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Supervisory Controller Design in Smart Grid Using Compressed Sensing

Sepideh Alaei Varnousfaderani

[1]*Student, Dept of Computer Engineering, Azad University, Isfahan, Iran*

Abstract - *Smart grids have emerged as a promising solution to meet increasing electricity demand and reduce environmental pollution. However, the high volume of data transmission and storage poses significant challenges, including delays, interference, increased power consumption, and storage limitations. This paper investigates data compression as a solution, focusing on Compressed Sensing due to its efficiency and low computational complexity. A smart grid model comprising wind turbines, solar panels, and battery banks connected to a DC bus is analyzed, with local controllers for generators and a supervisory controller for power allocation based on load demand, environmental conditions, and generator constraints. Data acquisition and compression units are incorporated to optimize data handling. Simulation results demonstrate that Compressed Sensing significantly reduces data volume while preserving signal accuracy.*

Key Words: Smart Grid, Data Compression, Compressed Sensing, Renewable Energy, Power Allocation.

1.INTRODUCTION

Smart grids have garnered significant global attention due to their numerous advantages, such as providing efficient and reliable power delivery systems [1], integrating renewable and alternative energy sources through automated control [2], and enabling real-time monitoring with offline analysis capabilities [3]. As a result, substantial research has been conducted to expand smart grid capabilities and address its challenges.

One major challenge in smart grids is the high volume of transmitted and stored data due to the extensive data exchange required among various control units and computational systems [4]. High data volume can lead to transmission issues such as delays, interference, excessive power consumption, increased network traffic, and demands for additional bandwidth. In terms of storage, limited space presents significant constraints. Data compression is a practical and efficient solution to address these issues. It offers three key benefits [4]: significant reduction of data volume, preservation of essential information, and high-precision reconstruction of data at the receiver.

Various data compression techniques have been explored for smart grids. Wavelet transform has been applied to electrical signals [3]-[5], including simulated data collected from Phasor Measurement Units (PMUs) [3], though not specifically within a smart grid model. Lossless compression methods, such as those defined by IEEE 1159 [6], achieve exact signal reconstruction but offer limited compression efficiency. The Discrete Cosine Transform (DCT) has also been utilized [7], but its effectiveness is limited to signals with sinusoidal properties.

Recently, Compressed Sensing (CS) has emerged as a promising technique for simultaneous signal sampling and compression [5]-[6]. CS exploits the sparsity of signals in one domain to achieve high-precision reconstruction from a reduced number of measurements in another domain [7]. It has been successfully implemented in applications such as large-scale wireless sensor networks [8]-[9], biological signals like ECG and EEG [10]-[11], and video rate control [12], demonstrating reduced communication costs and increased network capacity. Despite its success in these areas, CS has not been widely applied to electrical signals in smart grids. Given the sparsity of electrical signals in the DCT domain, CS presents a compelling method for addressing data volume challenges in smart grids.

This paper introduces a smart grid model comprising wind turbines, solar panels, and battery banks connected to a DC bus, managed through a two-level control architecture. The first level employs local sliding mode controllers for individual generators and a control algorithm for battery banks. The second level features a supervisory controller to allocate power references based on demand, environmental conditions, electricity prices, and generator constraints, along with a monitoring unit for system oversight.

High data volumes transmitted to the supervisory and monitoring units necessitate the introduction of two additional components: the Data Acquisition and Compression Unit (DACU) and the Data Analysis Unit (DAU). These units enable the application of compression algorithms to transmitted and stored data. Simulation results demonstrate that Compressed Sensing effectively reduces data volume while maintaining high-precision signal reconstruction, ensuring optimal performance of the supervisory controller and overall system efficiency.

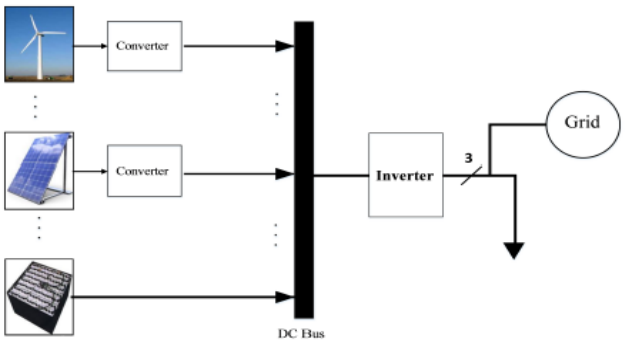

Fig-1: Model of Smart Grid: Electrical Energy Exchange Perspective.

