Wavelet Transform Based Compression of Electric Signal Waveforms for Smart Grid Applications

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ABSTRACT

With the advent of smart grid concept a massive wide variety of measurement devices and smart monitors are to be deployed in the distribution network to allow broad observability and real time monitoring of the behavior of power system. The volume of data generated by the smart monitors and measurement devices are a tough challenge for storage, computation and transmission through the power system. As a result, the complexity of the power system increases tremendously. In order to increase the robustness of the power system data compression techniques are evolved, that aims to improve the efficiency of the data transmission and to reduce the storage issues. In the current work, to reduce the issues of data transmission and volume of data in power system, an efficient wavelet transform based data compression is introduced. The compression technique is performed through signal decomposition, thresholding of wavelet transform coefficients and signal reconstruction. The proposed technique is applied for Electric signals with disturbances. The experimental result show that the proposed data compression technique yields high compression ratio and also this technique can efficiently reconstruct the original signal.

Keywords- Smart Grid, Data Compression, Power System, Wavelet Transform, Signal Decomposition.

1. INTRODUCTION

The evolution of the power grid towards a smart grid is based on a massive deployment of Information and Communication Technology (ICT) in sensing, analyzing and controlling the operations of the power grid, from generation to utilization. A smart grid includes a variety of operational and energy measures including smart meters, smart appliances, renewable energy resources, and energy efficiency resources along with application of digital processing and communications to the power grid, making data flow and information management central to the smart grid. Accordingly, there is a huge amount of data to be circulated and stored among utilities and control devices in a real time manner. Therefore, storage and transmission of the data is a challenging task in smart grid so that an effective data compression is needed. The data compression techniques will be desirable to reduce the burden of the data transmission and volume of data in power system applications. In addition to data compression, the most valuable information contained in the data should be maintained to the greatest extent possible so as to accurately reconstruct the original signal. The objective for data compression can be stated as follows.

- To compress the power system data at the sending terminals that should keep the valuable information contained in the data.
- To reconstruct the compressed data near-perfectly for analysis at receiving terminal.

Data compression schemes can be divided in two broad classes: lossless and lossy compression schemes [1]. In lossless compression, the reconstructed signal is identical to the original signal and the performance is measured by compression ratio. On the other hand, in lossy compression the reconstructed signal may differ from the original one and the performance must now be measured by the compromise between compression ratio and distortion. Lossless compression does not permit high compression ratio where as lossy compression achieve high compression ratio [2]. Among the existing lossy compression schemes, transform approach is one of the most effective strategies [3].

The transform approach whose basic components are formed by sine and cosine functions such as DFT (discrete Fourier transform) and DCT [3] are effective for the analysis of predominantly sinusoidal, periodic and stationary signals, since they provide good localization in the frequency domain [3],[4]. Since most of the electric signals are normally subjected to non-periodic and transient components and power frequency variations, the DFT alone can be inadequate to provide compact representations. The Slantlet transform (SLT) has been developed by employing the length of the discrete time and their moment in such a way that both time-localization and smoothness properties are achieved. But compression ratio (CR) and percentage of information retained is not up to the level to identify the signals [5].

Wavelet transform has recently emerged as powerful tool for a broad range of applications. They provide good localization in both frequency and time domains [6]-[8]. By a process of multiresolution analysis (MRA), wavelet transform (WT) can orthogonally decompose a time series into scaling coefficients (SCs) and wavelet coefficients (WCs), in which the trivial data points can be deleted such that the overall size of the data can be compressed. And the nature of WT satisfies a near-perfect reconstruction of the time series via an inverse MRA.

Hence, in this paper a wavelet transform based Data Compression technique is proposed. The wavelet based Data compression provides the good signal reconstruction quality and the high compression ratio. To justify the proposed approach, this paper utilizes a voltage sag signal. The performance evaluation is done by using Daubechies Wavelet Functions with different scales.

2. SMART GRID SYSTEM MODEL

The Smart Grid is expected to deliver electricity from multiple suppliers to end consumers using two-way communications, involving multiple distributed intelligent entities and including large-scale real-time data collection capability [9],[10]. This large-scale, accurate data collection and fusion of the monitored processes of the Smart Grid can provide the data in a reliable and timely manner. Fig. 1 is the network topology of Smart Grid electricity information collection system model.

