WAVELET TRANSFORM BASED DATA COMPRESSION FOR REAL TIME POWER QUALITY DISTURBANCES

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ABSTRACT

Memory space for storing the power quality signal are major concern due to penetration of novel power sources and highly sensitive loads in modern power system. Wavelet based data compression approach is presented in this paper for the automatic data reduction and signal analysis. Real time data of power quality signals have been processed with IEEE Power quality wave data, to deal with practical implementation. The method proposed, which can be processed in real-time, showing the potential in data reduction and accurate characterization of voltage power quality signal in power systems **.**

KEYWORDS

Power quality signals, Data compression, Wavelet analysis, Real time monitoring, Wavelet energy coefficient

1. INTRODUCTION

Storage of power quality signals data have been major concern in the era of Smart grid, Power deregulation, and Green energy market [1, 3, and 14]. Novel methods have been discussed for data reduction and real time applications [2, 5, and 10]. Power quality (PQ) signals crucial while consider their frequency of occurrence and the economical impact on commercial and industrial customers [7, 11]. Power system faults, Utility equipment malfunctions, starting large loads and ground faults are the common causes of voltage sag and the adverse effects are malfunction of electronic drives, converters, motor stalling, digital clock flashing, and related computer system failure. Swell disturbance is mainly caused by single line to ground fault, upstream failure, switching of large load, and the large capacitor bank. Such signals pose harmful consequences as insulation breakdown of equipments, tripping out of protective circuitry in some power electronics system. Harmonics and other high frequency events are the caused by penetration of nonlinear load, solar PV integration and other distributed generation [8, 14]

As per definition sag and swell have the wide range of different frequency bands, variation in magnitude and can be stationary or non-stationary which had been discussed [8] and [6]. Also satisfy the PQ standards [12], related to PQ characterization and monitoring. The development of new signal processing tools is required for on-line, real-time detection and analysis of short duration voltage variations in order to avoid their consequences. Wavelet based data compression technique is capable of efficient data reduction for monitoring devices. This paper has come up with solution of data storage, based on data compression technique using wavelet with standard test signals of real time data [13], and results have been evaluated in terms of Mean Square Error (MSE) and compression rate (CR). The organization of paper is such that, section- 2, provides basics of wavelet transform and ascertain the concept of basic data compression and proposed scheme. Section-3 deals with result analysis with comparison of evaluation parameters and major findings.

2. WAVELET TRANSFORM

Wavelet transform consists of a pair of transformations from one domain to another domain. The original domain is the time domain in wavelet transforms, while the transformed domain is called the time-scale domain. The transformation process from time domain to time-scale domain is a forward transform, because a given signal is decomposed into several other signals with different levels of resolution as discussed in [1, 8, 9]. It is possible to recover the original time domain signal without losing any information. This reverse process is called the inverse wavelet transform or signal reconstruction, these two transform compose the wavelet transform.

Let $x(t)$ be the time domain signal to be decomposed or analyzed. The dyadic wavelet transform (DWT) of $x(t)$ is then defined as

$$DWT_{\Psi}\, x(m,n) = 2^{-\frac{m}{2}} \int_{-\infty}^{\infty} x(t)\Psi^{*}\left(\frac{t-n2^{m}}{2^{m}}\right)dt \tag{1}$$

where * denotes a complex conjugate, m and n are scale and time-shift parameters and $\boldsymbol{\Psi}(t)$ is a function of mother wavelet [5].

The DWT is implemented using a multiresolution pyramidal decomposition technique. A recorded time signal $c_0(n)$ with a sampled version of $x(t)$ is decomposed into its detailed $d_1(n)$ and smoothed $c_1(n)$ signals using filters $g(n)$ and $h(n)$. $g(n)$ has a band-pass filter response. Therefore, the filtered signal $d_1(n)$ is a detailed version of $c_0(n)$ and contains higher frequency components (such as sharp edges, transitions, and jumps in the original power disturbance signals) than the smoothed signal $c_1(n)$, because filter $h(n)$ has a low-pass frequency filter response. The decomposition of $c_0\,(n)$ into $c_1(n)$ and $d_1(n)$ is first-scale decomposition and they are defined as follows:

$$\begin{cases} c_1(n) = \sum_k h(k-2n)c_o\,(k) \\ d_1\,(n) = \sum_k g\,(k-2n)c_o(k) \end{cases} \tag{2}$$

Increasing-order decompositions are performed in a similar manner [5].

