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Profoundly Robust Power Quality Event Classifier Based on Wavelet Transformation and Artificial Intelligence

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Abstract: The issue of power quality is presently perceived as a vital element of an effective electric power system. This is primarily because of the quick increment of loads, which create noise and, in the meantime, are delicate to the noise exhibit in the supply system. Therefore, power quality observing has turn into a vital issue in present day power system. In order to diminish the PQ issue happen in the power system we need to perceive which of kind of disturbances are produced when the system had problem. This paper proposes a novel methodology for the Power Quality (PQ) disturbances classification in view of the wavelet transform and artificial neural networks.The proposed method consists of three important stages they are PQ disturbance generation, feature extraction and classification. In the first stage, the different power quality disturbances are generated by utilizing the algebraic equations based on numerical modelling. In the second stage, the 8-level discrete wavelet transform (DWT) is applied on the generated PQ disturbance signals. Then from each level eight types of features are extracted they are mean, standard deviation, skewness, kurtosis, energy, Shannon entropy, log energy entropy and Renyi's entropy. These extracted features are given to the artificial neural network for training and based on these features PQ disturbances are classified and identified. Experimental result indicates that the proposed method has high enriched performance and best method suitable for power quality event classification.

Key words: Power Quality · Multi-resolution analysis · Discrete Wavelet Transform · Artificial neural network · Disturbances · Feature Extraction

INTRODUCTION

In the industrialized world, electric power systems have get to be contaminated with undesirable deviations in the voltage and current signal. Power Quality (PQ) problems [1] are fundamentally because of ceaselessly expanding sources of aggravations that happen in interconnected power grids, which contain extensive quantities of power sources, transmission lines, transformers and loads. Moreover, such systems are presented to ecological unsettling influences like lightning strikes. Besides, nonlinear power electronic loads, for example, converter driven hardware have turn out to be progressively regular in power framework. Low quality [2] is ascribed because of the different power line unsettling influences. In short, PQ issues can bring about system hardware breakdown; programmable logic controller controls and memory glitch of delicate loads, for example, PC, programmable logic controller controls, protection and transferring gear; and inconsistent operation of electronic controls [3].

Along these lines, it is important to screen these disturbances. Continuousmonitoring is obliged in view of the expanding interest of clean power [4-6] and monitoring standards [7]. With the expanding utilization of modern apparatus and computerization in electrical power systems, PQ disturbances and their programmed investigation are getting to be testing issues for power

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engineers [8]. PQ disturbances are recognized amid observing by the exceedance of a characterized threshold and are described by a set of proper parameters, including rms or peak voltage and length of time, for every disturbance occasion [9]. Common sorts of disturbances incorporate voltage sag, swell, interference, flicker, harmonics, intermittent transient and a few sorts of complex unsettling influences. PQ disturbances intrude on touchy assembling gadgets and produce genuine results. To enhance PQ, the disturbances ought to first be characterized, yet distinguishing and controlling PQ disturbances with short times and numerous sorts are convoluted tasks [10]. There is an emerging requisite to develop PQ monitoring methods that can classify the prospective sources of disturbances.

The established significant steps for classification of both PQ events and PQ disturbances are feature extraction and classification that establish a pattern recognition procedure. In first group of classification called PQ disturbance [11, 12]. The works is rich in relations of schemes for the classification of PQ issues. In this group, the identified disturbances are characterized in various regular classes, for example, voltage swells, voltage sags and intrusions and so on. In second group of the classification called event classification, the hidden reasons for disturbances, for example, faults, transformer energizing and capacitor switching are characterized [13, 14]. Feature extraction is normally called upon when there is a necessity to extract or concentrate particular data from the crude information, which regularly in power systems are the voltage and current waveform. The feature extraction of signals can be executed by direct procedures, for example, the RMS rate [15] of the rare specimens, or transformation methods, for example, the Fourier transform [16], wavelet transform [17] and S-transform [18]. The wavelet transform can be utilized to recognize power quality issues and distinguish their events regarding time, creating information in both time and frequency spaces through multiresolution examination. Fourier transform can be utilized with wavelet transform to concentrate on features that describe power quality events from voltage or current waveforms [19]. In classification stage, feature vectors that are acquired from the transformation procedure is connected the classifier technique, for example, support vector machines [17, 15], artificial neural network [20], expert system [21] etc.

The remaining part of this paper is structured as follows. Section 2 gives the important researches related to our proposed method. Section 3 gives how power quality disturbance are generated as well as the concept of wavelet transform with feature extraction and classification. The implementation and results of our proposed method are given in section 4 followed by conclusion in section 5.

Related Works: Some of the recent research works done in classification of power quality events are mentioned below:

Kumar R *et al.* [22] have dealt with a modified technique for the recognition of single stage and multiple PQ (Power Quality) disturbances. An algorithm based on ST (Stock well's-Transform) and ANN (Artificial Neural Network) based classifier and a rule based decision tree was proposed. An analysis and classification of single stage PQ disturbances consists of both events and variations such as sag, swell, interruption, harmonics, transients, notch, spike and flicker are presented. Moreover, proposed algorithm was applied on multiple PQ disturbances such as harmonics with sag, swell, flicker and interruption. A data base of these PQ disturbances based on IEEE-1159 standard was generated in MATLAB for simulation studies. The proposed algorithm extracted significant features of various PQ disturbances using S-transform and used as an input to this hybrid classifier for the classification of PQ disturbances. Satisfactory results of effective recognition and classification of PQ disturbances was obtained with proposed algorithm.

Valtierra-Rodriguez M. *et al.* [23] have proposed a new dual neural-network-based methodology to detect and classify single and combined PQ disturbances, consisting, on the one hand, of an adaptive linear network for harmonic and interharmonic estimation that allowed computing the root-mean-square voltage and total harmonic distortion indices. With these indices, it was possible to detect and classify sags, swells, outages and harmonics-interharmonics. On the other hand, a Feedforward neural network for pattern recognition using the horizontal and vertical histograms of a specific voltage waveform classifies spikes, notching, flicker and oscillatory transients. The combination of the aforementioned neural network allowed the detection and classification of all the aforementioned disturbances even they appear simultaneously. An experiment under real operating conditions was carried out and tested the proposed methodology.

Eris¸ti H. and Demir Y. [24] have presented a new approach for the classification of power quality events. Also, power quality disturbances, which occur in each phase of the power system after a fault event, classified with the proposed system. In the proposed recognition system, three-phase voltage signals are used in order to identify the type of power quality events. Three-phase voltage signals are subjected to normalization and segmentation processes. A wavelet transform method was used in order to obtain the distinctive features of event signals. An efficient feature vector, which represented the distinctive characteristics of three-phase event voltage signals and reduced data size, was extracted by applying the two-stage feature extraction process. Power quality event types are determined by using a support vector machine classifier. At the last stage of intelligent recognition system, types of power quality disturbances regarding each fault event are identified. Real power system data are evaluatedfor performance of the proposed approach.

Ray P.K. *et al.* [25] have presented the classification of PQ disturbances caused not only by change in load but also by environmental characteristics such as change in solar insolation and wind speed. Various forms of sag and swell occurrences caused by change in load, variation in wind speed and solar insolation are considered in the study. Ten different statistical features extracted through S-transform are used in the classification step. The PQ disturbances in terms of statistical features are classified distinctly by use of modular probabilistic neural network (MPNN), support vector machines (SVMs) and least square support vector machines (LS-SVMs) techniques. The classification study was further supported by experimental signals obtained on a prototype setup of wind energy system and PV system. The accuracy and reliability of classification techniques was also assessed on signals corrupted with noise.

Ozgonenel O. *et al.* [26] have presented the performance evaluation of support vector machine (SVM) with one against all (OAA) and different classification methods for power quality monitoring. The first aim of this study was to investigate EEMD (ensemble empirical mode decomposition) performance and to compare it with classical EMD (empirical mode decomposition) for feature vector extraction and selection of power quality disturbances. Feature vectors are extracted from the sampled power signals with the Hilbert Huang Transform (HHT) technique. HHT was a combination of EEMD and Hilbert transform (HT). The outputs of HHT are intrinsic mode functions (IMFs), instantaneous frequency (IF) and instantaneous amplitude (IA). Characteristic features are obtained from first IMFs, IF and IA. The ten features i.e., the mean, standard deviation, singular values, maxima and minima of both IF and IA are then calculated. These features are normalized along with the inputs of SVM and other classifiers.

Proposed Methodology for Power Quality Event Classification: This paper presents a novel methodology for power quality event classification technique utilizing wavelet transform and artificial neural networks. Initially power quality disturbance signals are produced by utilizing the algebraic equations based on numerical modelling. The benefit of utilizing algebraic equations is that it presents the flexibility of covering an extensive range of variables. Then the multiresolution analysis technique of wavelet transform is employed on the distorted signals to extract different features like mean, standard deviation, skewness, kurtosisenergy, Shannon entropy, log energy entropy and Renyi's entropy at different levels of resolution. Then the extracted features are used for training of artificial neural network classifier and then based on these features the power quality events are classified. The process flow of the proposed method is shown in Figure 1.

Power Quality Disturbance Generation: A data base of various PQ disturbances is needed for the recognition of these disturbances. Manufactured data of PQ disturbances is profitable in evaluating the speculation capacity of the classifier so it is accepted and generally utilized. The accessibility of genuine PQ disturbance data is restricted as it obliges a long checking time all the while at number of areas with vulnerability in the event of the PQ events. Hence, numerical models of the PQ disturbances are utilized for the simulation purpose in MATLAB. These simulated PQ disturbances got from numerical models nearly delineate the continuous data and can be created according to the universal norms. Numerous PQ disturbances are created from summation of numerical model of single phase PQ disturbances. Numerical modelling of single and various PQ disturbances [22] is displayed in Table 1. The power quality disturbances generated are sag, swell, interruption, flicker, oscillatory transient, harmonics, sag with harmonics, swell with harmonics, flicker with harmonics and interruption with harmonics.

Feature Extraction: In this process, the characteristic features for per event are extracted by utilizing Wavelet Transform and feature extraction method. The wavelet coefficients, detail and approximation, for each event are acquired by applying an 8-level multiresolution analysis. These coefficients contain effective feature data for event category. Eight types of features like Mean, Standard Deviation, Skewness, Kurtosis, energy, Shannon entropy, log energy entropy and Renyi's entropy are applied to the detail coefficients at each levels.

