

Transmission Line Monitoring Technology Based on Compressed Sensing Wireless Sensor Network

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Abstract—Given wireless sensor networks' significant data transmission requirements, conventional direct transmission often leads to bandwidth constraints and excessive network energy consumption. This paper proposes a transmission line monitoring technology based on compressed sensing wireless sensor networks to achieve real-time monitoring of ice-covered power lines. Grounded in compressed sensing theory, this method utilizes dual orthogonal wavelet transform sparse matrices for sparse representation of sensor data. Considering the practical requirements of power line monitoring, a data transmission model is established to implement compressed sampling transmission. The regularization orthogonal matching pursuit algorithm is employed for high-precision reconstruction of compressed data. The software and hardware components of the power line monitoring system are designed, and experiments are conducted under real-world conditions. The results demonstrate that: 1) the system operates stably with an ideal data compression effect, achieving a compression ratio of 93.191%. The absolute reconstruction errors for temperature, humidity, and wind speed sensor data are 0.064°C, 0.052%, and 0.128 m/s, respectively, indicating high reconstruction accuracy and effectively avoiding transmission impacts caused by bandwidth issues. 2) In a 36-hour energy consumption loss test, compared to direct transmission, the compressed transmission mode exhibits a lower rate of battery voltage decay, with a decrease of approximately 11.18%, effectively extending the network's lifespan.

Keywords—Compressed sensing; transmission line; wireless sensor network; orthogonal wavelet transform; data reconstruction

I. INTRODUCTION

As a crucial component of the power system, transmission lines are responsible for conveying the electrical energy generated by power stations to various distribution points and ultimate consumers. The stable operation of these infrastructures is vital to the reliability and security of the entire power system, and it also directly affects the continuity and quality of power supply [1]. In view of the uneven geographical distribution of China's power resources, transmission lines often have to traverse regions with complex geographical environments and adverse climatic conditions. Particularly in environments characterized by low temperatures, high humidity, and strong winds, the surfaces of transmission lines are highly susceptible to ice accretion, which increases the risks of galloping, breakage, overloading, and flashovers on insulator strings, severely threatening the stability and safe operation of transmission lines [2-4]. In response to these risk factors, it is particularly important to

implement real-time monitoring and develop efficient transmission line operational status monitoring systems. By employing advanced sensing technologies, image processing techniques and big data analytics, comprehensive condition monitoring of transmission lines can be achieved, enabling timely identification and response to existing or potential issues and effectively reducing the probability and impact of failures. Such monitoring systems not only provide early warnings of possible line failures but also offer real-time data support to operations and maintenance personnel, assisting them in making rapid and accurate decisions. Therefore, strengthening the real-time monitoring capabilities of transmission lines plays a crucial role in enhancing the levels of fault prevention and control, improving the system's emergency response and early warning capabilities, and ensuring the safe and stable operation of the power grid.

Currently, transmission line monitoring methods primarily include manual inspection, unmanned aerial vehicle (UAV) surveillance, infrared thermal imaging, and fiber optic sensing technologies. Tang [5] proposed a technical approach utilizing video surveillance systems for vibration analysis of transmission lines. This method involves the collection of video image data from transmission lines and the establishment of a relative coordinate system between the power tower and the transmission line, thereby enabling the tracking of vibration frequency and amplitude at specific line positions. Through such tracking, the dynamic characteristics and operational status of the transmission lines can be assessed. Although this technology has demonstrated certain effectiveness in vibration monitoring of transmission lines, its implementation relies on various equipment, and the operational process is complex with insufficient real-time capabilities, making it unsuitable for widespread deployment in large-scale transmission line systems. He [6] addressed the requirements of the sensor layer in the power Internet of Things by combining fiber optic sensing technology with big data and artificial intelligence for multi-risk monitoring of transmission lines. The monitoring system was deployed, and experiments were conducted using different monitoring scenarios, yielding good performance. However, the scheme is costly to implement, complex to install, and susceptible to temperature effects, leading to less-than-ideal practical application outcomes. Wireless Sensor Networks (WSN), which integrate microsensors, embedded computing, wireless communication, and information processing, coordinate among network nodes to monitor, sense, collect, and process information about the objects of interest, transmitting data wirelessly [7,8]. Sensors in WSN are less

affected by time, space, and environmental conditions during data collection and are widely used in various monitoring fields. However, the transmission of large volumes of data in WSN, when using traditional transmission methods, can lead to congestion in limited bandwidth, reducing the efficiency of data collection and increasing the energy consumption of nodes, thus affecting the network's lifespan. Consequently, some scholars have adopted compressed sensing technology to address the shortcomings of traditional WSN transmission methods. Compressed sensing is a novel signal acquisition theory that enables the reconstruction of sparse or compressible signals from sampling frequencies far below the Nyquist rate, offering advantages such as low sampling rates, strong anti-noise capabilities, efficient signal recovery, low energy consumption, and ease of implementation, and it is widely applied in various monitoring scenarios. Yang et al. [9] used a distributed wavelet transform theory based on hybrid decomposition, leveraging the computational capabilities of nodes to reduce communication overhead from inter-node exchange of wavelet coefficients, and employed adaptive wavelet transform to determine network overhead, resulting in significant improvements in network performance. Fute [10] utilized distributed data compression algorithms to reduce the total amount of data within WSN, decreasing the likelihood of data packet collisions on wireless media to enhance data transmission efficiency, reduce resource consumption within the network, and extend network lifespan. Jiang [11] proposed a compressed sensing algorithm with dynamic retransmission to address data packet loss due to unreliable wireless communication, achieving high-precision signal reconstruction to improve network energy utilization and lifespan, with the normalized mean absolute error (NMAE) reduced by 64.5%, and energy efficiency also correspondingly enhanced. Yang [12] estimated the signal's sparsity through an adaptive subspace pursuit algorithm, selected atoms using an approximate matching principle, and completed signal residual updates after multiple iterations to achieve signal reconstruction.