2. Smart Grid Model

The smart grid represents a transformative approach in power systems, gaining global recognition for its ability to enhance efficiency, reliability, and sustainability. This section presents a general smart grid model comprising wind turbines, solar panels, battery banks, local controllers, a supervisory controller, and a monitoring unit. The functionality of each component (except the monitoring unit, which is beyond the scope of this article) is discussed below.

The smart grid model, as shown in Fig. 1, integrates wind and solar generators connected to a DC bus via power converters. The DC bus voltage is regulated by the terminal voltage of the battery bank. Each generator is controlled by a local controller that adjusts the duty cycle of its converter to manage power generation effectively.

As depicted in Fig. 2, data from the generators is transmitted to a remote control room during each sampling period. This control room houses the supervisory controller and monitoring unit. To minimize wiring costs due to the physical distance between the control room and generators, communication networks are used for data transmission. The supervisory controller processes the received data along with generator constraints, environmental conditions, demand (load), and power costs to determine the reference power for each generator. Meanwhile, the monitoring unit analyzes the data to track environmental conditions and evaluate the performance of smart grid components.

This model ensures seamless integration of energy resources and facilitates efficient management, control, and monitoring of the smart grid system.

2.1 Wind Subsystem

The wind turbine in this model employs a Permanent Magnet Synchronous Generator (PMSG), which offers two significant advantages. First, the absence of rotor currents reduces maintenance costs. Additionally, PMSGs do not require a gearbox, minimizing the overall weight and cost of the turbine [13].

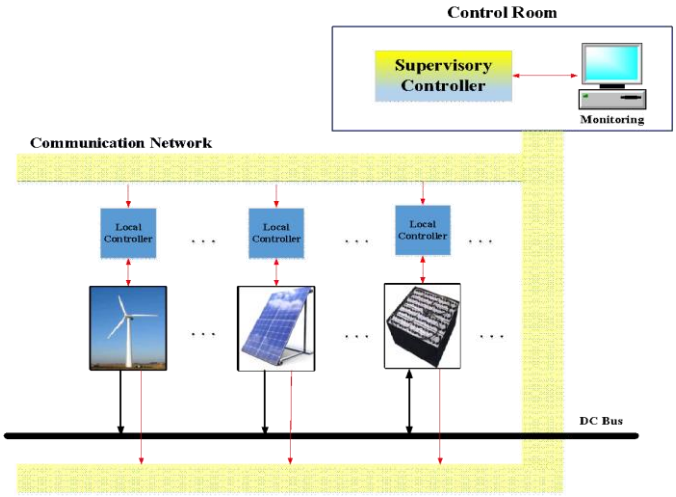

Fig -2: Model of Smart Grid: Data Exchange Perspective

The wind subsystem consists of a windmill, a PMSG, a rectifier, and a DC/DC converter. The windmill captures energy and drives the PMSG, which converts mechanical energy into electrical energy. The rectifier converts the AC output of the PMSG into DC, while the DC/DC converter regulates the DC output and connects the turbine to the DC bus.

To control the turbine's operating point and consequently its generated power, the voltage at the PMSG terminals is adjusted by modifying the duty cycle of the DC/DC converter. The dynamic model of the turbine in a rotor reference frame is provided in [14].

2.2 Solar Subsystem

The solar subsystem comprises photovoltaic (PV) panels connected to the DC bus through half-bridge buck DC/DC converters. The operating point of the PV panels is controlled by adjusting the state of the converter, allowing for efficient power regulation.

The mathematical model of the PV panels is described in [15].

2.3 Battery Bank

The battery bank in the smart grid model plays a crucial role in balancing energy supply and demand. It compensates for energy shortages by discharging and stores excess energy by charging, thereby mitigating sudden power fluctuations. In this model, the battery is a

conventional 48-volt rechargeable battery. Since the voltage drop across the battery's internal resistor and capacitor is negligible, its voltage is assumed constant. Consequently, the DC bus voltage, determined by the battery bank voltage, remains constant as well.