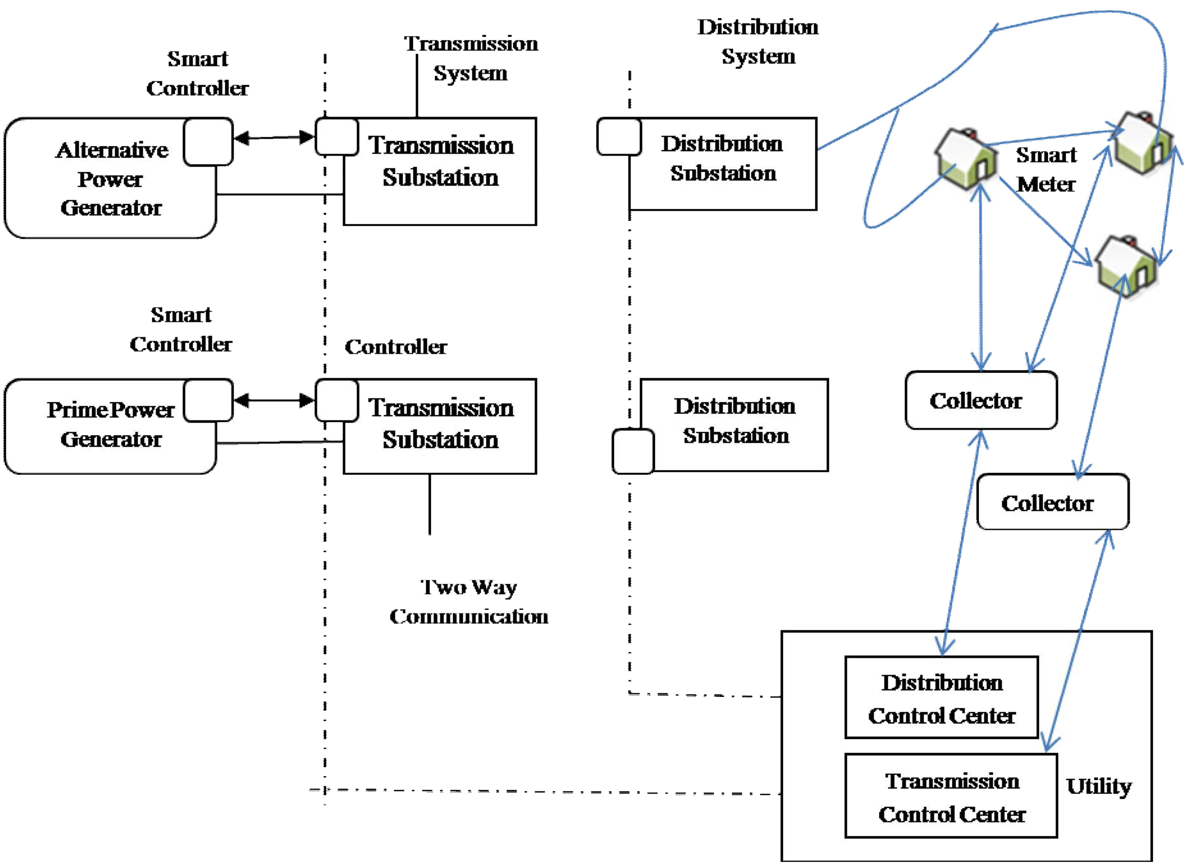


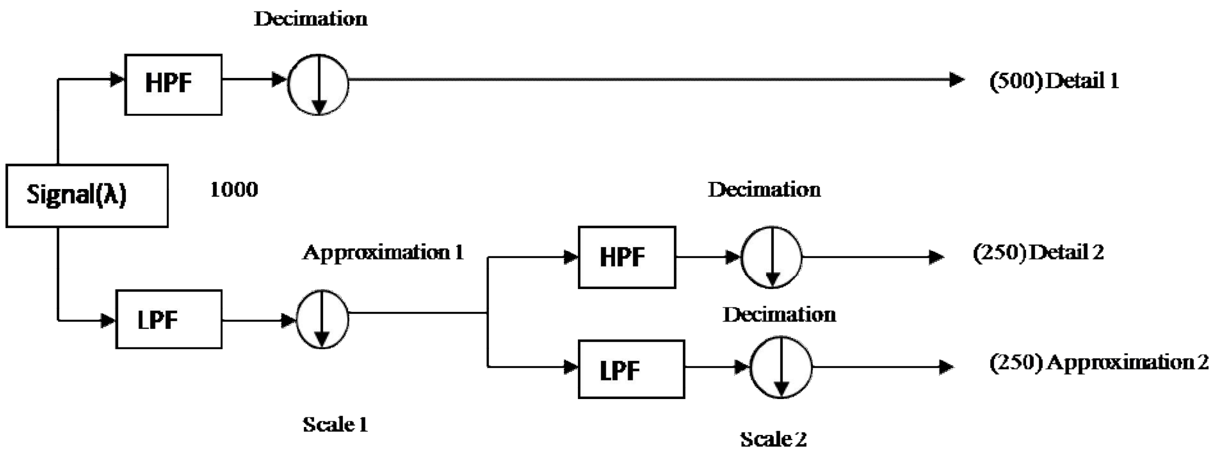
Fig.1 Smart Grid Electricity Information Collection System Model

