform (DWT) is defined and shown in Eq. 2. The function $\varphi_{m,n}(k)$ in Eq. 1 is the mother wavelet. The mother wavelet is dilated and translated discretely by selecting $a = a_0^m$ and $b = nb_0a_0^m$, where a_0 and b_0 are fixed constants with $a_0 > 1$, $b_0 > 0$, and m and n as positive integers.

$$\varphi_{m,n}(k) = a_0^{\frac{-m}{2}} \varphi(a_0^{-m}k - nb_0) \quad (1)$$

$$DWTx(m,n) = \sum_k x(k)\varphi(\frac{k - nb_0a_0^m}{a_0^m}) \quad (2)$$

Since $x[n]$ is a discrete signal, we can put $c_0[n] = x[n]$. The multi-resolution signal decomposition (MSD) technique decomposes $c_l[n]$ at scale l into the smoothed signal, $c_{l+1}[n]$, and the detailed signal, $d_{l+1}[n]$, in the form of wavelet transform coefficients where $h[n]$ and $g[n]$ are low-pass and high-pass filters, respectively.

A complete decomposition of $x[n]$ can be achieved by repeatedly applying MSD to the smoothed parts of the various scales [4-5].

$$c_{l+1}[n] = \sum_k h[k-2n]c_l[k] \quad (3)$$

$$d_{l+1}[n] = \sum_k g[k-2n]c_l[k] \quad (4)$$

The Daubechies wavelet with four filter coefficients (db4) is used in this work. An example of the use of the db4 wavelet for analyzing short-duration disturbances is shown in Fig. 1. The original signal is transformed into the approximated (A_1) and detailed (D_1, D_2, D_3) signals. Four signals, (A_1) and (D_1, D_2, D_3), are used in the experiments.

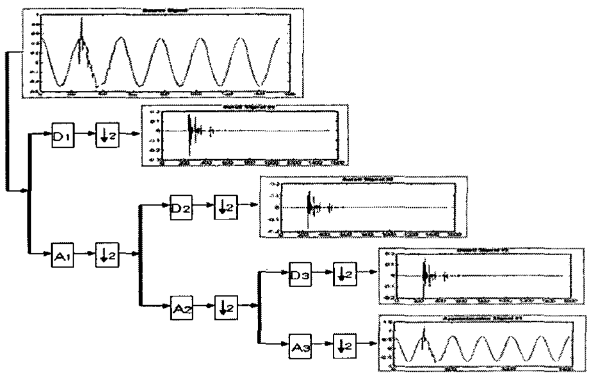


Fig. 1 DWT of short-duration disturbances

3. Neural Networks

Neural networks with one or more hidden layers are called multilayer neural networks or multilayer perceptrons (MLP) [6]. The multilayer neural network has been studied for a long time and has been applied to solve various problems. It is constructed by an input layer, a hidden layer, and an output layer as shown in Fig. 2. Normally, each hidden layer of the network uses the same type of activation function. The output activation function is either sigmoidal or linear, and there are weights between each layer. Choosing the appropriate activation functions and training weights in the next stage is necessary for obtaining positive results.

The back-propagation (BP) is a general method for iteratively solving a multilayer perceptron's weight and biases. The chain rule used in deriving the BP algorithm necessitates the computation of the derivative of the activation functions. In this paper, the hyperbolic tangent function is used as in the following Eq. 5.

$$Tanh \qquad y(I) = \frac{e^{\alpha I} - e^{-\alpha I}}{e^{\alpha I} + e^{-\alpha I}} \quad (5)$$

In the above equation, α is the slope parameter. Usually alpha is chosen as 1 but other slopes can be used. This formulation for the derivative makes the computation of the gradient more efficient since output $\Phi(I)$ has already been calculated in the forward pass.

The BP algorithm is an optimization technique designed to minimize the objective function [7]. The most commonly used objective function is the squared error function as defined in Eq. 6.

$$\varepsilon^2 = [T_q - \Phi_{qk}]^2 \quad (6)$$

The network syntax is defined and shown in Fig. 2. The neural networks are composed of 3 layers. In the notation, x, w, I, and Φ are described respectively as follows:

x = input value
w = weight value
I = internal activation
Φ = neuron output

The output for the two layer network, using the logistic activation function in both layers, can be calculated from Eq. 7.

