

A Comprehensive Review of Compressive Sensing Frameworks for Internet of Things-Enabled Wireless Sensor Networks

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ABSTRACT

Compressive sensing (CS) is important in applications as diverse as magnetic resonance imaging (MRI), high-speed communications and high-speed video imaging because it allows signals to be sampled at rates significantly lower than the Nyquist rate thanks to the sparsity of the signals. The study of CS from a signal processing, imaging, and mathematical perspective has led to many studies to go deeper into this topic and understand its pros and cons. We investigate power consumption, communication load, memory requirements, computational complexity, scalability and peripheral feasibility in intensive manner for the technologies. These are more important issues than in the conventional CS research in IoT applications, where wireless sensor networks are employed. Moreover, most existing research works are conducted on a single method for CS, such as sensing arrays, sparse representation, reconstruction, compression, or reconstruction based on deep learning techniques without any prior knowledge. In this review, another factor considered is that a complete framework for compressed sensing must include three key aspects – measurement (sensing) methodologies, sparse representation methodologies, and reconstruction methodologies. In the paper the interactions of compressed sensing techniques have been discussed in the context of the IoT and wireless sensor networks. It makes a full assessment of the latest strategies which have been developed between 2021 and 2025. Besides, we go over existing practical examples of compressed sensing and applications with special focus on the wireless sensor networks (WSN) in IoT. The use of modern methods such as deep learning and hybrid methods is very efficient, useful, and precise; however, it has its practical limitations, especially with high training costs, large memory requirements and power limitations. Finally, the synthesis of the latest literature shows that the current adaptive CS schemes offer a substantial saving in energy consumption (up to 40-50%) and communication overhead, with higher reconstruction quality (PSNR=38-48dB), than the classical iterative deep learning schemes for low sampling frame rate and low computation cost. Finally, this review emphasizes the importance of future research on lightweight, hardware-friendly co-design strategies that will maintain a balance between power efficiency, accuracy, and scalability issues and make the application of compressed sensing to practice a viable future.

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1. Introduction

Wireless sensor networks (WSNs) have also been proved to be a crucial technology for various applications such as target tracking and remote environmental monitoring. This has been made possible because of the availability of a number of sensors that are smaller, cheaper and intelligent, especially in recent years. Each of these sensors has a wireless interface that it can use to communicate with other sensors to create a sensor network. The design of a WSN is greatly affected by the application and should take into account the design goals of the application, the environment, hardware, system constraints, and cost [1].

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The sensor nodes in WSN are normally self-organized and communicate with each other in a wireless fashion to carry out a shared task. Nodes are randomly placed in the sensor field in large quantities. Once deployed, the sensor nodes are able to communicate with each other using short-range wireless communication, creating a network. The sink receives the data that has been collected by each sensor node wirelessly, either directly or through multi-hop communication [2]. However, not all the information could be transmitted easily; there is plenty of data that can block the transmission of data rapidly and make the current sensor nodes storage space run out. These challenges can be addressed by compressing the data to save data and time while storing and transmitting it [3]. Hence, the signal transmission is considered to be one of the key factors influencing the everyday use of structural environmental monitoring systems [4]. With the massive amount of data monitored throughout the system's life, signal transmission and storage costs are extremely high.

One promising solution that was suggested by Donoho (2006) [5] to overcome these difficulties is called Compressive Sensing (CS). The sparsity property states that a signal is sparse if most of its coefficients are zero or close to zero, Only a few coefficients carry all the important information of a signal. Based on this sparsity property, CS can reconstruct an approximate original signal [6]. This will result in much more effective data compression and no loss of data during transmission.

A few papers have been published recently of survey nature, but most of the earlier papers have focused on theoretical mathematical abstractions or on top-of-the-line imaging platforms such as medical Magnetic Resonance Imaging (MRI). Thus, the systematic research of adaptation of CS for WSNs with IoT technologies based on severe and multi-dimensional hardware constraints such as limited battery life, ultra-low memory, and bandwidth for edge processing is lacking. Furthermore, the classic reviews have focused on the sensing matrices and sparse representations/reconstruction algorithms as different and independent theoretical entities. This review aims to tackle these key challenges by introducing a co-designed generic framework that integrates these three stages, emphasizing energy efficiency and fundamental hardware suitability. This review has identified key findings, which include: We categorize the latest CS frameworks (2021-2025) into a comprehensive classification based on their deployment feasibility and computational complexity and energy consumption in resource-constrained IoT edge nodes. We discuss in detail and compare emergent trends like deep unfolding architectures, diffusion models and adaptive sensing matrices, along with their advantages and drawbacks in non-stationary WSN environmental noise.