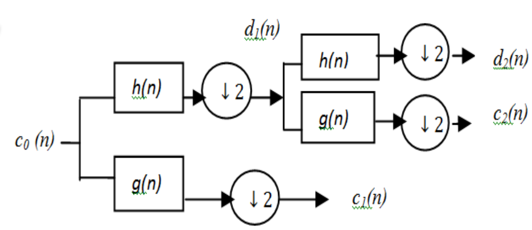


Fig **1.** Decomposition of $c_0(n)$ into **2** scales

Because the family of the dilated wavelets constitutes an orthonormal basis for $L^2(R)$, the original signal $x(t)$ could be recovered from its coefficients $DWT_{\Psi}x(m,n)$. The reconstructed signal is defined as:

$$x(t) = 2^{-\frac{m}{2}} \sum_{k} \sum_{n} DWT_{\Psi}\, x(m,n) \Psi^{*}\left(\frac{t - n2^{m}}{2^{m}}\right) \qquad (3)$$

2.1 Wavelet Based Data Compression

Wavelet transforms decompose any P Q signal into different scales at detailed resolutions. At each scale, the wavelet transform coefficients which associates with specific disturbance event are larger than those do not correspond to PQ disturbances, therefore specific disturbance coefficients are taking in account while others irrelevant events are leftover, so the amount of stored data can be drastically reduced. Now the compressed data can be used to reconstruct the original signal, with very little loss of information [1]. It was reviewed and discussed that the Data storage requirement is minimized and transmission time while preserving the reconstructed signal in such a way that it is drastically reduced from the original [1, 4, 6 and 10]. This study reveals new dimensions and offer great potential as a new tool for automatically classifying power quality disturbances. Data- compression procedure has been given in flow chart shown in figure 2.

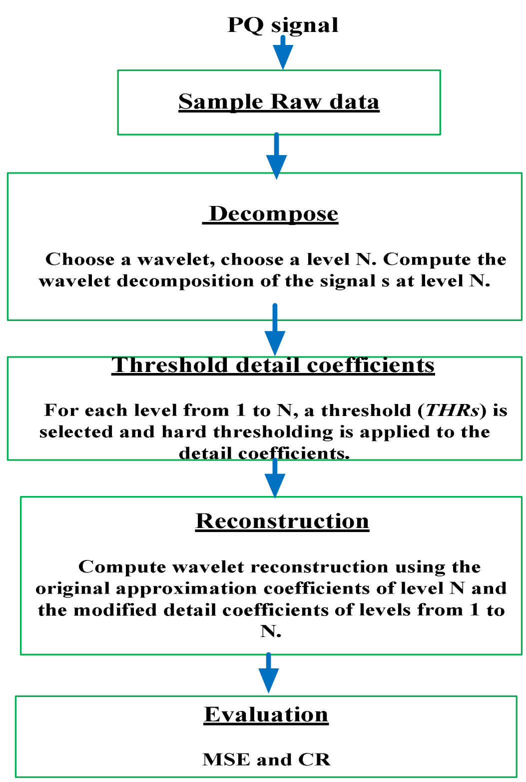


Fig 2. Flow chart of Data compression scheme

The method discussed in [1] is that, the magnitude of wavelet transform coefficients associated with PQ disturbance events is larger than normal signals. The compression is carried out in the wavelet domain by retaining wavelet transform coefficients associated with disturbance events and discarding all other disturbance free coefficients. The most-smoothed version of the original recorded signal $c_0(n)$ also kept for reconstruction purposes. Here thresholding of wavelet can be performed easily by removing WTC (Wavelet Transform Coefficients) below a specific value, which may vary scale to scale. Threshold (*THRs*) is based on the absolute maximum value of wavelet coefficients at associated scales s, $d_s(n)$, as given below in eq. (4):

$$THRs = (1-\mu) \times max\{\,|d_s(n)|\} \tag{4}$$

Where $0 \leq \mu \leq 1$. $|\, d_s(n)|$, the absolute value of detailed coefficients, that are smaller than THs are removed, and those that are larger, are stored. Now the signal after thresholding process, is $\widehat{d_s}\ (n)$. as given by eq. (5),

$$\widehat{d_s}\,(n) = \begin{cases} d_1(n) & |d_s(n)| \geq THRs \\ 0 & |d_s(n)| < THRs \end{cases} \tag{5}$$

