# Classification of Power Quality Disturbances using Features of Signals

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***Abstract-*** This paper proposes a power quality disturbance classification technique based on the energy of the distorted signals. The multiresolution analysis technique of DWT is employed on the distorted signals to extract the energy distribution features at different levels of resolution. To identify the different power quality disturbances the energy difference at each decomposition level is calculated with respect to the energy of the pure sinusoidal signal. Then probabilistic neural network is applied to classify the power quality disturbances. The simulation results validate the accuracy and efficiency of the proposed method.

***Index Terms***- Power Quality, Wavelet Energy, Probabilistic Neural Network.

## I. INTRODUCTION

Poor quality of electric power is normally caused by power line disturbances, such as impulses, notches, glitches, momentary interruption wave faults, voltage sag, swell, harmonic distortion and flicker resulting in misoperation or failure of end use equipment. A feasible approach needs to be introduced [1] so that the signals of interest will be recognized, captured and classified automatically. Poor power quality may cause many problems that affect the load such as malfunction, instability, short lifetime and so on. According to the survey by IEEE Transactions on Industrial Applications, power quality disturbances lead to losses of $4 billion to $10 billion in the USA alone [2]. Therefore, the research of power quality issues has captured ever increasing attention in the power engineering society.

The wavelet transform can be used to detect power quality problems and identify their occurrences in terms of time, generating data in both time and frequency domains via multiresolution analysis. Fourier transform can be used with wavelet transform to extract unique features that characterize power quality events from voltage or current waveforms [3]. These features are important to assist power engineers in pinpointing the cause of a disturbance event. Among various power quality assessment methods, one of the important methodologies is disturbance classification. A novel power disturbance classifier using a rule based method and a wavelet packet based hidden Markov model has been presented in [4]. This method classified six types of actual recorded power quality disturbances. Another novel approach for the classification of power quality disturbances based on inductive learning by using decision trees has been presented in [5]. The wavelet transform has been utilized to produce representative feature vectors that can capture the unique and salient characteristics of each disturbance. A new fast processing method based on mathematical morphology theory combined with threshold theory is proposed in [6] to denoise and locate the disturbance of the power quality signals corrupted by noise. Wavelet transform can be used in conjunction with Kalman filter for online real-time detection and classification of voltage events in power systems [7]. Wavelet analysis has been used for detection and estimation of the time related parameters of an event and the extended Kalman filtering is used for confirmation of the event and for computation of the voltage magnitude during the event.

A lot of research works have been carried out in the classification of power quality events using intelligent techniques including rule based fuzzy expert system [8]. The authors in [9] proposed the design of a tool to quantify power quality parameters using wavelets and fuzzy set theory. Wavelet transform extracts features of power quality events and fuzzy classifiers classify events using these features. A wavelet based fuzzy reasoning approach to power quality disturbance recognition and identification has been presented in [10]. To extract power quality disturbance features the energy distribution of the signal at each wavelet decomposition level is considered. A hybrid technique for characterizing power quality disturbances based on discrete wavelet transform and Kalman filter for extracting features from the captured distorted waveform has been discussed in [11]. The fuzzy expert system has been used to characterize the power quality events in the captured waveform.

Artificial neural network can be used to solve power quality problems particularly when traditional approaches have difficulty in achieving the desired speed, accuracy and selectivity. It also plays a vital role in classification of faults [12]. The concept of discrete wavelet transform for feature extraction of power disturbance signal combined with artificial neural network acts as a powerful tool for detecting and classifying power quality problems [13, 14]. An effective wavelet based feature extraction method for classification of power quality disturbances is presented in [13]. The detection and classification of transient signals are widely applied in many fields of power system. Power system transients can also be classified using wavelet and neural network [16, 17]. A neural fuzzy technology based classifier for the recognition of power quality disturbances have been proposed by the authors in [18]. The classifier adopts neural networks in the architecture of frequency sensitive competitive learning and learning vector quantization. A wavelet based feature extraction method for classification of power quality disturbance signals have been presented in [19]. In [20] the wavelet transform and multiresolution analysis technique have been employed to detect and locate disturbances. In order to classify these disturbances an algorithm grouped them into classes by applying artificial neural network resulting in a hybrid system. More recently S-transform has been proposed in power quality analysis to overcome the drawbacks of the wavelet transform [21]. S-transform based neural network classifier can effectively detect and classify different power quality events [22] and [23].

In this paper different stationary and nonstationary power quality disturbances such as sag, swell, interruption, flicker, oscillatory transient, harmonic, sag with harmonic, swell with harmonic, notch and spike are considered for pattern recognition and classification. The distorted signals are analyzed by $db_4$ mother wavelet upto 12 levels of decomposition. The energy values of all the detail levels are given as input to the neural network.

## II. WAVELET TRANSFORM

Wavelet transform is used as a feature extraction tool to identify power quality disturbances. It finds applications in different areas of engineering due to its ability to analyze stationary and non-stationary disturbances in signals. The major advantage of this method includes two aspects; the first one is that it can significantly reduce the dimensionality of the analyzed data for *i* levels of decomposition. The second advantage is that this method keeps all the necessary characteristics of the original waveform for analysis.