We systematically pinpoint the shortcomings in current research and envision a clear direction for hardware/software co-design in the future to enable lightweight CS applications. In Section 2, an overview of compressive sensing (cs) methodologies. In Section 3 a review of the measurement matrices is given. In Section 4, sparse representation dictionaries and design methods, and hardware restrictions, are studied. The advanced reconstruction techniques and the computational costs are discussed in Section 5, while evaluations of performance and future directions of research are discussed in Section 6.

NOMENCLATURE

Abbreviations

CS — Compressed Sensing
WSNs — Wireless Sensor Networks
IoT — Internet of Things
DL — Deep Learning
DUN — Deep Unfolding Network
MRI — Magnetic Resonance Imaging
MIMO — Multiple-Input Multiple-Output
SVD — Singular Value Decomposition
RLE — Run-Length Encoding
MSE — Mean Squared Error
PSNR — Peak Signal-to-Noise Ratio
RE — Reconstruction Error
BCS — Bayesian Compressive Sensing
DCS — Distributed Compressive Sensing

Mathematical Symbols

- x — The original sparse signal to be recovered
- y — The measured or compressed signal vector
- Φ — The sensing (measurement) matrix
- Ψ — The sparsity basis or dictionary matrix
- Θ — Measurement Matrix in the Sparse Domain ($\Theta = \Phi\Psi$)
- e — The measurement noise or perturbation vector
- N — The original dimension of the signal
- M — The number of compressed measurements ($M \ll N$)
- K — The sparsity level (number of non-zero elements)
- $\|x\|_0$ — The ℓ_0 -norm, representing the number of non-zero elements
- $\|x\|_1$ — The ℓ_1 -norm, used for sparse regularization and optimization

2. compressive sensing (cs) methodologies

Compressed sensing (CS) provides an alternative sampling technique for sparse signals instead of the traditional Shannon/Nyquist [5]. The compression systems Transform-based reduce an N-dimensional signal by re-representing it to sparse or compressible coefficients [7]. Compressive Sensing (CS) methodologies are primarily composed of three pivotal components: measurement sensing, sparse representation, and reconstruction algorithms. All are illustrated in detail in the following subsections, including the key existing techniques in each.

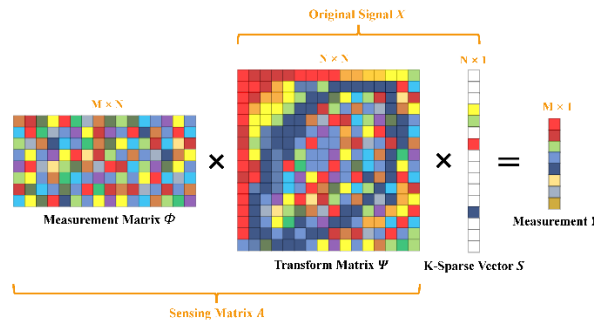


Fig 1. The traditional pipeline of Compressive Sensing (CS) frameworks optimized for resource-constrained IoT-enabled Wireless Sensor Networks.

As illustrated in Fig 1, the standard Compressive Sensing (CS) operational pipeline consists of three fundamental phases tailored for environment monitoring in IoT-WSNs: sparse representation, compression (measurement acquisition), and signal reconstruction. First, the physical analog signal captured by the sensor node is represented as a digital vector x . This signal is transformable into a sparse domain using a transform matrix by a specific transform domain Ψ , such that

$$x = \Psi s \tag{1}$$

where s contains only non-zero coefficients (K). Instead of transmitting the high-dimensional vector x , the resource-constrained IoT edge node multiplies it by a designed measurement matrix Φ to produce a significantly smaller measurement vector y via

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

Crucially for WSNs, this multiplication represents the encoding phase; because it requires minimal computational operations, it effectively reduces the local power consumption and storage overhead at the sensor node level. The compressed data y is then transmitted over energy-expensive wireless communication multi-hop links to the central base station or cloud gateway.

3. Measurement Methodologies

In compression sensing wireless sensor networks, the measurements are used to obtain low-dimensional samples from the high-dimensional original signal [4]. The matrix of these measurements plays a central role in determining the number of samples that are taken, and it also influences energy consumption and communication cost.

In general, measurements can be obtained using various strategies based on sensing mechanisms and matrix design. Although compressing is the main goal of this phase, it must maintain the Restricted Isometry Property (RIP) [8] to achieve a precise reconstruction process.