A key parameter for rechargeable batteries is the state of charge (SOC), which is defined as:

$$SOC(t) = SOC(t_0) - (1 / Qmax^c) \int[t_0 \text{ to } t] i(\tau) d\tau \quad \textbf{(1)}$$

Where t is Time (hours), $Qmax^c$ is Maximum capacity of the battery (ampere-hours, Ah), and $i(\tau)$ is Battery current (amperes, A).

The SOC is always a value between 0 and 1, where values closer to 1 indicate a fully charged battery, and values closer to 0 represent a discharged state. Monitoring SOC is essential for efficient and safe operation of the battery bank in the smart grid.

2.4 Wind Local Controller

The primary objective of the wind local controller is to ensure the turbine tracks the reference power determined by the supervisory controller whenever feasible. If the reference power cannot be achieved, the turbine operates to generate the maximum available power. Additionally, the controller is responsible for maintaining the stability of the wind subsystem.

To achieve these control objectives, this paper employs a sliding mode controller designed using the differential geometric approach outlined in [16]. This method ensures robust performance and stability under varying operating conditions.

2.5 Solar Local Controller

The controller considered to set the performance of the solar panel is a sliding mode controller proposed in [17]. The objective of the solar local controller is like the wind subsystem controller.

2.6 Battery Bank Controller

The performance characteristics of a rechargeable battery are significantly influenced by its type, size, and manufacturer. To ensure optimal operation of the battery bank in the smart grid model, the proposed controller performs two essential functions.

First, the controller limits the battery bank's exchanged current with the DC bus to remain below the rated current. This prevents potential damage to the battery and helps stabilize the DC bus voltage by minimizing voltage drops. Second, to extend the battery's lifespan, the controller adjusts the battery current based on its state of charge (SOC). When the SOC reaches 1 (fully charged), the input current is set to zero. Conversely, when the SOC reaches 0 (completely discharged), the output current is set to zero. This approach ensures safe and efficient operation of the battery bank while maintaining system stability.

2.7 Supervisory Controller

In order to calculate the proper reference power of each generator based on demand, environmental conditions, cost of electricity, and limitations of each generator, a supervisory controller is needed. In this paper, the supervisory controller is an optimal controller similar to [6]. The advantage of this supervisory controller is applying the restrictions easily as well as simplicity.

In this paper, based on the cost of electricity, the supervisory controller has two different working modes. When electricity is cheap, it is not economical that smart grid sells electricity to the grid. Thus, reference powers are calculated using an optimal algorithm and sent to the local controllers. On the other hand, when the electricity is expensive, the reference is set on the maximum available power of each generator.

2. Data Transmission and Compression in Smart Grid

The smart grid model and its components, introduced in the previous section, include a supervisory controller and monitoring unit typically located remotely from the generators. Both units require data to function effectively.

The sampling time of the local controllers is smaller than that of the supervisory controller, resulting in a high volume of data generated during each sampling interval. This data includes parameters such as generator voltage and current. The supervisory controller uses the latest sample of this data to simulate the smart grid's behavior during the next sampling period and calculate appropriate reference values. Meanwhile, the monitoring unit requires all samples to continuously track environmental conditions and assess the smart grid's performance.

Since data for both the supervisory controller and monitoring unit is transmitted via a shared communication network, the volume of transmitted data can become significant, potentially causing network congestion. To address this issue, the proposed solution involves modifying the smart grid model by incorporating two additional units: the Data Acquisition and

Compression Unit (DACU) and the Data Analysis Unit (DAU). The updated model is shown in Fig. 3.

The DACU collects and compresses data to reduce its volume before transmission. The compressed data is then sent to the DAU through an appropriate communication network. In the DAU, the data is reconstructed with high precision and subsequently forwarded to the monitoring unit and supervisory controller.

Since the compression method employed is Compressed Sensing (CS), the structure and functionality of the DACU and DAU are explained in detail following an introduction to CS.

3.1 Compressed Sensing (CS) Fundamentals

Compressed Sensing (CS) is a technique used to compress and reconstruct signals by exploiting their sparsity. A signal can often be represented as a combination of specific base vectors, where only a few coefficients (entries) are nonzero. This property is known as sparsity.