The main components of a Smart Grid (Fig. 1) are electric power generators, electric power substations, transmission and distribution lines, controllers, smart meters, collector nodes, and distribution and transmission control centers [11]-[13]. Power generators and electric power substations use electronic controllers to control the generation and the flow of electric power. End consumers and collector nodes may communicate through a two-way communication network. Two-way communication paths are also used between collectors and the utility. The smart meters collect the power readings and send them to the collectors. These readings are stacked up and then sent together to the control center of utility by collectors. In this model, the collectors play an intermediary role and need to deal with huge amounts of data, when numerous smart meters are installed. As a result, the complexity of the power system increases tremendously. In order to improve the collection and transmission efficiency of Smart Grid system with huge amount of data, a wavelet transform based data compression is proposed in this paper.

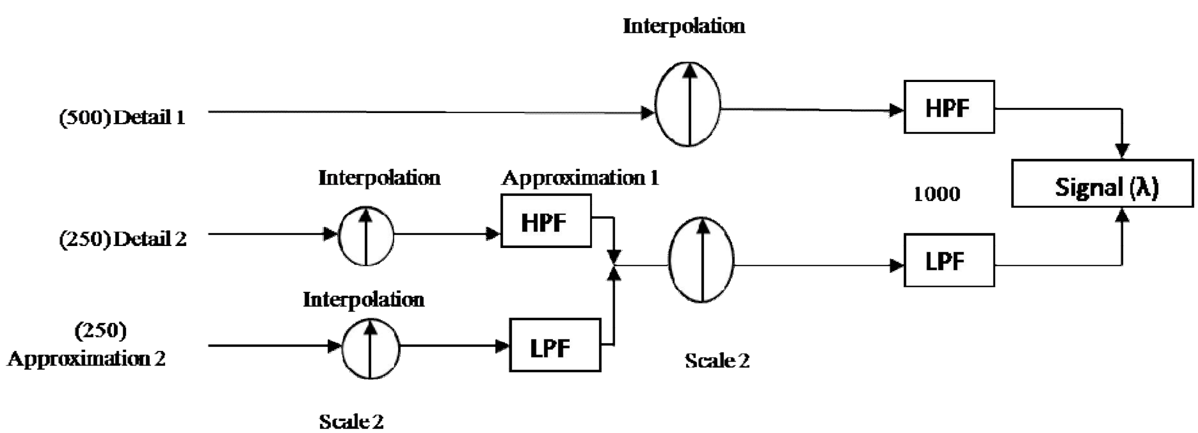
3. WAVELET TRANSFORM

Wavelet transformation has the ability to analyze the electrical signals in both time and frequency domain. The signal representation can be obtained through a hierarchical filter bank which is implemented using a recursive algorithm known as multi-resolution pyramid decomposition [14].

Initially, the signal is decomposed into approximation and detail signals, $a_1$and d_1, using a low-pass and high-pass filters and followed by decimation by two. The same process is applied to the approximation signals. This process is repeated in N stages, where each stage is associated to a scale or level of resolution. WT-based MRA is illustrated in Fig. 2, where (a) shows the procedure for decomposing a signal and (b) shows the procedure for reconstructing a signal. As a result the decomposition Process of discrete wavelet transform generates the approximation/scaling coefficients vector a_3 and the details/wavelet coefficients vectors d_1, d_2 and d_3. Note that as the signals are decimated by two at each resolution level, the number of wavelet transform coefficients remains the same as the number of samples of the original signal.



(a)



(b)

Fig. 2 (a) Procedure for Decomposition Process of Discrete Wavelet Transform

(b) Procedure for Reconstruction Process of Discrete Wavelet Transform

There are different types of wavelet filters that can be employed, such as Daubechies, Symlets, Coiflets, among others [5], [6]. Fig. 3 shows the detail coefficients and the approximation coefficients of the voltage sag signal obtained by using the DWT with Daubechies four wavelet filters.

