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Power Signal Disturbance Classification Using Wavelet Based Neural Network

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Abstract: In this paper, the power signal disturbances are detected using discrete wavelet transform (DWT) and categorized using neural networks. This paper presents a prototype of power quality disturbance recognition system. The prototype contains three main components. First a simulator is used to generate power signal disturbances. The second component is a detector which uses the technique of DWT to detect the power signal disturbances. DWT is used to extract disturbance features in the power signal. These coefficients obtained from DWT are further subjected to statistical manipulations for increasing the detection accuracy. The third component is neural network architecture to classify the power signal disturbances with increased accuracy of detection.

Keywords: Discrete Wavelet Transform, Power Quality Disturbances, Learning Vector Quantization, Multi Resolution Analysis (MRA).

1 Introduction

The quality of power supplies has become a major concern of electricity users. The quality of the power supply is not good then it may result in malfunctions, instabilities, short life time, and so on. Poor power quality is mainly due to adjustable speed drives. The power signal disturbances are classified as impulse, notches, glitches, momentary interruption, voltage sag/swell, harmonic distortion and flicker. These disturbances may cause malfunctioning of the equipments. To improve the quality of the power supply detection of the disturbance must be done accurately. The power quality events should be detected, localized and classified accurately so that proper mitigation measures could be applied [1, 2]. Recent advances in technologies of signal processing and artificial intelligence have made it feasible to develop more sophisticated automated recognition techniques [3-5].Angrisani et al proposed to employ the continuous wavelet transform (CWT) to estimate the disturbance time duration and the DWT to estimate the disturbance amplitude [6]. Chung et al. [7] presented a novel classifier using a rule based method and a wavelet packet based hidden Markov model (HMM). In this paper DWT is employed to

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capture the time of transient occurrence and extract frequency features of power disturbances. These DWT coefficients when applied as inputs to the neural networks require large memory space and much learning time. Hence along with the MRA technique the statistical methods are used to extract the disturbance features of the distorted signal at different resolution levels. PNN is used to classify disturbance type. The learning efficiency of PNN is very fast, and it is suitable for signal classification problems. Distorted signals were generated by the power system block set in Matlab. The accuracy rate is improved using wavelets along with the statistical differentiation of the various power signal disturbances.

2 Wavelet Transform

The wavelet analysis block transforms the distorted signal into different time-frequency scales detecting the disturbances present in the power signal. The wavelet transform (WT) uses the wavelet function φ and scaling function ϕ to perform simultaneously the Multi Resolution Analysis (MRA) decomposition and reconstruction of the measured signal. The wavelet function φ will generate the high frequency components (details) and scaling function ϕ will generate the low frequency components (approximations) of the distorted signal.

A multiresolution analysis (MRA) and decomposition.

Discrete Wavelet Transform (DWT) is the basic tool for feature extraction. DWT is the discrete counterpart of the Continuous Wavelet Transform (CWT). The CWT of a continuous time signal $x(t)$ is defined as

$$CWT_{\Psi} x(a,b) = \int_{-\alpha}^{\alpha} x(t) \Psi^{*}_{a,b}(t) \, \mathrm{d}t, \quad a,b \in R, a \neq 0,$$
$$\Psi^{*}_{a,b}(t) = \frac{1}{\sqrt{a}} \Psi^{*}\left(\frac{t-b}{a}\right). \tag{1}$$

The unction $\Psi(t)$ is the mother wavelet, and the asterisk denotes a complex conjugate. a and b are the scaling and translating parameters respectively. The sampled signal x_k is used to replace the CWT of x_t such that

$$DWT_{\Psi} x(m,n) = \sum\nolimits_{k} x_k \Psi^{*}_{m,n}(k) \, , \tag{2}$$

where

$$\Psi^{*}_{m,n}(k) = \frac{1}{\sqrt{a_0^m}} \Psi^{*}\left(\frac{k - nb_0 a_0^m}{a_0^m}\right). \tag{3}$$

