Smart Grid Data Compression and Reconstruction by Discrete Wavelet Transform

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Abstract—**A smart grid offers safe, reliable, and useful electricity. Phasor measuring units, smart meters, and other monitoring and measurement devices in the smart grid keep track of statuses at every grid level. As a result, utilities, control centers, and customers must exchange and retain an enormous amount of data in real time. As a result, data storage and communication require efficient data compression. To accurately reflect status of the system and regenerate nearly flawlessly on receiving side, compression should preserve all of the data's critical information. This work uses the discrete wavelet transform to recover compressed voltage sag signals. With reduced data, the disruptions can be communicated more quickly. Because the proposed system uses lesser filters and few decomposition layers, it is simpler than the previous design. The results of the simulation demonstrate improvement in the reconstruction error and compression ratio by minimizing their values. This design is time-saving and simple to use.**

Index Terms—**compression, decomposition, reconstruction, noise, smart grid, wavelet transform**

I. Introduction

The current electrical grid has been uncertain, susceptible to blackouts and brownouts, giving significant transmission losses, low power quality, providing insufficient electricity, and discouraging the combination of distributed energy sources. Restructuring the power delivery system from the ground up was necessary to mitigate these problems. A developing combination of many technologies, the smart grid, or modernization of the electric grid, aimed to significantly alter the electrical power grid [1]. To enable widespread observability and real-time monitoring, a significant quantity of smart devices like meters and monitors were installed across the distribution network. In terms of computing knowledge, an interaction interface, and the ability to deal with signals and share knowledge, it generated new requirements. Consequently, there was a significant rise in data storage and interchange. Achieving an effective usage of channel bandwidth and a decreased requirement for storing electrical data were crucial in that situation [2].

The smart grid's unique characteristics included improved power security, detailed analysis to support system control, monitoring capability with data integration, and efficient communication to satisfy power demand. Some of the smart grid's amazing features were low costs and efficient energy use. The installation of the smart grid necessitated sophisticated communication between the devices that generated and consumed power. Choosing and using the most advanced digital signal processing algorithms had a significant impact on these devices' efficiency [3]. Data produced by the Phasor Measurement Unit (PMU) had been compressed using the wavelet transform. Two separate wavelets, Coiflet1(coif1) and Daubechies2, were used for compression. The results showed that db2 compressed PMU-generated signals much more effectively than coif1 [4]. It suggested using compressed sensing to identify frequencies of harmonics that disrupted the fundamental current and voltage signals in power networks. By choosing a small number of samples at random, generated a measurement matrix, and then moved the signal in compressed form from time to frequency form using linear transform. The signal was then reconstructed using the inverse linear transform on a few recorded samples [5].

It used a compression method for electrical disturbing signal with Wavelet Packet Transform (WPT) and, Discrete Wavelet Transform (DWT). Minimal Description Length (MDL) was a criterion for selecting an appropriate wavelet function and ideal quantity of wavelets preserved elements for signal reconstruction [6]. A lossy mechanism to compress data in smart distribution system was presented by Singular Value Decomposition (SVD). The proposed technique notably reduced the data quantity while accurately recreating the original signal [7].

It was important to use multiple compression techniques for data with diverse characteristics. The research suggested a fusion lossy and lossless data compression technique based on signal properties to overcome such problems [8]. The wavelet packet transform on which it was based optimized the data compressing in accordance with the intended data loss. A specialized reconstructing technique that effectively created images straight from the compressed data was further developed [9]. The challenge of processing and storing excessive amounts of aging data in IGBT failure diagnosis was addressed by an adaptive threshold wavelet compression technique [10]. Wavelet decomposition was used, followed by range coding and quantization appropriate for floating-point data [11]. An innovative multivariate data compression approach was put forth for Internet of Things smart metering. To

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minimize data dimension, the method took advantage of the cross-correlation between several variables that smart meters sensed [12]. The matrix having ideal quantity of singular values was subjected to the Optimal Singular Value Decomposition (OSVD); the remaining values were ignored. The ratio of compression and retrieved data quality allowed goal achievement [13]. Sub bands or wavelet transform decomposition levels were used to segment the modified spectrum in the models that were suggested to estimate the adaptive spectral envelope [14].