The aforementioned research has provided valuable guidance for the study of Wireless Sensor Networks (WSN); however, due to the complexity of the algorithms, their adaptability in the transmission line monitoring networks with parallel transmission of large volumes of data is not optimal. In light of this, this paper draws on the theory of Compressed Sensing (CS) as the design cornerstone and designs a transmission line monitoring network based on real-world

scenarios. The biorthogonal wavelet transform algorithm is utilized to construct a sparse sampling model for signal compression, while the Regularized Orthogonal Matching Pursuit (ROMP) algorithm is employed for high-precision signal reconstruction. Based on this, a transmission line monitoring system is designed to ensure the real-time and stable monitoring of lines, which holds positive implications for the secure operation of power systems and the extension of the service life of monitoring networks.

The remainder of the paper has been organized as follows. The compressed sensing theory in Section II introduces an innovative method for transmission line monitoring using Compressed Sensing (CS) theory. It discusses CS's ability to reconstruct sparse signals from low-frequency samples, crucial for dense wireless sensor networks (WSNs). To tackle non-sparse signal transmission challenges, the paper proposes a method in Section III utilizing biorthogonal wavelet transform for signal sparsity and the ROMP algorithm for efficient reconstruction. It details network architecture and sparse sampling model, emphasizing adaptive signal analysis via wavelet transformation. Additionally, it explains the ROMP algorithm's iterative process, highlighting its role in enhancing accuracy and handling noise. The paper also discusses the system design, including hardware components and data transmission mechanisms in the design and implementation of the monitoring system in Section IV. The experimental results and analysis in Section V validate the proposed method's efficacy, showcasing high compression ratios, low reconstruction errors, and reduced energy consumption compared to existing algorithms. Finally, conclusions emphasize the significance of the proposed scheme in enhancing transmission line monitoring efficiency and extending network lifespan, offering practical value for energy-efficient management of monitoring systems in Section VI.

II. COMPRESSED SENSING THEORY

Compressed Sensing (CS) is a novel signal sampling method proposed by Candès et al. in 2004, aiming to address the shortcomings of traditional signal acquisition and processing [13]. This theory indicates that if the original signal exhibits sparsity and orthogonality, it can be reconstructed from observation values at a sampling frequency much lower than the Nyquist theorem requires. In other words, it is possible to reconstruct the signal using a much lower sampling frequency and an appropriate reconstruction algorithm. Fig. 1 illustrates the concept of compressed sensing data collection.

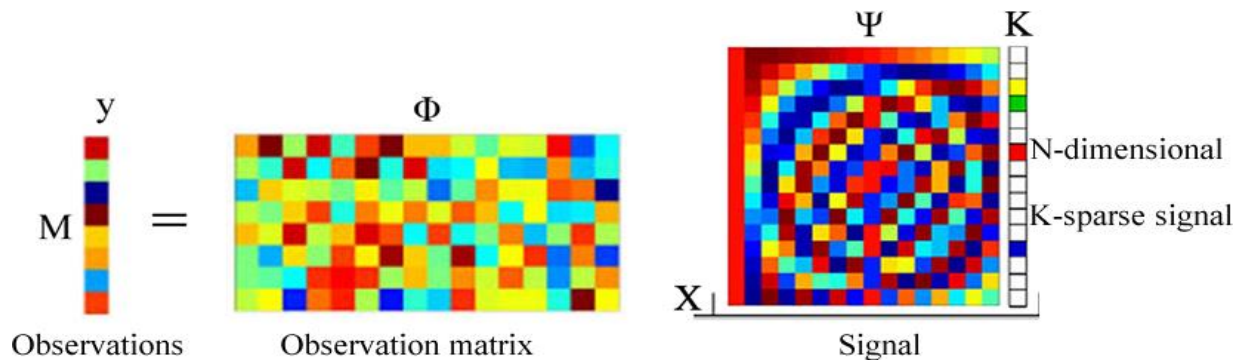


Fig. 1. Schematic diagram of compressed sensing data collection.

Wireless sensor networks are characterized by dense sensor node deployment and high signal sampling frequencies, making the original signals compressible [14]. However, in most cases of transmission line monitoring networks, signal values are not zero, indicating a lack of sparsity [15]. Therefore, it is necessary to employ methods for transforming continuous-time domain signals into sparse signals. If X is an N -dimensional column vector representing the original signal and, α is the coefficient vector under the basis Ψ , the sparse processing can be expressed as follows:

$$X = \Psi\alpha \quad (1)$$

Assuming the sparsity level K represents the number of non-zero points in the sparse domain. If $K = n$ ($n \ll N$) is satisfied, the data can be sampled using the observation matrix Φ ($M \times N$) to obtain the observation values y . The observation matrix Φ is randomly generated from a Gaussian matrix with a mean of zero and a variance of $1/M$. If the performance meets the requirements, the observation values y contain the essential information from the original signal X .

