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ASSESSMENT OF PQ DISTURBANCES CLASSIFICATION AND COMPRESSION ALGORITHM USING DTCWT

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ABSTRACT

Electrical power quality (PQ) disturbance has become an important issue in India. On a distribution network, it is mainly caused by various nonlinear loads. Due to the varying power produced, it is affected by penetration of solar PV system as well. Therefore it is necessary detect and classify PQ events in account of evaluating a PQ problem. In other side due to increase of smart meters in smart grid, need to analyze huge collected data for small period, requires compression technique to reduce the data storage and transmit as well. This paper presents Dual Tree Complex Wavelet Transform (DTCWT) based PQ classification based on sub bands energy levels. Two stages FFNN architecture is designed to classify different PQ events to improve classification process. This also presents DTCWT based data compression algorithm to reduce the PQ data and develop algorithm, which is suitable for real time applications in smart grids.

KEYWORDS: Classification, compression, DTCWT, neurons, PQ signal.

I. INTRODUCTION

For present Technology, Reliable and real-time monitoring of electric power has become an important issue. All consumers, manufacturers and distributors of the electric power are responsible to achieve good quality of power in present smart grids. The Power Quality (PQ) disturbances cause an enormous financial loss to electric utilities, electrical equipment suppliers and customers particularly like industrial customers, medical field. As a result, it is important to monitor, classify and detect PQ disturbances in order to increase Quality of Power. PQ disturbances like voltage sag, voltage swell, Harmonics and interrupts are caused due to power system fault and the faults depends upon factors like environment, age of equipment, and the its maintenance [1]. Wavelet analysis through inductive inference methods are used extraction from the decision tree [2]. Wavelet transform is utilized to extract feature vectors for various PQ disturbances based on the multiresolution analysis (MRA) [3].The disturbance classification schema is performed with wavelet-neural network (WNN). It performs a feature extraction and a classification algorithm composed of a wavelet feature extractor based on norm entropy and a classifier based on a multi-layer perceptron [4].Analysis of power signals done using complex wavelet transform. Various features like energy, kurtosis, entropy, skewness etc. were extracted using ‘db4’ and complex wavelet decomposition up to 11 levels. A neural network based on these parameters was trained and tested [5]. Comparative study of Discrete Wavelet Transform and Dual-tree Complex Wavelet Transform techniques to the spatial video denoising, through the comparison results [6]. A generalized empirical wavelet transform (GEWT) for the recognition of single and combined power quality (PQ) disturbances. The FFT based frequency estimation is adaptive, requires no prior information and is also capable to diagnose all the PQ disturbances and a simple rule based decision tree (DT) for accurate recognition of most significant PQ disturbances [7]. Voltage disturbances can cause productivity losses and therefore it is required to be monitored. Continuous monitoring of PQ quality is based on data logging from smart meter and this data will be in Giga byte of information .For data logging, monitoring and analytics of larger size of data it is required to compress data and transmit data over power line[8] [9].

II. TECHNIQUES FOR POWER QUALITY MEASUREMENTS

In order to measure power quality of a given signal, there are various approaches, statistical and deterministic. The input signal is first transformed into frequency domain samples through a process called segmentation. Signal for which power quality is to be measured is first segmented into frames and for each frame, transformation is carried out. From the frequency domain samples obtained, the significant features are extracted to find out the power quality factors that are being affected due to disturbances. Based on the features extracted, classification is carried on either statistical approach or deterministic approach. Figure 1 shows the block diagram of PQ signal analysis.

