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Fast Algorithm for PQ Data Compression using Integer DTCWT and Entropy Encoding

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Abstract

Smart meters are an integral part of smart grid which in addition to energy management also performs data management. Power Quality (PQ) data from smart meters need to be compressed for both storage and transmission process either through wired or wireless medium. In this paper, PQ data compression is carried out by encoding significant features captured from Dual Tree Complex Wavelet Transform (DTCWT) sub bands. The DTCWT filter coefficients are scaled to integer values and fixed point algorithm is developed to improve computation speed. The bands corresponding to PQ disturbances such as Swell, Sag, Harmonics and Transients are captured accurately from corresponding DTCWT sub bands. A novel thresholding and quantization algorithm is developed to convert the bands to packets by reducing data size with minimum loss. Run Length Encoding (RLC) and Huffman Coding algorithm encodes the data further to achieve compression. The proposed algorithm achieves PSNR of 42dB and an improvement is achieved. Significant PQ disturbances signal are retained and redundancies in insignificant PQ data are minimized to achieve compression ratio of 67%.

Keywords: Power Quality, Data Compression, Complex Wavelets, Smart Grid.

INTRODUCTION

Information and Communication Technology for power generation, distribution and monitoring been used for Smart grids. The advanced monitoring systems will upgrade the grid performance such as self-healing from power disturbances, energy management, and automation and highly developed metering infrastructures (smart metering), integration of distributed power generation, renewable energy resources and storage units as well as high power quality and reliability [1]. By using smart metering Infrastructure sustains the bidirectional data transfer and also decrease in the environmental effects. With this resilience and reliability of power utility network can be improved effectively. Work highlights the need of development and technology encroachment in smart grid communications [2]. Due to Continuous monitoring of PQ data based on data logging from smart meter. This leads data will be in Giga byte of information [3] [4]. In [5], compression of power quality disturbance data in wavelet transform combined with adaptive arithmetic encoding, proposed demonstrating with 7.09% CR and mean square error by $1.42x10^{-3}$NMSE, compared with result of wavelet coefficient threshold of 13.67%CR and $1.88x10^{-3}$NMSE for voltage sag. In [6], compression technique algorithm used based on Huffman coding to improve compression ratio, different input samples are taken as input. In [7], input data's are transformed into wavelet of sub bands to gain multi resolutions, so that the PQ disturbances are chosen and noise is eliminated to reach advanced compressions. In [8], the techniques are based on different wavelet theory and also multi-resolution analysis. By using of data compression technique, power quality disturbances are reconstructed. In [9], adaptive quantization technique is proposed to select considerable data from the PQ signals after Parks transform. The quantizers are considered to predictive logic so that inverse process is carried out without loss during reconstruction process. The limitations of wavelet transform are the shift variance and loss of directional selectivity. The power fluctuations can lead to time delays in PQ signals are being monitored and using DWT will lead to change in PQ signal metrics as DWT is shift variance. Dual

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Tree Complex Wavelet Transform (DTCWT) will overcome shift variance limitations as DTCWT has real and imaginary filters that will generate wavelet coefficients that are shift invariant. In this paper, novel algorithm based on DTCWT is proposed to compress PQ signals and suitable encoding schemes are presented to compress PQ signals achieving advanced compression. Section 2 presents brief introduction to DTCWT, Section 3 discusses the proposed PQ data compression algorithm based on DTCWT, Section 4 presents the experimental setup and flow diagram for software implementation of proposed algorithm. Section 5 presents the results and finally conclusion is presented in Section 6.

DUAL TREE COMPLEX WAVELET TRANSFORM ALGORITHM

The input signal are decomposes to low pass and high pass sub bands in DTCWT, which is similar to DWT but generates imaginary sub bands in adding up to real sub bands. The wavelet filter coefficients for computation of real and imaginary sub bands are orthogonally shifted and which are associated by Hilbert transform. The complex wavelet transform is represented by Eq. (1),

$\Psi(t) = \Psi n(t) + j\ \Psi g(t)$ ---------------------- (1)

Where, $\Psi g(t)$ is Hilbert transform of $\Psi n(t)$.