The basic formula for continuous wavelet transform is

$$W(s,\tau) = \int_{-\infty}^{\infty} f(t) \frac{1}{\sqrt{|s|}} \psi^* \left( \frac{t-\tau}{s} \right) dt \qquad (1)$$

where ψ(t) is the mother wavelet. The transformed signal is a function of two variables, translation ( $\tau$ ) and scale (s). $\frac{1}{\sqrt{|s|}}$ is called the normalization factor. Analysis of a signal at different frequencies with different resolution is called Multi Resolution Analysis. Here every spectral component is not resolved equally. MRA is designed to give good time resolution and poor frequency resolution at high frequencies and good frequency resolution and poor time resolution at low frequencies. This approach makes sense especially when the signal at hand has high frequency components for short duration and low frequency components for long duration.

### 2.1 Theory of Discrete Wavelet Transform (DWT)

Calculation of wavelet coefficients at every possible scale is a fair amount of work and it generates a lot of data. The analysis becomes more efficient and very accurate if we choose scales and positions based on powers of two which are called dyadic scales and positions. We obtain such an analysis from the discrete wavelet transform. For most of the signals the low frequency content is the most important component which gives the signal its original identity. The high frequency component imparts flavor or nuance. We identify the high frequency component by 'details' and low frequency component by 'approximations'. The details are the low scale high frequency components and the approximations are the high scale low frequency component. The original signal 'S' passes through two complementary filters and emerges as two signals as shown in figure 1. But unfortunately if we perform this operation on a real digital signal then if original signal 'S' contains 1000 samples of data, each of approximation and detail will contain 1000 samples, for a total of 2000. To overcome this problem the notion of down sampling is introduced. This simply means throwing away every second data point resulting in 500 samples of data for each of approximation and detail as shown in figure 2.

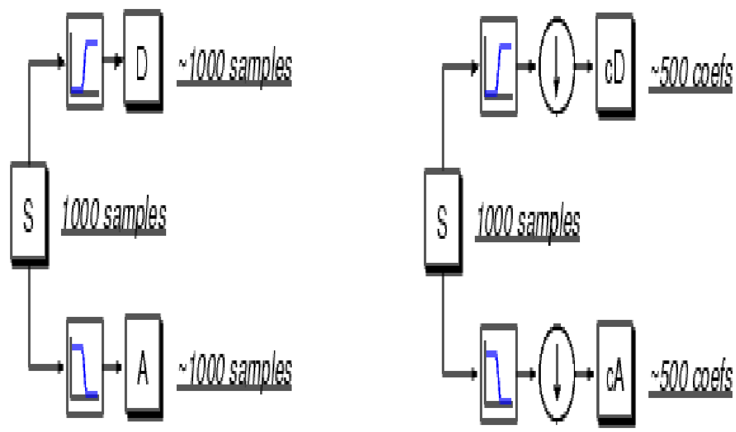



**Figure 1: Approximation and detail containing**
**Figure 2: Approximation and detail twice the data as the original one using notion of down sampling**

Figure 3 shows a one stage discrete wavelet transform of a signal. The signal under consideration is a pure sinusoid with high frequency noise added to it. The decomposition process can be iterated, with successive approximations being decomposed in turn so that one signal is broken down into many lower resolution components. This is called wavelet decomposition tree as shown in figure 4.

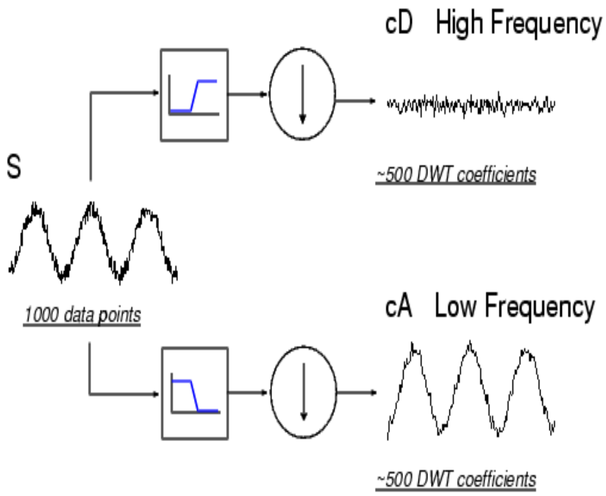



**Figure 3: Decomposition of signal with high frequency noise**

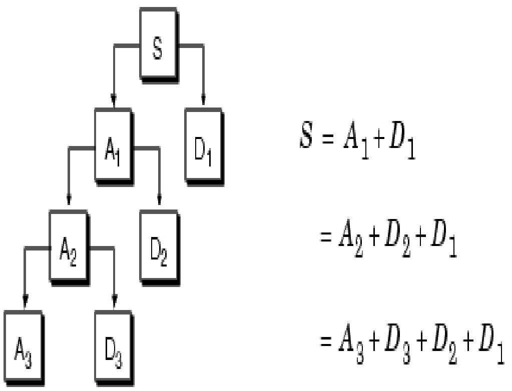



**Figure 4: Multilevel decomposition**

Since the analysis process is iterative, theoretically it can be continued indefinitely. In reality the decomposition can proceed only until the individual details consist of a single sample. In practice a suitable number of levels are selected based on the nature of the signal or on a suitable criterion like entropy.