It used basis, matching, and orthogonal matching pursuit as sensing methods to recover signals lost as a result of transmission line power failures. The actual data represented the real time current and voltage levels. Although it required more samples than orthogonal matching pursuit, matching pursuit was the best choice for actual electrical fault recovery as it required just a little of machine time. Basis and orthogonal matching employed fewer random samples, but they required more processing time for signal restoration [15].

Wavelet Packet Decomposition (WPD) were utilized to analyze, denoise and compress smart grid system data. WPD provided sufficient redundancy removal and feature property retention to enhance noise mitigation, boost compression, and control data accuracy degradation [16]. It used weight-based entropy to identify the optimum basis tree from complete WPT for denoising and signal compression. A modified minimum description length technique could be used to modify the denoising threshold without requiring a noise measurement computation [17]. A comprehensive assessment had been done for the importance of wavelet transform for different simulated or actual data by comparative studies on digital signal processing techniques [18]. It worked on a wavelet-based method that applied DWT to reduce noise and compress smart grid data [19]. This technique tested the effectiveness on Phasor Measurement Unit data by using wavelet packet transform to break down the signal for one to five scale [20]. A wavelet packet transform design for level three, data compression and reconstruction was represented utilizing lower-order wavelets. It operated on the phasor measurement unit current magnitude signals and voltage sag signals [21]. In order to obtain excellent compression of power quality disturbances, it investigated the best wavelet and the ideal number decomposition scale [22]. A fuzzy-based data compression method was put forth with the goal of lessening the computing load associated with data analysis in smart grids [23]. A traditional method of evaluating manufacturing quality involved reconstructing the shape of manufactured workpieces to create a digital version of the physical product and assessing the quality further [24]. Surface reconstruction techniques were applied to a cloud of data points taken from the workpiece using reverse engineering techniques. The approach used the bat algorithm, a well-known metaheuristic technique. For huge ultrasonic data compression, it created neural network models based on unsupervised learning as well as a novel multilayer autoencoder with excellent compression capabilities [25]. It explained the Huffman method [26], contrasted it with run length encoding and arithmetic coding, and discussed how these three algorithms were used in JPEG compression. Compression technology was revolutionized by the emergence of large artificial intelligence models that were trained on enormous volumes of data [27]. The computational difficulties utilized the advantages of lossless compression in a lossy mode and vice versa for data restoring, associated intelligent compressive sensing rebuilding, effective domain-independent solutions [28]. It also encouraged machine learning in data compression.

The method was computationally complex. The matrix made the compressed sensing approach complicated [15, 19–22]. By employing level 1 with the wavelet Db3, levels 2, 3 with the wavelets Db2, and level 4 with Db1, DWT was employed to compress and denoise smart grid signal [19]. Using wavelet Db3 for level 1, Db2 for 2, 3, 4 levels, and level 5 with Db1 using WPT, it reduced and cleaned smart grid data [20]. The novel approach integrated level 1 with Db3, level 2 with Db2, and level 3 with Db1 using the wavelet packet transform [21]. It used a Db4 wavelet at level 3 to compress the voltage sag signal via wavelet transform [22].

The reconstruction error and compression ratio can be improved, and the complexity can be further reduced. Consequently, the novel approach proposes integration of several minimum-order wavelet functions and a level-based suitable threshold by employing discrete wavelet transform. Achieving excellent compression and reconstruction by decomposing at level 3 simplify the process. The outcomes will be compared with those of [15, 20–23].

II. Methods

A strong mathematical tool for analyzing non-stationary signals in terms of time-frequency was Discrete Wavelet Transform. For signal analysis, multi-resolution filter banks were employed. Time-domain discrete data was converted to time-frequency domain using the Discrete Wavelet Transform. A signal was sent through a number of filters to determine its DWT. A high pass filter, HPF and a lower pass filter, LPF were applied to the signals at the same time. Each level of decomposition resulted in the branching of the input data into two outputs, one corresponding to the input signal's upper half-band and the other to its lower half-band. Half of the input data for each branch was used as the sampling rate. The overall sample rate stayed the same as a result. Only the lowest half-band branch of the DWT has undergone decomposition. For many signals, the most crucial details were included in lower-frequency part to identify the signal. The contents in high-frequency provided signal details. The high-scale or low-frequency components were used as an approximation. The lower-scale, high-frequency components were the details. The coefficients were the values of the converted data in the time-frequency. Whereas the coefficients with big absolute values conveyed more information about the data than noise, the coefficients with lower absolute values were dominated by noise. The wavelet coefficients were either cancelled out to zero (hard threshold) or reduced (soft threshold) in the second phase if they did not cross a predetermined threshold level. Reconstructing the signal from the resulting coefficients utilizing Inverse Discrete Wavelet Transform, IDWT was the final step [29].