The signal reconstruction can be solved through non-deterministic polynomial (NP) optimization problems, expressed as follows:

$$y = \Phi X \quad (2)$$

$$\begin{cases} \alpha^{(0)} = \arg \min_{\alpha \in R^N} \|\alpha\|_0 \\ y = \Phi X = A\alpha \end{cases} \quad (3)$$

Since the term $A = \Phi\Psi$ belongs to a non-convex combinatorial optimization problem, convex relaxation approximation methods can be employed for solving:

$$\begin{cases} \alpha^{(1)} = \arg \min_{\alpha \in R^N} \|\alpha\|_1 \\ y = \Phi X = A\alpha \end{cases} \quad (4)$$

III. MODEL CONSTRUCTION

A. Network Structure and Sparse Sampling Model for Signal

The transmission line monitoring network adopts a tree structure, as illustrated in Fig. 2. Sensor nodes transmit collected information through long-distance communication modules. After convergence nodes compress the observations, the information is transmitted to the remote monitoring platform through GPRS and the Internet. The monitoring platform utilizes corresponding algorithms to reconstruct the data information, thereby achieving the identification of the original signal for monitoring and early warning purposes.

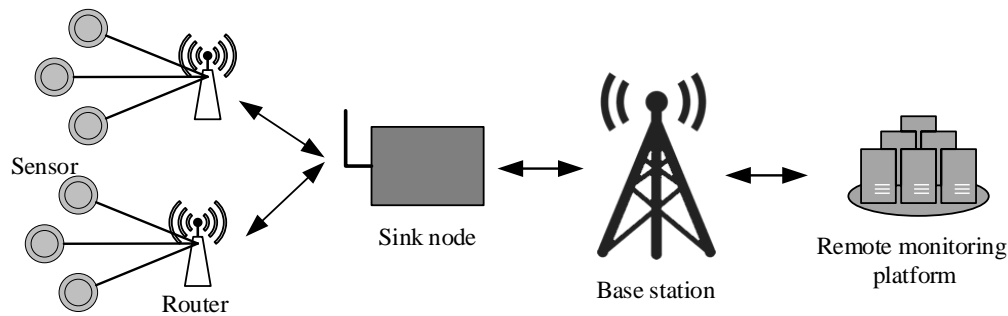


Fig. 2. Transmission line monitoring network structure.

Various sensor nodes exchange information with convergence nodes through a wireless network in the perception area. The temporal characteristics of signals collected by various sensors exhibit continuity and piecewise smoothness, and they have approximate spatial regularity. Based on spatiotemporal characteristics, the biorthogonal wavelet transform can locally transform the signal in both time and frequency. Using translation and scaling operations, it achieves multi-scale refinement of signals, meeting the

adaptive analysis requirements of time-frequency signals. This makes it suitable for sparse representation of signals in monitoring sensor networks [16]. Therefore, based on the characteristics of the transmission line monitoring signals, a sparse sampling model is constructed using the biorthogonal wavelet transform algorithm to achieve signal compression. The detailed signal transmission steps are shown in Fig. 3, where the dashed box represents the sparse sampling process.

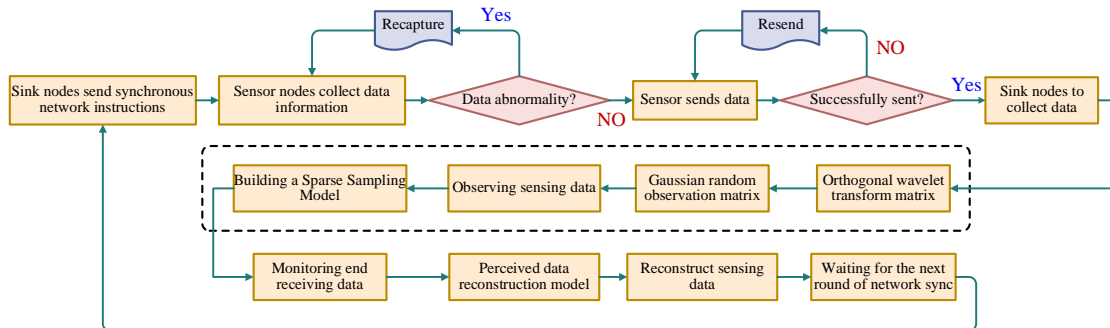


Fig. 3. Compressed sensing-based signal transmission process.

B. Data Information Reconstruction

The Regularized Orthogonal Matching Pursuit (ROMP) algorithm represents an improvement over the classical Orthogonal Matching Pursuit algorithm. The ROMP algorithm enhances signal reconstruction accuracy and stability by incorporating greedy algorithm principles, convex optimization methods, and regularization conditions during iterations [17].

In this algorithm, atoms in the sparse representation are systematically selected through iterations, considering both the sparsity of the signal and regularization conditions. This approach efficiently achieves the reconstruction of the original signal, contributing not only to improved reconstruction accuracy but also enhanced capability in handling noise and complex signal structures, showcasing excellent performance in practical applications.