### 2.2 DWT for Feature Extraction

The major power line disturbances are sag, swell, harmonics, flicker, interruption, harmonics with swell, harmonics with sag, notch, oscillatory transient and spike. In this paper these power quality disturbance signals are generated by using the algebraic equations given in table I. The advantage of using algebraic equations is that it introduces the flexibility of covering a wide range of parameters.

In this section wavelet transform is used for feature extraction of different power quality disturbances. The signals are decomposed in 12 levels by DWT. The Daubechies 4 wavelet function is adopted as mother wavelet. The energy of detail coefficients at each level of the decomposed signals is calculated. Those energy values are used to calculate the energy difference values.

To calculate the minimum decomposition level, the level where the maximum energy deviation can be achieved with respect to the reference signal is required. On the basis of that number of decomposition level is required to specify.

The procedure for the determination of the minimum level of decomposition has been discussed by authors in [2]. If $f_s$ is sampling frequency and $f_{ref}$ is the frequency of the reference signal then

$$\log_2\left(\frac{f_S}{f_{ref}}\right) - 1 \le N \le \log_2\left(\frac{f_S}{f_{ref}}\right) \qquad (2)$$

where $f_s$ = 5KHz and $f_{ref}$ =50Hz.

From Eq.2 we get $5.64 < N < 6.64$ (3)
Hence N can be considered as 6.
Now $N_{min} = 2*N$ (4)
Therefore we get $N_{min} = 2 * N = 2*6 = 12$.

Hence we have chosen 12 levels of decomposition and the maximum deviation is at 6$^{th}$ level.

**Table I: Different types of Power Quality Disturbances**

| DISTURBANCES | EQUATION | PARAMETERS |
|---|---|---|
| Pure | $y(t)=sin(\omega_d t)$ | $\omega_d = 2\pi * 50$ rad/sec |
| Sag | $y(t)= \sin(\omega_d t)[1-\alpha(u(t-t_1)-u(t-t_2))]$ | $0.1 \le \alpha \le 0.9, T \le t_2 - t_1 \le 9T$ |
| Swell | $y(t)= \sin(\omega_d t)[1+\alpha(u(t-t_1)-u(t-t_2))]$ | $0.1 \le \alpha \le 0.9, T \le t_2 - t_1 \le 9T$ |
| High frequency signal | $y(t)=\alpha_1 \sin(\omega_d t)+\alpha_2 \sin(3\omega_d t)+\sin(5\omega_d t)+\alpha_4 \sin(7\omega_d t)+\sin(9\omega_d t)$ | $\alpha_1 = 1, \alpha_2 = 0.6$ to $.06$, $\alpha_3 = 0.2$to$0.02$ $\alpha_4 = 0.08$ to $.008, \alpha_5 = 0.05$ to $.005$ |
| Flicker | $y(t) = [1+\alpha \sin(2\pi\beta t)]\sin(\omega_d t)$ | $0.1 \le \alpha \le 0.2, 5Hz \le \beta \le 20Hz,$ |
| Interruption | $y(t)= \sin(\omega_d t)[1-\alpha(u(t-t_1)-u(t-t_2))]$ | $0.9 \le \alpha \le 1, T \le t_2 - t_1 \le 9T$ |
| High frequency with swell | $y(t) = [\alpha_1 \sin(\omega_d t)+\alpha_2 \sin(3\omega_d t)+\sin(5\omega_d t)] * [1+\alpha(u(t-t_1)-u(t-t_2))]$ | $\alpha_1 = 1, \alpha_2 = 0.6$ to $.006$,, $\alpha_3 = 0.02$ to $.002$ $0.1 \le \alpha \le 0.9$, $T \le t_2 - t_1 \le 9T$ |
| High frequency with sag | $y(t) = [\alpha_1 \sin(\omega_d t)+\alpha_2 \sin(3\omega_d t)+\sin(5\omega_d t)] * [[1+\alpha(u(t-t_1)-u(t-t_2))]]$ | $\alpha_1 = 1, \alpha_2 = 0.6$ to $.006$, $\alpha_3 = 0.02$to $.002$, $0.1 \le \alpha \le 0.9, T \le t_2 - t_1 \le 9T$ |
| Spike | $y(t) = sin(\omega_d t) + sign(sin(\omega_d t)) * \{\sum_{n=1}^{i} k * [u(t-(t_1+0.002n)) - u(t-(t_2++0.002n))\}]$ | $0.1 \le k \le 0.4, 0.01T \le t_2 - t_1 \le 0.05T,$ $0 \le t_1, t_2 \le 0.5$ |
| Oscillatory transient | $y(t) = \sin(\omega_d t) + e^{((t_1-t)/\tau)(u(t-t_1)-u(t-t_2))} * \sin(2\pi f_n t)$ | $0.1 \le \alpha \le 0.8, 0.5T \le t_2 - t_1 \le 3T$ $300Hz \le f_n \le 900Hz, 5ms \le \tau \le 40ms$ |
| Notch | $y(t) = sin(\omega_d t) + sign(sin(\omega_d t)) * \{\sum_{n=1}^{i} k * [u(t-(t_1+0.002n)) - u(t-(t_2++0.002n))\}]$ | $0.1 \le k \le 0.4,$ $0.01T \le t_2 - t_1 \le 0.05T, 0 \le t_1, t_2 \le 0.5$ |