The input signal S(z) is decomposed into low frequency part $S_{l1}(z)$ and high frequency part $S_{h1}(z)$ and can be represented as in Eq. (2),

$S(z) = S_{l1}(z) + S_{h1}(z)$ ---------------------- (2)

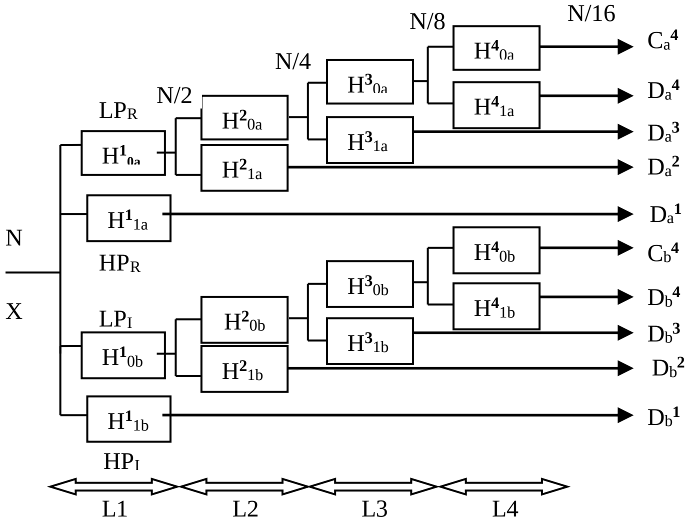

Figure 1: DCTWT algorithm for four-level decomposition

DCTWT algorithm for four-level decomposition is shown in Figure 1. The input signal are represented by X, that consisting of N samples are decomposed to 10-sub bands are represented of real and imaginary bands of DTCWT outputs consisting of N/16 samples. The transform is twice expansive as it generates 2N DWT coefficients for N-point input signal. Table 1 represents the filter coefficients used for real tree and imaginary tree for first level decomposition. There are 10 coefficients are considered for each of low pass and high pass filters of real and imaginary decomposition tree structures. The filter coefficients need minimum of 16-bits for representation and hence time consuming in terms of performing arithmetic operations.

In this work, the filter coefficients are scaled to nearest integers and fixed points arithmetic based algorithm and data representation is proposed. The scaled filter coefficients are presented in Table2

Table 1: DTCWT filter coefficients for first stage

DTCWT Filter Coefficients (Real)		**DTCWT Filter Coefficients (Imaginary)**	
LOW PASS	HIGH PASS	LOW PASS	HIGH PASS
0	0	0.01122679215254	0
-0.08838834764832	-0.01122679215254	0.01122679215254	0
0.08838834764832	0.01122679215254	-0.08838834764832	-0.08838834764832
0.69587998903400	0.08838834764832	0.08838834764832	-0.08838834764832
0.69587998903400	0.08838834764832	0.69587998903400	0.69587998903400
0.08838834764832	-0.69587998903400	0.69587998903400	-0.69587998903400
-0.08838834764832	0.69587998903400	0.08838834764832	0.08838834764832
0.01122679215254	-0.08838834764832	-0.08838834764832	0.08838834764832
0.01122679215254	-0.08838834764832	0	0.01122679215254
0	0	0	-0.01122679215254

Table 2: Scaled filter coefficients.

DTCWT Filter Coefficients (Real)		**DTCWT Filter Coefficients (Imaginary)**	
LOW PASS	HIGH PASS	LOW PASS	HIGH PASS
0	0	2	0
-22	-22	2	0
22	2	-22	-22
178	22	22	-22
178	22	178	178
22	-178	178	-178
-22	178	22	22
2	-22	-22	22
2	-22	0	2
0	0	0	-2

DTCWT algorithm of four levels decomposition generates ten sub bands denoted by {C_a^4, D_a^4, D_a^3, D_a^2, D_a^1, C_b^4, D_b^4, D_b^3, D_b^2, and D_b^1}. The subscripts are used as a and b represent real tree and imaginary trees respectively. C represents approximation output, D represents detail output. The subscripts represent the levels. The parameters C_a^4 and D_b^4 are obtained at level-4 represents real and imaginary low pass coefficients. The low pass coefficients contain the lowest band of PQ signal (pure sine wave) and the high pass band contains the detail features such as PQ disturbances.