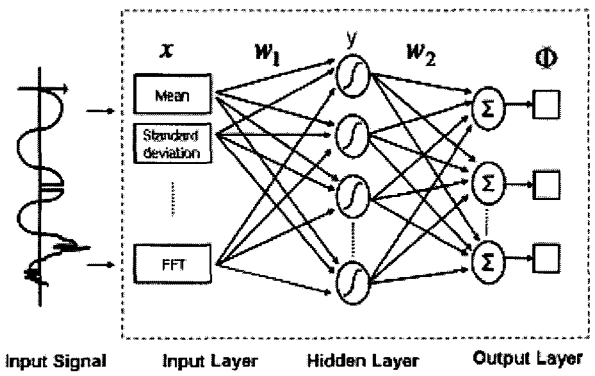


Fig. 2 Block diagram of MLP neural network

$$\Phi = \sum \{w_2 \times [y \sum (w_1 \times x + b_1)] + b_2\} \tag{7}$$

w_1 = first layer weight matrix
w_2 = second layer weight matrix
b_1 = first layer bias vector
b_2 = second layer bias vector

Equation 8 is a more compact representation of the results calculated by substituting all bias vectors, $b_1 = b_2 = 0$.

$$\Phi = \sum \{w_2 \times [y \sum (w_1 \times x)]\} \tag{8}$$

The construction of the firmware algorithm flow for an auto-classifying system is presented in Fig. 3. Input features of the input layer are calculated by the wavelet transform form input signals. The system detects PQ problems using the wavelet transform and calculates the features to classify them.

4. Feature Extraction

In order to recognize the types of disturbances more effectively, the dimensions of the feature vectors should

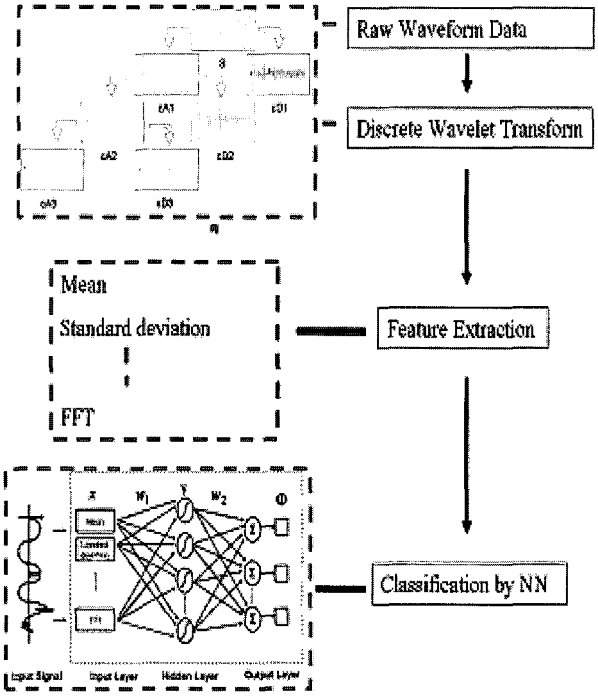


Fig. 3 Block diagram of MLP neural network

be reduced. The most useful features must be extracted first from the coefficients for reducing the dimension of the feature vectors. Eight features of different power quality events are extracted by using the following formula: mean (μ), standard deviation (σ^2), skewness (g_1), kurtosis (g_2), RMS, form factor (*FF*), crest factor (*CF*), and fast fourier transform (*X(k)*).