The ROMP algorithm plays a crucial role in signal reconstruction and is well-suited for handling large-scale sensor data generated in transmission line monitoring. Through meticulous and robust signal reconstruction, the ROMP algorithm provides an effective mathematical tool for accurately restoring the transmission line monitoring signal. This not only aids in reducing data transmission volume and improving network efficiency but also effectively addresses complex environmental conditions and multi-source interference, offering robust support for the reliability and robustness of monitoring systems.

Assumption: r_t represents the residual of the observed data, Φ represents the empty set, λ_t represents the column indices obtained after the t -th iteration, A_t represents the set of columns of matrix A selected according to the index Λ_t , a_j represents the j -th column of the matrix, Λ_t represents the index set for the t -th iteration, $\langle \bullet, \bullet \rangle$ represents the inner product of vectors, \cup represents the set union operation, θ_t represents the column vector after the t -th iteration, $abs[\bullet]$ represents the absolute value operation. The algorithmic process can be described as follows:

Input: N -dimensional observation vector y , sensing matrix A , sparsity level K

Output: Estimated sparse representation coefficients $\hat{\theta}$, N -dimensional residual $r_K = y - A_K \hat{\theta}_K$

Initialization:

Iteration: $\Lambda_0 = \Phi$, $A_0 = \Phi$, $r_0 = y$, $t = 1$

1) Compute $u = abs[A^T r_{t-1}]$ by obtaining K largest values and corresponding column indices set J of matrix A .

2) *Regularization*: Search for a subset J_0 within J satisfying the condition of $|u(i)| \leq 2|u(j)|$ $i, j \in J_0$, and select J_0 with the maximum correlation.

3) Set $\Lambda_t = \Lambda_{t-1} \cup J_0$, $A_t = A_{t-1} \cup a_j$ ($j \in J_0$)

4) Solve for $y = A_t \theta_t$ by finding the least squares solution: $\theta_t = arg \min \|y - A_t \theta_t\| = (A_t^T A_t)^{-1} A_t^T y$.

5) Update the residual $\theta_t = arg \min_{\theta} \|y - A_t \theta_t\| = (A_t^T A_t)^{-1} A_t^T y$.

6) $t = t + 1$. If $t \leq K$, return to step 3; if $t > K$ or $\chi_t = 0$ or $\|\Lambda_t\|_0 \geq 2K$, stop the iteration, and reconstruct θ by placing all non-zero elements at the positions Λ_t .

After iterations, perform wavelet inverse transform on the obtained high-frequency signal and low-frequency part to complete the data reconstruction.

C. Key Model Parameters

The determination of key model parameters not only affects the efficiency of signal compression sensing and the quality of reconstruction but also governs the learning efficiency and accuracy of the model. Therefore, a comprehensive list of key parameters for the model has been constructed, taking into account the actual requirements of the model and the need for real-time and stable monitoring. The list is presented in Table I.

TABLE I. KEY PARAMETERS OF THE MODEL AND DETERMINATION

Parameter	Description
Wavelet Basis	In the realm of compressed sensing, the selection of an appropriate wavelet basis is of paramount importance, as it directly influences the sparsity representation and the quality of signal reconstruction. This study employs the Morlet wavelet to construct a sparse sampling model through experimental comparison, aiming to achieve signal compression. The Morlet wavelet, which combines a Gaussian function with a sine wave, aids in the identification of abrupt changes within signals, thereby facilitating line monitoring.
Regularization Parameter	The regularization parameter λ is utilized to control the degree of sparsity in the Regularized Orthogonal Matching Pursuit (ROMP) algorithm, striking a balance between data fidelity and sparsity to better capture the signal's sparse structure and enhance the quality of the reconstructed signal. This paper determines λ based on the minimum reconstruction error derived from leave-one-out cross-validation experiments, with the Mean Squared Error (MSE) serving as the evaluation metric for signal reconstruction error.
Sparsity	Sparsity is employed to regulate the balance between the greedy search and regularization in the ROMP algorithm, constraining the number of non-zero elements in the solution vector of the algorithm to prevent overfitting and underfitting phenomena. This study estimates sparsity by integrating the characteristics of the signal with prior knowledge and applying threshold processing.
Atom Dictionary	The Atom Dictionary dictates the representational capacity of the signal during the reconstruction process, reducing the number of atoms that need to be processed, lowering computational complexity, and enhancing computational efficiency. In this paper, the optimal Atom Dictionary is assessed, adjusted, and determined through cross-validation, based on the signal's characteristics and the degree of matching.
Initial Estimate	The Initial Estimate significantly impacts the convergence rate of the algorithm and the quality of the final solution. An appropriate Initial Estimate can effectively reduce computational complexity and minimize the influence of noise and outliers on the reconstructed signal. This research utilizes the Iterative Soft Thresholding Algorithm (ISTA) for sparse reconstruction as the Initial Estimate for the ROMP algorithm.

IV. DESIGN AND IMPLEMENTATION OF MONITORING SYSTEM

Conditions for the formation of ice on transmission lines include environmental temperature $\leq 0^{\circ}\text{C}$, air relative humidity $\geq 85\%$, and wind speed $> 1\text{m/s}$, among others [18]. Therefore, temperature, humidity, and wind speed sensors were chosen as monitoring nodes. The hardware and software components of

the transmission line monitoring system were designed by combining the network structure mentioned above and the algorithmic model. These components underwent detailed analysis and testing to ensure that, under stable system operation, the comprehensive performance indicators met the design requirements. The hardware structure of the system is illustrated in Fig. 4.