PQ DATA COMPRESSION USING DTCWT BASED ALGORITHM

DTCWT based new PQ data compression algorithm is presented in Figure 2. The input raw data's are pre-processed to eliminate noise, later preprocessing operation. The noise filtered PQ signal is processed by the DTCWT block, which is to generate sub bands. The level select input denoted by N is set to find out the number of levels required. The N is input, set based on input sampling frequency. The sub bands coefficients are processed by the thresholder and quantizer unit by setting the threshold level and quantization level respectively. In this process the insignificant coefficients and redundant information in the sub bands are eliminated. The entropy encoding schemes such as Run Length Coding (RLC and Huffman Coding process the quantized data to achieve compression. Later these compressed data are grouped into number of packets and is prepared for storage or transmission in the smart meter sub module.

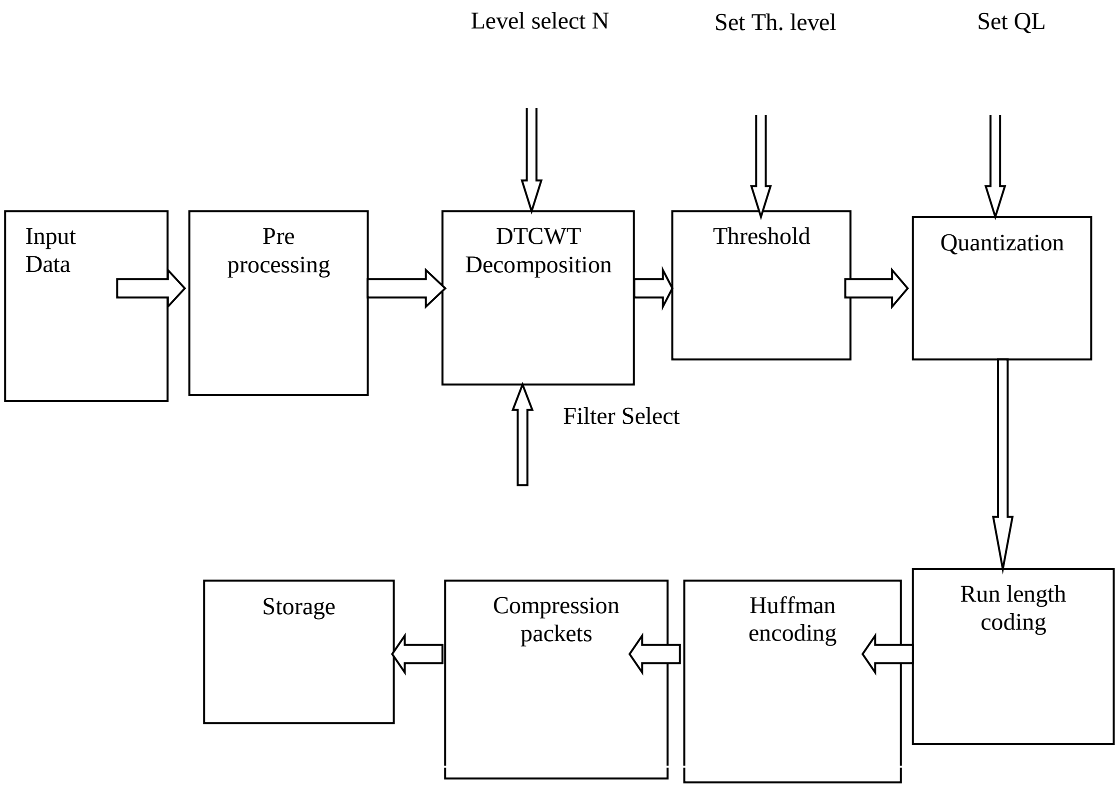

Figure 2: Block diagram of DTCWT based PQ data compression algorithm

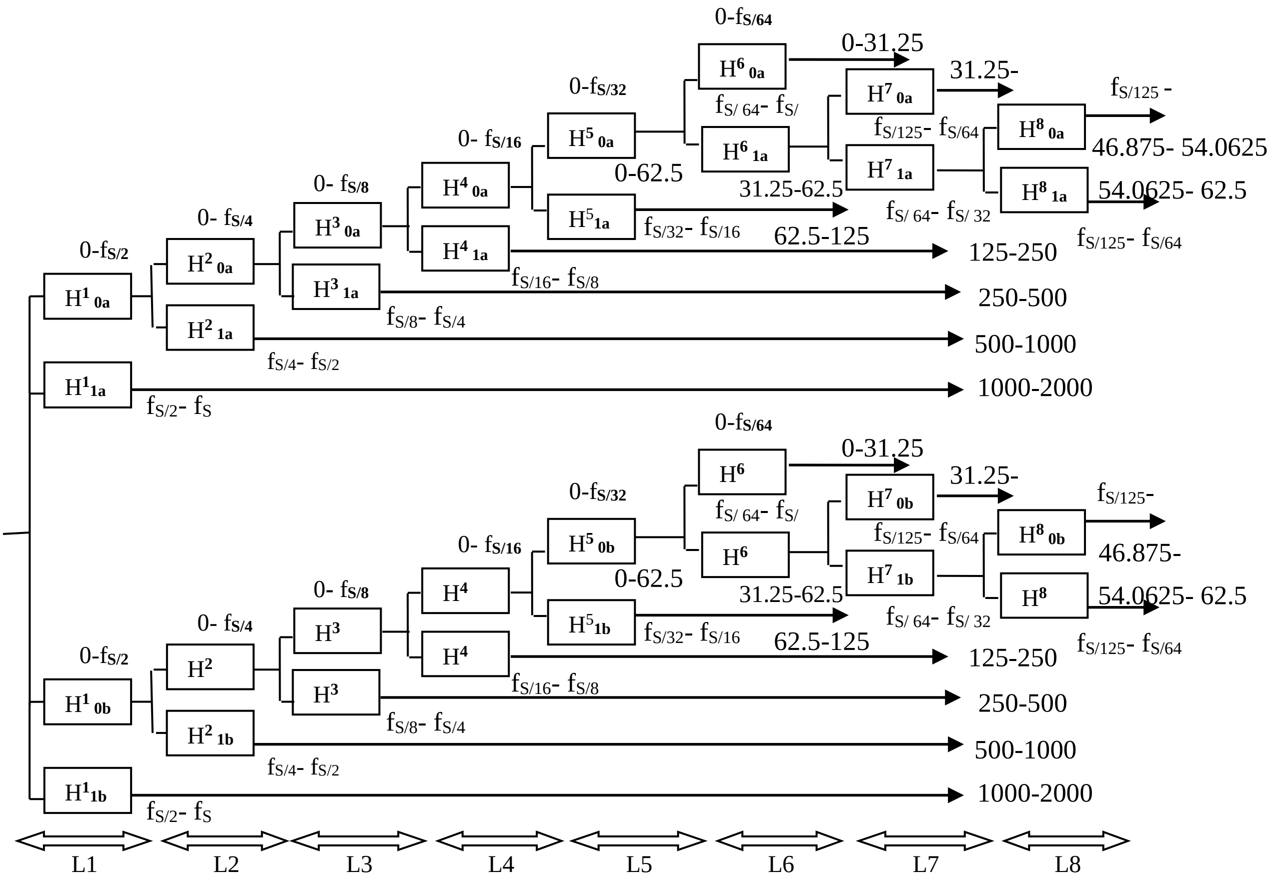

Figure 3: DTCWT algorithms to capture PQ disturbances

Table 3: Selected DTCWT sub bands for data compression

bands	**band 1**	**bands2**	**band 3**	**Band 4**	**Band 5**	**band 6**	**band 7**	**band 8**	**Band 9**
Sub bands	$DDC^8_{a/b}$	$DDD^8_{a/b}$	$DC^7_{a/b}$	$C^6_{a/b}$	$D^5_{a/b}$	$D^4_{a/b}$	$D^3_{a/b}$	$D^2_{a/b}$	$D^1_{a/b}$
Frequency Range (Hz)	46.875-54.0625	54.0625-62.5	31.25-46.875	0-31.25	62.5-125	125-250	250-500	500-1000	1000-2000
PQ Signal	Sag/ Swell	PQ undefined	Sag/ Swell	Noise	Hormonics1	Harmonics (2-5)	Harmonics (5-10)	Interrupt	Interrupt
Threshold	No	Yes	No	Yes	No	No	Yes	No	No