$$\mu = Ex_t = \frac{1}{N}\sum_{t=1}^{N} x_t \tag{9}$$

$$\sigma^2 = E(x_t - Ex_t) = \frac{1}{N}\sum_{t=1}^{N}(x_t - \mu)^2 \tag{10}$$

$$g_1 = \sqrt{\frac{1}{6N}}\sum_{t=1}^{N}\left(\frac{x_t - \mu}{\sigma}\right)^3 \tag{11}$$

$$g_1 = \sqrt{\frac{N}{24}}\left\{\frac{1}{N}\sum_{t=1}^{N}\left(\frac{x_t - \mu}{\sigma}\right)^4 - 3\right\} \tag{12}$$

$$rms = \sqrt{\frac{1}{N}\sum_{t=1}^{N} x_t^{\,2}} \tag{13}$$

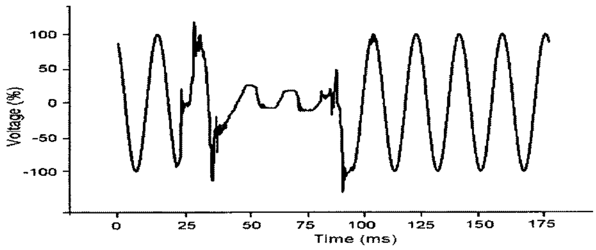
$$FF = \frac{\mu}{rms} \tag{14}$$

$$CF = \frac{peak}{rms} \tag{15}$$

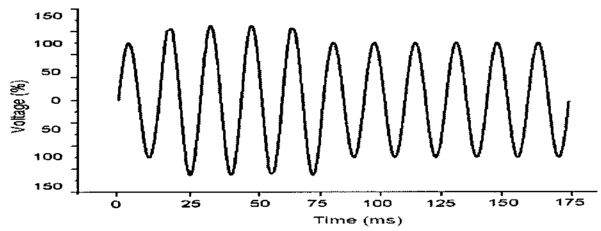
$$X(k) = \sum_{n=1}^{N}\left\{x(n)\times \exp\left(\frac{-j\omega(k-1)(n-1)}{N}\right)\right\} \tag{16}$$

5. Training and Test

The input data signals of the PQ disturbances studied are shown in Fig. 4. Four types of PQ disturbances, such as, sag, swell, transient, and harmonics are considered with normal waveforms for the simulations in this work. Each normal and PQ disturbance group consists of 20 different waveforms. In total, 100 waveforms are used for training and testing.



(a)



(b)

Fig. 4 Example of PQ disturbance input signals: (a) Sag waveform (b) Swell waveform

Figure 6 shows the software flowchart for the neural network's training. The MLP neural network is trained about 20,000 times to fix the weight of the neurons. The target value of the root mean square error (RMSE) of the MLP neural network is given as 0.02.

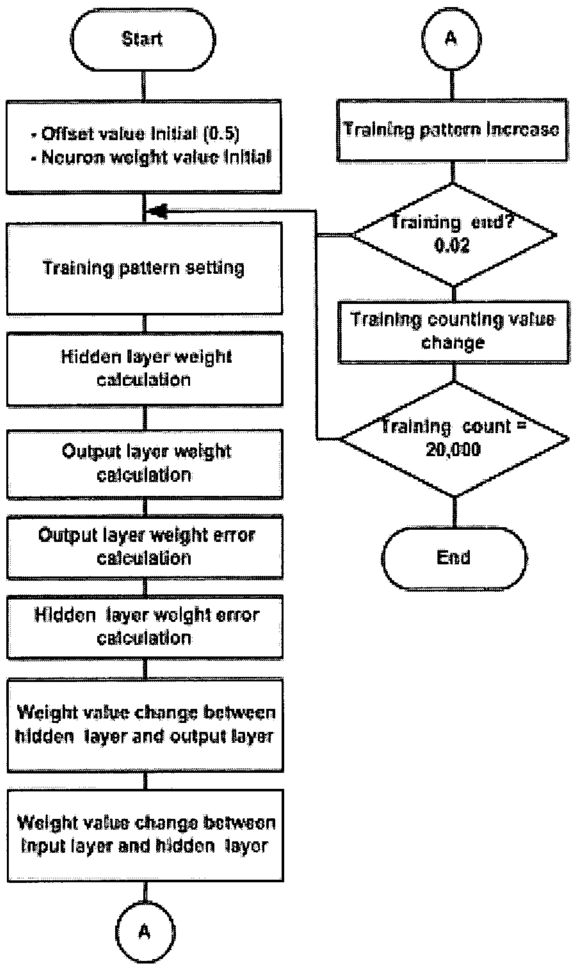


Fig. 5 Simulation Flowchart of MLP network

As an example of PQ monitoring and classification, the results of the training vector and running are shown in Fig. 7 through the neural network training. The BP algorithm is used as the training weights of the hidden layer of the MLP neural network.