In CS, a signal is compressed by multiplying it with a measurement matrix, producing a shorter representation called the measurement vector. The measurement matrix is designed to preserve the essential information of the original signal, even after compression. This ensures that the signal can be accurately reconstructed later.

To reconstruct the signal, the CS process identifies the sparse representation of the signal using the measurement vector, the measurement matrix, and the knowledge of the sparse basis. The original signal can be recovered by solving an optimization problem. Since finding the sparsest representation (using the $\ell 0$ norm) is computationally challenging, an alternative optimization problem using the $\ell 1$ norm is solved instead. This approach is computationally efficient and yields accurate results.

Applying CS involves three main steps. First, a suitable basis is chosen where the signal is sparse, such as DCT, DWT, DST, or FFT. Second, an appropriate measurement matrix is designed, often using random matrices with specific properties. Finally, a reconstruction algorithm is applied to recover the original signal. Two common categories of reconstruction algorithms are Basis Pursuit (BP), which offers high precision but is slower for large-scale problems, and Greedy Algorithms, which are faster but less precise.

In summary, CS is a powerful method for compressing signals with high efficiency and reconstructing them accurately, provided the signal is sparse in a chosen basis, and the measurement and reconstruction processes are well-designed.

3.2 DACU and DAU

The Data Acquisition and Compression Unit (DACU) requires memory, a processor, a transceiver, and a power supply unit. With Compressed Sensing (CS) chosen as the compression method, a portion of the memory is dedicated to storing an appropriate measurement matrix. Another portion of the memory is used to store incoming data during each specified interval, corresponding to the sampling time

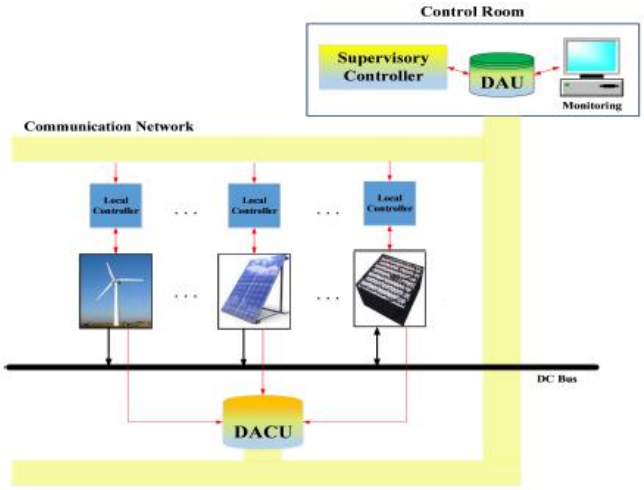

Fig -3: Updated Model of Smart Grid

of the supervisory controller. The structure of the DACU is depicted in Fig. 4.

The processor in the DACU performs the task of multiplying the measurement matrix by the input data, enabling efficient compression. This operation is computationally simple, resulting in high processing speed. The same measurement matrix can be used for compressing data sets with similar sparsity characteristics. The input data is represented as a matrix with dimensions N×J, where N is the number of data samples for a specific type over the specified time interval, and J is the number of different data types.

The Data Analysis Unit (DAU), shown in Fig. 5, also consists of memory, a processor, a transceiver, and a power supply. A portion of the DAU memory is allocated for storing the measurement matrix, which must be identical to the matrix stored in the DACU. This ensures that the data can be accurately reconstructed to closely match the original signal. The reconstruction algorithm applied in the DAU can be either a Basis Pursuit (BP) method for high precision or a greedy algorithm for faster

processing, depending on the specific requirements of the application.

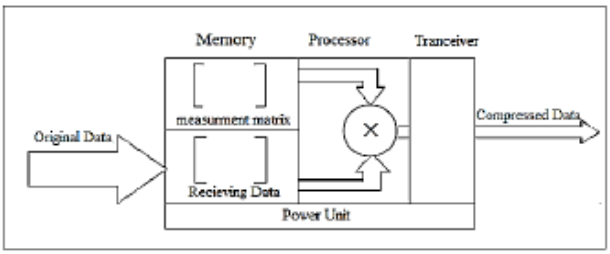

Fig -4: DACU Model

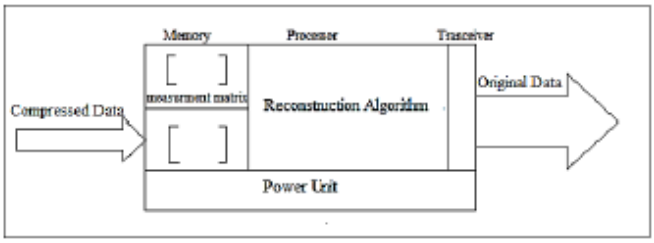

Fig -5: DAU Model.