Both the scaling factor a_0^m and the shifting factor $nb_0 a_0^m$ are functions of the integer parameter *m*, where *m* and *n* are scaling and sampling numbers respectively and $m = 0,1,2,\ldots$ By selecting $a_0 = 2$ and $b_0 = 1$, a representation of any signal x_k at various resolution levels can be developed by using the MRA. It is implemented by a set of successive filter banks with the low pass filter $h(n)$ and its dual high pass filter $g(n)$. The approximation and the detail coefficients are obtained from the input sequence $c_{j\text{-}1}(n)$.

$$c_j(n) = \sum_k h(k-2n)c_{j-1}(k)\,, \tag{4}$$

$$d_n(n) = \sum_k g(k-2n)c_{j-1}(k)\,, \tag{5}$$

where c_j represents the coefficients of the approximate signal at level *j*, and d_j represents the detailed coefficients of the signal at level *j*.

3 Feature Extraction, Recognition and Classification of Power Signals

Feature extraction is a preprocessing operation that transforms a pattern from its original form to a new form suitable for further processing. Mapping the data of the distorted signal into a wavelet domain is the first step in performing the feature extraction process.The power signal with disturbance when subjected to DWT will generate a discontinuous state at the start and end points of the disturbance duration. For each of the disturbance, the DWT coefficients generated have variations which are used to recognize the various power signal disturbance and thereby classifying the different power quality problems.By applying DWT, the distorted signal can be mapped into the wavelet domain and represented by a set of wavelet coefficients.

There are different wavelets that can be used to decompose the distorted signal and extract the feature vector. Here the Daubechies "db4" wavelet function is used to decompose the signal by DWT. Since maximum energy localization is obtained using db4 and db8 when compared to the other type of wavelets db4 is used.The parameters of the voltage waveforms during Power Quality (PQ) events are statistically different from those that are calculated during an event free time period. This statistical difference is used for effective detection of the PQ events like sag/swell, momentary interruption, transients etc… The statistical behavior of the feature vectors is obtained. Local statistical properties of the waveform vary with the PQ events. The sample mean and sample variance are the most commonly used statistical parameters for detection. The sample mean takes the whole signal as a combination of time samples that are statistically independent and performs an averaging along these samples. The voltage samples are correlated to each other. To find the between sample correlations, the auto correlation function can be used. This gives the information about the relation of the samples with each other.

Using MATLAB 7.0, the most commonly occurring disturbances are initially simulated. The categories that are simulated are normal sinusoid, sudden sag, sudden swell, transients, momentary interruption, and notches. The signals generated are sampled at a frequency of 1 kHz. The unique attributes for each disturbance type are used and allowed to change randomly, within specified limits, in order to create different disturbance cases.

The first step in applying the DWT technique is data generation. The frequently occurring power quality events like sags, swells, momentary inter–ruption, notches, and transients are chosen. For each type of disturnace, 200 different signals was generated. Each signal is 0.6 second length, sampled at a frequency of 1 kHz. The sag and swell duration is randomly varied for different time durations. For a signal with sag the voltage magnitudes were randomly chosen from 0.5 to 0.9 per unit. Similarly for a signal with swell the voltage magnitudes were randomly chosen from 1.1 to 1.8 per unit. For the other type of disturbances similar variation with position or magnitudes was made randomly. The pure sinusoidal signal and the signals with disturbance is first analyzed using the orthogonal wavelets. This decomposition by wavelets results in approximation and detail coefficients.

These coefficients, when subjected to statistical analysis gives a good indication about waveform disturbances due to various power quality events. Changes in the characteristics of the analyzed waveform due to PQ events reflect to the residual error signal samples in the sense of an increase in variance. This increase indicates a heavy tailed Probability Density Function (PDF).