## III. NEURAL NETWORK

A neural network is a system composed of many simple processing elements operating in parallel whose function is determined by network structure, connection strengths, and the processing performed at computing elements or nodes. Artificial neural networks offer a completely different approach to problem solving. An artificial neural network is a model built through learning from a number of examples of this behavior. It transforms the given data pertaining to a problem into a model or predictor, and then applies this model to the present data to obtain an estimate. Following are some of the advantages of neural networks:

- Ability to account for complex functional dependency.
- One goes straight from the data to the model without simplification or questionable interpretation.
- No conditions on the predicted variable.
- Insensitivity to (moderate) noise or unreliability in the data.
- The final model is continuous and derivable and lends itself easily to further work.
- Speed: 10 microseconds when hardwired, a few milliseconds on a 1 GHz computer.

Probabilistic neural networks (PNN) are a kind of radial basis network suitable for classification problems and the architecture is feed forward in nature. PNN is supervised learning algorithm but includes no weights in its hidden layer. Instead each hidden node represents an example vector, with the example acting as the weights to that hidden node. Figure 5 illustrates a sample PNN structure.

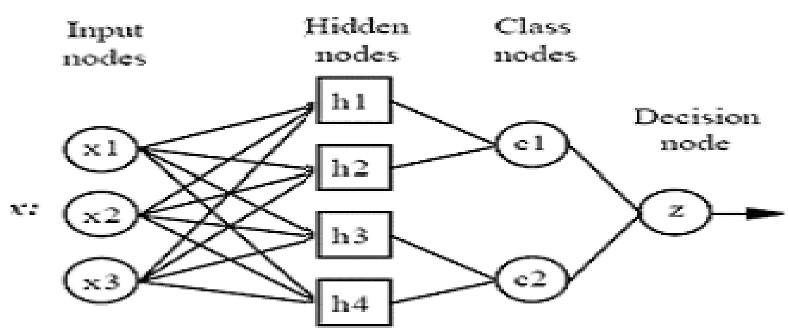



**Figure 5: Architecture of PNN**

Basically, PNN consists of an input layer, which represents the input pattern or feature vector. The input layer is fully interconnected with the hidden layer, which consists of the example vectors. The actual example vector serves as the weights as applied to the input layer. The output layer represents each of the possible classes for which the input data can be classified. The hidden layer is not fully interconnected to the output layer. The example nodes for a given class connect only to that class's output node and none other. The other important element of the PNN is the output layer and the determination of the class for which the input layer fits. This is done through a winner-takes-all approach. The output class node with the largest activation represents the winning class.

In PNN algorithm, calculating the class-node activations is a simple process. For each class node, the example vector activations are summed, which are the sum of the products of the example vector and the input vector. The hidden node activation, shown in Eq. 5 is simply the product of the two vectors (*E* is the example vector, and *F* is the input feature vector).

$$h_i = E_i F \tag{5}$$

The class output activations are then defined as

$$C_j = \frac{\sum_{i=1}^{N} e^{\frac{h_i - 1}{\gamma^2}}}{N} \tag{6}$$

where $N$ is the total number of example vectors, $h_i$ is the hidden-node activation and $\gamma$ is a smoothing factor. The smoothing factor is chosen through experimentation. If the smoothing factor is too large, details can be lost; again if the smoothing factor is too small, the classifier may not generalize well. In this paper PNN has been considered for the classification of power quality disturbances.

## IV. METHODOLOGY

The inputs to the neural network are the preprocessed distorted signal. Discrete wavelet transform is applied to the signal to extract the energy features. Feature extraction is the key for recognizing the exact nature of the disturbance present in the signal. A feature extractor should reduce the pattern vector (original waveform) to a lower dimension which contains most of the useful information from the original vector.

In this paper $db_4$ mother wavelet has been considered to decompose the signals considering the sampling frequency to be 5 kHz. The minimum level of decomposition is found to be 12. The energy of the detail coefficients at each decomposition level i.e. $d_1$ to $d_{12}$ is calculated and it is divided by the energy of the original signal. The energy at detail level $i$ is calculated according to the following formula:

$$\text{Energy} = 100 * \frac{(norm(D_i))^2}{(norm(x_k))^2} \tag{7}$$

where $D_i$ is the detail wavelet coefficient at level $i$ and $x_k$ is the amplitude of the signal at *kth* sampling instant.

$$\text{Norm } D_i = \sqrt{\sum |D_{ij}|^2}, \quad j = 1, 2, \ldots\ldots, m \tag{8}$$

where $m$ is the total number of *ith* detail level coefficients.

$$\text{Norm } x_k = \sqrt{\sum x_k^2}, \quad k = 1, 2, \ldots\ldots\ldots\ldots\ldots, \text{n}. \tag{9}$$

where n is the total number of samples in the signal. As the sampling frequency is 5000Hz and the total duration of the signal considered is 1 sec the total number of samples is 5000.