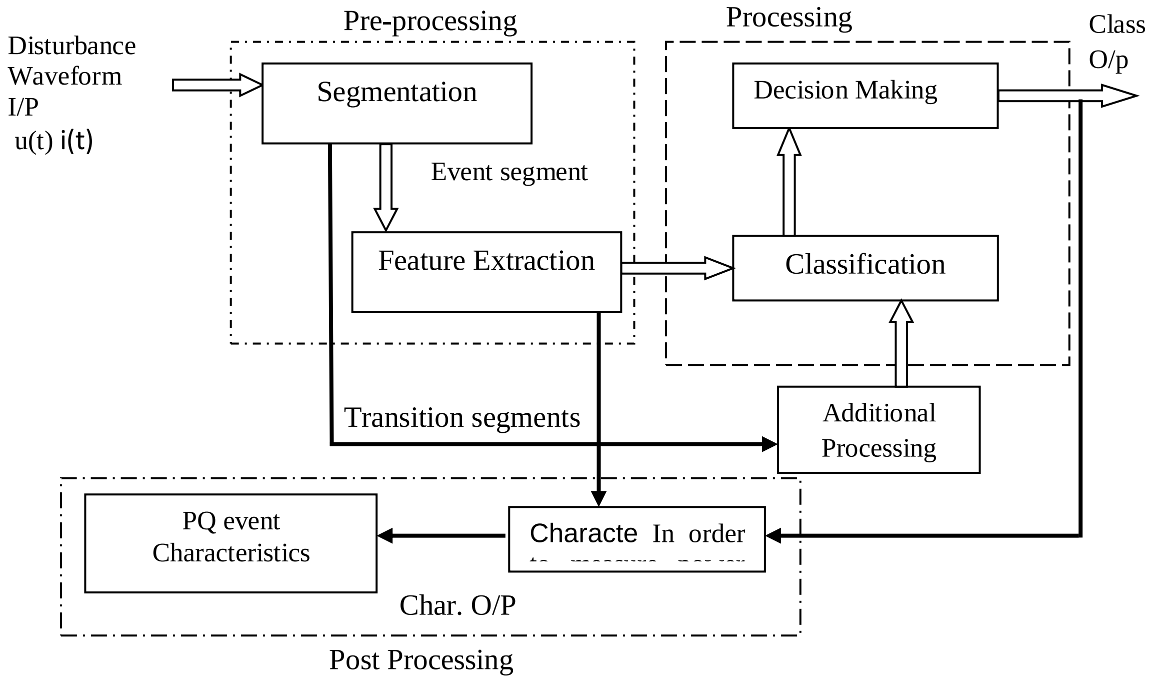

Figure 1 Block diagram of PQ signal analysis

Input signal is pre-processed for feature extraction and is classified based on the extracted feature. The decision-making unit classifies the PQ signal event, PQ signal characterization is not performed, and this work addresses both classification and characterization.

III. PROPOSED METHODOLOGY FOR DTCWT ENERGY LEVELS OF VARIOUS PQ DISTURBANCES

The PQ classifier algorithm is presented in Figure 2 for classification of synthetic power signal of different events. The New algorithm has two stages first one is to detect the feature extraction with DTCWT and second one is to classifier using ANN. PQ events such as sag, swell, harmonics, interrupts, sag with harmonics and swell with harmonics are generated using parametric equations that are considered as reference. Feed Forward Artificial Neural Network (FFANN) is designed and trained to classify the DTCWT energy features. The characterization is proposed based on energy components obtained from 10 sub-band levels -levels. MATLAB Software reference model is developed for PQ analysis based on the logic. The energies of the decomposed sub-band components are computed and are expressed in dB. The energy components are represented graphically and compared for analysis. To verify the functionality, input signal representing power line distortions are mathematically modelled. The Control parameters are used in the mathematical model in generating various distortions. The input signal is generated for time duration of 10 seconds, is divided into multiple frames of size 2048 samples. Each frame of data is processed using DTCWT and 10 sub-bands are computed along with the energy levels, which have unique values for various distortions. Based on the unique values of energy levels, PQ classification is performed. PQ distortion is identified is based on the classification algorithm, Feed forward neural network (FFNN) architecture with 10 inputs, 16 neurons in the hidden layer and 4 neurons in the output layer are designed.