Fig. 1: Process flow of proposed method

Table 1: Numerical Modelling of Simulated Power Quality Disturbances

PQ Events	Numerical Model	Parameters
Sine Wave	$V(t) = A\sin(\omega t)$	$A = 1(pu)$, $\omega = 2\pi 50\ rad/\sec$
Sag	$V(t) = (1-\alpha(u(t-t_1) - u(t-t_2)))\sin\omega t$	$0.1 \le \alpha \le 0.9$, $T \le t_2 - t_1 \le 9T$
Swell	$V(t) = \left(1+\alpha\left(u\left(t-t_1\right)-u\left(t-t_2\right)\right)\right)\sin\omega t$	$0.1 \le \alpha \le 0.8, T \le t_2 - t_1 \le 9T$
Interruption	$V(t) = \left(1-\alpha\left(u\left(t-t_1\right)-u\left(t-t_2\right)\right)\right)\sin\omega t$	$0.9 \le \alpha \le 1.0, T \le t_2 - t_1 \le 9T$
Flicker	$V(t) = \left(1+\alpha_f \sin\left(\beta\omega t\right)\right)\sin\omega t$	$0.1 \le \alpha_f \le 0.2, 5 \le \beta \le 20Hz$
Oscillatory Transient	$V(t) = \sin\left(\omega t\right) + \alpha e^{\frac{(t-t_1)}{\tau}} \sin\omega_n\left(t-t_1\right)\left\{u\left(t_2\right)-u\left(t_1\right)\right\}$	$0.1 \le \alpha \le 0.8, 0.5T \le t_2 - t_1 \le 3T$, $8ms \le r \le 40ms, 300 \le f_n \le 900Hz$
Harmonics	$V(t) = \alpha_1\sin\left(\omega t\right)+\alpha_3\sin\left(3\omega t\right)+\alpha_5\sin\left(5\omega t\right) +\alpha_7\sin\left(7\omega t\right)$	$0.05 \le \alpha_3, \alpha_5, \alpha_7 \le 0.15, \sum \alpha_i^2 = 1$
Sag with harmonics	$V(t) = \left(1-\alpha\left(u\left(t-t_1\right)-u\left(t-t_2\right)\right)\right) \begin{pmatrix}\alpha_1\sin\left(\omega t\right)+\alpha_3\sin\left(3\omega t\right)+\alpha_5\sin\left(5\omega t\right)\\ +\alpha_7\sin\left(7\omega t\right)\end{pmatrix}$	$0.1 \le \alpha \le 0.9, T \le t_2 - t_1 \le 9T$ $0.05 \le \alpha_3, \alpha_5, \alpha_7 \le 0.15, \sum \alpha_i^2 = 1$
Swell with harmonics	$V(t) = \left(1+\alpha\left(u\left(t-t_1\right)-u\left(t-t_2\right)\right)\right) \begin{pmatrix}\alpha_1\sin\left(\omega t\right)+\alpha_3\sin\left(3\omega t\right)+\alpha_5\sin\left(5\omega t\right)\\ +\alpha_7\sin\left(7\omega t\right)\end{pmatrix}$	$1.1 \le \alpha \le 1.8, T \le t_2 - t_1 \le 9T$ $0.05 \le \alpha_3, \alpha_5, \alpha_7 \le 0.15, \sum \alpha_i^2 = 1$
Flicker with harmonics	$V(t) = \left(1+\alpha_f \sin\left(\beta\omega t\right)\right) \begin{pmatrix}\alpha_1\sin\left(\omega t\right)+\alpha_3\sin\left(3\omega t\right)+\alpha_5\sin\left(5\omega t\right)\\ +\alpha_7\sin\left(7\omega t\right)\end{pmatrix}$	$0.1 \le \alpha_f \le 0.2, 5 \le \beta \le 20Hz$ $0.05 \le \alpha_3, \alpha_5, \alpha_7 \le 0.15, \sum \alpha_i^2 = 1$
Interruption with harmonics	$V(t) = \left(1-\alpha\left(u\left(t-t_1\right)-u\left(t-t_2\right)\right)\right) \begin{pmatrix}\alpha_1\sin\left(\omega t\right)+\alpha_3\sin\left(3\omega t\right)+\alpha_5\sin\left(5\omega t\right)\\ +\alpha_7\sin\left(7\omega t\right)\end{pmatrix}$	$0.9 \le \alpha \le 1.0, T \le t_2 - t_1 \le 9T$ $0.05 \le \alpha_3, \alpha_5, \alpha_7 \le 0.15, \sum \alpha_i^2 = 1$

Wavelet Transform: Wavelet transform are utilized in different fields of Engineering because it has the ability to analyse stationary as well as non-stationary disturbances in signals. It has two main advantages they are it considerably reduce the dimensionality of the examined data for n levels of decomposition and this method retains all the essential characteristics of the original waveform for analysis. The wavelet transform can be continuous wavelet transform or discrete wavelet transform. In most of the real-world applications, the discrete wavelet transform (DWT) is generallyutilized. The DWT is generallyexecuted by Mallat's algorithm. DWT utilizes low pass filter and high pass filter to split the frequency band of the input signal $f(k)$ in particular low and high frequency elements into octave bands. The low pass filter $l(k)$ is obtained from the scaling function and high pass filter $h(k)$ is obtained from both wavelet function and scaling functions which is given by:

Wavelet Function, $$\psi(k) = \sqrt{2}\sum_n h(k)\phi\left(2k-n\right) \quad (1)$$

Scaling Function, $$\phi\left(k\right) = \sqrt{2}\sum_n l(k)\phi\left(2k-n\right) \quad (2)$$

where n represents the number of samples which is an integer. While the low pass filter generates approximations A_j and high pass filter generates details D_j of the decomposition. The connection between approximation coefficients and detail coefficients in between two levels is given by;

$$A_{j+1}(k) = \sum_{n} l\left(n-2k\right) A_j(n) \tag{3}$$

$$D_{j+1}(k) = \sum_{n} h\left(n-2k\right) A_j(n) \tag{4}$$

where j represents level of frequency band.The wavelet transform multiresolution analysis is taking into account of decomposition of the input original signal into different signals at numerous levels of determination. In the first place, the input signal is gone through the two filters creating detail D_1 and approximate A_1 coefficients for j=1. At that point down sampling by a component of 2, then the approximate coefficients A_1 are gone through the same filters again to acquire the coefficients of j=2. Of course after down sampling, the approximate coefficients are then filtered again to get the next level of coefficients. This operation of filtering proceeds thusly. A given signal is extended in term of its orthogonal premise of scaling and wavelet functions. Generally, it is characterized by one situated of scaling coefficients and one or a few arrangements of wavelet coefficients which is given by;

$$f(k) = \sum_{n} A_1(n)\phi(k-n) + \sum_{n}\sum_{j=1} D_j(n) 2^{-j/2} \psi\left(2^j k - n\right) \tag{5}$$

There are numerous wavelet functions called as mother wavelet. The decision of mother wavelet is imperative on the grounds that diverse sorts of mother wavelet has distinctive properties. In our proposed method we have chosen db4 wavelet which is broadly utilized as a part of electromagnetic transient examination [27]. The detail coefficient having a place with every levels is utilized to extract the features. In our technique, for each PQ disturbance signal, statistical features like mean, standard deviation, skewness, kurtosis, energy, Shannon entropy, log energy entropy and Renyi's entropy are extracted from the detail coefficients.

Mean: The mean is represented by μ which provides the average value of a signal. It is produced by adding all samples together and divide by N which is given by;

Mean, $$\mu_i = \frac{1}{N}\sum_{j=1}^{N} C_{ij} \tag{6}$$

Standard Deviation: The standard deviation is alike to the average deviation, excluding the averaging is done with power in its place of amplitude. This is attained by squaring each of the deviations before taking the average. The mathematical form is given by;

Standard Deviation, $$\sigma_i = \sqrt{\left(\frac{1}{N}\sum_{j=1}^{N}\left(C_{ij}-\mu_i\right)^2\right)} \tag{7}$$

Skewness: Skewness is a measure of symmetry, or more precisely, the lack of symmetry. A distribution, or data set, is symmetric if it looks the same to the left and right of the center point. It is given by

Skewness, $$\gamma_i = \sqrt{\frac{1}{6N}}\sum_{j=1}^{N}\left(\frac{C_{ij}-\mu_i}{\sigma_i}\right)^3 \tag{8}$$

Kurtosis: Kurtosis is a measure of whether the data are peaked or flat relative to a normal distribution. That is, data sets with high kurtosis tend to have a distinct peak near the mean, decline rather rapidly and have heavy tails. Data sets with low kurtosis tend to have a flat top near the mean rather than a sharp peak. A uniform distribution would be the extreme case. The mathematical form is given by;

Kurtosis, $$K_i = \sqrt{\frac{N}{24}}\left(\frac{1}{N}\sum_{j=1}^{N}\left(\frac{C_{ij}-\mu_i}{\sigma_i}\right)^4 - 3\right) \tag{9}$$

Energy: Energy of the signal is given by

Energy $$E_i = \sum_{j=1}^{N}\left|C_{ij}\right|^2 \tag{10}$$

Shannon Entropy: Shannonentropy gives the measure of randomness. The mathematical form is given by;

Shannon Entropy $$SE_i = -\sum_{j=1}^{N} C_{ij}^2 \log\left(C_{ij}\right)^2 \tag{11}$$

Log Energy Entropy: Log energy entropy is also type used in signal processing techniques and its mathematical form is given by;

Log energy entropy $$LEE_i = \sum_{j=1}^{N} \log\left(C_{ij}^2\right) \tag{12}$$

Renyi's Entropy: Renyi's Entropy is non-shannon measure of entropy. Its mathematical form is given by;

Renyi's Entropy $$RE_i = \frac{1}{1-\alpha}\log\left(\sum_{j=1}^{N}\left(C_{ij}^{\alpha}\right)^2\right) \quad \alpha \neq 1, \alpha > 0 \tag{13}$$

where i=1, 2… l is the decomposition level and N denotes number of coefficients of detail at each decomposition level. And C represents detail coefficients at each level of decomposition. Thus, aneight dimensional feature vector is made for 8 level wavelet decomposition. The feature vector is indicated by;

$$\text{Features} = \begin{bmatrix} \mu_1,\mu_2,....,\mu_8 \cdots \sigma_1,\sigma_2,....,\sigma_8 \cdots \gamma_1,\gamma_2,...,\gamma_8 \cdots K_1,K_2,...,K_8 \cdots E_1,E_2,...,E_8 \\ \cdots SE_1,SE_2,...,SE_8 \cdots LEE_1,LEE_2,...,LEE_8 \cdots RE_1,RE_2,...,RE_8 \end{bmatrix} \tag{14}$$

Classification: An artificial neural network (ANN) is a data preparing ideal model that is motivated by the natural sensory systems, for example, the brain, process data etc. The key component of this standard is the novel structure of the data handling framework made out of an extensive number of profoundly interconnected processing components (neurons) working as one to tackle the particular issues. Neural network is a non-linear, information driven self-versatile system and is a promising instrument for classification. These can alter themselves to the information with no express particular of practical or distributional structure for the fundamental model. The neural network recognizes a given pattern by experience which is obtained amid the learning ortraining stage when an arrangement of limited illustrations is displayed to the network. ANNs are not customized in the routine sense; maybe they figure out how to tackle the issue through interconnections with environment.