4. Real Data Study

To demonstrate the effectiveness of Compressed Sensing (CS) in data compression, this technique was applied to a set of real electrical data provided by the Isfahan Regional Electricity Dispatching. The dataset includes frequency, voltage, current, power factor, power, and phase, with a sample interval of one minute.

A compression method is considered effective if it achieves a high compression percentage while ensuring accurate reconstruction of the original data. The **c**ompression percentage in CS is defined as:

$$\text{Compression Percent} = [(N - M) / N] \times 100 \quad \textbf{(2)}$$

Here, N is the length of the original signal, and M is the length of the compressed signal.

After analyzing the real data, it was observed that these signals are sparse in the Discrete Cosine Transform (DCT) domain, making them suitable for compression using CS. For instance, the power signal, along with its DCT coefficients for 100 samples, are shown in Fig. 6 The small number of nonzero DCT coefficients compared to the total samples confirms the sparsity of this signal in the DCT domain.

To compress these signals using CS, the measurement matrix was defined as:

$$\varphi = \text{sign}(\text{randn}(M, N)) + \text{ones}(M, N) \quad \textbf{(3)}$$

Reconstruction accuracy is evaluated using the Normalized Mean Square Error (NMSE), calculated as:

$$\text{NMSE} = \|X - \hat{X}\|_2^2 / \|X\|_2^2 \quad \textbf{(4)}$$

where X is the original signal, and $\hat{X}$ is the reconstructed signal. A lower NMSE indicates higher reconstruction accuracy.The Orthogonal Matching Pursuit (OMP) algorithm was employed for reconstruction, with M=300, corresponding to a compression percentage of 70%. This setup yielded an NMSE of less than 0.01 for all signals, demonstrating satisfactory performance.

Reconstructed power signal using OMP for 1000 samples is depicted in Fig. 7, showcasing the accuracy and effectiveness of CS in compressing and reconstructing real electrical data.

5. Case Study

In the smart grid model, a significant volume of data is transmitted during each sampling interval from the smart grid to the supervisory controller for proper operation and to the monitoring unit for overseeing system performance and environmental conditions. However, transmitting such a large volume of data introduces various challenges. To address this, data is first compressed in the Data Acquisition Unit (DACU) before being sent to the supervisory controller and monitoring unit. Subsequently, the data is reconstructed in the Data Analysis Unit (DAU) and distributed to the respective units as required.

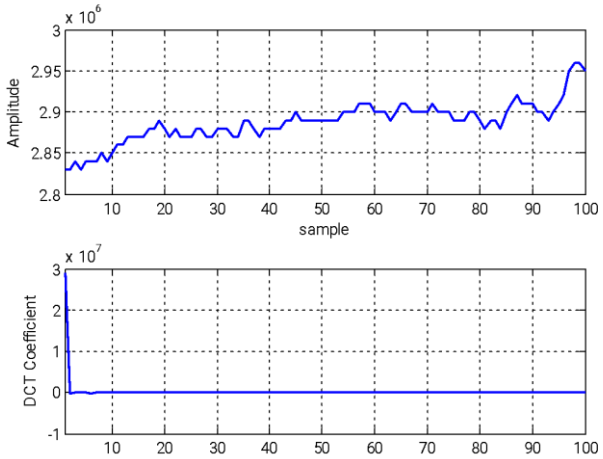

Fig -6: Power Signal and Its DCT Coefficients (100 Samples).