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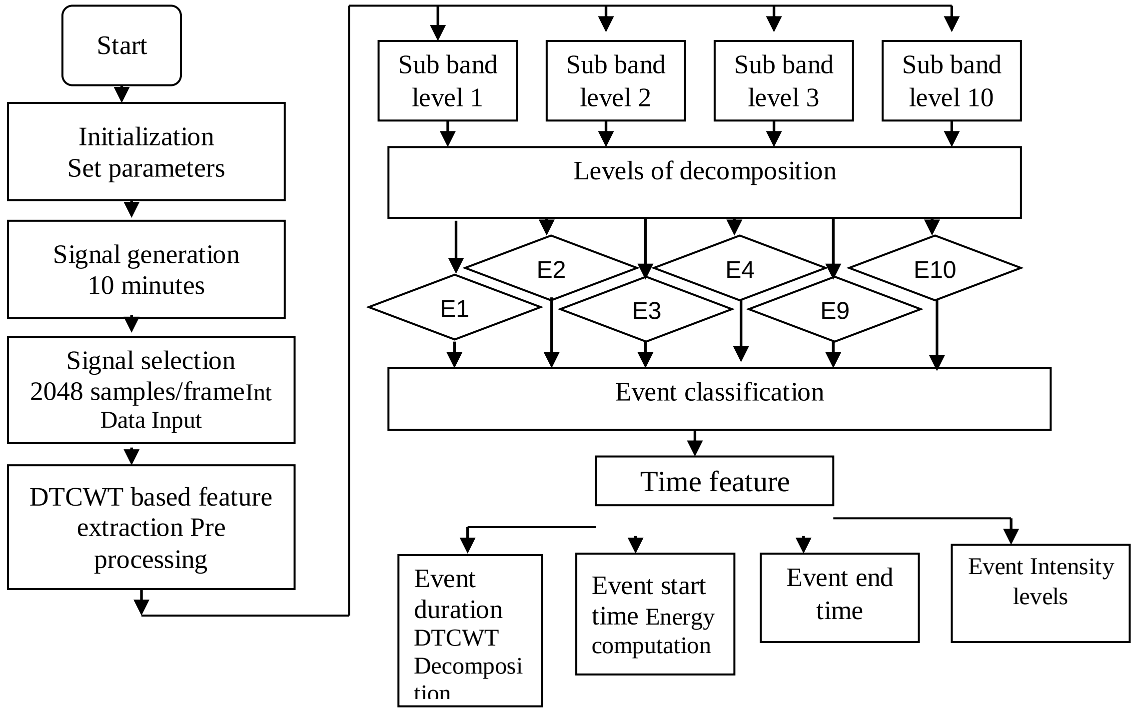

Figure 2 Proposed DTCWT based PQ classifier block diagram

IV. COMPRESSION IN DUAL-TREE COMPLEX WAVELET TRANSFORM

The dual tree complex wavelet transform is comparatively recent advancement to the discrete wavelet transform, The Dual Tree CWT has a real filter and an imaginary filter for both low pass and high pass and so a total of four filters for every level. The real and imaginary coefficients are used to compute amplitude and phase information of the signal, which are required to describe the energy localizations of the functions on the wavelet basis.

Let $\{h_0(n), h_2(n)\}$, $\{h_1(n), h_3(n)\}$ denote the low-pass and high-pass filter pair for real part decomposition and let $\{g_0(n), g_2(n)\}$, $\{g_1(n), g_3(n)\}$ denote the low-pass, high-pass filter pair for imaginary part decomposition. The imaginary signal part is obtained by Hilbert transform of the real signal. Figure 3(a) gives the structure of dual tree complex wavelet transform decomposition of a signal x (t).