The ANN consists of a single input layer and a single output layer in addition to one or more hidden layers. All nodes are composed of neurons except the input layer. The number of nodes in each layer varies depending on the problem. The complexity of the architecture of the network is dependent upon the number of hidden layers and nodes. Training an ANN is to find a set of weights that would give desired values at the output when presented with different patterns at its input. The two main process of an ANN is training and testing. Figure 2 shows the structure of artificial neural network [28-31].

The proposed neural network consists of 64 input neurons they are feature vector obtained at the feature extraction process, one output neuron and M hidden units (M=5). First, the input data is transmitted to the hidden layer and then, to the output layer. This is called the forward pass of the back propagation algorithm. Each node in the hidden layer gets input from the input layer, which are multiplexed with appropriate weights and summed. The output of the neural network is obtained by the equation (15) given below.

$$C = \sum_{m=1}^{M} \frac{w_m^O}{1+\exp\left[-\sum_{n=1}^{N} F_n w_{nm}^I\right]} \tag{15}$$

where C represents final output, m represents hidden neurons, n represents input neurons, w_m^O represents weights assigned between hidden neuron and output neuron, w_m^I represents weights assigned between input neuron and hidden neuron and F_n is the nth input value.The output of the hidden node is the non-linear transformation of the resulting sum. Same process is followed in the output layer. The output values from the output layer are compared with target values and the learning error rate for the neural network is calculated, which is given in equation (16).

$$e_l = \frac{1}{2}(R-O)^2 \tag{16}$$

where e_l represents l^{th} learning error, R represents actual output and O represents obtained output. The error between the neurons is transmitted back to the hidden layer. This is called the backward pass of the back propagation algorithm. Then the training is repeated for some other training dataset by changing the weights of the neural network. The error can be minimized using back propagation algorithm. Initially the weights are assigned to hidden layer neurons. The input layer has a constant weight, whereas the weights for output layer neurons are chosen randomly. Then, the output is calculated using equation (15). The back propagation error (BP_{error}) is calculated by using equation (17).

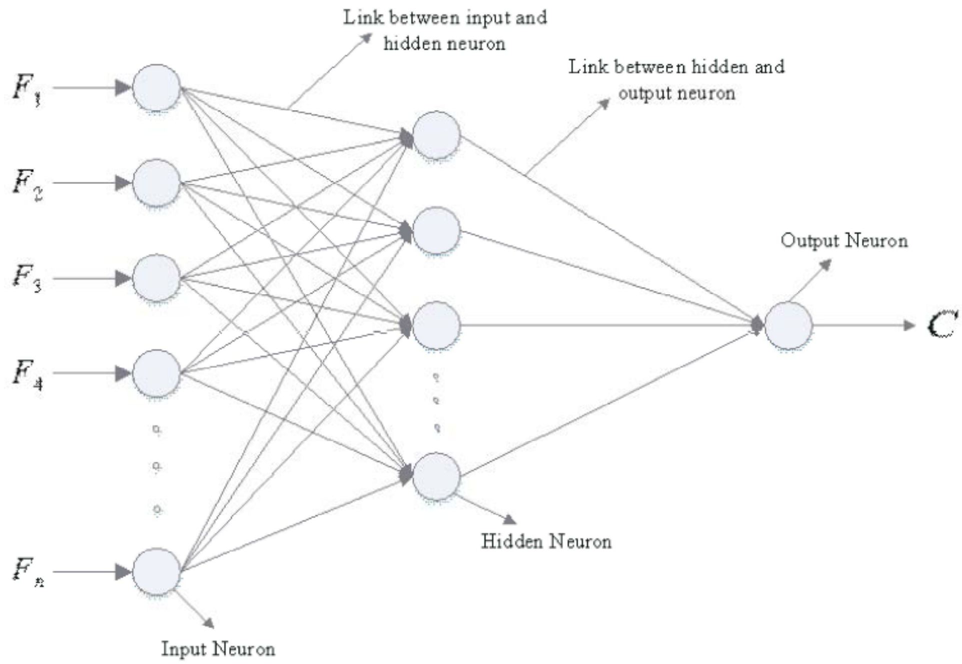

Fig. 2: Structure of neural network

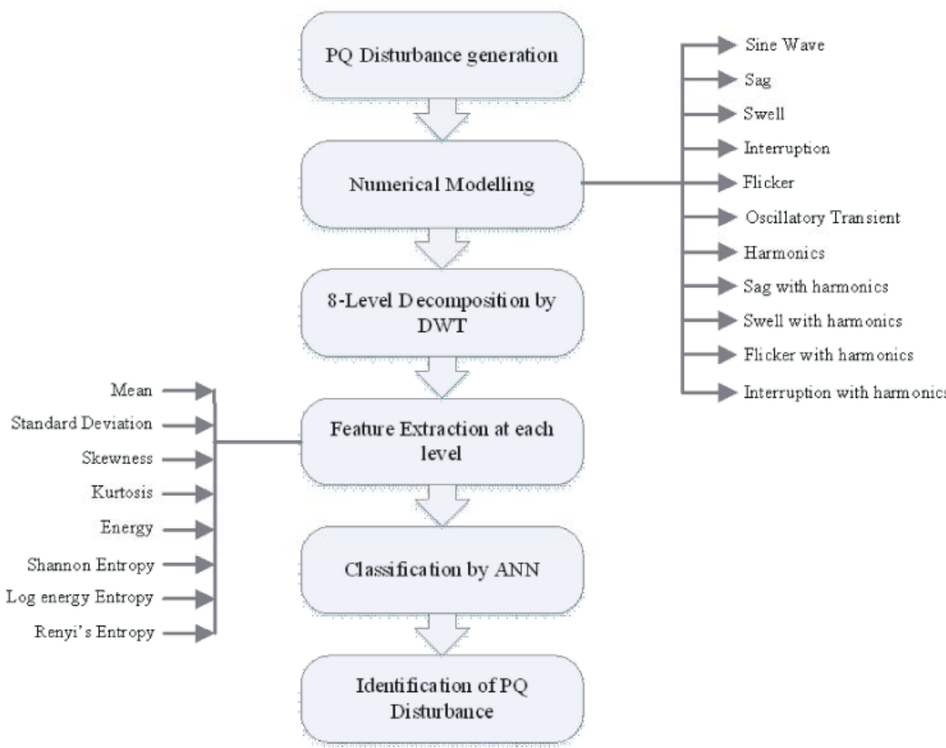

Fig. 3: Structure of Proposed System

$$BP_{error} = \sum_{l=1}^{k} e_l \tag{17}$$

The weight deviation in the hidden neurons is calculated by using below equation.

$$\Delta w = BP_{error} \cdot \gamma \cdot \delta \tag{18}$$

where Δw is the weight deviation, γ is the learning rate, which can be chosen between 0.2 to 0.5 and δ represents the average of hidden neurons output which is given by;

$$\delta = \frac{1}{T}\sum_{i=1}^{T} H_i = \frac{1}{T}\sum_{i=1}^{T}\left(\frac{1}{1+\exp\left(-\sum_{n=1}^{N} F_n w_{nm}^{I}\right)}\right) \tag{19}$$

where, δ is the average of hidden neurons output, N represents total number of input neurons, T represents total number of training samples and H_i is the ith activation output at input side. The new weights is calculated by using equation (20) which is given below.

$$w_{new} = w + \Delta w \tag{20}$$

where, w_{new} is the new weight and w is the current weight. This process is repeated until the $Bp_{error} < 0.1$. If the Back propagation error reaches a minimum value, then artificial neural network is ready for classification.

The overall structure of the proposed system is shown in Figure 3.

From Figure 3, we can clearly understand the concept of proposed system for PQ event classification. Initially, the PQ disturbances are generated by using numerical modelling of algebraic equations. Then 8-level DWT is applied to the generated signals. Then at each level eight types of features are extracted they are mean, standard deviation, skewness, kurtosis, energy, Shannon entropy, log energy entropy and Renyi's entropy. Then these features are trained in artificial neural network and finally type of PQ disturbance is identified.

RESULTS AND DISCUSSION

The proposed method is implemented in the working platform of MATLAB with the following specification:

Processor	: Intel i5 @ 3GHz
RAM	: 8GB
Operating system	: windows 8
Matlab version	: R2013a

Dissimilar types of power quality disturbances are utilized for classification and the signals are generated using MATLAB. Table 1 gives the signal generation modelling equations and their control parameters. Utilizing the parameters given in Table 1 the training and testing signals can be created in a wide range and the signals thus simulated are very close to the real situation. Total number of signals generated are 2200 signals out of that 1540 signals are used for training purpose and 330 signals are used for testing purpose and remaining 330 signals used for validation. Figure 4-14 shows some the sample signals generated in our proposed system.

Our main goal is to classify the above generated PQ disturbances and identification of single and multiple PQ events. For that, we have considered the following two kinds of test signal for analysis of proposed system. The sample test input single event signal is shown in Figure 15.