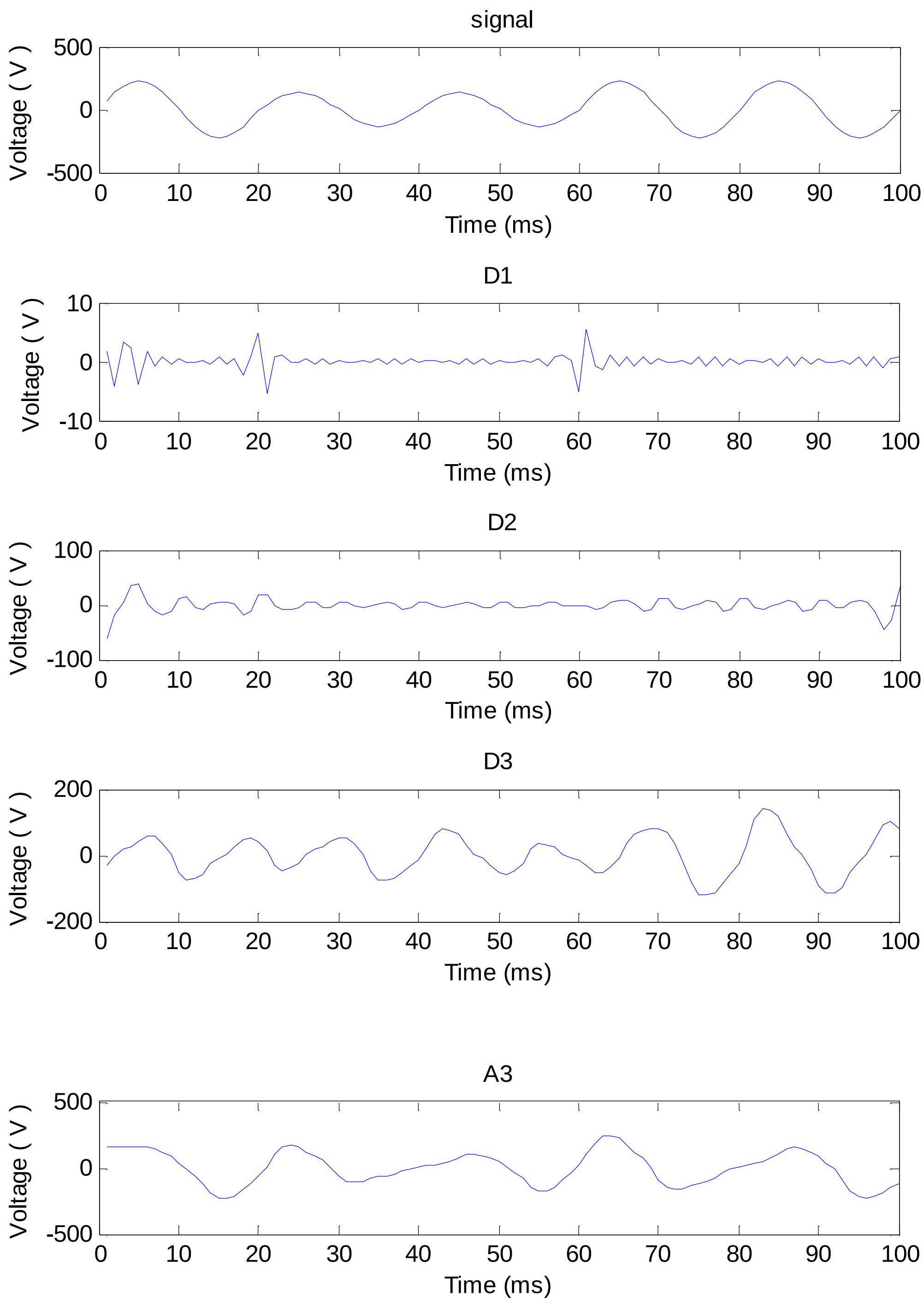


Fig.3 Detail and approximation bands for a voltage sag signal

In WT Compression method, a threshold value is fixed to discard some coefficients. Accordingly, some coefficients are discarded which results in reduction of the original signal length.

4. WAVELET BASED DATA COMPRESSION

In this work, the wavelet transform is used for the signal compression. The compression technique is performed through signal decomposition, thresholding of wavelet transform coefficients and signal reconstruction. A compressed signal and its reconstructed signal are obtained from the described methodology. A typical block diagram of the methodology is depicted in Figure 4.