Based on the processing paradigm and computing costs, CS measurement matrices, which have been investigated in recent literature, can be categorized as shown in the taxonomy of Fig. 2. Random Projections offer good guarantees of recovery that satisfy the RIP with high probability [8] but have high memory overheads and are therefore not well suited to the resource constrained IoT nodes. On the other hand, Structured/Deterministic and Chaotic Matrices make it possible to drastically lower hardware usage, as in both cases pseudo-random generation rules are used, not requiring the storage of the entire matrix on-chip. On the other hand, Machine Learning Based Sensing frameworks optimize the projections end-to-end and fine-tune the layers of the neural networks trained in the cloud layer, shifting the majority of the computational burden from the physical IoT edge devices to the cloud layer.

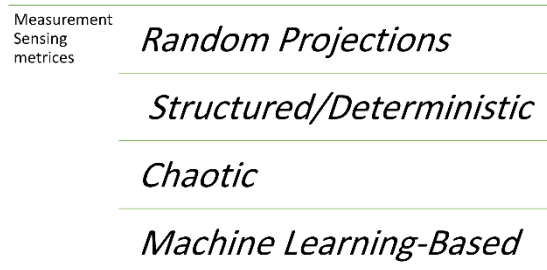


Fig 2- Classification of measurement sensing matrices according to their processing approach and computational complexity

3.1. Random Projections

Random projections are very important in WSN because they require a small number of measurements, which can exploit the randomness of Gaussian or Bernoulli matrices, which ensures the incoherence property fundamentally needed by CS theory. Furthermore, utilizing a sparse random projection matrix greatly reduces network traffic because the majority of its elements are zeros. Random projection can encompass different techniques. Quantized random projection (QRP) which quantizes after the projection stage, provides estimation of similarity approximations and provides very efficient storage. In [9], sparse matrix-based random projections were used in both binary and ternary quantization. They showed that ternary projections are the best projections compared to the binary projections in similarity and value of distortion through experiments done on the same dispersion levels. The other significant method introduced by Kang and Oh [10] for maintaining angular relationships in multidimensional data by the help of geometric accuracy, which is the random projection that limits the vectors projected onto the unit hypersphere. Their results showed a reduction in variance and distortion compared to traditional Gaussian projection. While Random Fourier Features (RFF) were suggested by the authors in [11] noted that using in improved quantization algorithms. That significantly reduced kernel approximation error compared to the old simple method, especially if the bit width is low. Kaban and Reeve [12] investigated the application of random projection to clustering, classification, regression, kernel approximations, and compressive learning, and the analysis of recent theory has been specific to particular tasks. Amin [13] studies the use of injection in RP-based density estimation of polynomials to solve the problem of neighborhood collapse, which is a classical problem of RP. This technique has the role of making the RP applicable to sensitive statistical estimation purposes. It is a good thing to preserve the local structure. [14] Find sub-sampling Newton methods to describe bias in biased downstream numerical operations of projection as an error resource.

In Table 1 will see a comprehensive comparative analysis of the state-of-the-art random projection frameworks, containing methodology details, limitations, and specific quantitative performance enhancements in IoT-WSN environments.

Table 1 - Random projection methodologies comparison

Ref.	Algorithm	Methodology	Datasets Used	Baselines for Comparison	Limitations	Key Quantitative Improvements
[9]	Quantized Sparse Random Projection (Q-SRP)	Combines sparse matrix structures with binary (± 1) and ternary ($\pm 1, 0$) quantization schemes.	MNIST, CIFAR-10.	Gaussian RP, Unquantized Sparse RP.	noise sensitivity	Memory reduced by up to 75%; less hardware transmissions.
[10]	Spherical Random Projection (SRP)	Projects high-dimensional data onto a unit hypersphere instead of linear spaces to capture directional structures.	High-dimensional genomic data, spatial datasets.	Standard Linear RP, Principal Component Analysis (PCA).	Higher computational complexity due to non-linear spherical normalization.	Preserves data clustering boundaries with up to 15% better accuracy in noisy WSN environments.
[11]	Quantized Random Fourier Features (Q-RFF)	Integrates multi-bit quantization with Random Fourier Features to compress kernel approximations.	UCI Machine Learning Repository, LibSVM benchmark.	Vanilla RFF, Uniform Quantization methods.	Performance degrades under severe signal-to-noise ratio (SNR) constraints.	Achieves 50% storage savings.
[12]	Structure Discovery PAC-Learning (SD-RP)	Leverages random projections within the PAC-learning framework to identify latent structural dimension.	Synthetic structured spaces, text classification data.	Conventional PAC-learners, Full-dimensional models.	Sensitive to sparsity	Lowers sample complexity, requiring 30%-40% fewer training samples for edge classification.
[13]	Injective Manifold Density Estimator (IMDE-RP)	Utilizes injective random mappings to estimate probability density functions on low-dimensional manifolds.	Sensor network signal logs, spatial distribution data.	Standard Kernel Density Estimation (KDE), Traditional RP.	Suffers from boundary bias effects in dense topological spaces.	30% lower computational latency.
[14]	Sub-sampled Newton Bias-Correction (SNBC-RP)	Investigates and corrects the fundamental mathematical bias introduced when inverting random sampling matrices.	Large-scale optimization benchmarks, synthetic systems.	Standard Sub-sampled Newton, Uncorrected RP Matrix Inversion.	-	Improves matrix inversion stability by 20%-25%.