A pure sinusoidal signal at 50 Hz. is considered as reference and the energy of the pure signal at all the 12 levels of decomposition are calculated according to the formula given in Eq. 7. Hence if $E_{pure}$ is the energy of the signal then

$$E_{pure} = [E_{1pure}, E_{2pure}, \quad , E_{12pure}] \tag{10}$$

If $E_{signal}$ is the energy of the distorted signal then

$$E_{signal} = [E_{1signal}, E_{2signal}, \quad , E_{12signal}]. \tag{11}$$

$$\Delta E = E_{signal} - E_{pure} \tag{12}$$

The resultant feature vector $\Delta E$ obtained by subtracting the detail energy values of the distorted signal at each level from that of the pure signal is considered as the input to the artificial neural network. Probabilistic neural network model is considered for classification since the learning speed of this model is very fast making it suitable for signal classification problems in real time. The authors in paper [2] have used the energy of the detailed information for pattern recognition of the signals. They have not considered the per unit energy values. In this paper the energy refers to the per unit energy value contained in the detail level of a particular distorted signal. The advantage of considering per unit values is that the per unit energy being of lower order can be easily handled using digital computer. Hence the computational effort is much reduced.

## V. PATTERN RECOGNITION OF POWER QUALITY DISTURBANCES

Different types of power quality disturbances are considered for pattern recognition and the signals are generated in MATLAB. Table I gives the signal generation models and their control parameters. Using the parameters given in Table I the training and testing signals can be generated in a wide range and the signals thus simulated are very close to the real situation. Sampling frequency of the signals is 5 kHz. The total simulated time is 1second and fifty power frequency cycles is considered. The energy difference values of each power quality disturbances are plotted considering energy difference values in y axis and number of decomposition levels in x axis.

### 5.1 Energy Pattern for Signal with Sag and Interruption

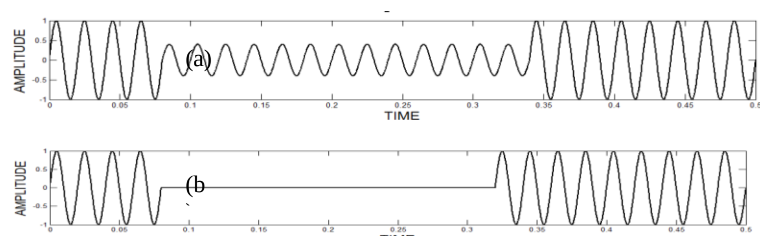



**Figure 6: Signals with (a) sag and (b) interruption**

Figure 6 represents pure sine wave with sag and interruption. Figure 7 represents the energy difference values for different sag and interruption signals. It shows negative deviations at $6^{th}$, $7^{th}$ and $11^{th}$ levels. $6^{th}$ level shows the maximum deviation.

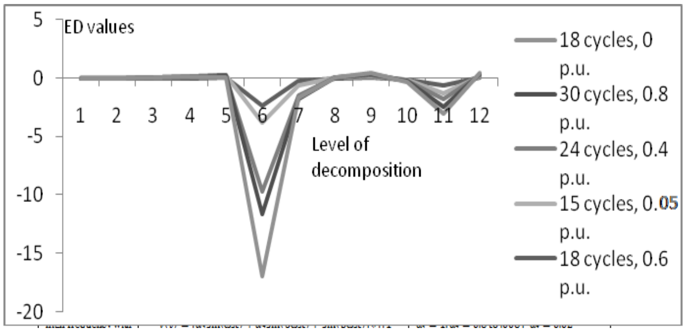



**Figure 7: Energy difference patterns for different signals with sag and interruption**

### 5.2. Energy Pattern for Signal with Swell

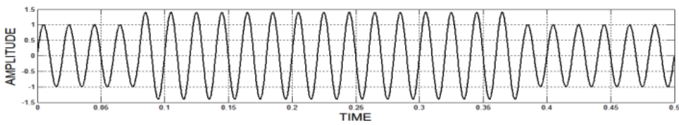



**Figure 8: Signal with voltage swell**

Figure 8 shows a pure sine wave with swell. The energy difference patterns are given in figure 9. It represents the positive deviations at the levels of 4, 5, 6, 7 and negative deviation is at 11th level.