Quantization	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Next step is to process of DTCWT algorithm decomposes input signal into multiple sub bands, each of these sub bands represents information in different frequency ranges varying from F_s to $F_{s/2}{}^N$. PQ disturbances such as swell, sag, harmonics and interrupts, the PQ signal undistorted will be 50Hz signal assuming a noise of 10% the frequency of the PQ signal will be in the range of 45 Hz -55 Hz. PQ disturbances such as Voltage, current causes amplitude variations that lead to frequency fluctuations, as well, The disturbances such as harmonics and interrupts will always be fall in higher frequency bands. In the novel algorithm shown in Figure 3, DTCWT decomposition is carried out to capture these signals accurately. 8-levels of decomposition are carried assuming the input sampling frequency to be of 2000 Hz. The seventh and eight level decomposition is carried out on high pass coefficients, as the high pass band in level 6, which will hold the PQ signal of interest. Later the low pass bands in level 6 are discarded. The low pass band in level 8 is in the frequency range of 46.875 Hz to 54.0625 Hz, which will capture the undistorted PQ signal. The high pass band in level 8 captures the PQ signal in frequency range of 54.0625 Hz to 61.15 Hz and hence will contain the voltage sag and voltage swell distortions. The low pass band in level 7 is in the frequency range of 31.25 Hz to 46.875 Hz and this band will also hold the voltage sag and swell distortions. From 8-level decomposition the DTCWT sub bands of importance are shown in Table 3 along with the information content. PQ events are captured in $DDC^8_{a/b}$, $DC^7_{a/b}$, $D^5_{a/b}$, $D^4_{a/b}$, $D^2_{a/b}$, $D^1_{a/b}$ sub bands.