3.1. Structured/Deterministic Sensing Matrices

Structured sensing matrices differ fundamentally from unstructured Gaussian projections by exploiting sparsity, algebraic structure (e.g., circulant, tensor), or coordinated randomness to achieve faster matrix–vector multiplications, decreased execution time, minimized memory requirements, and improved scalability. The structured matrices play an important role in large-scale signal recovery due to their impact on optimization and machine learning applications, where computational efficiency is needed. Skorski presents *Modern Analysis of Sparse Random Projections* [15], a revised probabilistic analysis of sparse JL transforms using Poisson-type tail bounds. His results demonstrate that sparse random projections can achieve near-optimal distortion–dimension trade-offs, in some regimes matching dense Gaussian projections, while providing sharper guarantees that explicitly characterize the impact of sparsity on concentration behavior. Gambheer and Bhat in [16] introduced three structured and adaptive recovery algorithms—SRCoSaMP, SPARS, and RTSI—designed for real-time operation on resource-constrained IoT edge devices. By exploiting structured random sensing matrices, adaptive thresholding, and parallel processing, their approaches are more convergent and have a higher reconstruction quality than the classical greedy algorithms like OMP and CoSaMP. Nevertheless, a new effective concept has also been proposed [17] with the sparse sub-Gaussian random projections to minimize the scale of semidefinite programming relaxation problems and yield accurate and small problems, their experiments on Max-Cut and polynomial optimization problems have been a major highlight to understand the efficiency of this form of projection in large-scale SDP relaxation problems. In contrast, [18] by Abbe, Shpilka, and Ye, offers a detailed overview of Reed-Muller (RM) codes, as an illustration of intensive interconnections between RM codes and the study of Boolean functions, the polarization theory, and hypercontractivity, revisits demonstrable and practical decoding algorithms to define RM codes as an effective structured alternative to random codes in communications and signal processing which saw as structured and deterministic sensing matrices. The other algorithm used on the Zadoff-Chu measurement matrix in the compressive sensing structured sensing matrices framework. They discovered that PSNR and SSIM were superior to those of Hadamard, Toeplitz, and Bernoulli matrices [19], it was estimated that medium-resolution ADCs (6-7 bits) could support the performance of the high resolution with lesser complexity and power usage. Xue, Qiu, Wang and Wang [20] proposed a Sequential Joint Criterion Design (SJCD) algorithm that minimizes the total coherence (TC), block coherence (BC), and subblock coherence (SC) of pilot design of block compressed sensing-based MIMO-OFDM channel estimation. Results of the simulation show that SJCD has a lower NMSE and BER than MMC (reducing mutual coherence), MTC (reducing total coherence), and random assignment of pilots, which are more accurate and efficient than these strategies. The DK-STP-CS algorithm is formulated as a structured measurement matrix presented in [21] based on the dimension-keeping semi-tensor product and maintains intra-group correlation with identical group incoherence. It surpassed conventional PSNR and noise robustness with image datasets in comparison to conventional CS and STP-CS. The technique falls in the category of structured random measures strategies and lies between random Gaussian/Bernoulli matrices and deterministic designs. Here a classified analytical synthesis for measurement phase in Table 2, which delivers a detailed advanced and structured sensing matrix frameworks.