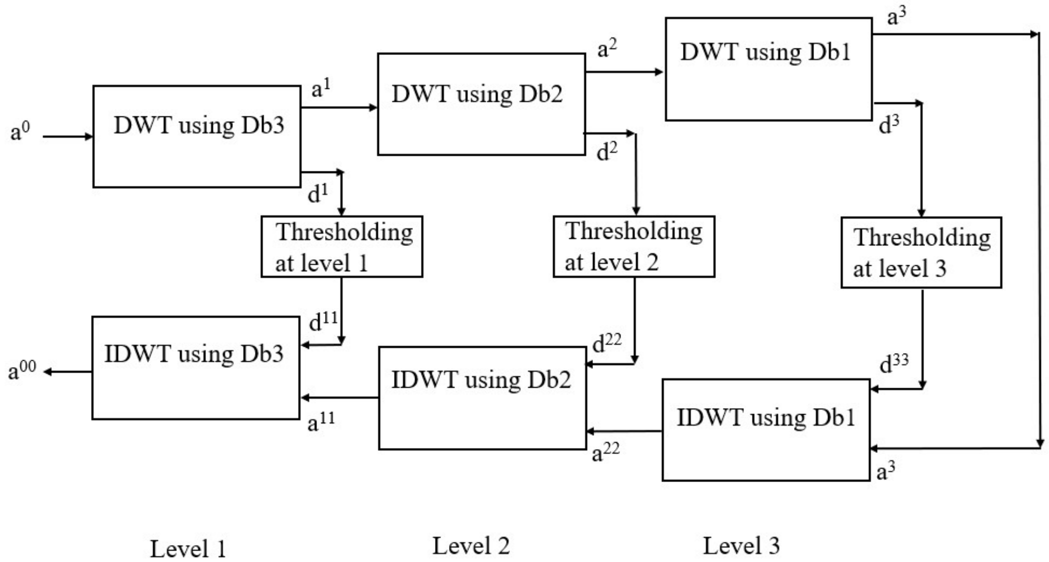


Fig. 1. Proposed approach for compression and reconstruction.

The signal in Fig. 1 is divided into approximate and detail elements using DWT, and after it is reconstructed using IDWT. The compressing method uses the Daubechies filters Db3, Db2, and Db1 at levels 1 through 3, and the reconstruction process uses the same filters in reverse. When the voltage sag signal is generated in SIMULINK in MATLAB 2021a, a waveform including 357, 379, 412, 501, and 512 samples (data points) is produced. There is a voltage sag signal that represents the load voltage data.

Both high and low pass filters are applied to the set of input data a^0, length N in this procedure. The coefficients of each filter are $N/2$. The coefficients of approximation a^1 at resolution level one, are the outcome of LPF. The detail coefficients d^1 of the level first resolution are the outcome of HPF. For a second pair of wavelets, a^1 can be applied as the input to generate the coefficients of approximation a^2 and, details d^2 at second level resolution. The procedure continues up to resolution level 3. At each level, the detail coefficients are subjected to hard thresholding. The coefficients a^{22} is produced during reconstruction using the detail coefficients after hard thresholding d^{33} and the pure approximation coefficients a^3. To retrieve the signal a^{00}, the operation will be repeated continually.