If f is a probability density function for random variable *X*, the associated cumulative distribution function (cdf) *F* is given by (6)

$$F(x) = P(X \leq x) = \int_{-\alpha}^{\alpha} f(t)\,\mathrm{d}t\,. \tag{6}$$

The cdf of a value *x*, $F(x)$, is the probability of observing any outcome less than or equal to *x*. A cdf has two theoretical properties. The cdf ranges from 0 to 1. If $y > x$, then the cdf of *y* is greater than or equal to the cdf of *x*. The cdf function as applied to the approximations and details at two levels results in a variable p that contains the probabilities associated with the normal cdf with parameters $\mu = 0$ and $\sigma = 1$ at the values in *x*.

The power signal with sag disturbances occurring at various instances of time and with various magnitudes are decomposed by DWT. The power signal is decomposed to approximations and details at two levels. The approximations coefficients and detail coefficients are used for detecting the signal disturbance. The approximation coefficients (A1), the detail coefficients (D1) at the first level and approximation coefficients (A2), the detail coefficients (D2) are considered for disturbance recognition and categorization of the power signal. These approximations and details at the two levels are examined for three different characterization of the power signal disturbances. The first characterization is by finding the square of the approximation coefficients at the first level. The square of the approximation coefficients at level 1 is calculated for the normal sine waveform and the signal with power disturbances. Then these power signals withand without disturbances are subjected to probability distribution function (PDF) and cumulative distribution function (CDF) for categorization of the signal to clearly distinguish the features. The second characterization is by subjecting the approximations at two levels by Probability Density Function as explained above. The third characterization is by subjecting the details at two levels by Cumulative Distribution Function as from Eq. 6. It was found that the categorization feature of the signal is more predominant in the details at lower levels, when the detail coefficients are subjected to PDF and CDF.

The pure sine signal is decomposed by Db4 at two levels. The decomposition at the first and the second level results in approximation and detail coefficients.

First the squared approximation coefficients are calculated which is shown in the Fig. 1. Then the approximation and details at level 1 are subjected to CDF and PDF. Later the approximation and details at level 2 are subjected to CDF and PDF. In all these calculations from the waveform it could be observed that there are no disturbances for a pure sine wave and henceforth it could be viewed that the waveforms are identical over entire period.

Then a signal with sag (Fig. 2.a) is subjected to similar type of characterization. Various signals with sag occurring at different instants of time with different magnitudes are subjected to the calculations as in the case of a pure sine signal. In the Fig. 2b three different case are shown. It could be clearly shown that the exact location of the occurrence of the disturbance and the end of the disturbance is clearly identified. Whereas for a pure sine signal, no such differentiation could be seen. With 200 different samples of a sag signal a test pattern is generated.These samples for the various sag signals are used for training the neural network architectutre.