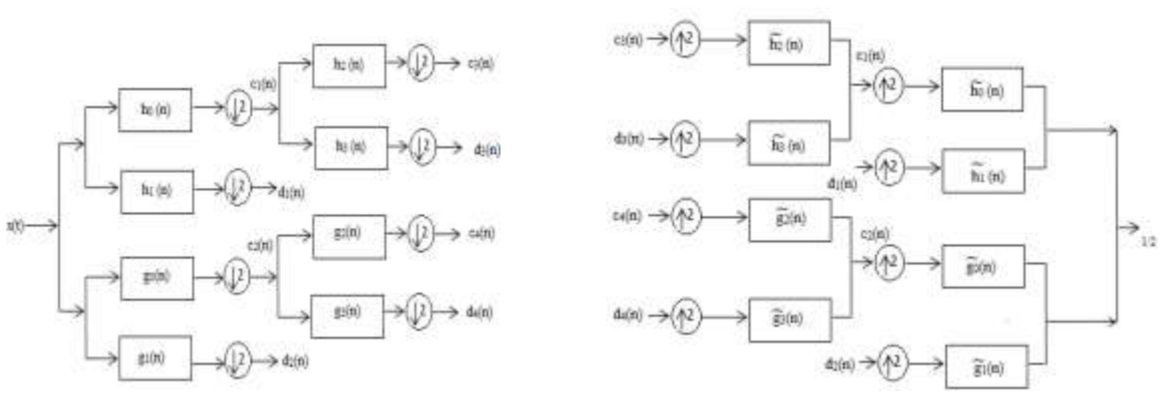

Figure 3 (a) Decomposition of signal using DTCWT. (b) Reconstruction of signal using DTCWT.

Real and the imaginary part are each inverted for reconstruction back to original signal; later These two signals are averaged to acquire the final output. The original signal can be recovered from either the real part or the imaginary part alone. Figure 3(b) gives the structure of dual tree complex wavelet transform of reconstruction of a signal x (t).

The filters are designed to satisfy the PR conditions and so that the complex wavelet $\psi(t) = \psi_h(t) + \psi_g(t)$ is approximately analytic. Where $\psi_h(t)$ and $\psi_g(t)$ are real and imaginary transformations. Pairs of Daubechies wavelet filters do not satisfy the requirement that $\psi_g(t) \approx H\{\psi_h(t)\}$. If the DTCWT is implemented with filters not satisfying this requirement then the transform will not provide the full advantages of analytic wavelets. Figure 4 shows the Flow Diagram of proposed Wavelet decomposition

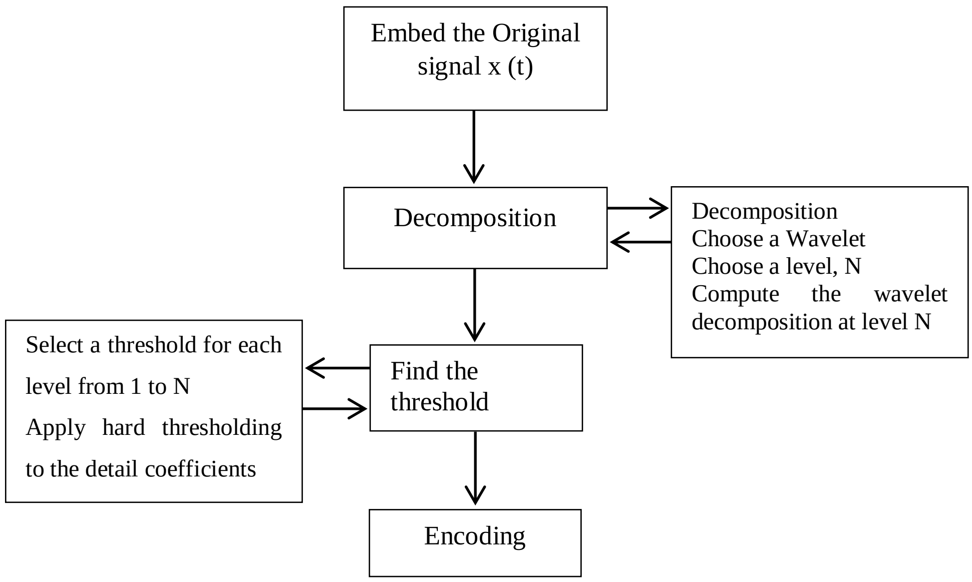

Figure 4 Flow Diagram of Wavelet decomposition systems

Compression Ratio is the ratio of difference between obtained sample points after encoding and sample points obtained after threshloding to the sample points obtained after Thresholding. By choosing a different threshold value, a different compression ratio can be obtained. After thresholding these sample points are passed to the RLC and Huffman encoding which leads less number of samples to store and transmitting cost are reduced significantly. Compression Ratio is defined equation (1) as

$$\text{Compression ratio} = \frac{|X-Y|}{Y} * 100 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \; (1)$$