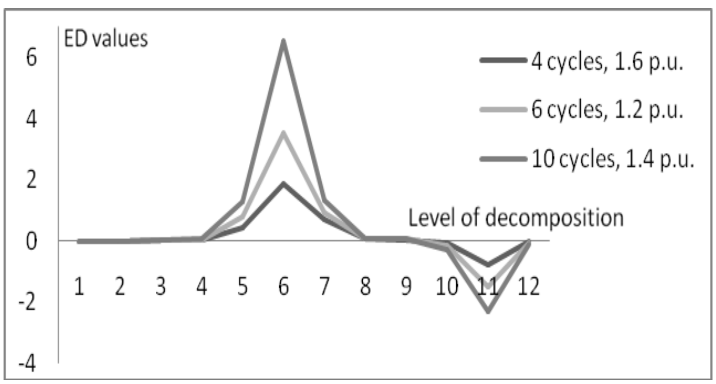



**Figure 9: Energy difference patterns for signal with swell**

### 5.3. Energy Pattern for the harmonics and harmonics with amplitude deviations

Signal with harmonics, harmonics with swell and harmonics with sag is shown in figure 10. Figure 11 shows the energy difference patterns. Energy difference values show the pattern where the positive deviations are at 4th, 5th and 11th level and negative deviations are at 6th and 7th levels for the signal with harmonics and harmonics with amplitude deviations.

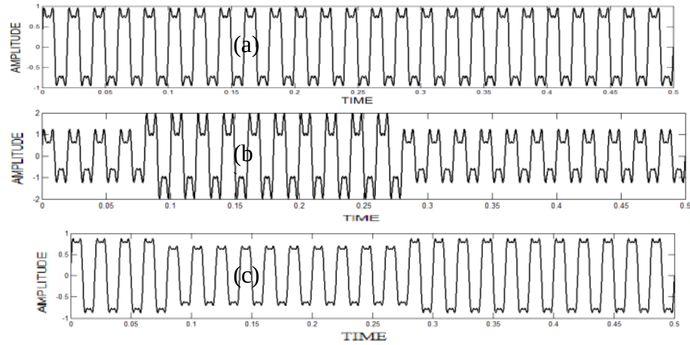



**Figure 10. (a) Harmonic signal (b) harmonics with swell (c) harmonics with sag**

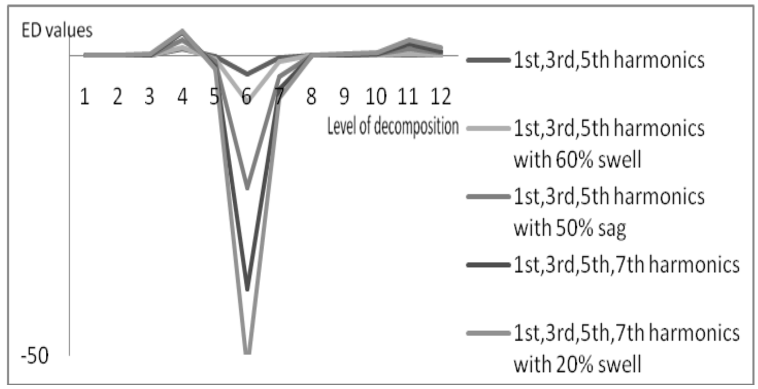
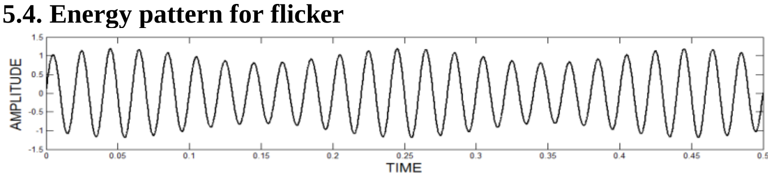
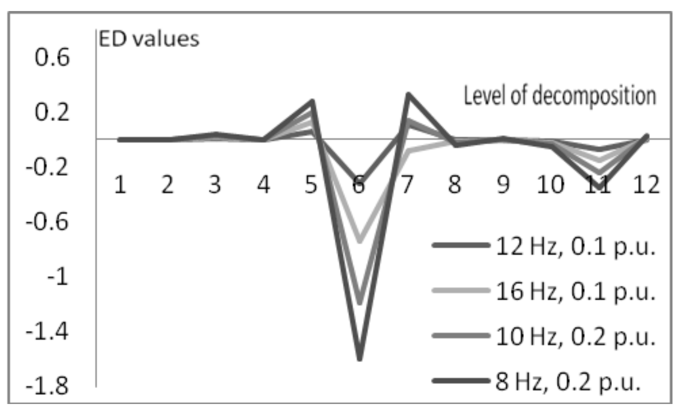



**Figure 11: Energy difference patterns for harmonics, harmonics with swell, and harmonics with sag**

### 5.4. Energy pattern for flicker




**(a)**

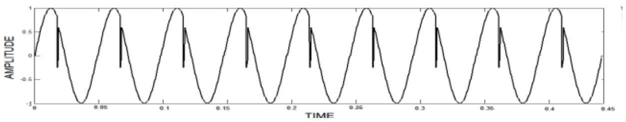



**(b)**

**Figure 12: (a) Flicker and (b) Energy difference patterns for flicker**

Figure 12 (a) shows a signal with flicker and the corresponding energy difference pattern for flicker is given in figure 12 (b). Flicker of frequency greater than 13 Hz shows the positive deviations are at 3rd, 5th and 7th levels and negative deviations are at 6th and 11th levels. The flickers with the frequency less than 13 Hz shows the negative deviation 7th level.