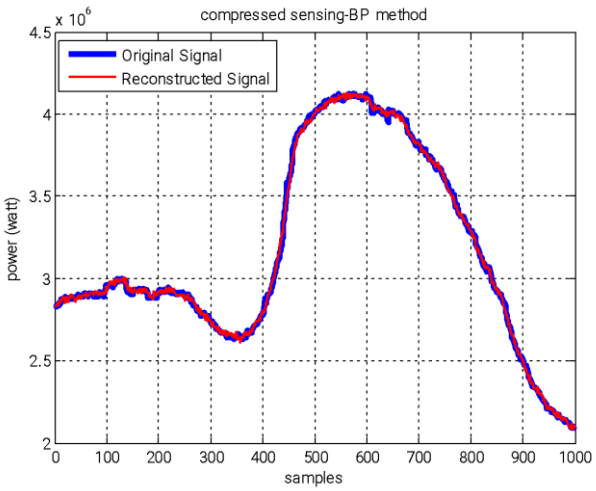

Fig -7: Original and Reconstructed Power Signal.

Simulations conducted in this study demonstrate that using Compressed Sensing (CS), data compression is achieved effectively, and signals are reconstructed with high precision. Additionally, despite the reduced data volume, the supervisory controller maintains satisfactory performance.

To reduce the volume of data in the smart grid, data from each sampling interval of the supervisory controller is first sent to the Data Acquisition Unit (DACU). Since the data volume from batteries is relatively small, no compression is applied to them. Additionally, solar data, despite its high volume due to the low sampling rate of the local controller, does not require all samples to be transmitted due to its dynamic nature. Therefore, before applying compression algorithms, an average of the solar data over a specified time interval is calculated. The method used in this study for data volume reduction is Compressed Sensing (CS).

In the Compressed Sensing (CS) method, data is multiplied by an appropriate measurement matrix stored in the memory of the Data Acquisition Unit (DACU). After analyzing the smart grid signals, the selected measurement matrix is defined as:

$\varphi = \text{sign}(\text{randn}(M, N)) + \text{ones}(M, N)$

Here, N is the dimension of the original signal, and M is the dimension of the compressed signal. This random matrix effectively preserves the essential information of the signal while ensuring high reconstruction accuracy. The compression process involves a simple matrix multiplication, highlighting the computational simplicity of this approach. Consequently, the processing time is very short, enabling the algorithm to operate in real-time.

Compressed data is sent to the Data Analysis Unit (DAU), where it is reconstructed using either an optimization-based method or a greedy algorithm. The optimization method offers high precision, while the greedy algorithm provides faster processing, making it essential to consider these trade-offs in a real-world network. Once reconstructed with high accuracy, the necessary data is transmitted to the supervisory and monitoring units.

Applying Compressed Sensing (CS) to smart grid data demonstrated that compressed signals could be reconstructed with high precision, comparable to the results achieved using wavelet transform. This confirms the effectiveness of CS for data compression and reconstruction in smart grid applications.

The sampling time of the supervisory controller is set to 10 minutes. During each interval, the supervisory controller requires specific data to allocate power correctly to each generator. This data includes wind speed, direct and quadrature currents, rotational speed of each turbine generator, solar panel voltage, temperature, light intensity, solar panel output current, and battery state of charge.

Additionally, data sent to the monitoring unit includes environmental parameters such as temperature, light intensity, and wind speed for monitoring environmental conditions. Performance-related data such as currents, rotational speed, generated power, the difference between generated and reference power for each turbine, voltage, current, and power of the solar panel, along with the state of charge, output power, and power difference of the battery, is also sent to the monitoring unit for overseeing the performance of the smart grid.

In the smart grid model, with the sampling time of the wind controller set to 0.1 second, and considering the case study from the previous section (six turbines, one solar panel, and one energy storage unit), each wind signal generates 6000 samples during the supervisory controller's interval. Given the number of turbines and required signals, the total number of wind data samples per interval is 216,000.

The sampling time of the solar controller is 0.1 milliseconds. Since it is unnecessary to transmit all data, the average of each solar signal over 1-second intervals is calculated. As a result, each solar signal generates 600 samples per interval, and the total number of solar panel data samples is 4200.

To synchronize the received data, the initial time of each generator is also transmitted. Excluding the battery data (which is minimal), the total number of transmitted data

samples per interval is 220200. This approach ensures efficient data management within the smart grid.