Then by applying 8-level DWT decomposition of the test input signal we get the decomposed signal which is shown in Figure 16.

In the next step, we extract eight type of features mean, standard deviation, skewness, kurtosis, energy, Shannon entropy, log energy entropy and Renyi's entropy at each level of the decomposed signal. The feature value are shown in Table 2:

Then these features are given as input to the ANN classifier. By comparing the features obtained in the testing signal with the features already obtained from the training signals. It will produce the output with the type of PQ disturbance which is shown in Figure 17.

From Figure 18, we can the proposed method classifies the single event in order to prove that the proposed method also able to classify multiple power quality event we have considered another type of signal which is shown in Figure 18.

The decomposition signal obtained from 8 level DWT is shown in Figure 19.

Then at each level eight type of features are extracted which is shown in Table 3.

Then these features are given as input to the ANN classifier. The final output of the proposed method is shown in Figure 20.

From these results we can see that the proposed method, effectively classifies or recognizes single as well as multiple power quality events.

Performance Evaluation: The classification results obtained by our proposed method is shown in Table 4 which consists of type of event, number of training signals, number of tested signals and classification accuracy.

Table 2: Features Extracted at each level of the input signal

	Decomposition Levels							
Features	1	2	3	4	5	6	7	8
Mean	-0.015	-0.0172	0.0089	0.0077	0.0073	0.0087	0.0120	0.0056
Standard Deviation	0.4174	0.4054	0.3357	0.3313	0.3305	0.3314	0.3329	0
Skewness	-0.408	-0.4068	0.0924	0.0421	0.0266	0.0179	0.0109	0.0014
Kurtosis	2.4323	2.2886	0.7211	0.8548	0.4211	0.2124	0.1080	0.0026
Energy	7965.8	7841.7	8074.4	7784.8	7642.9	7742.1	7015.3	7011.9
Shannon Entropy	4.4789	4.1278	3.8871	3.8414	3.5678	3.4814	3.1298	3.4578
Log Energy entropy	-0.514	-0.876	-0.899	-0.921	-0.939	-0.949	-0.914	-0.910
Renyi's Entropy	6.9242	6.5147	6.5287	6.1423	5.8794	5.6746	5.6078	5.5547

Table 3: Feature Values at each levels

	Decomposition Levels							
Features	1	2	3	4	5	6	7	8
Mean	-0.028	-0.0291	0.0102	0.0098	0.0081	0.0094	0.0198	0.0079
Standard Deviation	0.3065	0.3943	0.2246	0.2202	0.2204	0.2203	0.2218	0.2145
Skewness	-0.519	-0.5179	0.1035	0.0532	0.0377	0.0280	0.0210	0.0025
Kurtosis	3.5434	3.3997	0.8322	0.9659	0.5322	0.3235	0.2191	0.1137
Energy	6854.7	6730.6	7063.3	6673.7	6531.8	6631.9	6904.2	6900.8
Shannon Entropy	2.2567	2.0056	1.6650	1.6202	1.3456	1.2602	1.0076	1.2356
Log Energy entropy	-0.302	-0.543	-0.566	-0.608	-0.606	-0.616	-0.611	-0.607
Renyi's Entropy	3.6010	3.2014	3.2054	3.0100	2.5461	3.3413	2.3044	3.3314

Table 4: Classification Performance of the Proposed Method

		Classification Accuracy (%)		
Type of Event	No of testing signals	Correctly Classified Signals	Misclassified Signals	Accuracy
Sine	30	30	-	100
Sag	30	29	1	96.7
Swell	30	30	-	100
Interruption	30	30	-	100
Flicker	30	29	1	96.7
Harmonics	30	30	-	100
Oscillatory Transient	30	29	-	96.7
Sag with Harmonics	30	28	2	93.3
Swell with Harmonics	30	30	-	100
Flicker with Harmonics	30	29	-	96.7
Interruption with Harmonics	30	30	-	100