The event in $C^6_{a/b}$ is noise and is discarded and the event in $D^3_{a/b}$, band is very high harmonics which is also discarded. The data in $DDD^8_{a/b}$ in PQ undistorted signal and is also interest. The process of quantization and thresholding is designed to retain the PQ events in bands 1,3,5,6,8,2,9. All other bands are discarded as the information content is very low. From the real and imaginary sub bands only the real band low pass coefficients are selected. As both of them have similarly energy levels. All the eight high pass bands are selected for encoding. The selected sub bands at level-4 will contain PQ disturbances such as voltage sag and swell. These disturbances may also be present in the low pass bands. The remaining three bands $\{D^3_{a/b}, D^2_{a/b}, D^1_{a/b}\}$ will contain all other disturbances. The $D^1_{a/b}$ sub band will have high frequencies disturbances and is considered with high priority.

Algorithm for Thresholding and Quantization are proposed in this work. Input signal of N samples reduced by half, after decomposition at every level. In this algorithm, a novel

thresholding algorithm is proposed to capture the PQ disturbances without loss by using variable thresholding method. To retain PQ disturbances in the high pass bands the thresholding level are set to {0.5,1,2,2} for$\{D^1_{a/b}, D^2_{a/b}, D^3_{a/b}, D^4_{a/b}\}$ bands respectively. Figure 4 shows the algorithm for variable Thresholding.

The sub band coefficients at each level will have different intensities and therefore in order to capture the PQ disturbances without loss of data, the Quantization levels are set as given in Eq. (3) - Eq. (6). By taking into account the maximum and minimum intensity levels at each band, the Q-levels are derived.

$$QD^4_{\frac{a}{b}} = \frac{(-1+2^8)}{2^1}\left[\frac{D^4_{\frac{a}{b}} - D^4_{\frac{a}{b}max}}{D^4_{\frac{a}{b}max} - D^4_{\frac{a}{b}min}}\right] \qquad \text{----- (3)}$$

$$QD^3_{\frac{a}{b}} = \frac{(-1+2^8)}{2^1}\left[\frac{D^3_{\frac{a}{b}} - D^3_{\frac{a}{b}max}}{D^3_{\frac{a}{b}max} - D^3_{\frac{a}{b}min}}\right] \qquad \text{------ (4)}$$

$$QD^2_{\frac{a}{b}} = \frac{(-1+2^8)}{2^0}\left[\frac{D^2_{\frac{a}{b}} - D^2_{\frac{a}{b}max}}{D^2_{\frac{a}{b}max} - D^2_{\frac{a}{b}min}}\right] \qquad \text{------ (5)}$$

$$QD^1_{\frac{a}{b}} = \frac{(-1+2^8)}{2^{-1}}\left[\frac{D^1_{\frac{a}{b}} - D^1_{\frac{a}{b}max}}{D^1_{\frac{a}{b}max} - D^1_{\frac{a}{b}min}}\right] \qquad \text{------ (6)}$$