Power quality disturbances such as normal (Class 1), sag (Class 2), swell (Class 3), transient (Class 4), and harmonics (Class 5) are simulated. Each type is treated as an individual class and assigned a classification identifier from 1 to 5. A total of 100 cases are used for testing, so each disturbance class consists of 20 cases. Classification results can be described in terms of a confusion matrix. The system can correctly classify 95 cases of the 100 pure disturbance cases in the testing set, as shown in Table 1. This means that it has a correct recognition rate at 1 out of 20 cases.

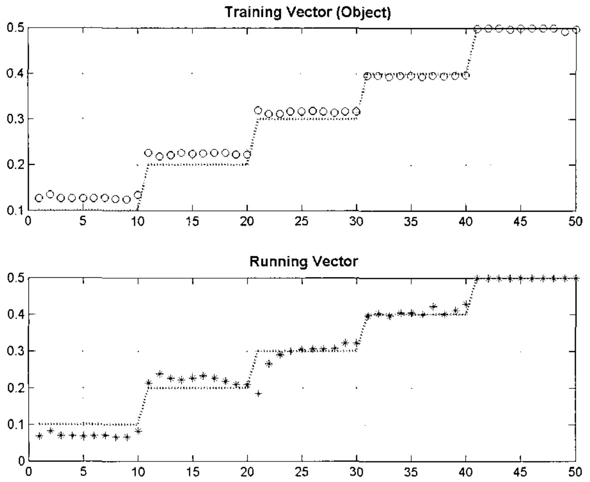


Fig. 6 Graph that display result about transient signal

Table 2 shows the percentage of recognition rate for 5 PQ disturbances, respectively. According to the results of Table 1, it is shown that two PQ disturbances of normal and swell are classified perfectly, but this system loses one sag PQ disturbance and two transient and harmonics PQ disturbances. The recognition rates are 95% and 90%, respectively. Therefore, the total correct classification rates are about 95% as shown in the results on Table 2.

Table 1 Classification Results

True class	Classification Results				
	1	2	3	4	5
1	20	0	0	0	0
2	0	19	0	0	1
3	0	0	20	0	0
4	0	0	0	18	2
5	0	0	0	2	18

Table 2 Percentage of Recognition Rate

PQ Event	Recognition Rate
Normal	100 %
Sag	95 %
Swell	100 %
Transient	90 %
Harmonics	90 %
Total	**95%**