Where X = sample points obtained after encoding
Y = sample points obtained after thresholding

The Mean Square Error (MSE) represents the cumulative squared error between the compressed and the original image, whereas Peak Signal to Noise Ratio (PSNR) represents a measure of the peak error, where The lower the value of MSE, the lower the error. This paper achieved a better compression ratio of real time signal and also obtains MSE, PSNR.

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V. RESULTS AND DISCUSSION

The developed MATLAB code for Classification of PQ signal is executed by considering the recorded PQ signal. The distorted PQ signals are extracted and classify using DTCWT algorithm, which are presented in Figure 5 (a) and (b). DTCWT decomposition of sag and swell wave analysis with different levels along with ten energy levels as shown in figure 6 (a) and (b) respectively. Table 1 gives the complete details of ten Sub band DTCWT energy levels of all PQ events.

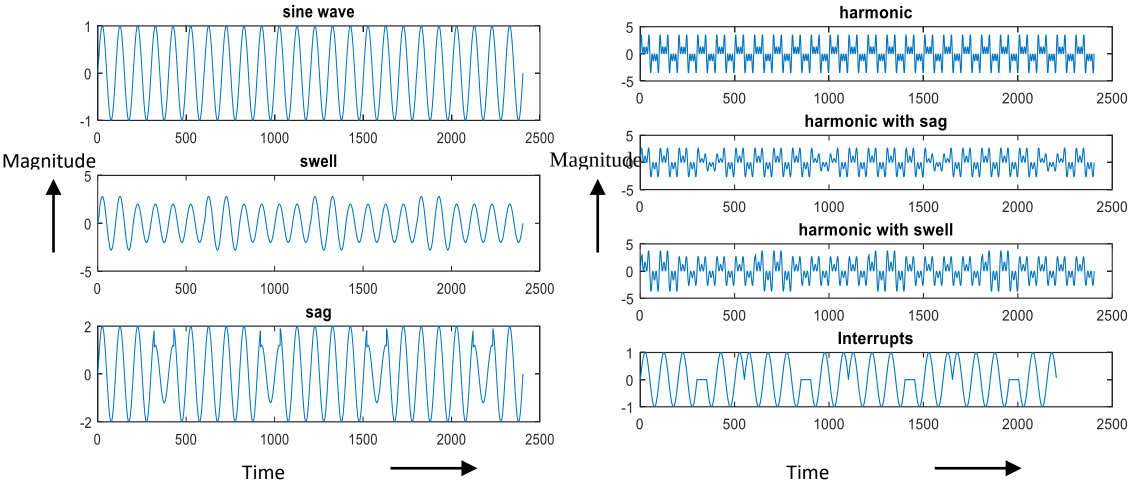

Figure 5 (a) PQ signals from sine to sag (b) PQ signals from harmonic to interrupt