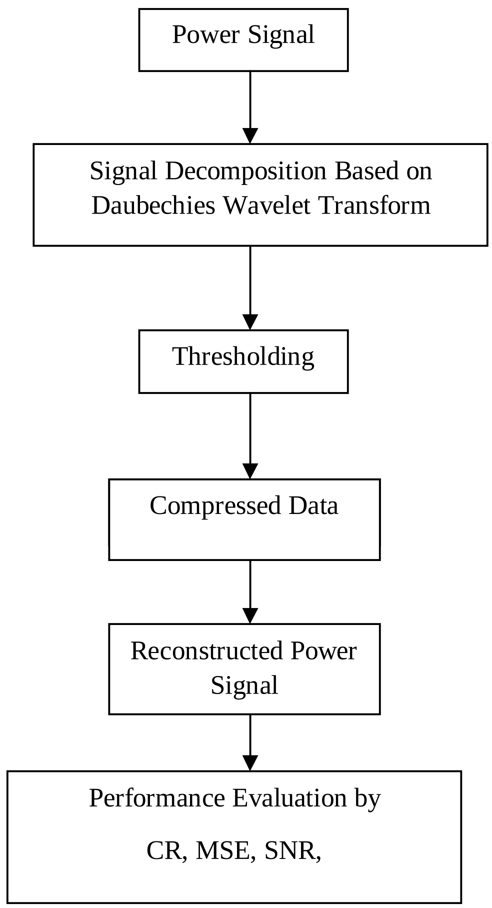


Fig.4 Block Diagram of the Proposed Wavelet Transform based Data Compression

Wavelet transforms decompose the power (Voltage Sag) signal into different scales at detailed resolutions. In this paper, Detail coefficients are considered to analyze this voltage sag signal. Threshold technique is adopted to compress the data. The threshold value helps to remove the coefficients below the set threshold value of coefficients. Here thresholding of wavelet can be performed easily by removing WTC (Wavelet Transform coefficients) below a specific value.

Threshold (*THR*) is based on the absolute maximum value of wavelet coefficients at associated scale, $d_s(n)$ as given below in eq. (1):

$$THR = (1-\mu) \times \max\{|d_s(n)|\} \qquad (1)$$

where $0 \le \mu \le 1$, $d_s(n)$ the absolute value of detailed coefficients, which are smaller than THR are removed, and those that are larger, are stored. Now the signal after thresholding process, is $\hat{d}_s(n)$, as given by eq. (2),

$$\hat{d}_s(n) = \begin{cases} d_s(n) & , |d_s(n)| > THR \\ 0 & |d_s(n)| \le THR \end{cases} \qquad (2)$$

Then the original signal could be compressed and also inverse MRA technique is used to reconstruct the original signal.

4.1 PERFORMANCE EVALUATION

The validation of a data compression technique can be evaluated by compression Ratio, Mean Square Error, Signal to Noise Ratio. These parameters measure the ability of compression technique to reconstruct the signal and to preserve the relevant information. To verify the quality of reconstructed signal following performance parameters are used.

4.1.1 Compression Ratio (CR)

The compression ratio (CR) is the key parameter for every signal compression methods. Generally, such methods are designed to achieve highest CR with imperceptible or at least tolerable distortion in the reconstructed signal. In general CR is defined as the ratio of the original signal size and compressed signal size, as given below.

$$Compression\,Ratio = \frac{Original\ file\,Size}{Compressed\ file\,Size}$$

4.1.2 Mean Square Error

MSE is the measure the error of signal quality as compared to the original signal, when a signal is compressed.

$$MSE = [\sum\sum f(x,y) - f'(x,y)]/(m*n)$$

where $f(x,y)$ is the original signal & $f'(x,y)$ is the reconstructed signal.

4.1.3 Signal to Noise Ratio (SNR)

Signal to noise ratio is the ratio of original signal to the noise signal that corrupts it.

$$SNR = 10 * \log_{10}\left(\frac{(f(x,y))^2}{(f(x,y) - f'(x,y))^2}\right)$$

5. RESULTS AND DISCUSSIONS

The proposed data compression methodology has been implemented using MATLAB and voltage sag signal is considered as the test signal. Simulation program developed to initially process the voltage sag signal data and decomposed the signal by using Discrete Wavelet Transform. The Daubechies wavelets have been chosen for signal compression because they have shown best performance in analyzing the signals.