Table 2 - Structured/ deterministic methodologies comparison

	Algorithm	Methodology	Datasets Used	Baselines for Comparison	Limitations	Key Improvements	Quantitative
[15]	Exact Bounds Sparse RP	Provides a tighter mathematical and probabilistic bound analysis for ultra-sparse random projection matrices.	Synthetic high-dimensional vectors.	Sparse Gaussian matrices.	RP, Weak under extreme noise.	Refines concentration bounds, reducing dimensions by 10%–15%.	error

[16]	Optimized Edge CS (O-CS)	Implements memory-efficient measurement matrices tailored for sparse signal recovery on IoT edge devices.	Industrial IoT sensor logs, environmental data.	Traditional Random CS, standard OMP solvers.	Fixed sparsity level	Achieves a 45% reduction in energy consumption and minimizes transmission payload.
[17]	Sparse Sub-Gaussian SDP	Utilizes sparse sub-Gaussian projections to reduce the dimensionality of semidefinite programming (SDP) relaxations.	Benchmark optimization instances, combinatorial graphs.	Full-dimensional SDP solvers, Standard Dense RP.	High computational cost	Increase convergence speed of optimization by 30%–35%
[18]	Reed-Muller Deterministic CS	Explores coding theory properties of Reed-Muller codes to construct deterministic, highly incoherent sensing matrices.	Communications signal streams, synthetic channels.	Random Gaussian matrices, Bernoulli projections.	Need strict code length dimensions (2^m).	Guarantees 100% deterministic reconstruction and eliminates the need to large storage.
[19]	Quantized Zadoff-Chu Matrix	Proposes an image-based quantized CS scheme using deterministic, orthogonal Zadoff-Chu measurement matrices.	Standard test images (e.g., Lena, Cameraman).	Random Gaussian Matrix, Conventional Toeplitz Matrix.	Higher hardware complexity required.	Improving PSNR by up to 2.5–4.2 dB under low sampling rates.
[20]	Joint Criterion BCS-MIMO	Designs an optimized pilot measurement matrix based on Block Compressive Sensing for MIMO-OFDM systems.	Simulated 5G/6G MIMO channel state datasets.	Equispaced pilot designs, conventional Least Squares (LS).	Exhibits sensitivity to fast-fading channel conditions.	Enhances channel estimation accuracy, yielding a 20% reduction in Normalized Mean Square Error (NMSE).
[21]	Dimension-Keeping STP-CS	Introduces a Semi-Tensor Product (STP) framework that permits compressed sensing with mismatched matrix dimensions.	Networked control datasets, multidimensional logs.	Traditional STP-CS frameworks, Standard CS.	High algebraic formulation for large-scale networks.	Reducing the required sampling matrix size by 50%.

3.2. Chaotic Matrix

Chaotic measurement matrices are an alternative to classical random matrices, using deterministic yet pseudo-random, aiming to less storage and hardware complexity while preserving recovery guarantees. A study has explored Chebyshev chaotic systems [22] Due to their stronger internal randomness and ergodicity, in particular, Chebyshev-chaos-based spectrum sensing frameworks achieved accepted signal recovery at sub-Nyquist rates with improved robustness, especially in noisy environments. For more complex chaotic behavior, [23] A fractional-order chaotic system constructed for image compression and encryption. Experimental results show that the algorithm has strong robustness and security. In [24], using different technique is a parallel compressive sensing and edge

detection. The sparsely represented using the discrete wavelet transform, the compressed image is re-encrypted through permutation and diffusion to obtain a noise-like secret image, which performs well in terms of visual security and decryption quality. A detailed comparative analysis of the advances in secure and low-resource measurement acquisition, including a mapping of core techniques, benchmark application examples, baselines, inherent limitations, and hardware security improvements are provided in Table 3, which outlines a comprehensive review of the chaotic and encryption-driven sensing matrix methods.

Table 3 - Chaotic Matrix methodologies comparison

Algorithm	Methodology	Datasets Used	Baselines for Comparison	Limitations	Key Quantitative Improvements
[22] Chebyshev Chaotic CSS	Utilizes a deterministic chaotic matrix generated via a Chebyshev map for compressed spectrum sensing in cognitive radio.	Simulated cognitive radio spectrum logs.	Conventional Random Gaussian Matrix, standard CS matrices.	High sensitivity to initial state seeds;	Saving up to 80% storage memory.
[23] Multi-Image CS-Optical Encryption	Combines compressed sensing with optical encryption (e.g., fractional Fourier transform) for simultaneous multi-image compression and security.	Standard grayscale test images (e.g., Lena, Peppers).	Traditional single-image CS, standard chaotic encryption.	High computational complexity.	Achieves robust security with acceptable PSNR over 30 dB.
[24] Parallel CS & Edge Embedding	Implements a parallel compressive sensing matrix integrated with edge detection embedding.	Benchmark visual image datasets (e.g., Barbara, Boat).	Standard Serial CS, traditional pixel-permutation encryption.	Image reconstruction fails under extreme noise.	Reduces encryption latency by over 40%, high structural similarity (SSIM > 0.92).