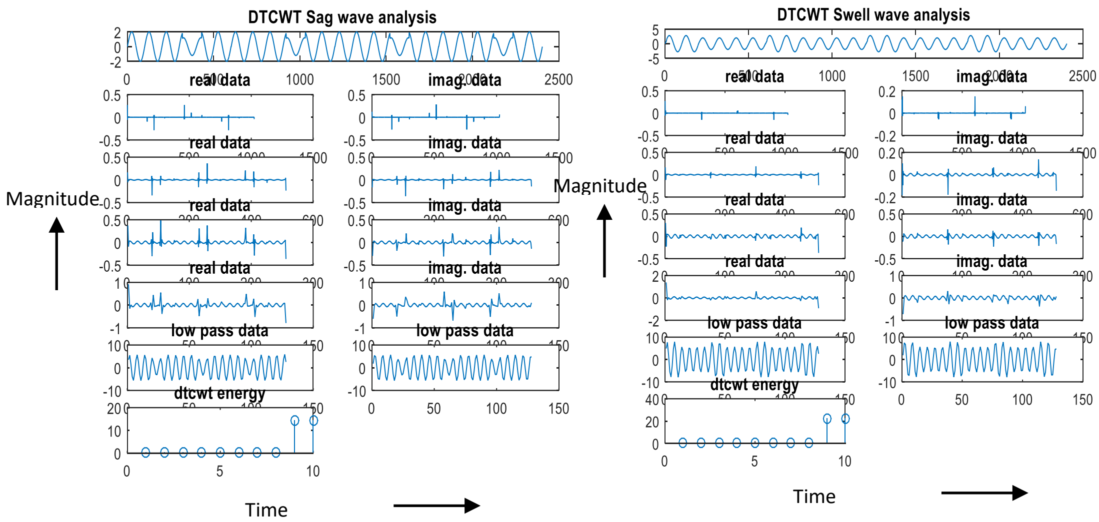

Figure 6 (a) DTCWT decomposition of sag (b) DTCWT decomposition of swell

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Table 1 DTCWT 10 sub band Energy levels of PQ signal

DTCWT Energy levels	Sine	Swell	Sag	Harmonics	Harmonics with swell	Harmonics with sag	Interrupts
Sub1	1.99E-05	0.000137	0.000371	0.003276	0.001464	0.001803	2.08E-05
sub2	5.42E-05	0.000396	0.001101	0.028076	0.004626	0.006116	6.17E-05
sub3	0.000398	0.002106	0.005102	2.468314	0.466609	0.716754	0.000484
sub4	0.00373	0.030153	0.027624	8.569848	6.23813	9.175324	0.005576
Sub5	5.74E-06	7.99E-05	0.000308	0.001567	0.000505	0.000847	6.60E-06
sub6	3.56E-05	0.000324	0.000806	0.025268	0.002725	0.004212	3.97E-05
sub7	0.00024	0.0017	0.002799	2.485433	0.452896	0.662299	0.000327
sub8	0.001534	0.012724	0.020683	8.72095	6.446904	9.616177	0.0037
sub9	3.998176	21.92961	14.15104	9.263175	8.34146	12.50206	3.410184
sub10	4.000876	21.94859	14.16427	9.102733	8.175389	12.18538	3.412575

PQ classification are done using Feed forward neural network (FFNN) architecture with 10 inputs, in which designed artificial neural network has number of inputs are 10, 16 neurons in the hidden layer and 4 neurons in the output layer. The results are obtained for magnitude of energy levels of 16 hidden neurons for different ten inputs. Where 16 neuron s are in X axies and magnitude of energy levels are represented in Y axis, which is shown in Figure 7 (a), (b). Figure 8 shows the neural network training display results.