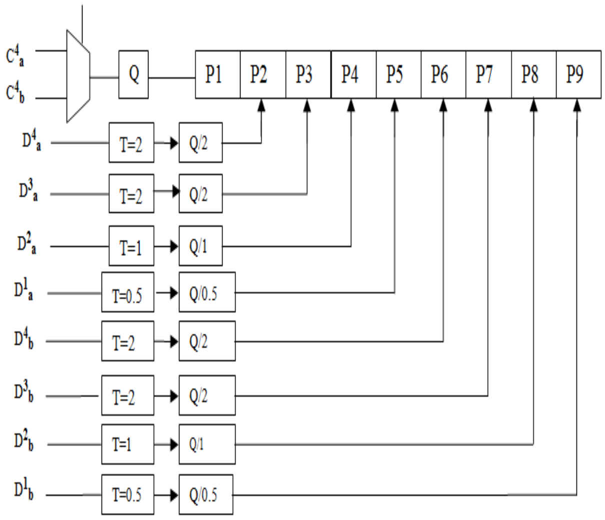

Figure 4: Variable threshold and quantizer module

Due to variable thresholding process the detail information is not lost. Similarly the quantizer designed is a variable quantizer. The low pass band is only quantized to prevent loss of data. The thresholded and quantized sub bands are combined into DTCWT packets denoted as {P1, P2, P3, P4, P5, P6, P7, P8, P9} as shown in Figure 4.The DTCWT packets are encoded using RLC encoder and Huff man encoder.

SOFTWARE MODELING AND IMPLEMENTATION

PQ analyzer EN50160 module is used to capture Real time PQ parameters by connecting the PQ analyzer to solar PV system along with net meter. Complete set up of solar PV connected to PQ recorder along with net meter are as shown in figure 5.

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Figure 5: Internal connection of PQ analyzer connected to PV system

Figure 6 and Figure 7 shows the RMS voltage and current data recorded from 10.11.16 to 12.11.16 respectively. RMS voltage, current of 4300 data samples obtained from three days are plotted. For PQ signal analysis, the average RMS values are used to generate actual PQ signal of 50Hz sine wave. From the generated PQ signal that comprises instantaneous RMS signals it is found that the distortions occur and are due to the switching ON and OFF PV inverters into the Grid constituting nonlinear loads.

The disturbances are recorded and stored in storage unit in the PQ instrument. The memory card reader is removed and the recorded PQ data is accessed in offline mode in Matlab environment for analysis.

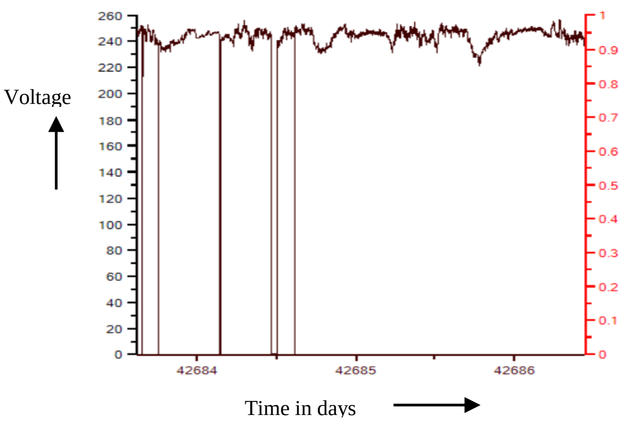

Figure 6: Continuous recorded voltage signal.

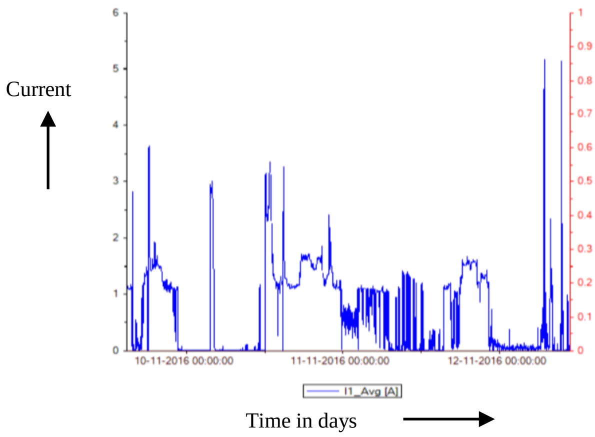

Figure 7: Continuous recorded current signal.

The proposed algorithm is modeled in Matlab and the performance metrics for data compression is computed to evaluate the advantages of DTCWT based compression algorithm as shown in Figure 8.