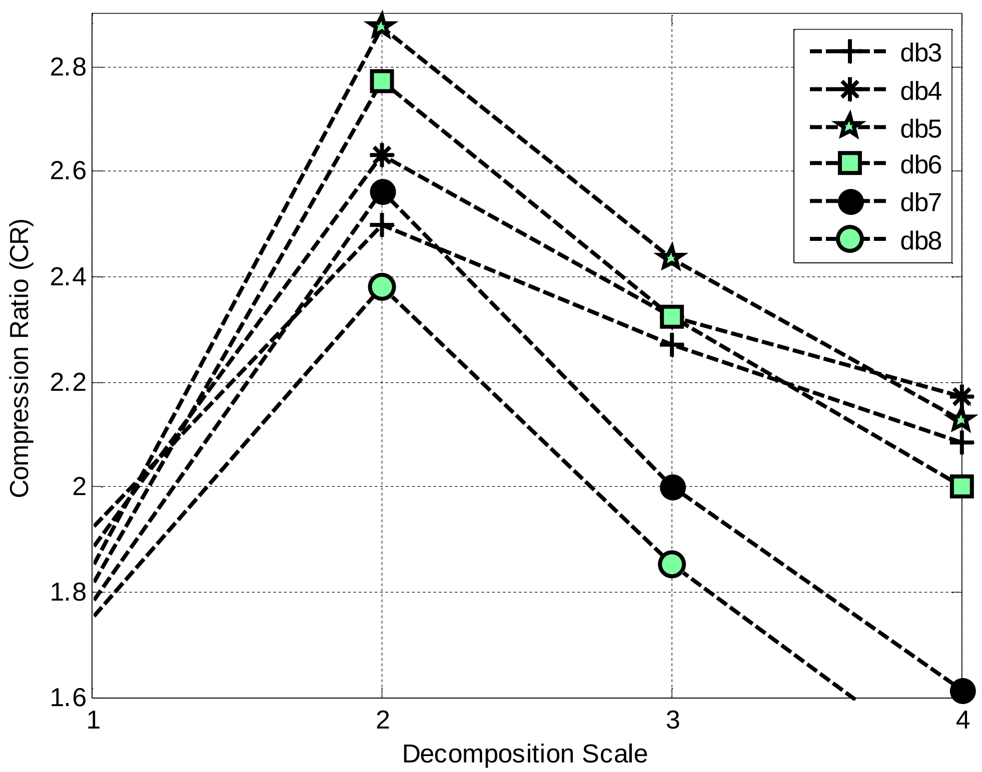
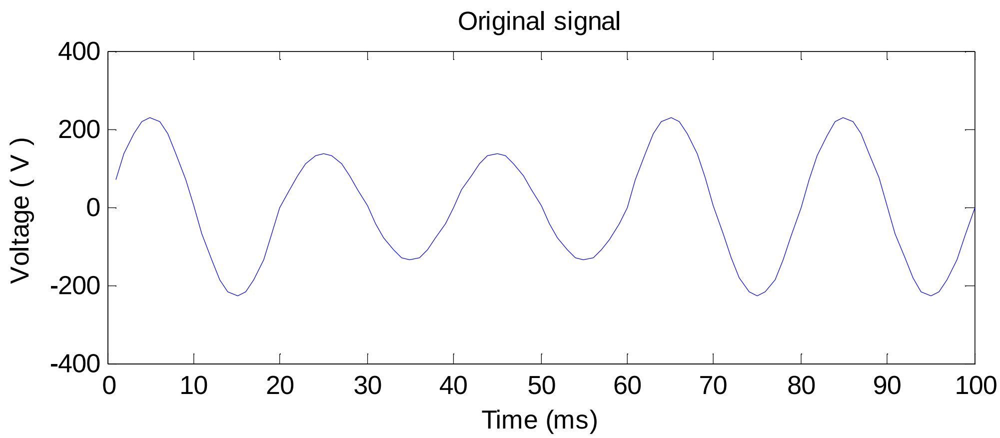