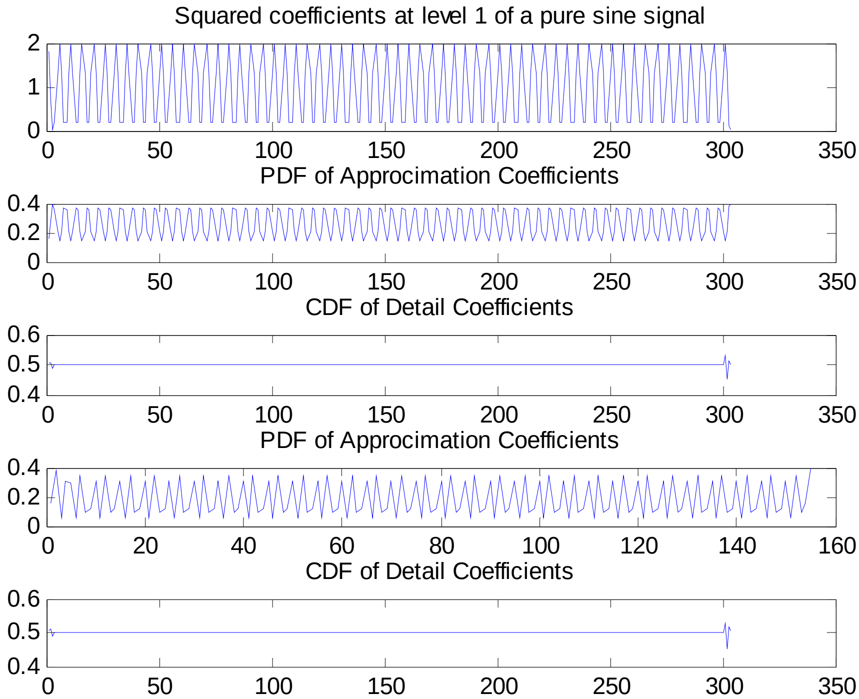

Fig. 1 – *Decomposition of a Pure Sine Signal at two Levels subjected to squared approximation coefficients, PDF and CDF of approximations and details.*

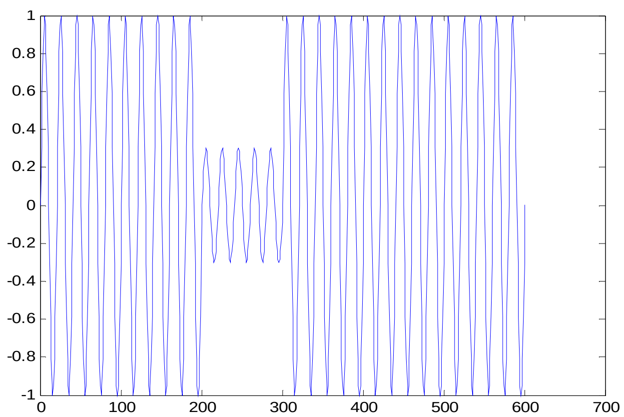

Fig. 2a – *Signal with sag.*

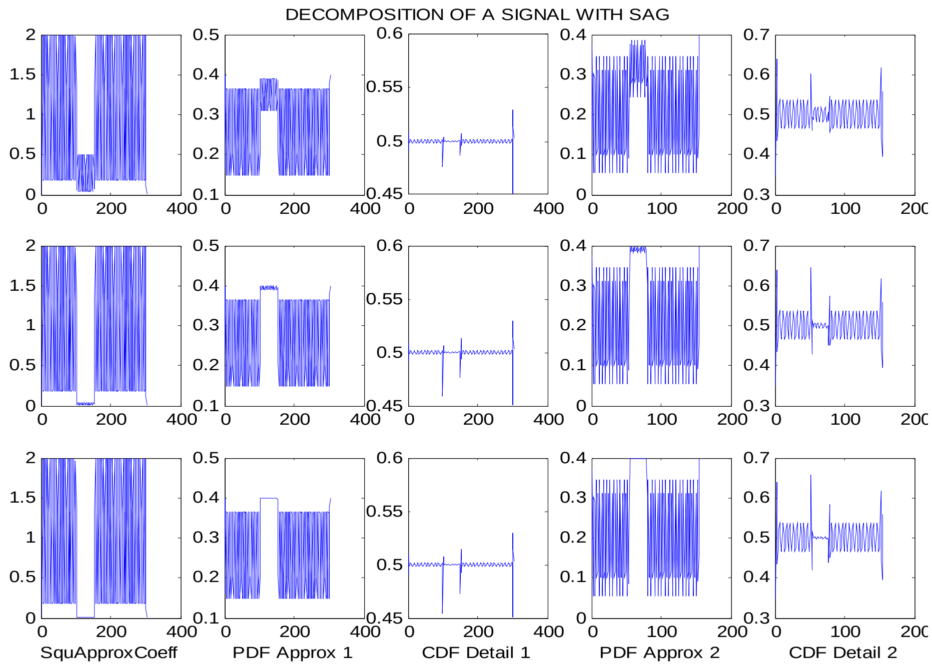

Fig. 2b – *Decomposition of a signal with sag using Db4 and the statistical computation.*

The other power signals that are used for categorization are power signals with swell, momentary interruption, transients and notches. These signals are subjected to DWT at two levels and the coefficients of the details and approximations are squared and their PDF and CDF are found to differentiate the various power signal disturbances. The power signal with a voltage swell, it's squared value of approximations and the PDF and CDF of approximations and details are shown in Fig. 3b. The signal with swell at different magnitudes and swell occurring at different instances are used for generating a test pattern.