Overall Classification Accuracy = 98.19%

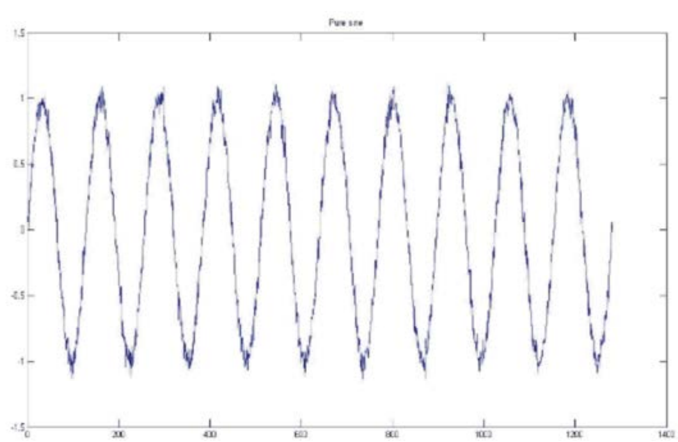

Fig. 4: Pure Sine Wave

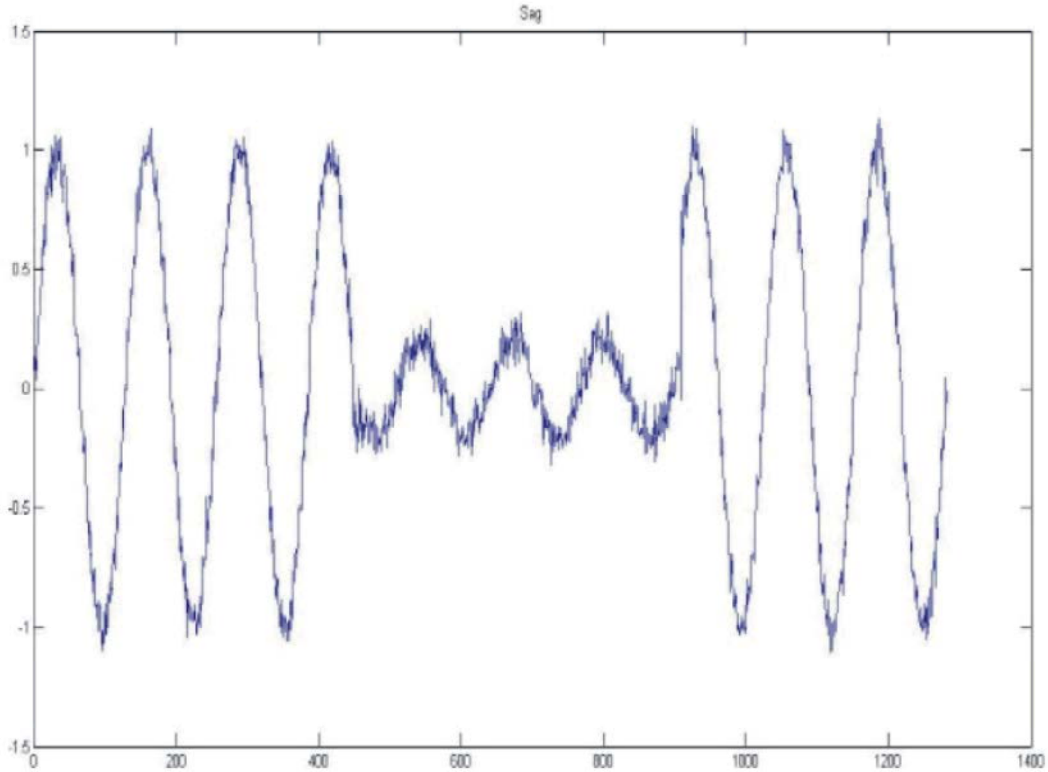

Fig. 5: Sag Wave

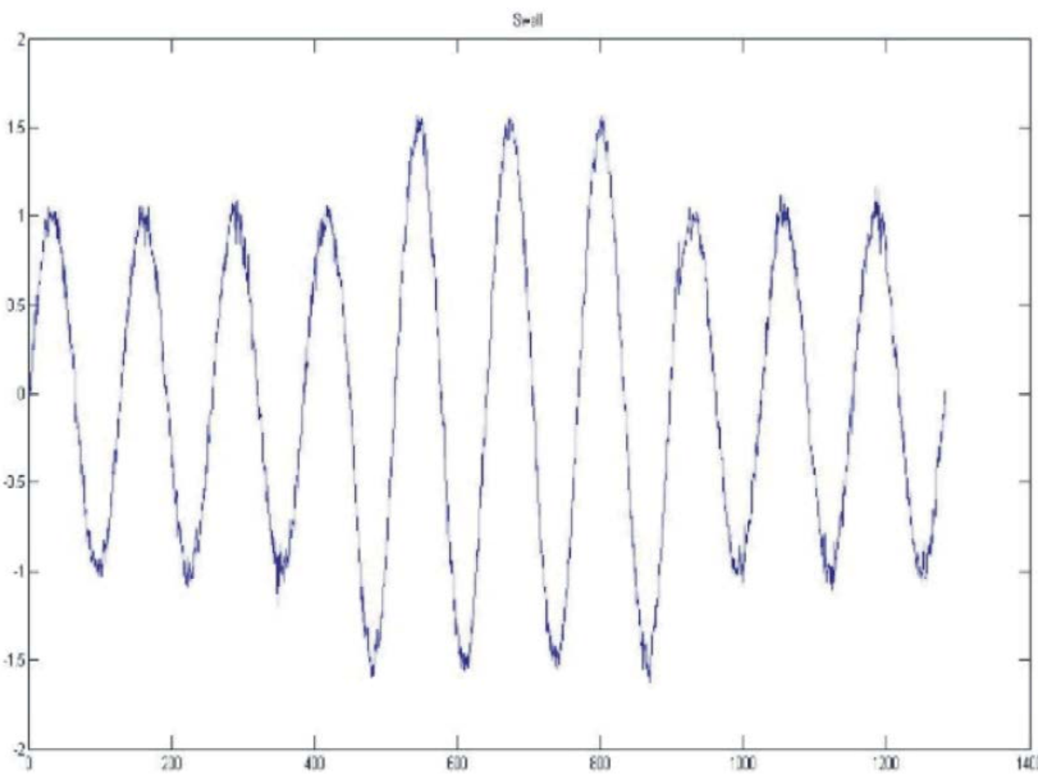

Fig. 6: Swell Wave

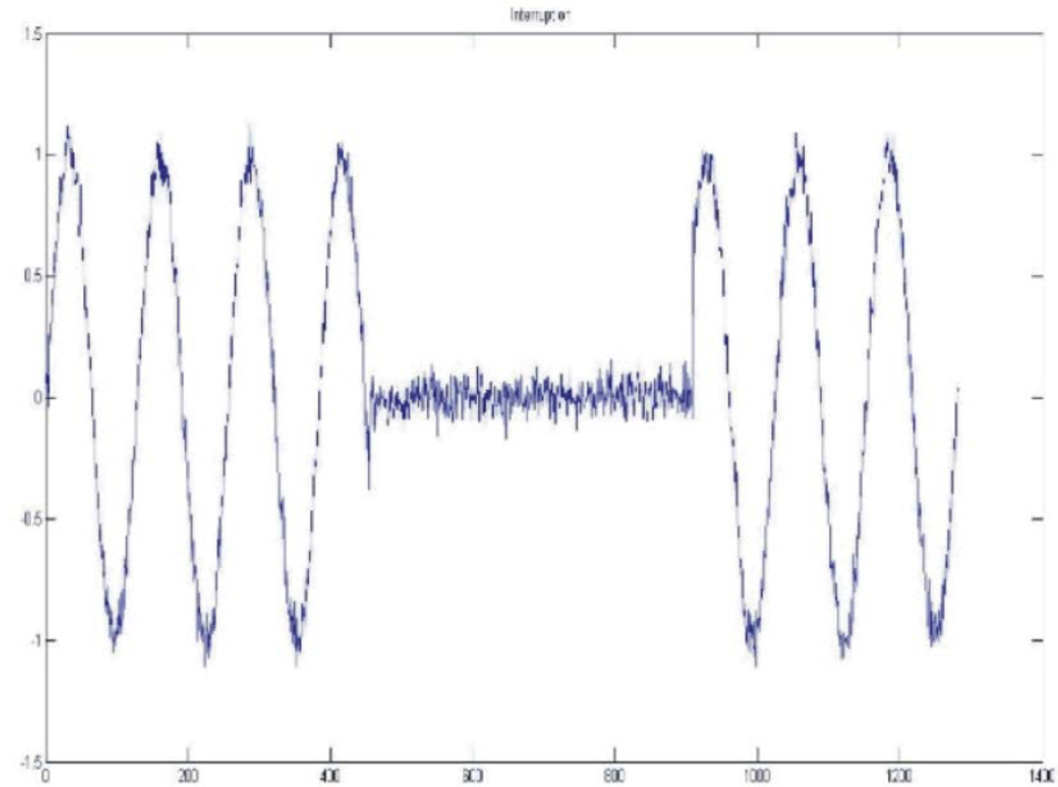

Fig. 7: Interruption Wave

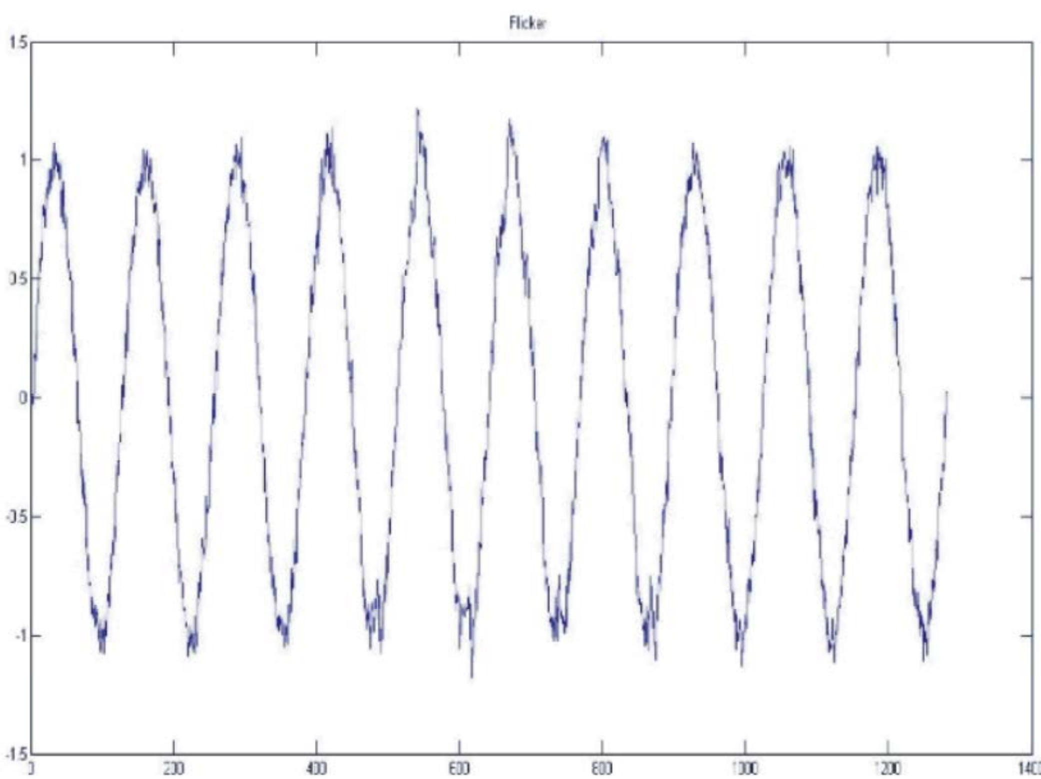

Fig. 8: Flicker Wave

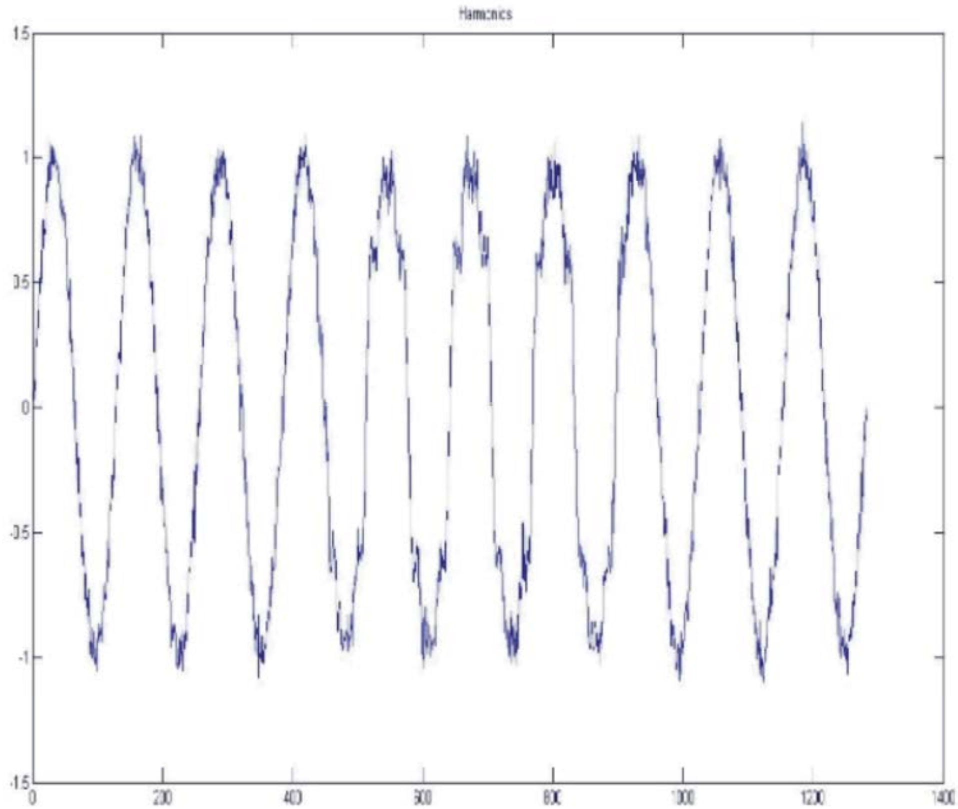

Fig. 9: Harmonics Wave

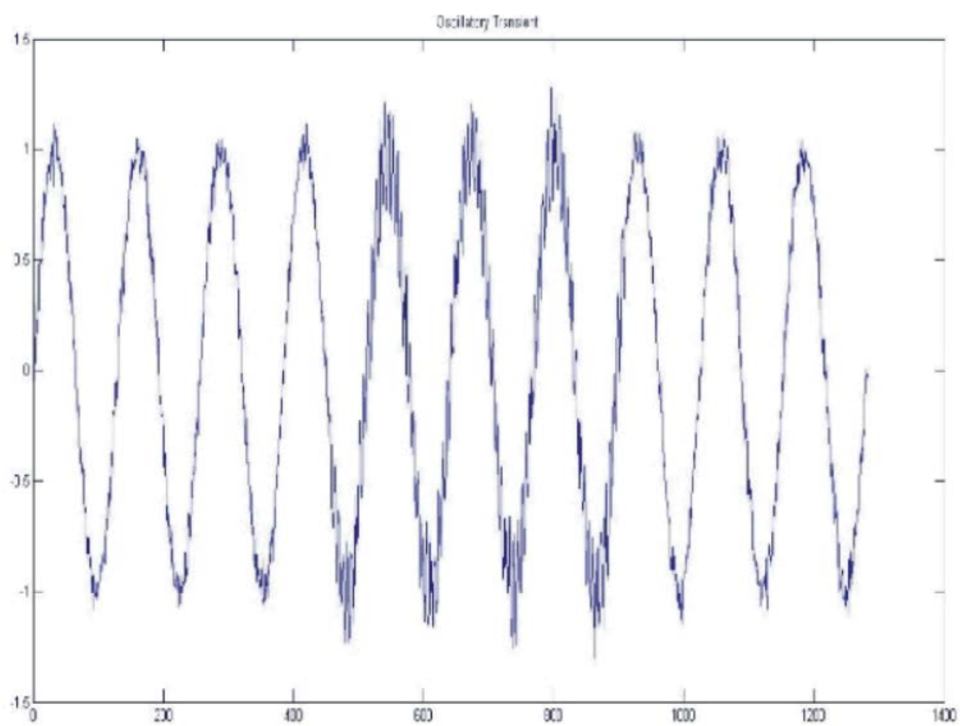

Fig. 10: Oscillatory Transient Wave

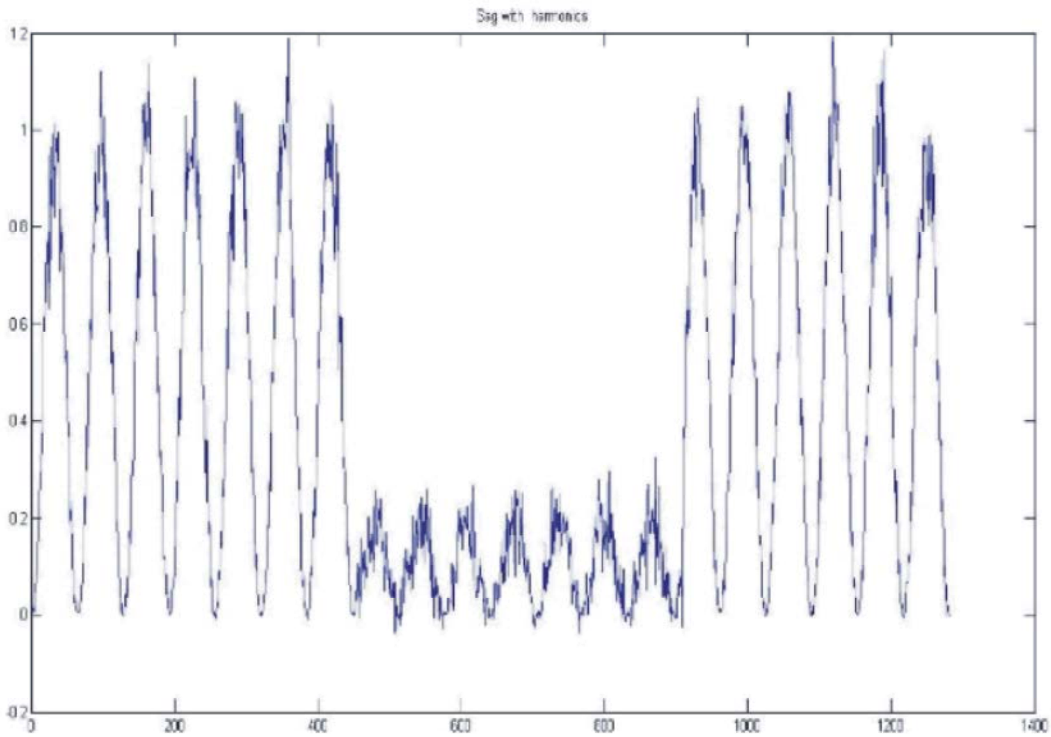

Fig. 11: Sag with Harmonics Wave