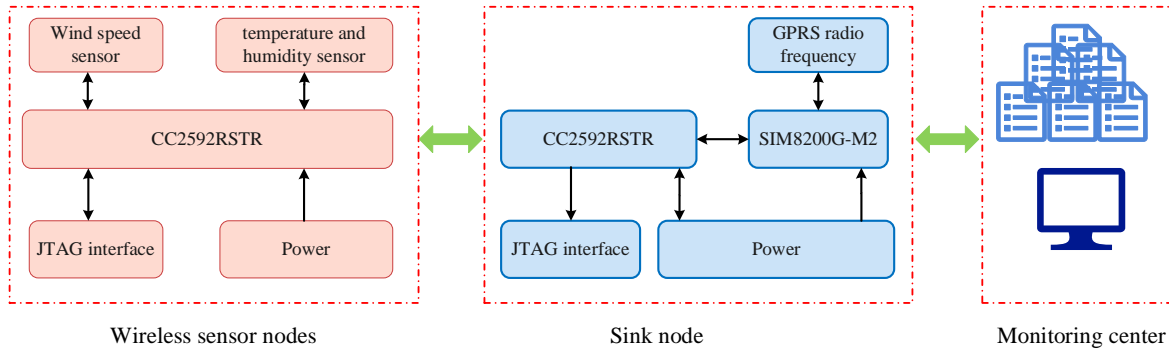


Fig. 4. System hardware structure.

The monitoring system utilizes the convergence node as the time reference point to send clock synchronization control signals to sensor nodes. Each node estimates its delay and makes corrections. Due to timing differences between sensor timers [19], each node is set with a 2.5s lead time to ensure timely responses. When receiving commands from the superior node, nodes exit sleep mode, correct their clocks, and collect and upload data. Upon receiving an ACK message from the convergence node, sensors transition to sleep mode to reduce power consumption. If a sensor node does not receive an ACK message, it continues data collection and uploads until receiving one. Once all nodes have received ACK messages, the convergence node performs data compression and observation processing.

The SHT31 sensor from Sensirion AG is employed for temperature and humidity sensing, with a temperature range of -40°C to 125°C and a humidity range of 0-100% RH, suitable for harsh weather conditions. The compact dimensions (2.5 x 2.5 x 0.9 mm) facilitate lightweight sensor node design. Wind speed measurement is achieved using the FS4G wind speed sensor from Renke Corporation, with a range of 0-60m/s.

The convergence node must perform data observation compression, remote transmission, and network management tasks. It is significantly affected by outdoor environmental factors. Overall, the convergence node should possess fast response, low power consumption, good sealing, and anti-interference capabilities. The SmartRF04-CC2592 chip from Texas Instruments, which integrates a 2.4GHz multi-channel RF transceiver supporting various standard protocols such as IEEE802.15 and ZigBee, is used. It has advantages such as small volume (QFP 4x4mm package), low current consumption (21.8mA when TX at 0dBm output, 12.2mA when TX at -12dBm output), programmable high output power, and strong anti-interference capabilities, making it suitable for the development and application of small wireless nodes. Based on this, the CC2592 chip is used for communication between network nodes and data observation

compression. It is connected to the SIM8200G-M2 wireless communication module via a serial bus, enabling communication with the monitoring center to ensure reliable and stable data transmission.

V. EXPERIMENTAL RESULTS AND ANALYSIS

A. Experimental Environment and Parameters

Experiments were conducted in the simulation laboratory of the State Grid Corporation of China (SGCC) Henan Province Power Grid Simulation Center to validate the feasibility of the proposed method. The span of the transmission line is 42.5m, and sensor nodes are deployed at positions 1, 2, 3, 4, 5, and 6. The convergence node is placed in the tower control box. The monitoring center is located in the simulation center building, 1.2km from the convergence node, and is responsible for receiving reconstructed convergence node data. The deployment of nodes is shown in Fig.5. LG18650 lithium batteries power all nodes with a nominal voltage of 3.7V and a capacity of 3200 mAh.

Data collection spanned five days from November 26 to 30 during the experimental period. Different time intervals (00:00-03:00, 8:00-10:30, 12:00-14:00, 17:30-19:30, 22:00-00:00) were selected to cover various working and environmental conditions, totaling 3450 minutes of sensor data collection. The analysis of diverse data aimed to ensure the reasonability and effectiveness of the experimental results.

Each sensor node's sampling and transmission intervals were set at 30 and 120 seconds, respectively. The observed temperature, humidity, and wind speed values were all 256. After compression by the convergence node, the final quantity was reduced to 768.

B. Reconstruction Error Performance Analysis

Sensor nodes collected environmental information using the parameters designed in the previous section as the basis for the experiment. The convergence node then compressed and

uploaded the data, ultimately achieving the reconstruction of compressed data in the monitoring center. Throughout the data compression and transmission process, the nodes operated collaboratively, meeting the requirements for system stability.

Taking the data collected during the time interval of 8:00-10:30 on November 28 as an example, the reconstructed temperature, relative humidity, and wind speed were compared with the original data, as illustrated in Fig. 6, Fig. 7, and Fig. 8.