### 5.5. Energy pattern for notch

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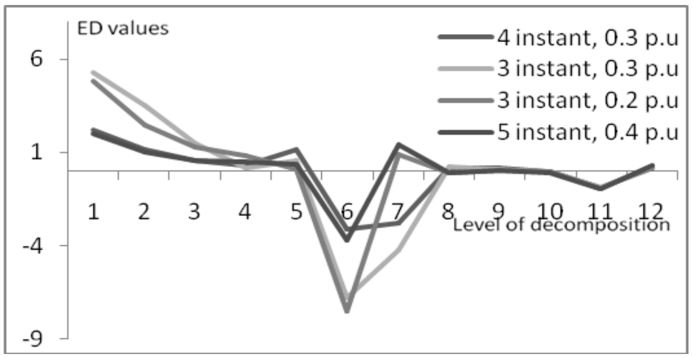
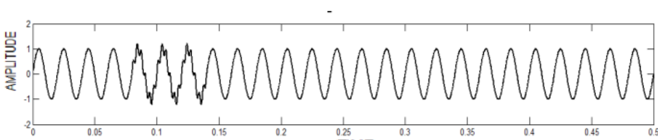



**(b)**

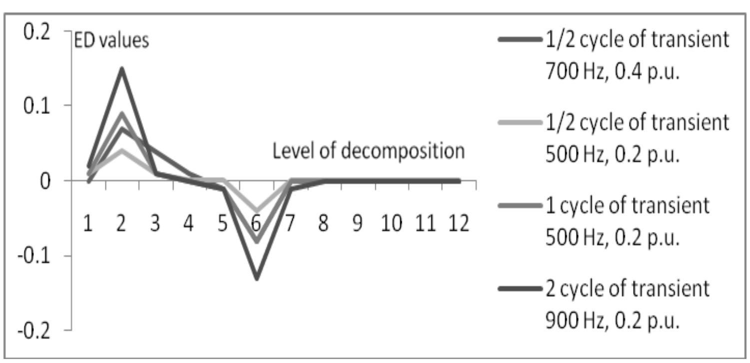
**Figure 13: (a) Notch and (b) Energy difference patterns for different signals with notch**

A signal with notch and its energy difference pattern is given in figure 13 (a) and figure 13 (b) respectively. When the notch occurs for 3 samples or more than that, it shows negative deviations at 6th, 7th and 11th levels. For the signals with notch for brief period of time i.e. less than 3 samples give the positive deviations of energy value at 7th level.

### 5.6. Energy pattern for oscillatory transient




**(a)**



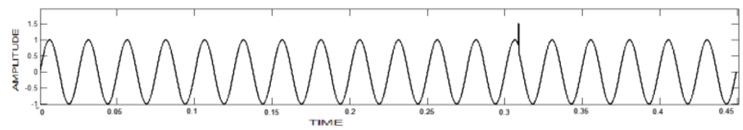

**(b)**

**Figure 14: (a) Oscillatory transient and (b) Energy difference patterns for oscillatory transient**

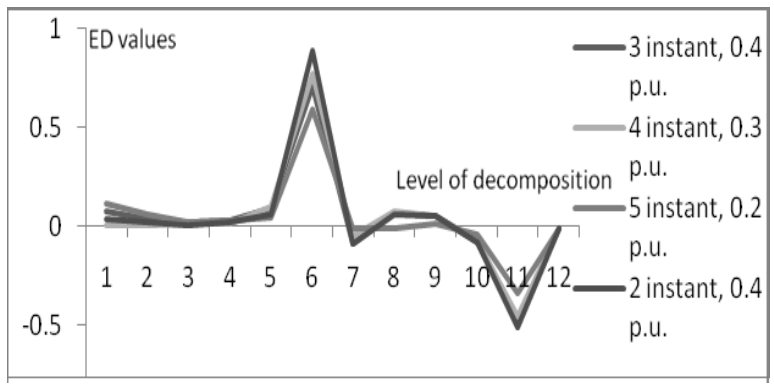
The signal consisting of oscillatory transient is shown in figure 14 (a). Oscillatory transient shows the positive deviations at 1st, 2nd, 3rd and 4th levels and negative deviations at 5th, 6th and 7th levels as shown in figure 14 (b).

### 5.7. Energy pattern for spike

Figure 15 (a) shows sinusoidal signal with spike. The signal with spike in 3 samples or less than 3 samples signifies positive deviations at 1st to 9th levels and negative deviations at 10th and 11th levels. When the spike occurs for greater than 3 sampling instant, it gives negative deviation of energy difference value at 7th level. The energy difference pattern for signals with spike occurred in different samples are shown in figure 15 (b).