Here the detailed WTCs given in eq.(5) is used in reconstruction process to reproduce approximate signal. The noise reduction and data compression can be made easy by choosing higher scales for MRA. Let us now define a compression ratio, *CR,* as follows:

$$CR = \frac{\text{ORIGINAL FILE SIZE}}{\text{COMPRESSED FILE SIZE}} \tag{6}$$

To evaluate the performance of the reconstructed signal $\widehat{c_0}(n)$, we calculate the mean-square error (*MSE*) between the original $c_0(n)$ and the reconstructed $\widehat{c_0}(n)$ signals as follows

$$MSE = c_0(n) - \widehat{c_0}(n) \tag{7}$$

Quality of reconstructed signal can be improved by reducing the *MSE*. In this way data compression is achieved effectively. The large amounts of data pose several practical problems in the storage and communication of the data from local monitors to the central processing computers. Data compression has, hence become issue of paramount importance in the PQ analysis area.

2.2. Energy of wavelet coefficients evaluation

Energy of wavelet coefficients are commonly employed as essential part of feature extraction. The parseval’s theorem provides the key idea to get the best feature of distorted signal. The energy of the distorted signal constitutes by energy in each of the expansion components, and the wavelet coefficients. This simple technique can be applied to a wide variety of PQ signals analysis, where no prior knowledge of PQ disturbance signal is required. Parseval’s theorem states that

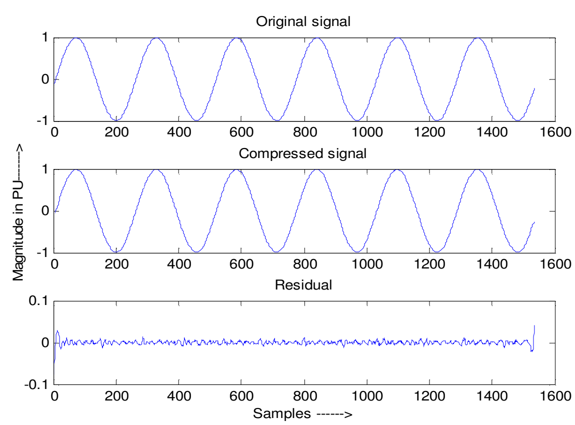
$$\int_{-\infty}^{\infty} |x(t)|^2 dt = \sum_{m}^{\infty} |c(m)|^2 + \sum_{m=0}^{\infty} \sum_{n=-\infty}^{\infty} |d(m,n)|^2 \quad (8)$$

Where $\sum_{m}^{\infty} |c(m)|^2$ is the energy of smoothen signal , represented as Ea and $\sum_{m=0}^{\infty} \sum_{n=-\infty}^{\infty} |d(m,n)|^2$ is the energy of detailed signal, represented as Ed. For evaluation of the compression analysis wavelet energy coefficients (WEC) of detailed version of decomposed signals are taken as measure parameters.

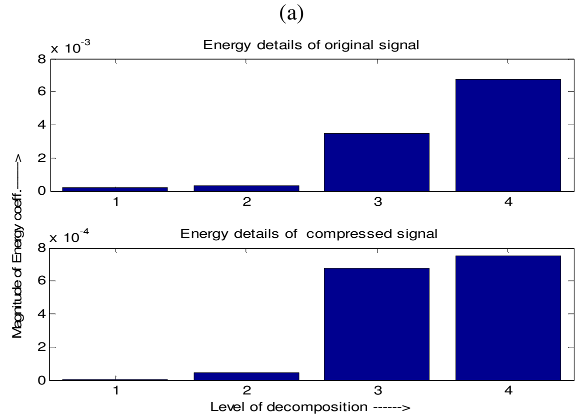
3. Result and Discussions

Real time PQ signals obtained from source IEEE working group [13]. These signals have been analysed using wavelet transform with MATLAB. Simulation program developed to initially process the raw data and decompose up to the fourth level of decomposition with choosing appropriate wavelet family; here Db4 has been chosen for analysis PQ disturbance signal and further applied the data compression technique as illustrated in Figure. 2.

Here data compression results are visually analysed and evaluated with MSE and CR parameters.