It is evident that transmitting such a large volume of data during each interval poses significant challenges. By applying a 75% compression rate to all signals (due to their similar sparsity levels), the transmitted data volume was reduced to one-fourth, amounting to 55,050 samples. This compression rate was chosen because higher compression resulted in reduced signal reconstruction accuracy.

The advantage of Compressed Sensing (CS) over wavelet transform becomes clear here. In wavelet transform, it is necessary to define a specific threshold level for each signal, which complicates the process. Using a uniform threshold leads to varying compression rates across signals. In contrast, CS provides consistent and efficient compression while maintaining high reconstruction accuracy.

To demonstrate the high reconstruction accuracy of wind turbine data compressed using Compressed Sensing (CS) at a 75% compression rate, the results are presented in Fig-8. The original wind speed signals (colored lines) and the signals reconstructed using CS (black lines) are displayed. For better clarity, the black lines in the figures represent the original signals, while the dotted colored lines represent the reconstructed signals. These visual comparisons highlight the effectiveness of CS in maintaining high reconstruction

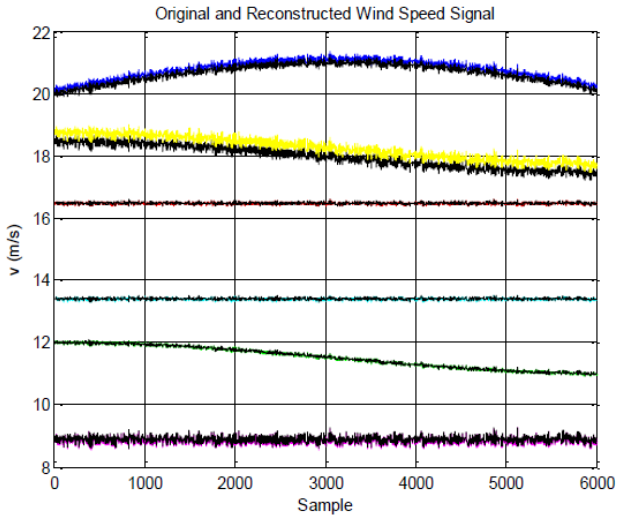

Fig -8: Original and Reconstructed Wind Speed Signal.

accuracy despite significant data compression. The reconstruction errors for these signals are below 0.001.

The results in this section illustrate that Compressed Sensing (CS) has been effective in reducing the volume of solar data while maintaining reconstruction accuracy. The findings presented in Fig-9 show the current and voltage signals of the solar panel. Similar to wind data, the reconstruction errors for these signals are below 0.001.

5. CONCLUSIONS

This study highlights the effectiveness of Compressed Sensing (CS) for data compression in smart grid applications. Using real electrical data from the Isfahan Regional Electricity Dispatching, CS achieved up to 75% compression with reconstruction errors (NMSE) below 0.001. Integrating Data Acquisition and Compression Units (DACU) and Data Analysis Units (DAU) effectively addressed high-volume data transmission challenges, ensuring efficient performance of the smart grid. CS proves to be a scalable and reliable solution for modern power systems, offering significant potential for improved data management.

ACKNOWLEDGEMENT

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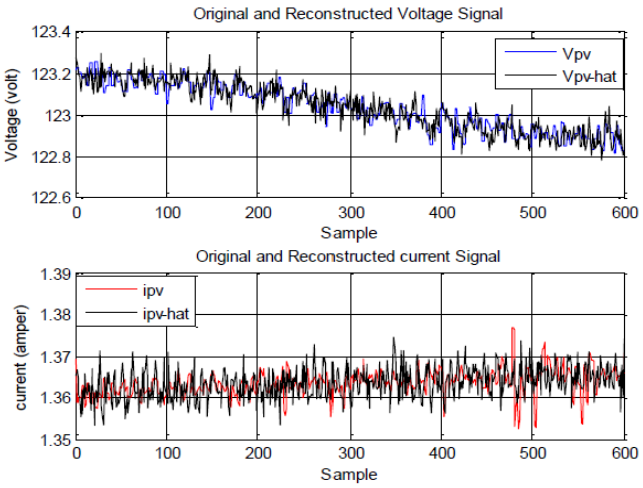

Fig -9: Original and Reconstructed Current and Voltage Signal.

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