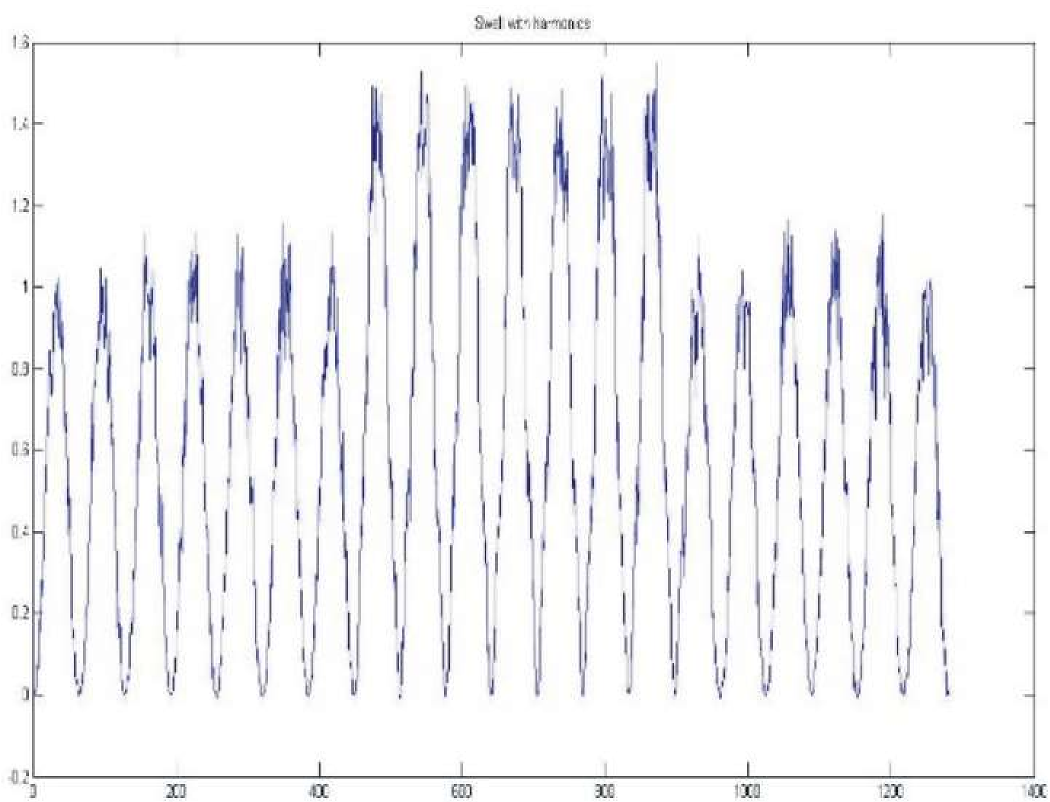

Fig. 12: Swell with harmonics Wave

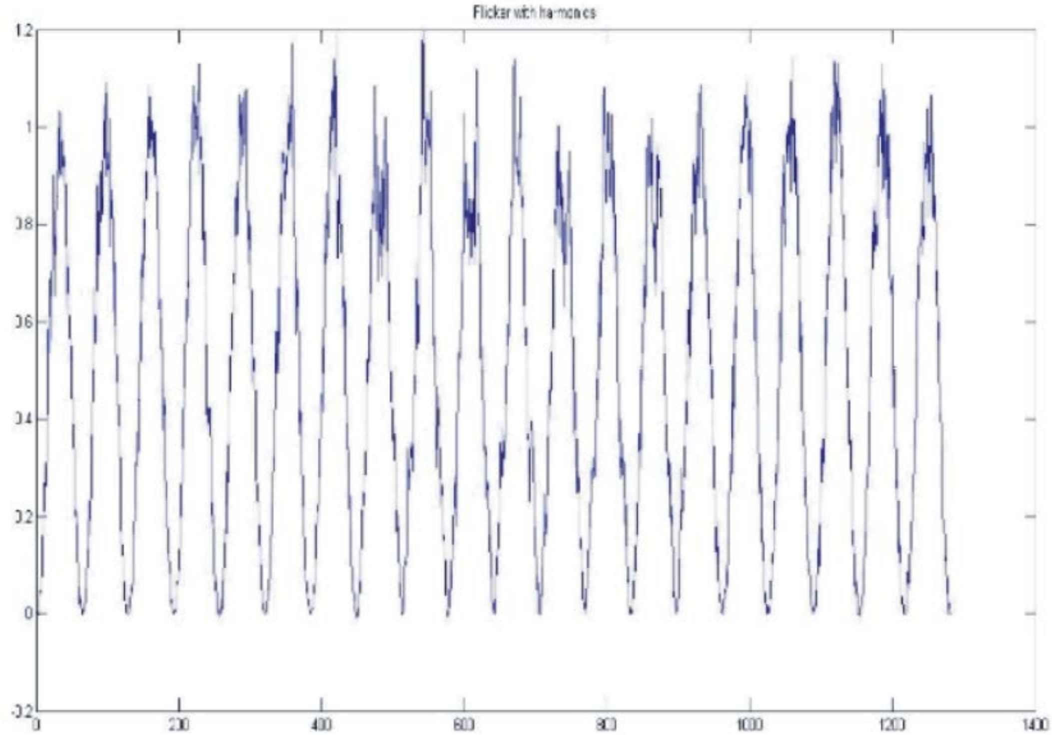

Fig. 13: Flicker with Harmonics Wave

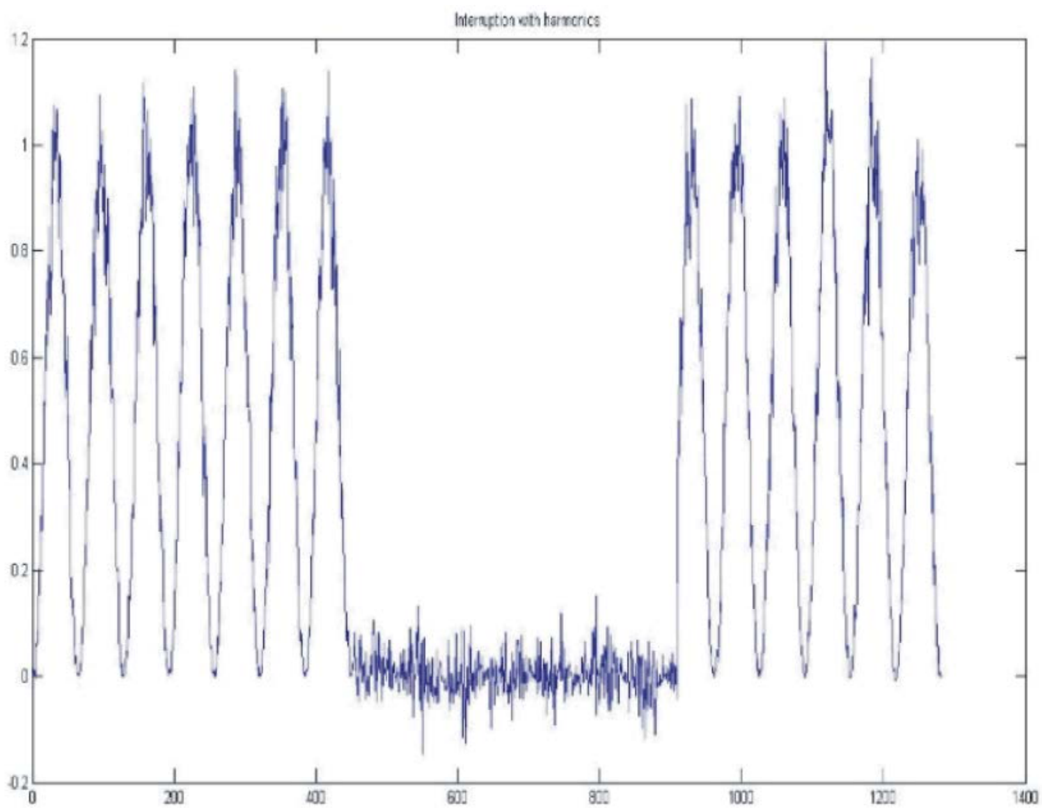

Fig. 14: Interruption with harmonics

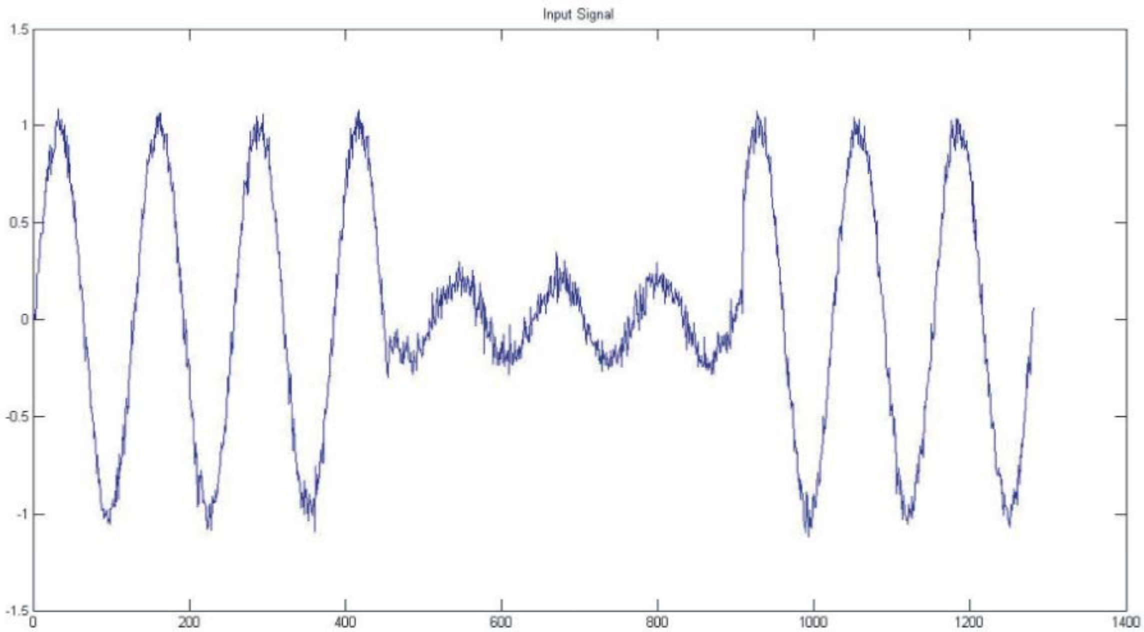

Fig. 15: Sample test input signal

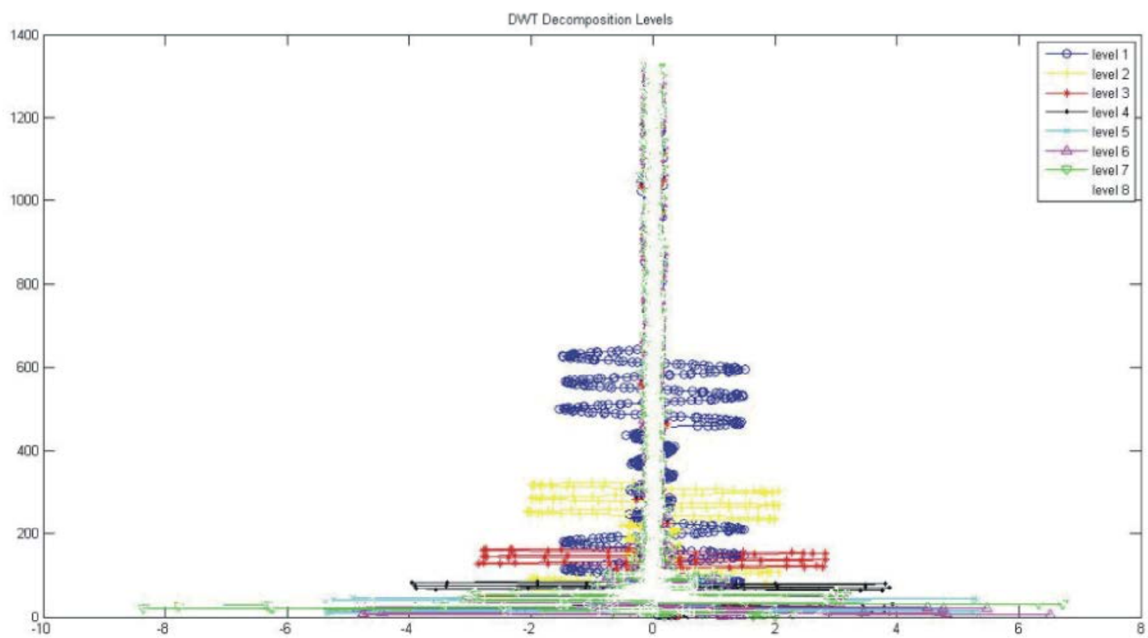

Fig. 16: Decomposed Input Signal

Table 5: Results of the proposed system

Parameters	Result
Accuracy	98.19%
Sensitivity or True Positive Rate	99.59%
Specificity or True Negative Rate	87.5%
Precision	91.52%