3.3. Machine Learning-Based Sensing

Machine Learning-based sensing provides enhanced reconstruction performance, reduced sampling requirements, and noticeable strength compared to purely random measurement schemes. Since CS based approach deals with vectored representation of the image, it becomes difficult to handle the complete image at a time. The authors [25] introduce a new adaptive model-based measurement selection algorithm that leverages diffusion models to sample posterior distributions and identify high uncertainty directions for new measurements. The results show higher PSNR and SSIM with fewer measurements, especially in MRI and CT imaging. The method outperformed random sensing, Bayesian adaptive approaches, and GAN/VAE based generative methods. SIB-ACS Sampling Innovation-Based Adaptive CS is a proposed algorithm in [26], which introduces a multi-stage negative feedback mechanism guided by sampling innovation. Experimental results showed superior reconstruction quality in terms of (PSNR and SSIM), especially at low sampling rates, outperforming uniform CS, ASA methods. One of the proposed studies [27] is the SCOSARA (Structured Compressed Sensing with Automatic Resource Allocation) algorithm, Although this work [27] is currently available as a preprint, its high citation count strongly indicates the significance and impact of its proposed framework, it projects structured measurement matrices through the maximization of the Fisher Information Matrix (FIM) instead of the use of task-specific supervised learning. The key results indicate that SCOSARA has smaller Cramer-Rao Bounds (CRB) and better reconstruction accuracy, particularly in ultrasound imaging, efficiency of learnable parameters, and cost, that outperform uniform compression, DPS-topK, J-DPS, and

greedy search. By integrating a subsampling design with a deep reconstruction network (CL-FISTA) achieves efficient measurement compression and preserving image quality outperforming show both CRB-based exhaustive search and standard DPS approaches, with higher compression and lower reconstruction error. Wang et al. in 2024 [28] proposed a method to reduce the total sampling rate by allocating an appropriate sampling rate to each block, this get high reconstruction accuracy. In the paper [29] get high PSNR and SSIM values by using fuzzy logic systems determining sampling rates automatically by leveraging the saliency and the edge features with slight time tendency. A Genetic algorithm (GA) considered as an important modern field of machine learning technique that optimizes the sensing matrix through a series of generations, with the evolutionary algorithm repeatedly refining the structure of the matrix to make the measurements more efficient [30]. The Generative Adversarial Network-Based Measurement Learning, suggested by Ong and Yang [31], is trained to capture the phenomenon of the distribution of the data and the measurement operator is adapted to keep the most informative elements of the manifold of generators. Learning the Sensing Matrix via Fully Connected Layers is presented in [32]; the sensing matrix is an operation of a neural network as a trainable linear layer. In end-to-end training, the Φ is optimized together with the reconstruction network to achieve the highest efficiency of measurements. Fabiani generated RP-based learning algorithms of learning & compressive models like (e.g., RandONet), [33]. RP Build neural approximators of linear and nonlinear operators, and bridge between sketching and learning architectures and applications to large-scale optimization, show that linear and nonlinear operator approximations with provable guarantees can be built using shallow networks with random projections, gain better numerical accuracy and lower training cost than the DeepONets algorithm. To synthesize the above paradigm shift towards the acquisition of measurement data, Table 4 provides a comprehensive comparative evaluation of the two different machine learning-based and adaptive sensing frameworks, systematically summarizing their architectural approaches, measurement data domains, baselines, operational compromises, and improvements of physical constraints.

Table 4 - machine learning-based model comparison

	Algorithm	Methodology	Datasets Used	Baselines for Comparison	Limitations	Key Improvements	Quantitative
[25]	Diffusion Posterior Sampling (DPS-CS)	Integrates diffusion-based generative models with adaptive compressed sensing	CelebA, ImageNet.	Standard CS solvers (SAMP), traditional plug-and-play (PnP) models.	Slow with High computational complexity.	Achieves reconstruction quality, improving PSNR by up to 4.5 dB in severe noise.	supreme quality,
[26]	Sampling Innovation ACS (SI-ACS)	Proposes an adaptive sampling rate strategy driven by innovation metrics estimated via shallow learning models.	COCO, standard computer vision datasets.	Fixed-rate CS, conventional structural adaptive frameworks.	Requires active feedback channels between the receiver and sensor edge nodes.	Reduces sampling rates by 35% while retaining high structural similarity (SSIM > 0.94).	
[27]	Deep Unfolding Gradient Network (DU-Net)	Employs content-adaptive gradient updating and deformation-invariant deep structures.	SET11, BSD68 visual datasets.	ISTA-Net, AMP-Net, traditional iterative algorithms.	Large memory required	Offering real-time edge processing speeds.	