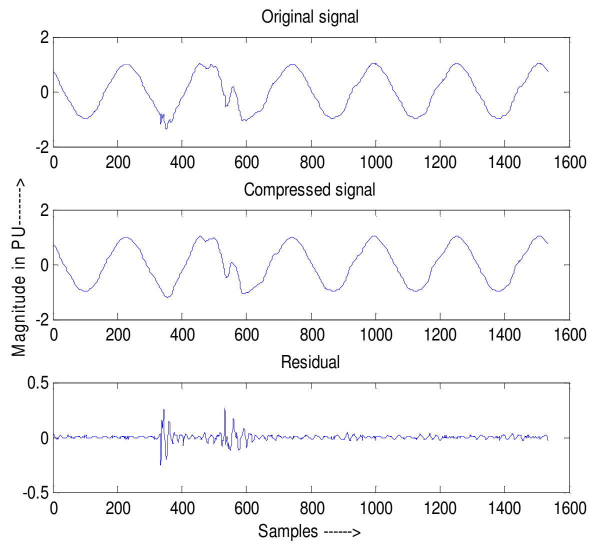
(a)



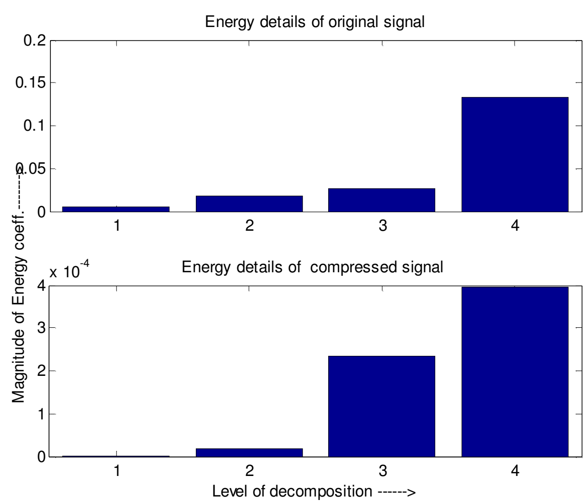
(b)

Fig 3 (a) Data compression for Pure sine wave (b) Variation in WEC

Distortion free sinusoidal waveform with some tolerance level, has widely been accepted as best power quality signal, Here in Figure 3(a), first subplot represents the original voltage pure sine wave without PQ disturbances, second subplot represents the compressed signal, and third subplot residual of signal after data compression, corresponding Energy coefficients magnitude variations is shown in Figure 3 (b) to support the data compression analysis. It is observed that hard threshold of detailed wavelet coefficients helps to get bumps free reconstructed signal as shown in second subplot.



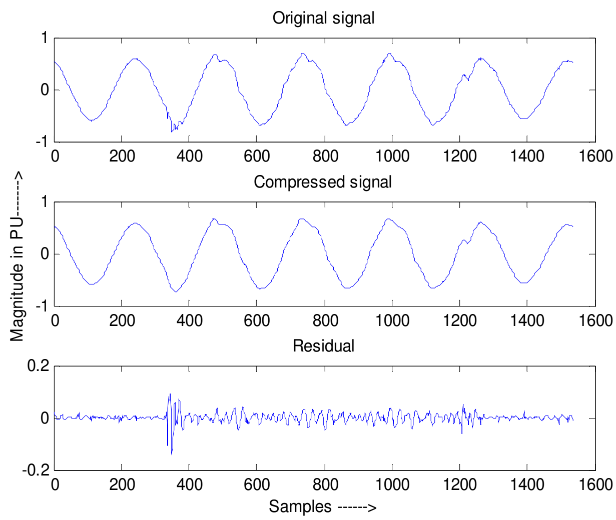
(a)



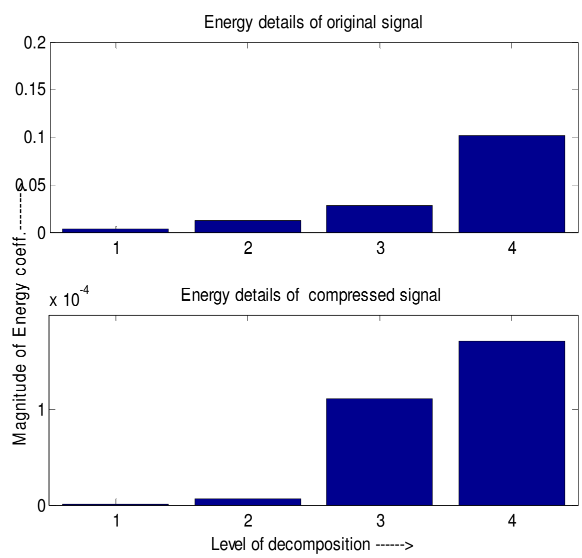
(b)

Figure 4 (a) Data compression for Transients (b) Variation in WEC

In Figure 4(a), first subplot represents the original voltage transients without PQ disturbances, second subplot represents the compressed signal, and third subplot residual of signal after data compression, corresponding WEC's magnitude variations is shown in Figure 4 (b) to support the data compression analysis. It is observed that hard threshold of detailed wavelet coefficients helps to get smooth distortion free reconstructed signal as shown in second subplot. From the energy plot it is observed that magnitude of WEC have drastically reduced as compared with WEC of pure sine wave.