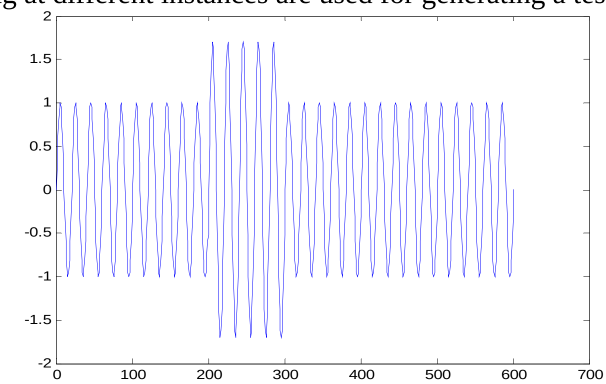

Fig. 3a –*Signal with swell.*

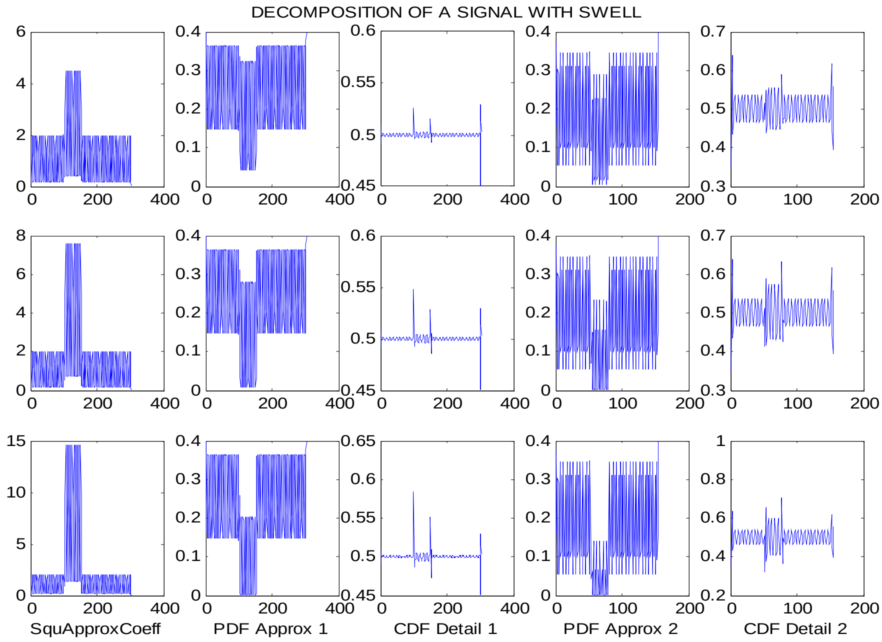

Fig. 3b – *Decomposition of a signal with swell using Db4 and the statistical computation*.

The next power signal disturbance that has been used is momentary interruption, Fig. 4a. The power signals with momentary interruption, it’s squared value of approximations and details along with PDF and CDF are shown in Fig. 4b. The signal with momentary interruption occurring at different instances are used for generating a test pattern, which is further used for training the neural network architecture.