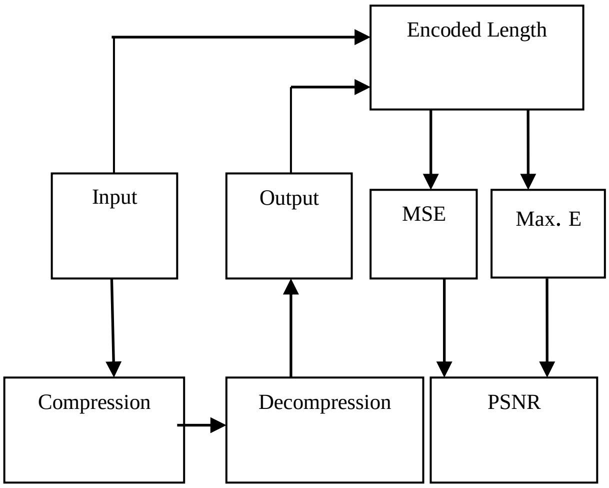

Figure 8: Performance evaluation setup

RESULTS AND DISCUSSION

MATLAB code for compression of PQ signal is executed by considering the recorded current PQ signal. The distorted PQ signal is presented in Figure 7. The DTCWT algorithm which is designed to compute eight levels of decomposition processes the PQ signal and the results are presented in Figure 9. The real and imaginary sub bands of eight levels of DTCWT decomposition are combined and displayed. From the results presented Continuous Current distortions with harmonics and interrupts that occur in data samples. Figure 10 presents the DTCWT results of Low pass real sub band that comprises of 17000 samples.

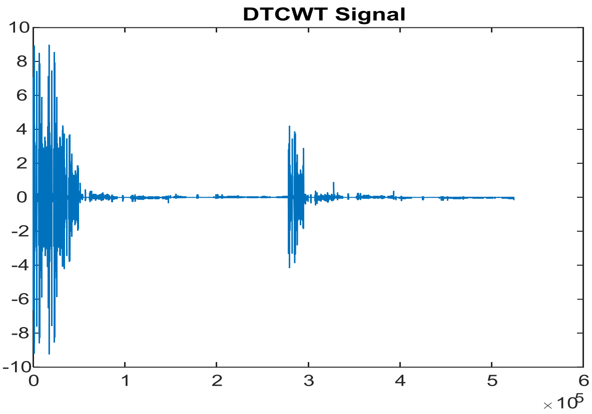

Figure 9: DTCWT sub bands

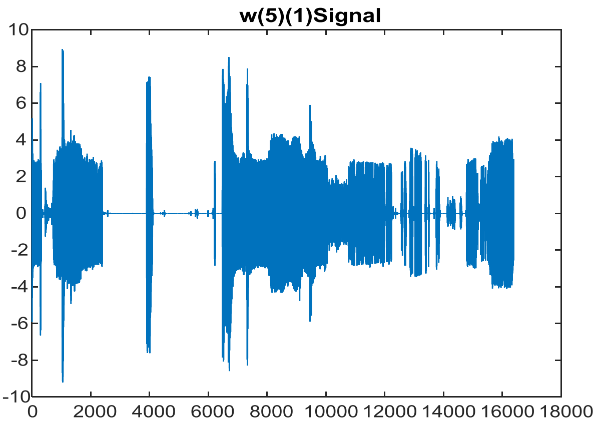

Figure 10: DTCWT low pass real sub band

Figure 11 presents the results of DTCWT sub bands after thresholding and quantization. Quantization process reduces the number of bits required to represent DTCWT samples thus constituting compression. Proposed quantization and thresholding logic ensures that the data loss does not exceed more than 2dB.

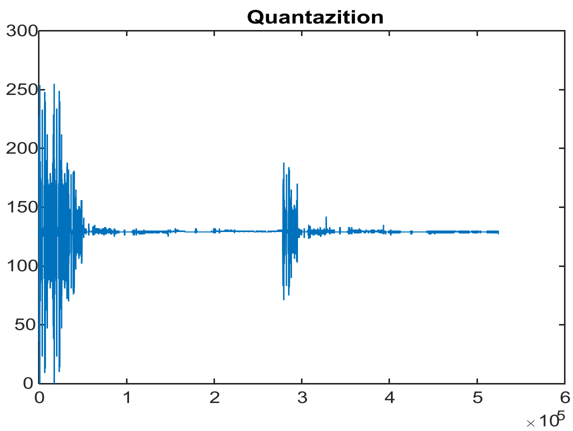

Figure 11: DTCWT sub bands after quantization and thresholding.