Fig.5. Effect of decomposition level on the compression ratio

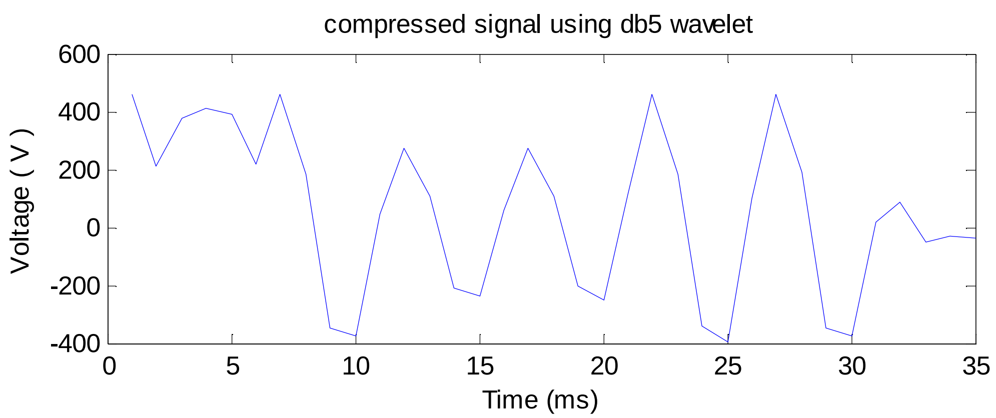
The voltage sag signal has been decomposed by using the Daubechies db3, db4, db5, db6, db7 and db8 wavelet at 1, 2, 3 and 4 scales of decomposition. This wavelet transform based data compression technique is used to evaluate the effect of decomposition scale, compressed signal length, Mean Square error, signal to noise ratio and wavelets on the quality of reconstructed signal. The 100 samples of voltage sag signal is decomposed by applying Daubechies wavelet at different decomposition scale and performance results are shown in Table 1. Fig.5 illustrates that the compression performance depends on the number of decomposition scales and the type of wavelet applied. For the voltage sag signal it has been noticed that the best performance can be obtained if the signal is decomposed by scale 2. For a desired compression ratio the best wavelet is the one that achieves the most retain information. It has been observed that the db5 wavelet performs better than the others.

Table 1: Data Compression values for different Daubechies wavelet order using DWT

	Scale 1			Scale 2			Scale 3			Scale 4		
Wavelet	**CR**	**MSE**	**SNR**	**CR**	**MSE**	**SNR**	**CR**	**MSE**	**SNR**	**CR**	**MSE**	**SNR**
Db1	1.333	18.51	24.43	1.428	19.59	23.35	1.428	19.59	23.34	1.428	19.59	23.34
Db2	1.887	15.42	27.52	2.127	17.97	24.97	2.083	18.39	24.54	1.960	18.39	24.54
Db3	1.923	8.93	34.01	2.500	16.63	26.32	2.273	16.62	26.31	2.083	16.62	26.31
Db4	1.886	2.95	39.98	2.631	15.67	27.26	2.326	15.91	27.02	2.173	15.95	26.98
Db5	1.851	5.85	37.09	**2.875**	14.05	28.88	2.439	14.31	28.62	2.127	14.45	28.48
Db6	1.818	8.55	34.39	2.772	13.26	29.67	2.326	13.34	29.59	2.000	13.16	29.78
Db7	1.785	9.51	33.43	2.564	12.42	30.52	2.00	12.48	30.47	1.612	12.48	30.46
Db8	1.754	9.08	33.25	2.381	14.32	28.61	1.85	14.56	28.38	1.449	14.56	28.38



(a)



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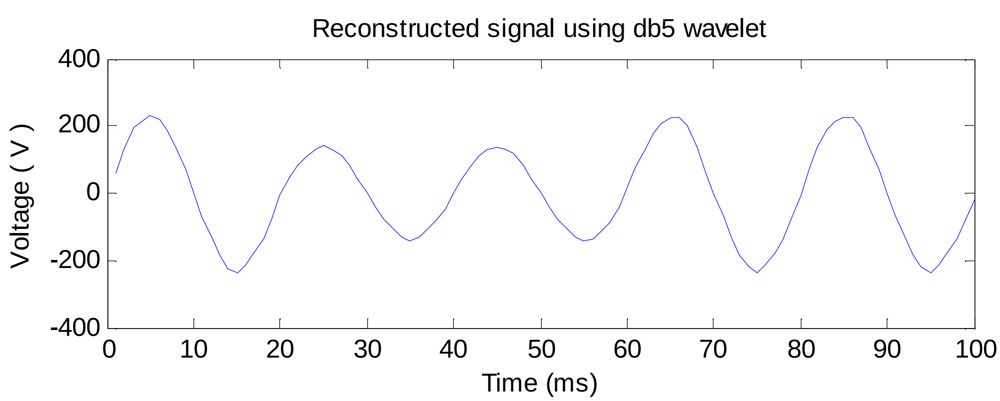


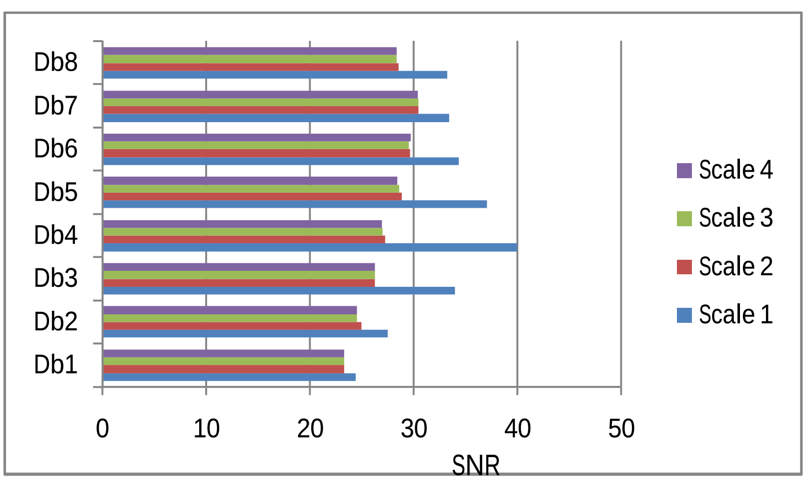
(c)