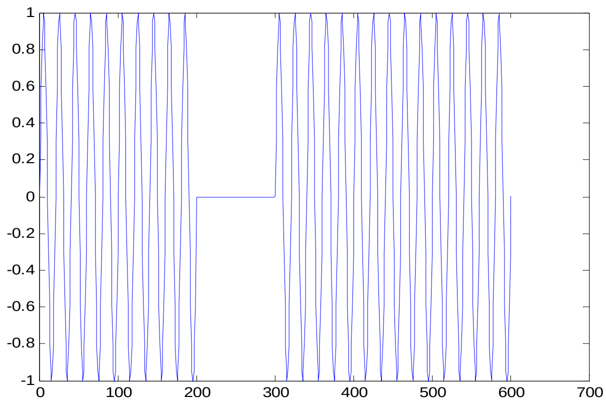

Fig. 4a – *Signal with momentary interruption.*

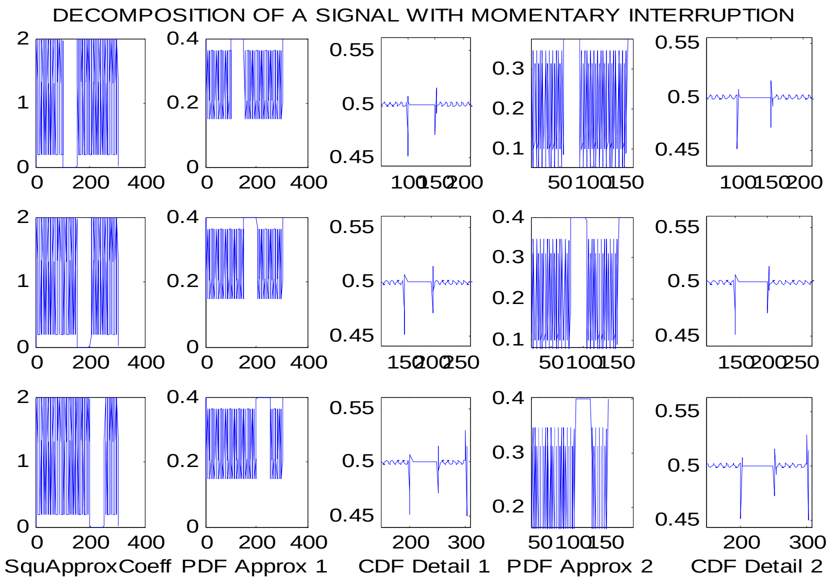

Fig. 4b – *Decomposition of a signal with momentary interruption using Db4 and the statistical computation.*

The next power signal disturbance that has been used is signal with transients, Fig. 5a. The power signals with transients subjected to wavelet decomposition gives a highly distinguishable approximation and detail coefficients. The squared value of approximations at level 1 and the approximations and details subjected to PDF and CDF for two levels are shown in Fig. 5b. The signal with transients occurring at different instances are used for generating a test pattern, which is further used for training the neural network architecture.