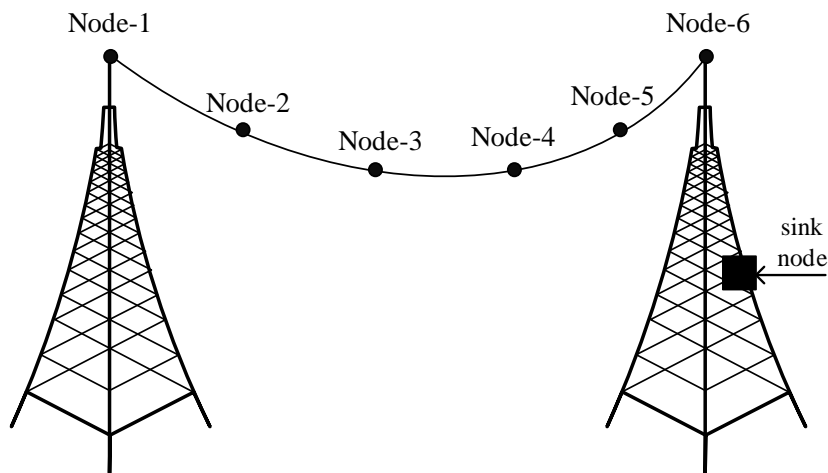


Fig. 5. Node deployment diagram.

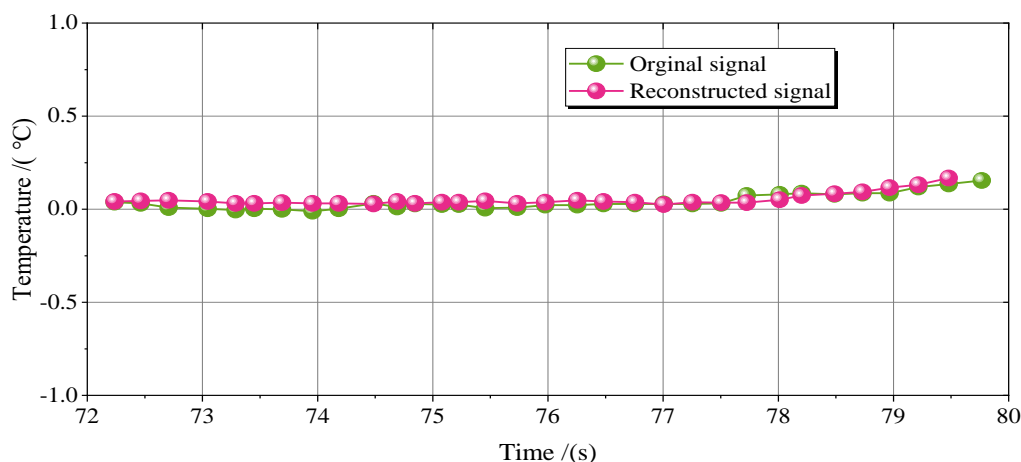


Fig. 6. Temperature comparison curve before and after reconstruction.

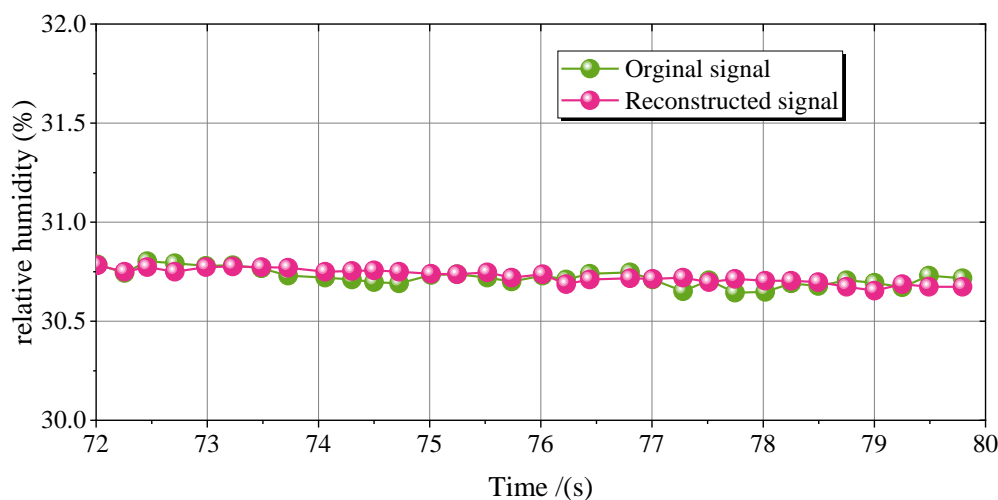


Fig. 7. Comparison curve of relative humidity before and after reconstruction.