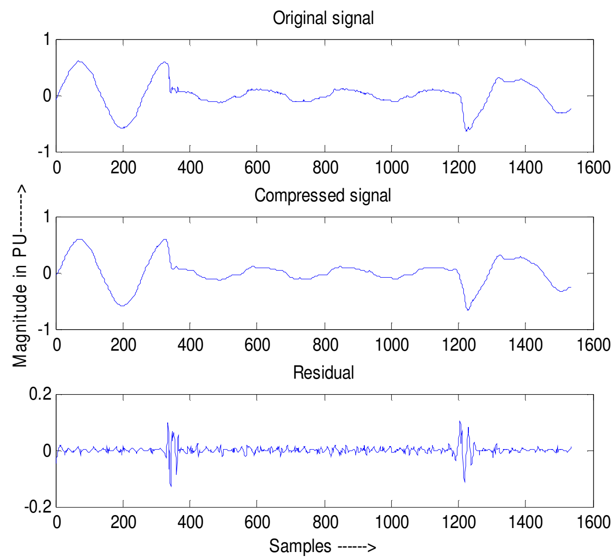
(a)



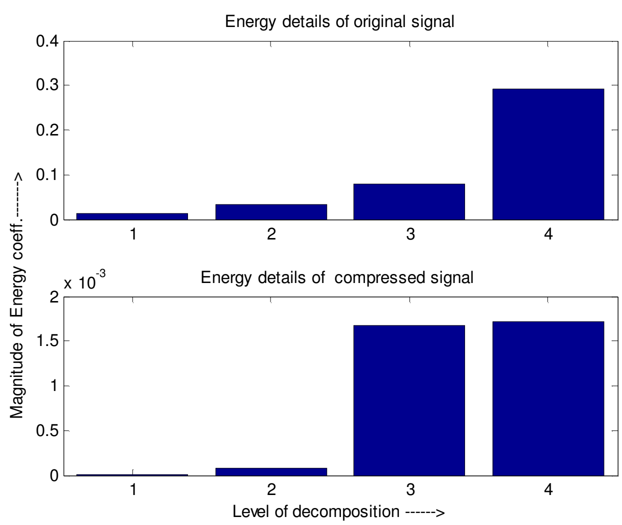
(b)

Figure 5 (a) Data compression for Swell with harmonics (b) Variation in WEC

First subplot in Figure 5(a), as the original voltage representing swell with harmonics, specific multiple PQ disturbances, second subplot represents the compressed signal, and signal after data compression, residual with harmonic variation clearly focused on third subplot. The corresponding WEC magnitude variations, here original signal have slightly less the WEC obtained from transient variations, are shown in Figure 5(b) to support the data compression analysis.



(a)



(b)

Figure 6 (a) Data compression for Sag (b) Variation in wavelet Energy Coeff.

In Figure 6(a), first subplot represents the original voltage sag as PQ disturbance, second subplot represents the compressed signal, and third subplot residual of signal after data compression, corresponding Energy coefficients magnitude variations is shown in Figure 6 (b) to support the data compression analysis. It is observed that hard threshold of detailed wavelet coefficients helps to get bumps free reconstructed signal as shown in second subplot. Performance evaluation has been given in Table1. MSE is compared MSE1(lower haue of THRs) and MSE2 (higher value of THRs) with CR.

Table 1 Data compression performance analysis

Performance Measures	PQ disturbances			
	Pure sine wave	Sag	Swell with Harmonics	Transients
MSE1	1.9069e-006	3.0819e-004	1.9047e-005	1.2611e-005
MSE2	3.1136e-005	2.4218e-004	9.3296e-004	5.0828e-005
CR	99.9892	99.5818	99.8543	99.8182

4. CONCLUSIONS

Modern power system with all new concepts of classification, control and planning deals with huge PQ data. Memory space required for PQ data storage is drastically minimized and real time signals have been employed to deal with real world data compression technique implementation. This approach also supports automated detection, feature extraction and classification of PQ disturbances using wavelet transform. Hard Threshold based scheme proposed here is simple, effective and easy to implement. The wavelet transform based data compression can be added with AI Techniques for further research work.

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