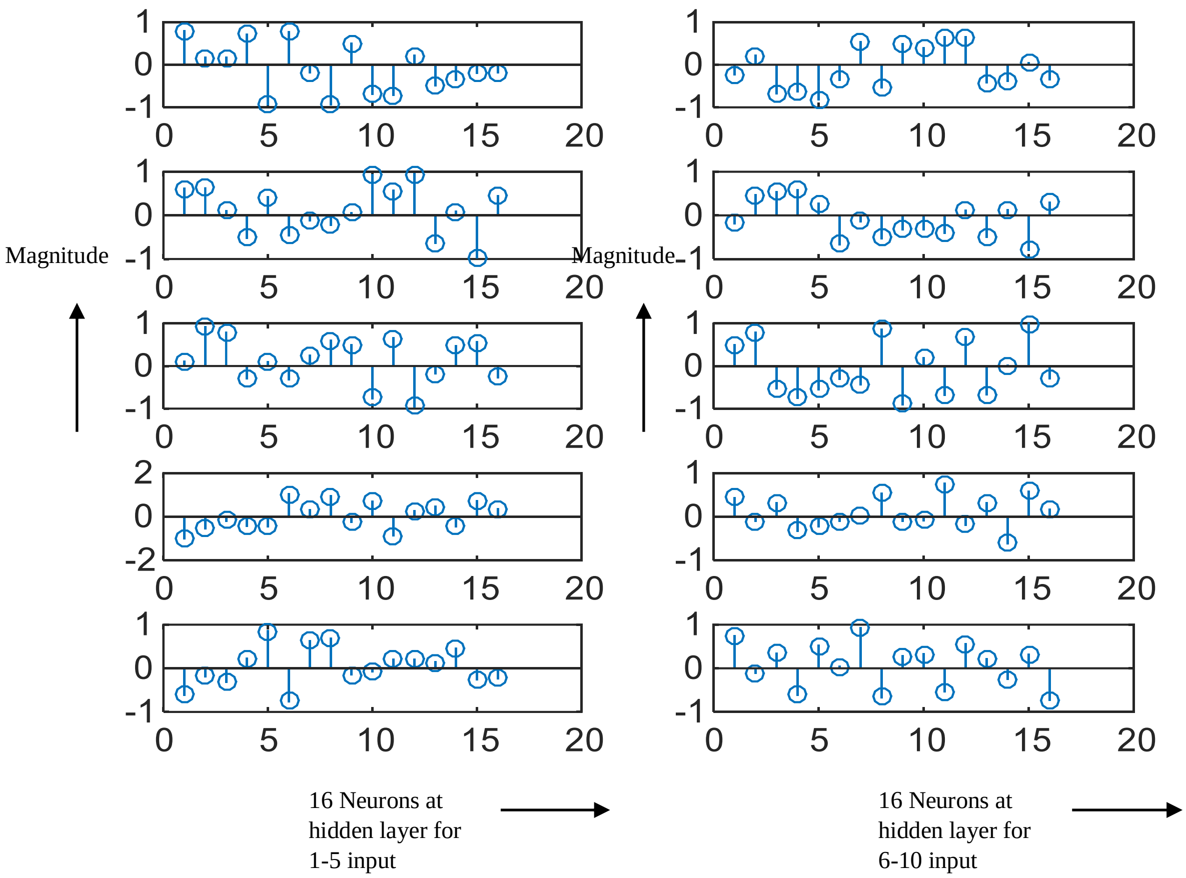

Figure 7 (a) Energy levels of 16 neurons for 1-5 PQ I/p (b) Energy levels of 16 neurons for 6-10 PQ I/p

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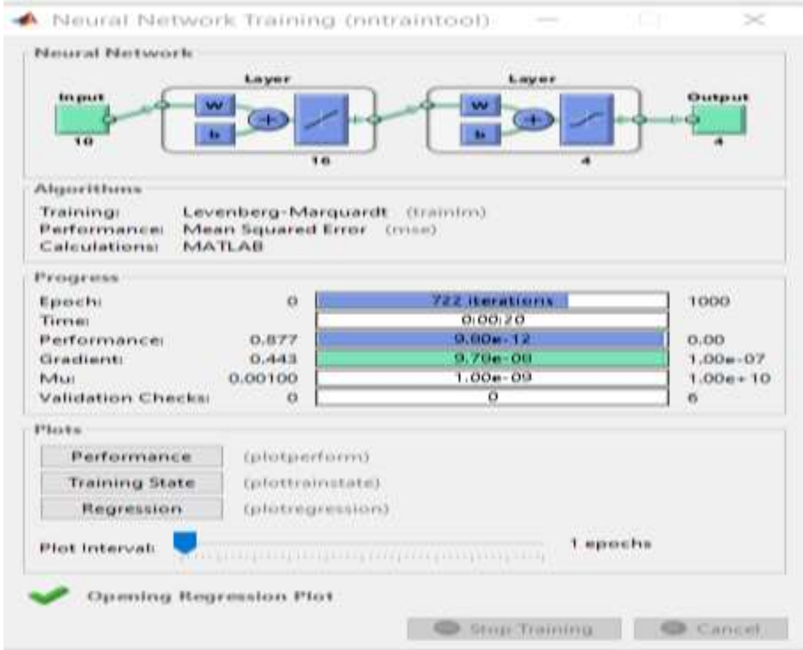