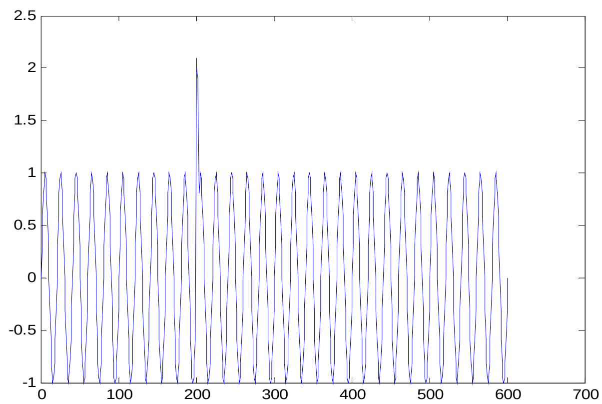

Fig. 5a – *Signal with transients.*

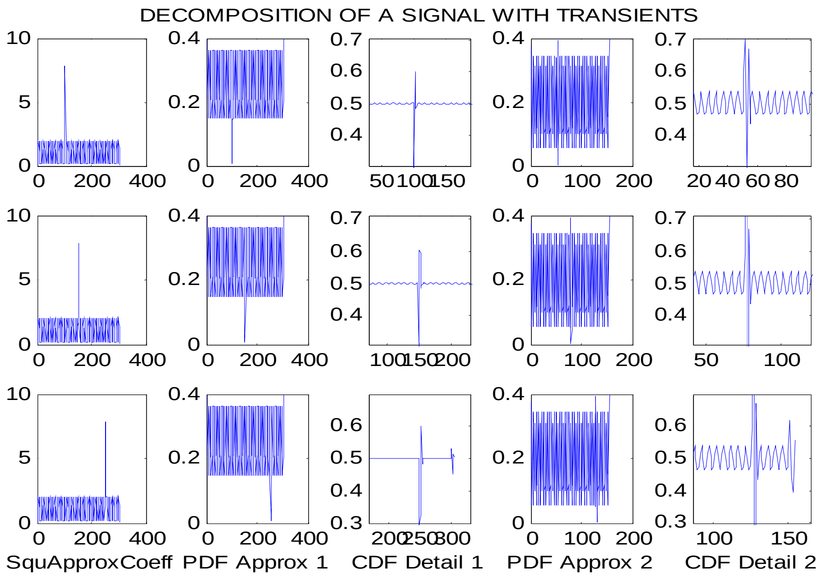

Fig. 5b – *Decomposition of a signal with transients using Db4 and the statistical computation.*

The next power signal disturbance that has been used is signal with notches, Fig. 6a. The power signals with notches subjected to wavelet decomposition gives a highly distinguishable approximation and detail coefficients. The squared value of approximations at level 1 and the approximations and details subjected to PDF and CDF for two levels are shown in Fig. 6b. The signal with notches occurring at different instances are used for generating a test pattern, which is further used for training the neural network architecture.

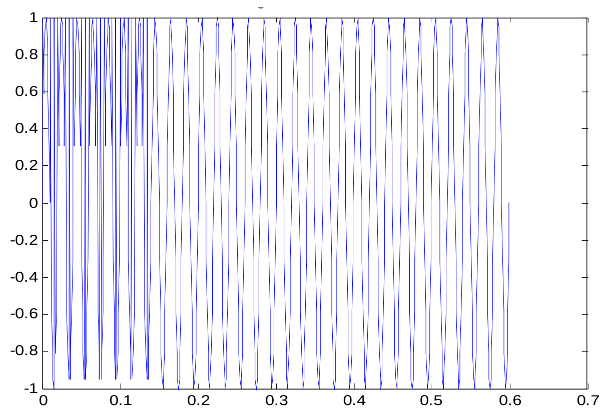

Fig. 6a – *Signal with notches.*

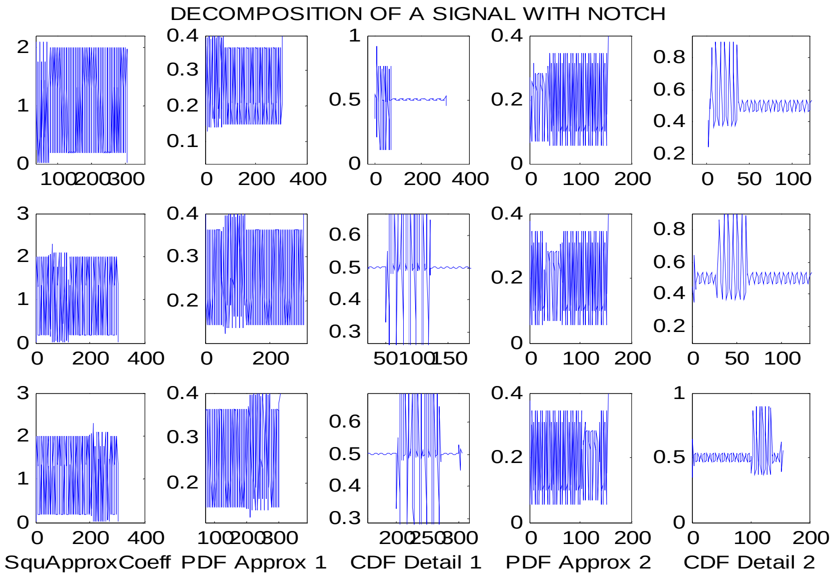

Fig. 6b – *Decomposition of a signal with notchess using Db4 and the statistical computation.*