**(a)**




**(b)**

**Figure 15: (a) Spike and (b) Energy difference patterns for different spike signals**

From the above analysis the following observations can be made:

- For sag signal we obtain the highest negative energy deviation at 6th level. In case of interruption signals, the energy difference patterns are following the same pattern like sag. The only difference from sag is that the range of maximum deviation is greater than the sag signals.
- For swell signal we get reverse pattern of sag that is highest positive energy deviation at 6th level.
- Harmonics implicate the negative energy difference at 6th level and a slight positive difference after the 6th level.
- Major deviation, for flicker is at 6th level which is negative and positive deviation at 7th level.
- The energy difference patterns for the signals harmonic with swell and sag follow the pattern of harmonic signals.
- Notch signals represents the major negative deviation at 6th level and positive variation at the preliminary levels such that 1, 2, 3

- For oscillatory transient we get maximum positive deviation at $6^{th}$ level and negative variation at the $11^{th}$ level.
- Spike follows the energy deviation pattern of oscillatory transient.

Since noise is omnipresent in electrical power distribution networks, the proposed method has been tested on the power quality disturbances in the noisy environment. Gaussian white noise with SNR 20 dB, 40 dB and 60 dB has been considered for pattern recognition. The energy difference patterns remain same for all the different types of power quality disturbances in noisy condition. Hence the pattern recognition method is immune to noise.

## VI. CLASSIFICATION

Probabilistic neural network is used to classify the power quality disturbances. The energy difference values computed for pattern recognition are used to construct the training and testing data to model the PNN program with the help of Matlab R2009b. Here the size of the input vector is 12 *11 *80 which comes to 10560, where the number of coefficients for each 11 types of distortions is 12. 80 sets of data are given for training in each class. The targets of this expert system are given as 1 2 3 4 5 6 7 8 9 10 11 which represents pure, sag, swell, harmonics, flicker, interruption, harmonics with swell, harmonics with sag, notch, oscillatory transient and spike signals respectively. For testing of signals by this expert system 648 distorted signals are used. Here 84 signals with sag, 100 signals with swell, 46 signals with harmonics, 54 signals with flicker, 64 signals with interruption, 31 harmonic signals with swell, 31 harmonic signals with sag, 64 signals with notches, 31 signals with oscillatory transients and 64 signals with spike are taken. Table 2 shows the classification results of power quality disturbances. In this expert system an accuracy of 92.28% is obtained. Out of 650 test signals 45 signals are not identified appropriately and rest 605 signals are identified.

In case of harmonics the expert system gives lesser accuracy i.e. 76%. It can be justified as the PNN program is modeled using the energy difference values and the energy difference patterns of harmonic signals are close to the harmonic signals with sag and swell. Therefore the expert system shows classes 7 or 8 i.e. harmonic signals with sag or harmonic signals swell in place of harmonics i.e. class 4. If we combine the three classes 4, 7 and 8 in to a single class then the expert system will classify the particular class with the accuracy of 98% and the overall accuracy of the system will increase to 95%.

Identify the constructs of a Journal – Essentially a journal consists of five major sections. The number of pages may vary depending upon the topic of research

**Table II: Classification results of PNN**

| ACTUAL CLASS | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | ACCURACY |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| PURE (1) | **80** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 100% |
| SAG (2) | 2 | **80** | 0 | 0 | 0 | 2 | 0 | 0 | 0 | 0 | 0 | 95% |
| SWELL (3) | 1 | 0 | **97** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 97% |
| HIGH FREQUENCY (4) | 0 | 0 | 0 | **35** | 0 | 0 | 5 | 6 | 0 | 0 | 0 | 76% |
| FLICKER (5) | 7 | 0 | 0 | 0 | **47** | 0 | 0 | 0 | 0 | 0 | 0 | 87% |
| INTERRUPTION (6) | 2 | 0 | 0 | 0 | 0 | **62** | 0 | 0 | 0 | 0 | 0 | 97% |
| HIGH FREQUENCY WITHSWELL (7) | 0 | 0 | 0 | 2 | 2 | 0 | **25** | 2 | 0 | 0 | 0 | 80% |
| HIGH FREQUENCY WITH SAG (8) | 0 | 0 | 0 | 3 | 0 | 0 | 1 | **27** | 0 | 0 | 0 | 87% |
| NOTCH (9) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | **64** | 0 | 0 | 100% |
| OSCILLATORY TRANSIENT (10) | 4 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | **26** | 0 | 86% |
| SPIKE (11) | 6 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | **55** | 86% |

## VII. CONCLUSION

In this paper, an attempt has been made for pattern recognition and classification of power quality disturbances. The pattern recognition methodology is based on wavelet transform. The energy values of different power quality disturbances are computed and compared with that of the pure signal. It has been found that the energy difference patterns remain same in noisy environment. Hence the pattern recognition method is immune to noise. The disturbance classification is performed by PNN. This PNN model is capable of identifying 11 different types of disturbances present in a signal including transient disturbance, short duration disturbance and harmonic distortion with high accuracy. Consequently the proposed approach has the potential for diagnosis of power quality disturbances in the area of power quality.

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