Figure 8 Neural network training display results

The neural network architecture is designed with 10 inputs representing the energy levels from 10 DTCWT sub bands. Figure 9 (a) and (b) represents the energy levels of sag and swell PQ events respectively, which are compared with undistorted PQ signal.

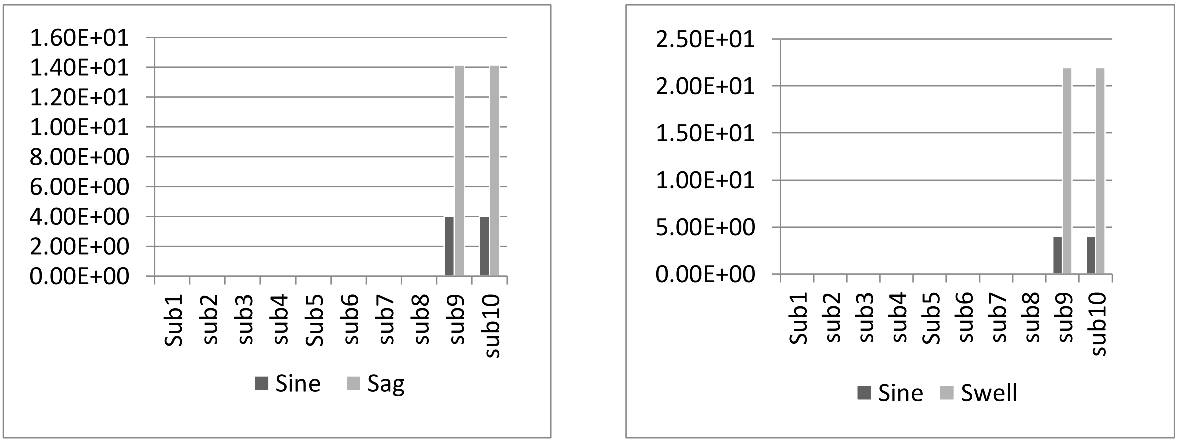

Figure9 (a) compared Energy levels of sag with sine events (b) swell with sine events

For analysis of compression of PQ signals are designed using DTCWT method The PQ data are compressed and reconstructed by performing inverse process. The reconstructed PQ signal is compared with the input data and performance metrics such as PSNR and compression ratio are computed. Compression parameter for real time PQ event are as shown in the Table 2 and also Table 3 shows the comparison results DWT and DTCWT for PSNR and compression ratio.

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Table 2 Compression parameter for PQ event

Parameter	Real time data sample
Original File Size(bytes) seqLen	2975778
Compressed File Size (bytes) encodedLen	954253
Compression Ratio (CR)	67.9327
Peak-Signal-to- Noise Ratio (PSNR)	42.4732
RMS err (MSE)	1.6482e-04

Table 3 Compression of DWT and DTCWT

Real time data samples	PSNR		Compression Ratio	
	DWT	DTCWT	DWT	DTCWT
Real time data sample	42.2111	42.4732	82.7240	67.9327

VI. CONCLUSION

In this paper a novel approach for Power Quality disturbances classification and data compression has been presented. Here we have discussed and analyzed about various PQ disturbances like voltage sag, voltage swell, harmonics, harmonics with sag, harmonics with swell and Interrupts. All these disturbances are analyzed based on Dual Tree Complex Wavelet Transform. Later theses signal been compressed using DTCWT compression algorithm. This work achieves better results. The obtained results of DTCWT compression data being compared with discrete wavelet transform (DWT). These concepts further implement in FPGA platform as a future work.

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