Negative Predictive Value (NPV)	100%
False Positive Rate (FPR)	12.5%
False Discovery Rate (FDR)	8.63%

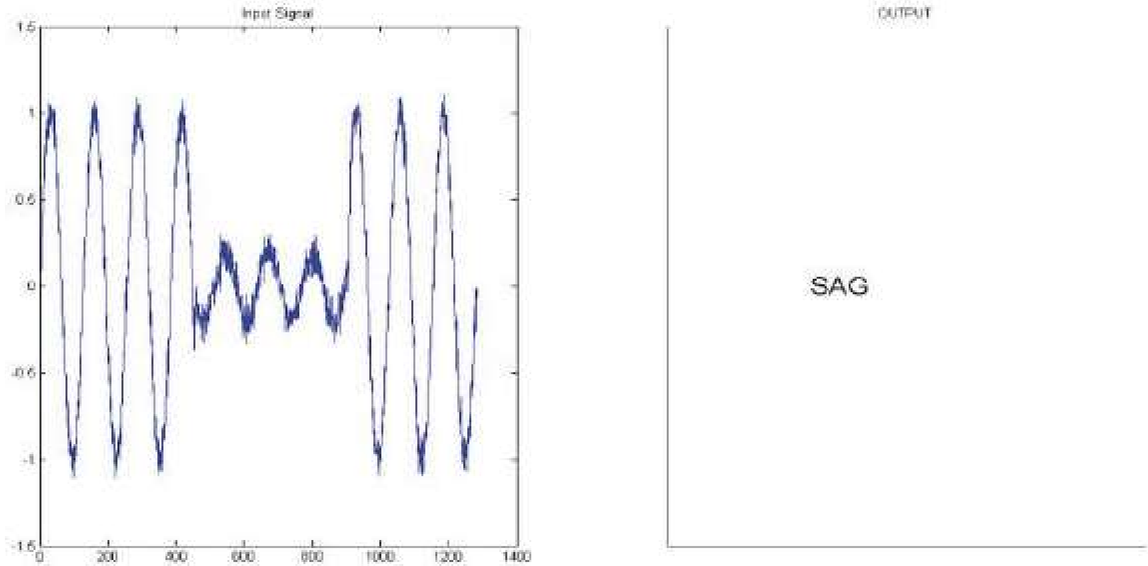

Fig. 17: Final Output of the Proposed Method

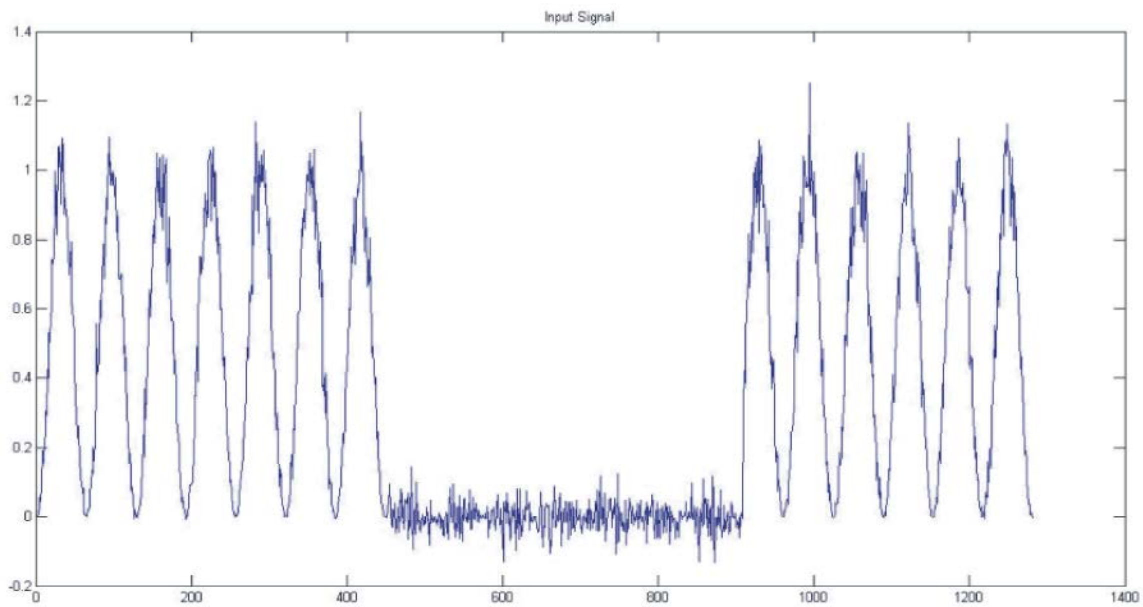

Fig. 18: Test Input Signal

In order to prove the effectiveness of our proposed method we have analyzed the performance of based on accuracy, sensitivity, specificity, precision, Negative predictive value (NPV), False Positive Rate (FPR) and False Discovery Rate (FDR). These values are given in Table 5 and the performance comparison chart is shown in Figure 21.