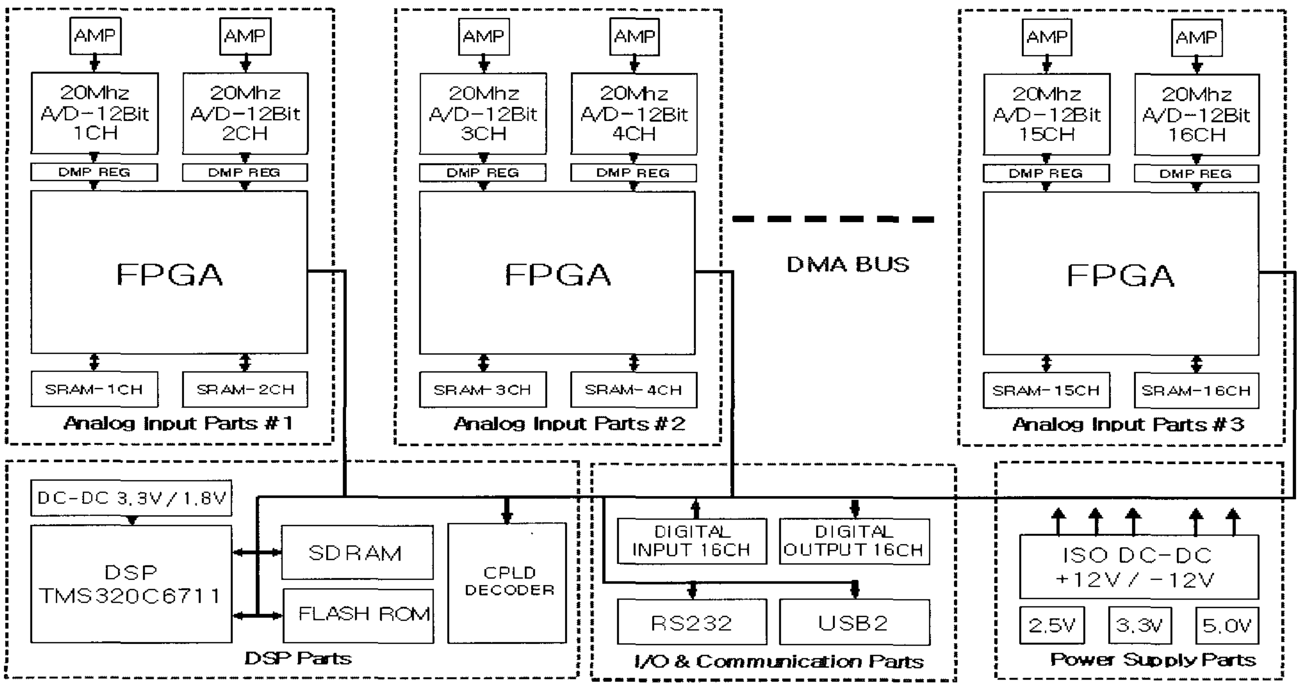


Fig. 7 Block diagram of hardware system

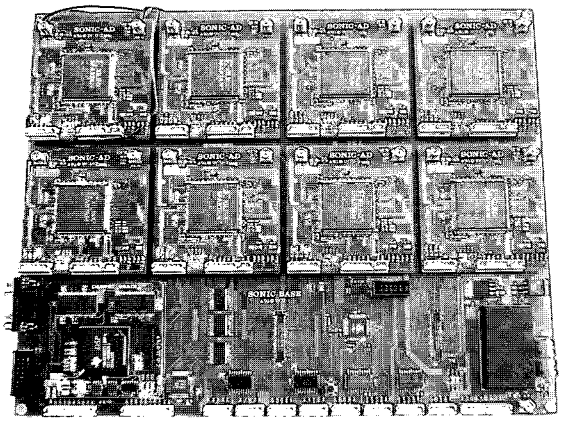


Fig. 8 Picture of the PQDAS board

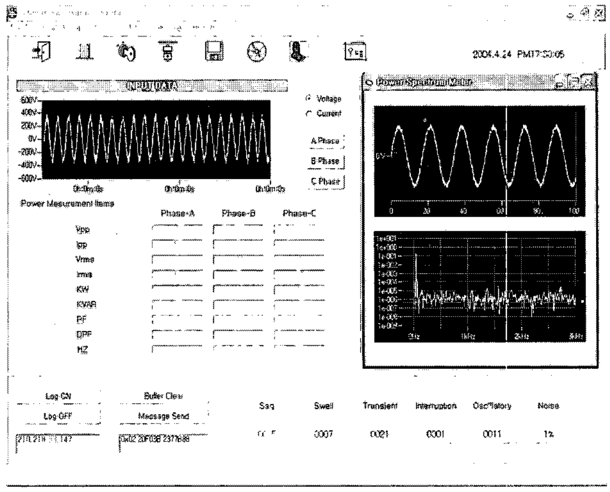


Fig. 9 GUI screen of the system program

6. Power Quality Data Acquisition System

The power quality data acquisition system (PQDAS) is developed for the analysis of PQ disturbances using a wavelet-based neural network in real time. Figure 7 shows the PQDAS hardware used in this work. It consists of a main DSP of TMS320C6711 (150 MHz), 4MB × 16 Flash ROM, 32MB × 32 SDRAM, 16 CH A/D and 1 CH D/A, and RS232C and USB2 ports.