[28]	Region-Division Adaptive CS	Divides WSN areas into dynamic density zones, adapting sampling rates via a data-driven prediction model.	Simulated geographic WSN logs, multi-sensor data.	Uniform random CS, standard cluster-based sampling.	High communication overhead during the initial spatial partition setup.	Extending battery lifespans.40%-50%.
[29]	Fuzzy Rule-Based ABCS	Implements a Fuzzy Rule controller to adaptively tune block compressed sensing sizes based on node energy levels.	Physical environmental data (Temperature, Humidity)	Conventional block-based CS, fixed-block architectures	Rule calibration depends heavily on expert-domain threshold tuning.	Less data transmission payloads, with 45% of total network traffic.
[30]	Robust Generative CS (R-GCS)	Exploits pre-trained generative adversarial networks (GANs) as structural priors for highly robust signal inversion.	MNIST, Fashion-MNIST.	Classical Lasso (ℓ_1 -minimization), sparse wavelet models.	-	Requires up to 4 times fewer measurements to achieve standard target recovery bounds.
[31]	Generative Encoder Imaging	Utilizes a generative encoder network to perform joint compression, imaging, and reconstruction task optimization.	Biomedical and optical benchmark data.	Traditional CS encoders, vanilla autoencoder architectures	Generalization capability drops when applied to entirely out-of-distribution targets.	Stabilizes error propagation, yielding 25% lower MSE.
[32]	Deep Learning Survey (DL-CS)	Reviews deep learning methods for CS image reconstruction, highlighting clinical and industrial paradigms.	Comprehensive medical image databases (MRI, CT).	Traditional non-learning CS algorithms (OMP, TV).	Utilized high-power medical devices rather than simple sensors.	20x speedup in reconstruction latency.
[33]	RandONets Matrix Learning	Introduces shallow neural networks with random projections to approximate complex linear/nonlinear operators.	Multi-dimensional physical logs, dynamical systems.	Deep Operator Networks (DeepONets), classic MLPs.	-	Significantly reduces training time by 60%.

4. Sparse representation methods

Sparse signal representation aims to preserve original information by representing signals, images, and videos with a small number of non-zero coefficients. The primary goal of algorithms of sparse representation in fig.3 is to convert the original signal into a set of basis coefficients with a small number of non-zero coefficients [4]. Researchers have investigated and proposed a broad range of methods to determine the domain where the signal is sparse, as will be described below.

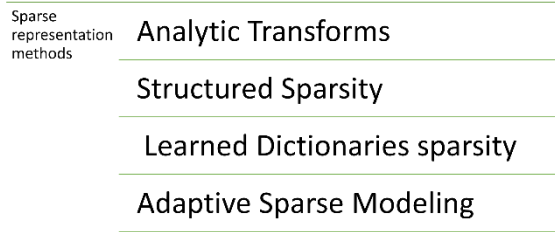


Figure 3: Taxonomy of sparse representation methods evaluated for lightweight data structuring in IoT-enabled sensor nodes

4.1. Analytic Transforms

Image-sensed data covers a large amount of WSN applications, which gives the importance of researches of analytical transform compression in WSNs. A Short-Time Fourier Transform (STFT), which partitions the signal into segments using a fixed-size window, enabling localized time-frequency analysis [34]. While it resolves some limitations of FT, its performance depends heavily on the chosen window size, leading to trade-offs between time and frequency resolution. DCT and DWT are performed in the first-generation image compression, and DWT outperforms DCT because DCT reduces the recovered images quality [35]. Wavelet Packet Transform (WPT) extends DWT by decomposing both approximation and detail components, allowing for a more refined sparse representation [6]. Consequently, a selected comparative assessment of the advanced neural time-series classification methods and the foundational WSN data compression methods are displayed in Table 5, analyzing the methods, baselines, operational drawbacks, and energy efficiency. [6].