The proposed design is evaluated using the performance metrics provided below. It communicates the compressed signal as a percentage of the compression ratio (% CR), like in (1). The lower the percentage of CR, the better the compression. The normalized root mean square error, or NRMSE, is employed to calculate the reconstruction signal error for the proposed design in accordance with "(2)" in [16] and [17]. Reconstruction is better when the reconstruction error is lower. In (3), the variable e represents the percentage relative error and in (4) it shows how the percentage of rebuilding, determines the existing design's effectiveness [5, 15].

$$\%\text{CR} = \frac{N'}{N} \times 100\% \tag{1}$$

$$\text{NRMSE} = \sqrt{\frac{\sum_{i=0}^{N-1}[X(i) - X_r(i)]^2}{N^2}} \tag{2}$$

$$e(\%\text{ relative error}) = \frac{\left|\sum_{i=0}^{N-1}[X(i) - X_r(i)]\right|}{X(i)} \times 100\% \tag{3}$$

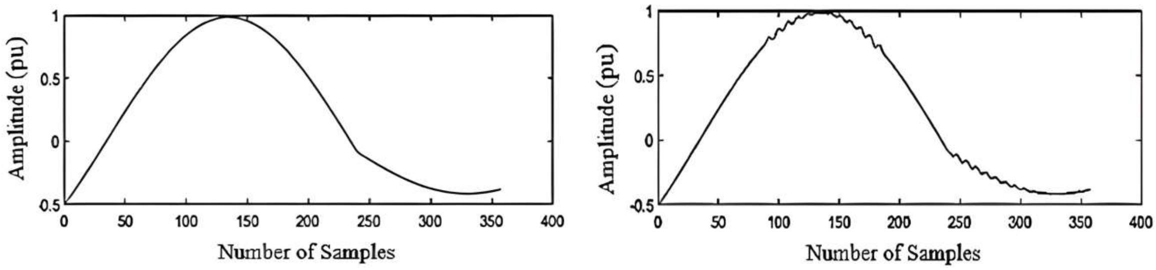
$$\%\text{Reconstruction} = 100 - e \tag{4}$$

The initial and regenerated signals are represented by $X(i)$ and $X_r(i)$, respectively. N' represents number for nonzero coefficients by threshold and N is original samples number.

III. Results

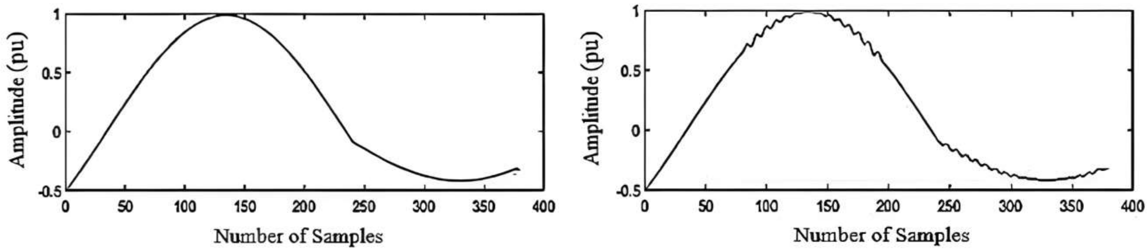
The following waveforms in MATLAB 2021a illustrate the outcomes of the suggested design, with the original signal or reconstructed signal amplitude in pu (per unit) on the y-axis and the number of samples on the x-axis.

Fig. 2 (a) to Fig. 6 (a) display the voltage sag signals of the original samples, while Fig. 2 (b) to Fig. 6 (b) display the signals which are regenerated using the recommended design. Fig. 2 (b) illustrates the reconstructed signal with an NRMSE of 4.13×10^{-4}, which is 99.99%, from the 357 original samples in Fig. 2 (a). For the 379 original samples displayed in Fig. 3 (a), 99.99% reconstructed signal with NRMSE 4.64×10^{-4} is displayed in Fig. 3 (b). For the 412 original samples shown in Fig. 4 (a), the 99.99% reconstructed signal with NRMSE 3.80×10^{-4} is shown in Fig. 4 (b). For the 501 original samples in Fig. 5 (a), the 99.94% reconstruction signal with NRMSE 3.29×10^{-4} is displayed in Fig. 5 (b). For the 512 original samples in Fig. 6 (a), the 99.98% reconstructed signal with NRMSE 2.74×10^{-4} is illustrated in Fig. 6 (b). The results are better than [15, 20–23]. The signal is more distorted for highly compressed signal. The signal is approximately reconstructed best for 512 voltage sag original samples with 99.98% reconstruction and smallest NRMSE 2.74×10^{-4}.