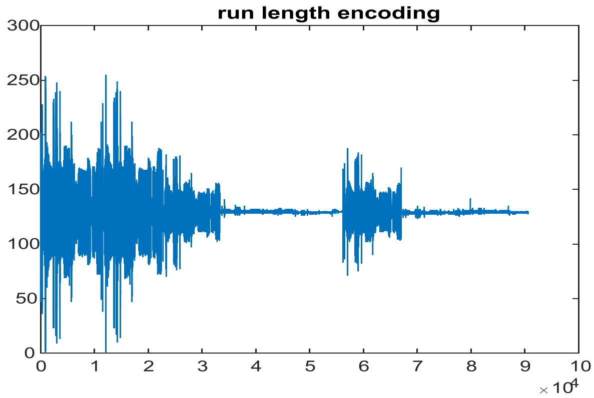

Figure 12: DTCWT sub bands after Run Length coding.

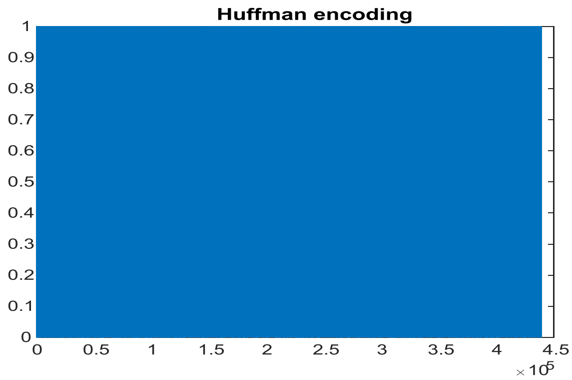

Figure 13: DTCWT sub bands after Huffman coding

The quantized DTCWT sub bands are entropy encoded using RLC and Huffman coding as shown in figure 12 and figure 13 respectively. The compressed PQ data is 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.

Table 4 presents results of PQ data compressed using the proposed algorithm DTCWT based algorithm for five sets of recorded data like voltage, current, Active power, Reactive power and Apparent power signal. The PQ voltage data recorded during 2016 has input sequence length of 2975778 samples (each of 8-bit) and is compressed to 954253 samples. The compression ratio is determined to be 67.9327 with maximum error of 5.8139, MSE of 3.7343 and PSNR of 42.4732. Eight-level DTCWT generates 18 sub bands of which 9 of them are real and 9 of them are imaginary. The shift invariant property of DTCWT is demonstrated by considering both of these bands. For compression of data only the real or the imaginary bands could be considered.

Table 5 gives the comparison of proposed method with reference paper on Measurement and Analysis for Power

Quality Using Compressed Sensing [10]. This proposed DTCWT produces higher peak signal to noise ratio (PSNR) and achieve less mean square error.

Table 4: DTCWT based algorithm results

Parameter	**Voltage**	**Current**	**Active power**	**Reactive power**	**Apparent Power**
Original File Size(bytes) seqLen	2975778	991926	3637062	2975778	3637062
Compressed File Size (bytes) encodedLen	954253	439036	410080	414683	443971
Compression Ratio (CR)	67.9327	55.7390	88.7250	86.0647	87.7931
Peak-Signal-to- Noise Ratio (PSNR)	42.4732	33.1159	88.4021	81.5907	88.4753
RMS err (MSE)	3.7343	0.0057	0.0021	0.0017	0.0021

Table 5: Comparison of results

Real time data	**Ref [10]**		**Proposed DTCWT method**	
	PSNR	**NMSE**	**PSNR**	**NMSE**
Real time Voltage Signal	29.4472	4.06	42.4732	3.7343
Real time Current Signal	15.2204	10.57	33.1159	0.0057
Active power Signal	54.4266	0.74	88.4021	0.0021
Reactive power Signal	52.328	0.39	81.590	0.0017
Apparent power Signal	74.506	0.09	88.475	0.0021

CONCLUSION

As a conclusion, the paper proposes power quality data compression based on DTCWT sub bands methods. This paper introduced new novelty of Thresoulding and quantization algorithm for reducing the size of PQ signal with minimum loss. An algorithm includes run length encoding Huffman coding technique to achieve the better results and obtain a PSNR of 42 db and Compression ratio of 67% of Real time PQ data, which has been obtained from grid.

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