From Figure 21, we can see that our proposed system has given high classification performance in every aspect like accuracy, sensitivity, specificity etc. From these results we can say that this proposed method is best method for classification and identification of different types of Power Quality Disturbances occurs in the power system.The selected eight type of features at eight levels of DWT multiresolution analysis in the proposed method has increased the performance of the classification of different events so in order to prove that we compare the performance of the proposed method with existing method based on different approaches is shown in Table 6.

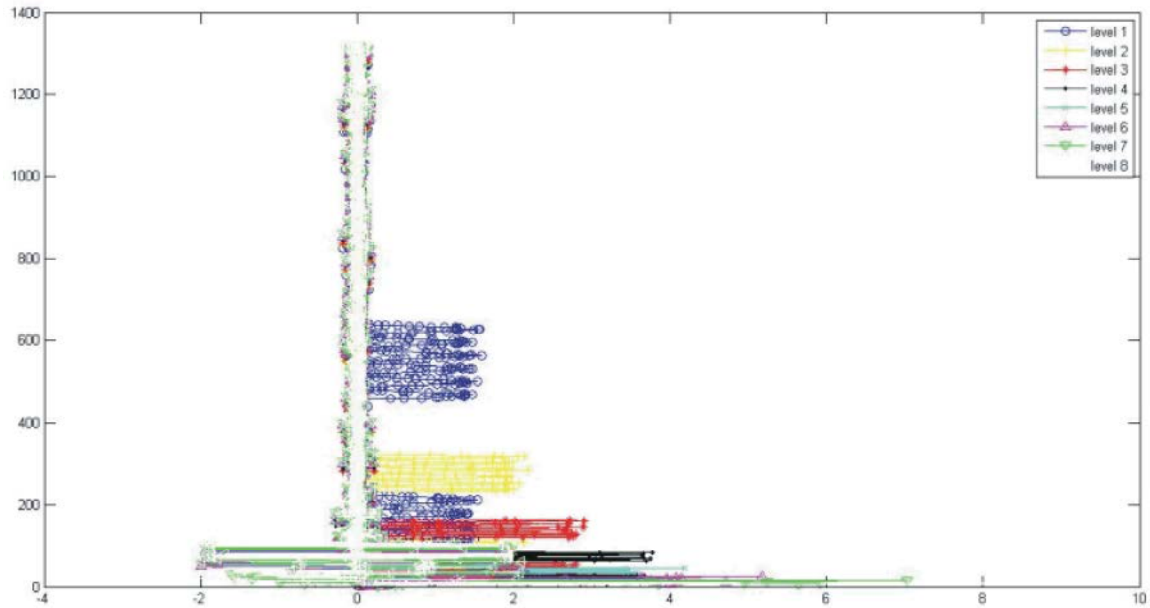

Fig. 19: Decomposed Test Signal

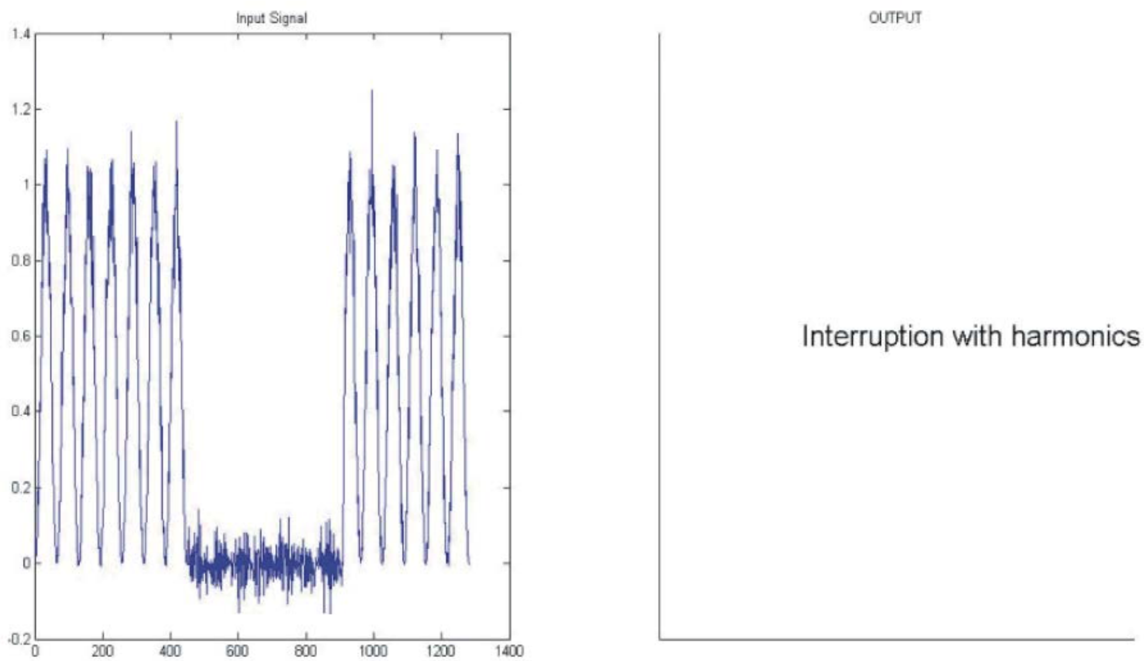

Fig. 20: Final Output of Proposed Method

Table 6: Performance Comparison with Existing Method

S.No	Methods	No of Features	Accuracy(%)
1	S-Transform and Probabilistic Neural Network [28]	4	97.4
2	Wavelet Transform and Support Vector Machine [29]	11	97.69
3	Feature extracted using S-Transforms and T-Transforms [30]	5	98.10
4	Wavelet Transform and RBFNN [31]	2	97.85
5	Proposed Method	8	98.19

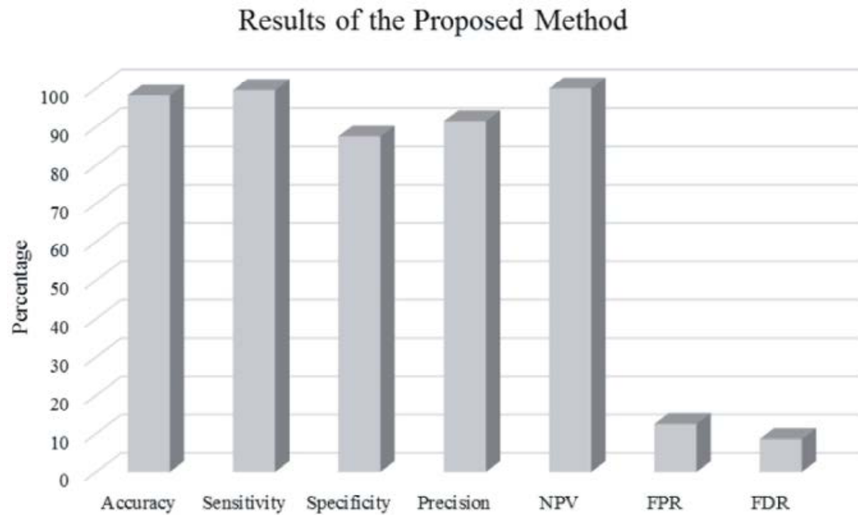

Fig. 21: Performance Comparison of Classifier Parameters

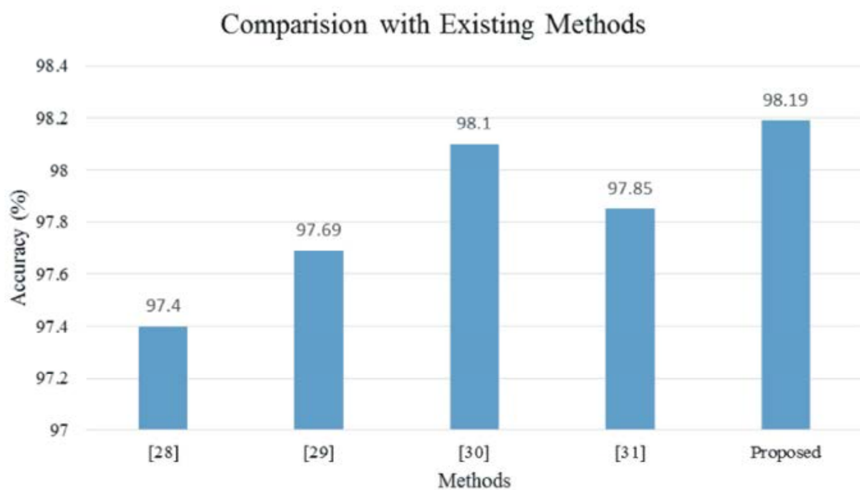

Fig. 22: Performance Comparison Chart

From Table 6, we can clearly see that our proposed method has achieved high classification accuracy with the proposed eight features this we can analyze clearly from the graph shown in Figure 22.

From Table 6 and Figure 22, it is seen the proposed method is more accurate in recognition and well suitable method for classification of single as well as multiple PQ events.

CONCLUSION

Recently, a noteworthy amount of research in literature has been done towards the advancement of methods for efficientautomatic classification of power quality disturbances. But still the classification performance of the power quality disturbances are not upto the mark it has problems in identification of events. So, in this work we made an attempt to classify different type of Power Quality (PQ) disturbances in view of the wavelet transform and artificial neural networks. In our proposed method, the different types of PQ disturbances are generated by utilizing algebraic equation based on numerical modelling. Then 8-level Discrete Wavelet Transform (DWT) is applied on the generated signals and then at each levels eight types of features mean, standard deviation, skewness, kurtosis, energy, Shannon entropy, log energy entropy and Renyi's entropy are extracted. These extracted features are given to the artificial neural network classifier for training purpose. In our proposed method, we have used 2200 signals out of that 1540 signals are used for training purpose and 330 signals are used for testing purpose comprises of different PQ disturbances. Experimental results indicate that the proposed method is best suitable methodfor classification of PQ events.

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