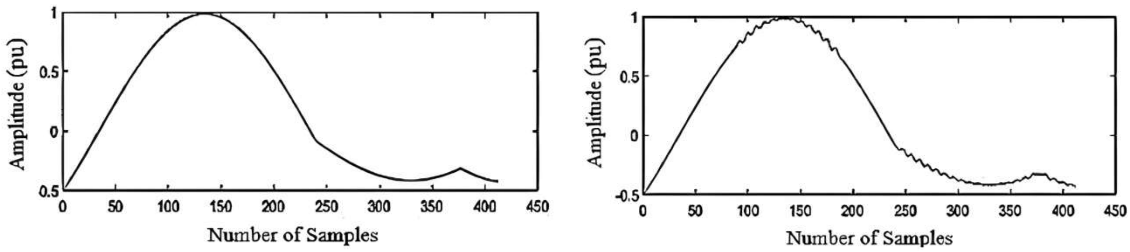
(a) (b)

Fig. 2. (a) Original voltage sag of 357 samples and (b) reconstruction 99.99% using DWT-based proposed design.



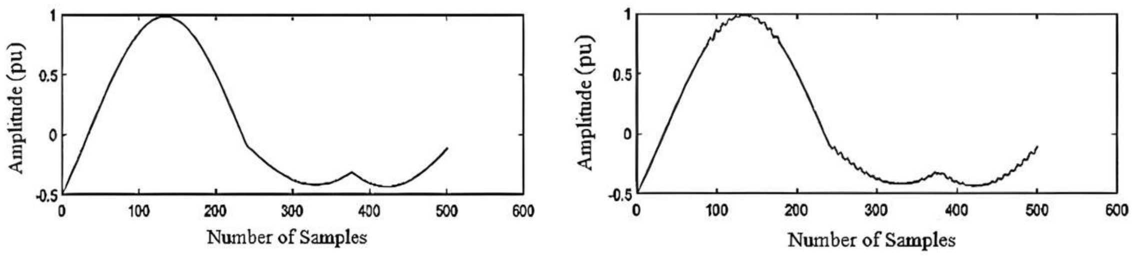
(a) (b)

Fig. 3. (a) Original voltage sag of 379 samples and (b) reconstruction 99.99% using DWT-based proposed design.



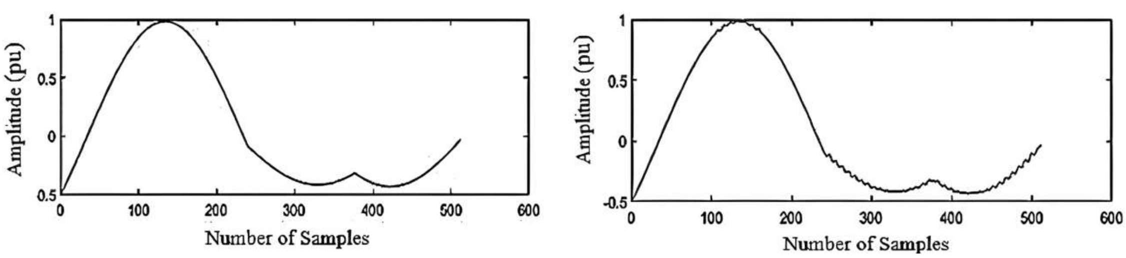
(a) (b)

Fig. 4. (a) Original Voltage sag of 412 samples and (b) reconstruction 99.99% using DWT-based proposed design.



(a) (b)

Fig. 5. (a) Original Voltage sag of 501 samples and (b) reconstruction 99.94% using DWT-based proposed design.



(a) (b)

Fig. 6. (a) Original Voltage sag of 512 samples and (b) reconstruction 99.98% using DWT-based proposed design.