Fig. 6 (a), (b) & c) Original, Compressed & Reconstructed signal for Daubechies Wavelet 5 & scale 4

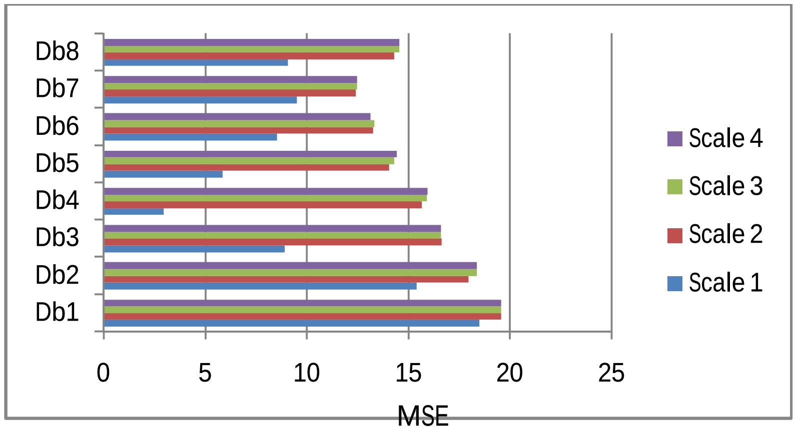
Fig. 6 (a), (b) & (c) shows the original, compressed & reconstructed signal by appying Daubechies wavelet transform. The Daubechies wavelet 2 is chosen as the wavelet function, and scale 5 is selected as the maximum decomposition scale. After compressing, the nonzero points in Wavelet Coefficients from scale 1 to scale 4 can be extracted so as to compress the length of the original Coefficients. The lengths of the compressed Coefficients are listed in Table 2, which shows that the lengths of the compressed Coefficients are reduced by around 1/2.8 times in comparison with the original wavelet Coefficients.

Table 2: Length of the Compressed Signal

Wavelet	Length of the compressed signal (Scale 1)	Length of the compressed signal (Scale 2)	Length of the compressed signal (Scale 3)	Length of the compressed signal (Scale 4)
Db1	75	70	70	70
Db2	53	47	48	51
Db3	52	40	44	48
Db4	53	38	43	46
Db5	54	**35**	41	47
Db6	55	36	43	50
Db7	56	39	50	62
Db8	57	42	54	6



(a)



(b)

Fig. 7 (a) MSE at different scales (b) SNR at different scales

Fig. 7(a) illustrates the Signal to Noise Ratio reached by Daubechies wavelet with different scales. In this figure, the horizontal axis is represents the Signal to Noise Ratio, and the vertical axis the different Daubechies wavelet are situated. This bar chart indicates that the proposed method reached a higher SNR at different Daubechies wavelet. In Fig. 7(b), the MSE at different scale is delineated, where the averaged value is computed to be different Daubechies wavelet. In this work it is found that when the number of Daubechies wavelet increases, the value of MSE decreases and vice versa. From the Fig.5, it reveals that the proposed method obtains a highest compression ratio at Daubechies wavelet db5 & scale 2.

6. CONCLUSION

This paper proposes a WT-based MRA to perform data compression for the smart grid applications. The proposed approach is capable of effectively compressing the size of voltage sag signal data. The Order 2 Daubechies wavelet and scale 5, respectively, as the best wavelet function and the optimal decomposition scale for voltage sag signal has been selected according to the criterion of the maximum compression ratio. A numerical simulation is conducted to exhibit the properties of WT-based MRA for data compression. The analysis for the results shows the effectiveness of WT-based MRA on data compression for voltage sag signals. The compression ratio for this db5 and scale 2 Daubechies wavelet compression ratio is 2.8. This means the compressed signal needs only 35% of the original signal file size. The results of simulations show that a better SNR and MSE can be achieved for a very good compression ratio. Without loss of generality, the proposed method can be implemented in smart grid to mitigate data congestion and improve data transmission and quality.

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