Input signals sensed by the electric current sensors, the high voltage division resistors and voltage sensors are passed through the A/D to the band pass filter. There are 16 input channels and every two channels consist of a FPGA and a high speed 16bit SRAM with 512KB signal data memory. The PQDAS collects the power disturbance data from the 3-phase 4-wire system simultaneously. The PQDAS is designed to detect voltage waveforms from –600 to +600 V range and a current 50 A range without special instruments, but it can be expanded with an additional amplifier and clamps. The wavelet transform and other features are calculated and classified inside the PQDAS under a steady state condition, and the general basic data are sent through the RS232C or USB2 to the main system in real time. Figure 8 shows a picture of the PQDAS board.

The GUI program is installed by using Microsoft Visual Basic. Figure 9 shows the main window of the GUI program. It contains the peak to peak magnitude, RMS value, PF, DPF and event counts in magnitude values and FFT (up to 50th) and event waveform in windows.

PQDAS is a system for detection of transient signals which occur at 1 μs as an impulsive and oscillatory transient.

The operation quality of the PQDAS is verified through the experiments on the PQ disturbance waveforms of the transients. Sag, swell and harmonics are generated by an arbitrary waveform generator and the AC power supply (ELGERSW5250), and tested in this PQDAS system. Figure 10 shows the PQ transient signal waveform presented in IEEE Std. 1159. After generating this kind of waveform by using the arbitrary waveform generator, the classification process is continued on the PQDAS board.

The overall experimental setup of the PQDAS is shown in Fig. 11. Various PQ disturbances generated by the arbitrary waveform generator and AC power supply are precisely classified.

7. Conclusion

In this paper, an auto-classifying system for power quality disturbances using a wavelet-based neural network is proposed. In this system, the db4 discrete wavelet transform and additional features are used for detecting short and medium duration disturbances. In addition, the BP is used as a classifier. PQDAS capability can be used in the design of an automated power disturbance classification system.

The system identifies five kinds of power quality disturbances accurately. From testing and classifying results, it is verified that it has a 95 % true classifying result.

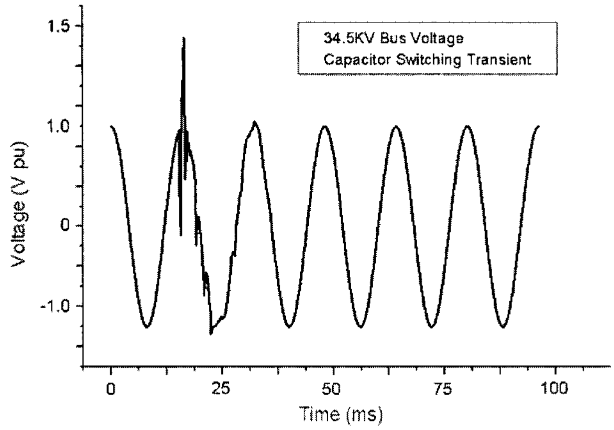


Fig. 10 Low frequency oscillatory transient by capacitor-bank energization (IEEE Std. 1159)

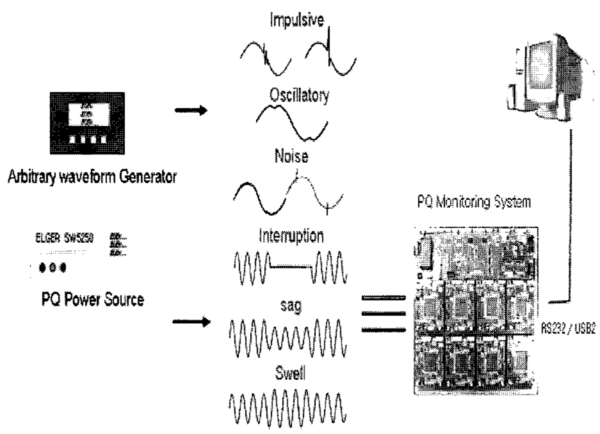


Fig. 11 Block diagram for an experiment

This system includes the technology of data acquisition from real waveforms, analysis using wavelet-based neural networks, and feature extraction and classification in a PQDAS. It saves the features and event waveforms and transmits them through the RS232C or USB2 in real time. Finally, real waveforms and some parameters are described in view of the GUI program.

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