Table I shows that the proposed approach achieves CR 19.05% and 99.99 % reconstruction with reconstruction error, NRMSE 4.13×10^{-4} for 357 original samples. For the 379 original samples, it gets CR 18.73% and 99.99% reconstruction with NRMSE 4.64×10^{-4}. For the 412 original samples, it obtains CR 18.45% and 99.99%

reconstruction with NRMSE 3.80×10^{-4}. For the 501 original samples, it gets CR 17.96% and 99.94% reconstruction with NRMSE 3.29×10^{-4}. It achieves CR 19.34% and 99.98 % reconstruction with NRMSE 2.74×10^{-4} for 512 samples of original signal. It achieves better results than those in [15, 20–23]. Compared to [15, 20–23], the signal is more compressed, maximum reconstructed, and has a lower reconstruction error.

TABLE I: RESULTS FOR DIFFERENT SAMPLES OF VOLTAGE SAG SIGNAL

References	Method/ Level	Sample Data Points	CR%	Reconstructed %	Error NRMSE
Proposed Design	DWT/ Three	357	19.05	99.99	4.13×10^{-4}
[15]	CS-OMP	357	-	90.19	-
[20]	WPT/Five	357	19.33	99.91	6.25×10^{-4}
[21]	WPT/ Three	357	19.33	99.97	5.20×10^{-4}
[22]	DWT/ Three	-	27.10	-	7.25×10^{-3}
[23]	Fuzzy Transform	-	31.00	-	18.01×10^{-2}
Proposed Design	DWT/ Three	379	18.73	99.99	4.64×10^{-4}
[15]	CS-OMP	379	-	97.46	-
[20]	WPT/ Five	379	19.00	99.79	6.06×10^{-4}
[21]	WPT/ Three	379	19.00	99.98	4.98×10^{-4}
Proposed Design	DWT/ Three	412	18.45	99.99	3.80×10^{-4}
[15]	CS-MP	412	-	90.89	-
[20]	WPT/ Five	412	19.66	99.91	5.81×10^{-4}
[21]	WPT/ Three	412	19.66	99.97	4.69×10^{-4}
Proposed Design	DWT/ Three	501	17.96	99.94	3.29×10^{-4}
[15]	CS-BP	501	-	97.57	-
[20]	WPT/ Five	501	18.76	99.33	5.31×10^{-4}
[21]	WPT/Three	501	18.76	99.90	3.69×10^{-4}
Proposed Design	DWT/ Three	512	19.34	99.98	2.74×10^{-4}
[15]	CS-BP	512	-	98.20	-
[20]	WPT/Five	512	19.53	99.67	4.78×10^{-4}
[21]	WPT/ Three	512	19.53	99.89	2.86×10^{-4}

The DWT-based proposed technique is significantly simpler, as shown in Table II, as fewer lower order filters Db3, Db2, Db1 are needed to lower only the approximation coefficients from decomposition level 1 to level 3. To further breakdown the coefficients for approximation & detail using WPT, filters are used at levels three with Db3, Db2, and Db1 wavelets in [21] and levels five with Db3, Db2, Db2, Db2, and Db1 wavelets in [20]. At level three, it uses the higher order filter Db4 in [22]. Because the designs in [20–22] break down both approximation and detail coefficients, they require more filters than the suggested method, making them more computationally demanding.

TABLE II: COMPLEXITY OF PROPOSED APPROACH

References	Proposed Approach	[22]	[21]	[20]
Method	DWT	DWT	WPT	WPT
Level	Three	Three	Three	Five
Wavelets	Db3, Db2, Db1	Db4	Db3, Db2, Db1	Db3, Db2, Db2, Db2, Db1
Complexity	Low	High	High	High

IV. CONCLUSION

This paper's goal is to compress and recreate smart grid voltage sag signals from different samples using proposed technique with discrete wavelet transform. Level 3 decomposes the signal in the suggested configuration. The suggested solution uses fewer lower order wavelet filters, which decreases complexity even though it produces more data compression than previous results. The suggested design attains CR 19.05% and NRMSE 4.13×10^{-4} with 99.99% reconstruction for 357 original voltage sag samples. With an NRMSE of 2.74×10^{-4} and a 99.98% reconstruction, it achieves CR 19.34% for 512 original voltage sag samples. Data compression, reconstruction error, and percentage reconstruction have all improved considerably compared to previous studies.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

The paper was written by R. Jadhav, who also designed the method, simulated the design, and compared the results. It was reviewed and corrected by A. Mahajan.

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