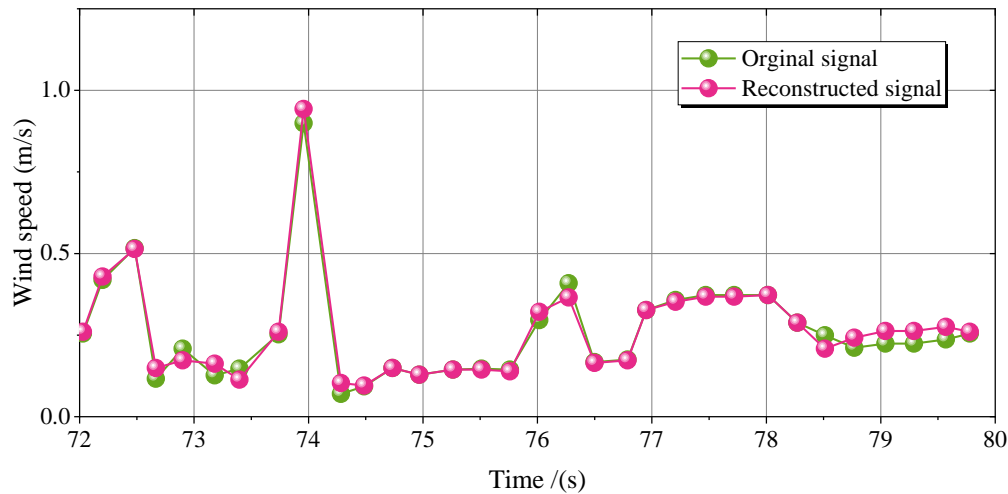


Fig. 8. Wind speed comparison curve before and after reconstruction.

The performance of the reconstruction algorithm is assessed by employing the Normalized Mean Square Error (NMSE) to calculate the mean square values of elements in the vector, thus evaluating the reconstruction error. Simultaneously, the data compression ratio ρ is used to measure the efficiency of data compression to obtain the maximum absolute and relative errors before and after reconstruction. The formulas for NMSE and ρ are expressed as Eq. (5) and Eq. (6), respectively:

$$NMSE = \frac{\| \hat{X}_j(n) - X_j(n) \|_p}{\| X_j(n) \|_p} \quad (5)$$

In the equations, $X_j(n)$ and $\hat{X}_j(n)$ represent the j -th values corresponding to the data before and after reconstruction, and the norm p takes a value of 2.

$$\rho = \frac{N-M}{N} \times 100\% \quad (6)$$

In the equations, M and N represent the quantities of observed data and original data, respectively. Table II presents the error situation of the reconstructed data.

TABLE II. RECONSTRUCTION DATA ERROR SUMMARY (N=3760)

Project	Data Compression Ratio ρ (%)	Mean Square Error NMSE (%)	Relative Error (%)	Absolute Error
Temperature	93.191	3.741	13.346	0.064°C
Relative Humidity	93.191	0.184	0.077	0.052%
Wind Speed	93.191	2.752	16.454	0.128m/s

As shown in Table II, the data sampling reconstruction method based on the joint use of the biorthogonal Wavelet algorithm and the ROMP algorithm achieves a high compression ratio, demonstrating excellent compression results and the ability to achieve the high-precision reconstruction of compressed data. Due to the relatively stable changes in

relative humidity compared to temperature and wind speed, the sparsity after wavelet transformation is greater, resulting in higher data reconstruction accuracy. The mean square error accuracy of wind speed reconstruction is relatively ideal, but the relative and absolute errors are higher. This is because the wind speed signal exhibits significant fluctuations, and the sparse sampling process did not adequately adapt to the changing characteristics of the signal.

C. Energy Consumption Analysis

This section analyzes the power consumption of the compressed sensing wireless sensor network. Considering that the convergence node mainly completes the compression observation of data, experiments were conducted in direct and compressed transmission modes to ensure the comparability of experimental results. The lithium battery was fully charged to the nominal value, and the system was set to run for 36 hours in both modes to measure the voltage decay. The experimental results are shown in Fig. 9.

From the power consumption decay curves in Fig. 9, it can be observed that the convergence node using compressed sampling transmission has a slower voltage decay rate. In a relatively short experiment period, the nominal battery voltage (3.7v) dropped to approximately 3.565v and 3.548v under direct and compressed transmission modes, respectively, with a decrease of about 11.18%. Therefore, the use of compressed sampling transmission can effectively extend the service life of the sensor network.

D. Comparative Experiments

To further corroborate the validity of the method proposed in this paper, experiments were conducted using the respective algorithms from study [9-11] under the premise of the same data transmission volume. A comparison was made between the reconstruction errors, computational efficiency, and energy consumption of each algorithm. Fig. 10 presents the results of the comparative experiments.

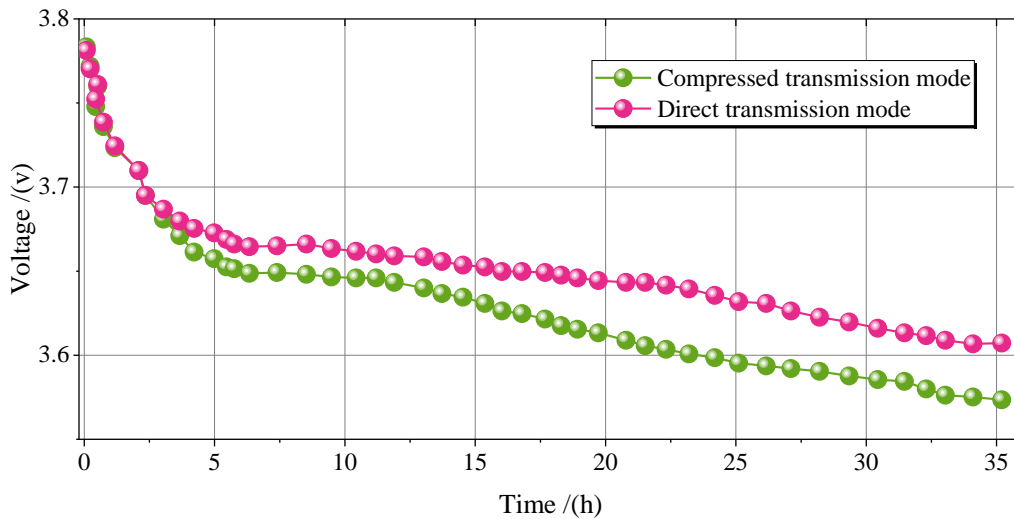


Fig. 9. Convergence node power consumption decay curve under different transmission modes.