Each of these power disturbances is characterized in its own way. The characterization of one power signal disturbance is different from the other. In each type of power disturbances 200 signals were generated and the signals were subjected to wavelet decomposition. The coefficients obtained are used for statistical computation to have a better accuracy in identifying the disturbance exactly. The other type of power disturbances also give a clear distinguishable identification.

4 ANN Structure Used for Fault Classification

Most of the classifiers, have poor classification performance hence Neural network architecture is used in this paper.Neural network can be applied to fault analysis because they are a programming technique applicable to problems in which the information appears in a vague, redundant, distorted or massive form. Also, they are able to learn using examples. In the problem of fault classification and fault location, they are potentially applicable because many parameters must be considered. There are methods to simulate in a quick and reliable way. When the conditions of electric system change, a neural network is able to adapt itself to the new state, immediately, just putting it under a new training. The ANN output is very fast, because its working consists in a series of very simple operations. Here LVQ network is used for classification.

The input to the network is from the coefficients of the wavelets. For 200 samples of data in each class of disturbance the various statistical details like squared A1, PDF of A1, PDF of A2, CDF of D1, CDF of D2. The data for a normal sine waveform is also given to the neural network architecture. The patterns generated for each of the disturbance is applied as input to the neural network. For each of the pattern the target is specified. For a sag pattern the target is specified as [0 1 0 0 0 0]. For a patern with swell the target is specified as [0 0 1 0 0 0]. Similarly for each pattern classification, the target is specified such that the particular pattens target is classified as 1 and the rest of the classes is made zero.There are six neurons in the output. For a pure sine wave the target is [1 0 0 0 0 0]. The output of the ANN structure will be Normal sine waveform, signal with sag, signal with swell, signal with momentary interruption, signal with transients and signal with notches. Two hundred data in each type of disturbance were used for training. After training the network, 200 test data were applied to the network for checking out the classification. For comparison the rms value of the signal is used for classification. This type of classification was not accurate as feature extraction was not done properly.

The categorization of the signal is tabulated as follows.

Table 1

Classification Results using the raw samples of voltage and the samples subjected to wavelet along with statistical computation to a neural classifier.

Class	**Classification Results**											
	RMS Classifier						**Neural Classifier**					
	Pure	**Sag**	**Swell**	**Mom int**	**Transient**	**Notches**	**Pure**	**Sag**	**Swell**	**Mom int**	**Transient**	**Notches**
Normal sine waveform	200	0	0	0	0	0	200	0	0	0	0	0
Sag signal	75	125	0	0	0	0	2	198	0	0	0	0
Swell signal	55	0	145	0	0	0	2	0	198	0	0	0
Signal with momentary interruption	0	35	0	165	0	0	0	3	0	197	0	0
Signal with transient	10	0	15	0	175	0	0	0	1	0	199	0
Signal with notches	0	15	12	5	13	155	0	0	2	0	0	198

5 Conclusion

In this work, we have proposed a method to detect and classify types of PQ events accurately. Around instances of PQ events, most of these parameters become relatively large in magnitude. Hence the detection of the PQ events could be detected accurately. The classification accuracy has increased since more number of inputs is applied to the neural network. The wavelet neural classifier along with the statistical computation has increased the classification accuracy.Though the complexity of the neural network architecture has increased the accuracy also has increased. It was also found that for classifycation, higher level decomposition signal manipulation does not give much information for categorization.

6 References

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