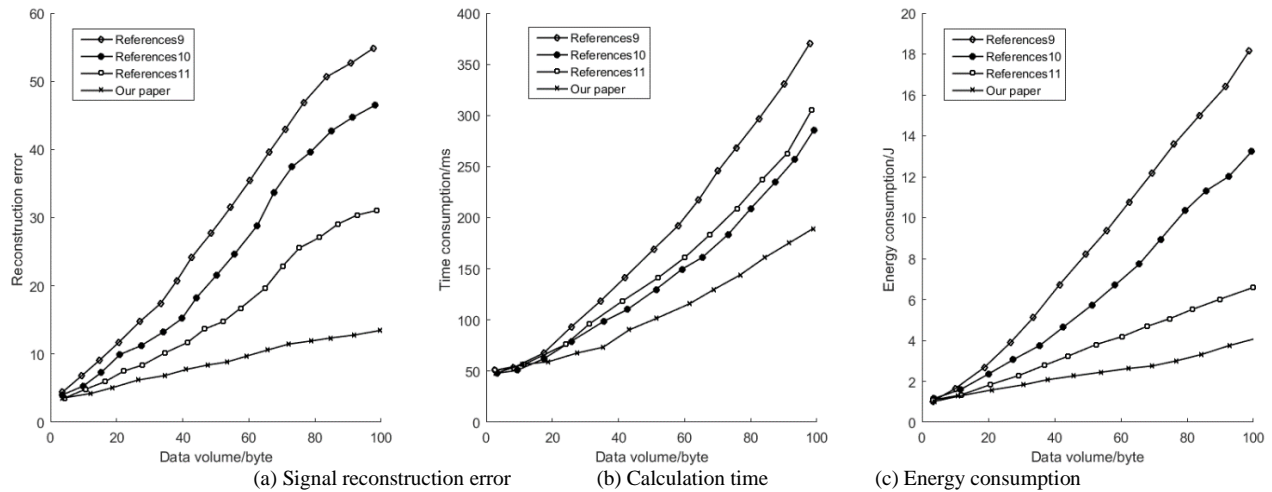


Fig. 10. Comparison of performance indicators of different algorithms.

Fig. 10(a) illustrates that with the increase in data volume, the reconstruction error of different algorithms escalates progressively. The signal reconstruction errors for the distributed optimal wavelet compression algorithm from reference 9, the distributed data compression algorithm from reference 10, and the dynamic retransmission-based compressed sensing algorithm from study [11] are notably higher. In contrast, the method proposed in this paper exhibits a relatively lower reconstruction error and superior stability, which can be attributed to the incorporation of a regularization condition within the iterative process. As observed in Fig. 10(b), when the data volume reaches 100 bytes, the data processing time for the methods described in references [9], [10], and [11] all exceed 250 ms, whereas the processing time for the method introduced in this paper is reduced to only 163 ms, fulfilling the requirements for real-time monitoring and rapid response of transmission lines. According to Fig. 10(c), the energy consumption of the method designed in this paper is significantly reduced to 2.7 J, which is considerably lower than that of the other three algorithms. This indicates a higher energy utilization rate for sensor nodes, which is conducive to

extending the operational lifespan of the transmission line monitoring network and reducing maintenance costs.

VI. CONCLUSION

Focusing on addressing the technical challenges in transmission line monitoring, this paper proposes an innovative wireless sensor network monitoring scheme based on compressed sensing theory. The scheme leverages the combination of compressed sensing technology and orthogonal wavelet transform to achieve sparse representation and efficient compressed sampling transmission of sensor data. By employing the Regularized Orthogonal Matching Pursuit (ROMP) algorithm, the rapid and accurate reconstruction of compressed data is successfully realized. In terms of hardware and software co-design, system architecture suitable for transmission line monitoring is constructed according to the proposed algorithm model. Rigorous experimental validation has demonstrated that the designed monitoring method achieves a high compression ratio of 93.191%, with low signal reconstruction error and superior stability. Moreover, the method features reduced data processing time, meeting the

requirements for real-time monitoring and rapid response. Additionally, by introducing a compressed transmission mechanism at the sink node, the energy consumption of the system operation is significantly reduced, slowing down the rate of energy decay, and effectively prolonging the service life of the wireless sensor network. This scheme holds important practical value and long-term significance for optimizing the energy efficiency management of transmission line monitoring systems and enhancing the system's sustained operational capability.

COMPETING OF INTERESTS

The authors declare no competing of interests.

AUTHORSHIP CONTRIBUTION STATEMENT

Shuling YIN: Writing-Original draft preparation, Conceptualization, Supervision, Project administration.

Renping YU: Formal analysis, Methodology

Longzhi WANG: Software, Validation

DATA AVAILABILITY

On Request

DECLARATIONS

Not applicable

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