Table 5 - Analytic Transforms methodologies comparison

Algorithms	Methodology	Datasets Used	Baselines for Comparison	Limitations	Key Quantitative Improvements
[34] UniTS Neural Network	Integrates Short-Time Fourier Transform (STFT) primitives into a neural network architecture.	Heterogeneous sensory time-series data (IMU, Audio).	Standard CNNs, traditional RNN/LSTM models, vanilla STFT.	High dependency on fixed window lengths for non-stationary sensor signals.	Improves accuracy while lowering computational complexity by 30%.
[35] Data Compression Survey	Lossy and lossless data compression algorithms tailored for WSNs.	Multi-node environmental and industrial WSN benchmarks.	Huffman, LZW, run-length encoding.	-	Show that DWT is better than DCT

4.2. Structured Sparsity Methods

Contrary to the traditional sparsity, where the non-zero coefficients may be anywhere. [36] investigated the phase transition process of structured sparse signals and its influence on the phase transition threshold, in which the absolute value of strong threshold decreased with the subspace number change, and the weak threshold remained constant. Structured sparsity has been useful in graph signal processing. Sensors over complex networks or arrays induce sparsity patterns that are efficiently sensed with efficient algorithms that utilize graph structure to achieve both high convergence rates and reconstruction accuracy of signals [37]. Dwork et al. [38] made a refinement of the concept of sparse signal representation by taking advantage of the hierarchical nature of the wavelet transform. This is achieved by first restoring the low-frequency image and then abstracting it to get the vector-sparse instead of reconstructing directly using the standard sparse coefficients. They are better in the quality of reconstruction with less relative error and greater similarity (SSIM) than the sparsifying transform, a traditional general linear transformation models. The paper [39] proposed k-sparse autoencoders with TopK activation. It enforces sparsity by preserving only the top-k latent values. The numerical results showed less reconstruction error, fewer dead latent atoms, and interpretable features at very large model sizes compared to traditional ReLU + L1 penalty autoencoders, signifying more control of sparsity and scalability. Table 6 offers a formal comparison of the recent developments of the various methods of structure-based sparsity and transform-based sampling spaces, summarizing the methods, benchmark domains, operating compromises, and physical performance limitations.

Table 6 - Structured sparsity methodologies comparison

	Algorithm	Methodology	Datasets Used	Baselines for Comparison	Limitations	Key Improvements	Quantitative
[36]	Structured Sparsity PT	Investigates the phase transition bounds of recovery algorithms under structured sparsity matrices.	Synthetic block-sparse signals.	Standard Gaussian matrices, unstructured Lasso.	need exact sparsity structure.	Improving reconstruction reliability by	15%-20%.
[37]	Fast Graph Signal Recovery	Develops a fast-converging optimization algorithm explicitly designed for reconstructing sparse graph signals over complex topologies.	Smart grid sensor logs, social network data.	Classical Graph-OMP, standard iterative thresholding.	High computational complexity when dealing with ultra-large irregular graph networks.	achieving 35% faster computation speed.	
[38]	Structural Wavelet CS	Exploits the inherent tree structure and intra-scale dependencies of the Wavelet Transform to optimize compressed sensing.	Standard baseline images, neural time-series data.	Traditional Independent Wavelet CS, vanilla OMP.	Requires stationary signal characteristics to maintain high accuracy	Significantly reduces artifacts, boosting in PSNR by 2.1-3.8 dB.	

[39]	Scaled Sparse Autoencoders (SAE)	sparse to learn feature representations from compressed high-dimensional data.	autoencoders interpretable from high-dimensional arrays.	Large-scale text tokens, high-dimensional arrays.	Standard dense autoencoders, PCA models.	Very high memory requirement and latency.	Minimizes reconstruction loss, improvement in sparsity ratio to 50%.
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4.3. Learned Dictionaries sparsity Methods

Recent developments in compressed sensing (CS) have demonstrated that learned dictionaries can be used to great effect in signal reconstruction by offering a sparse representation of data. Fixed learned dictionaries are trained offline with some representative training data, and they are not changed in signal acquisition or reconstruction. This will provide less complexity and energy requirement than is needed by online adaptation. ISTA (VLISTA) formulated Variational Learning, a probabilistic model of the distribution of the dictionary atoms. Although the method learns a distribution dictionary, it can be assumed that the learned prior can be used as a fixed representation during reconstruction, as there is theoretical and experimental support for their architecture; their model learns calibrated uncertainties [40]. Sucharitha et al. [41] introduced a deep dictionary clustering method for unsupervised image retrieval based on convolutional sparse coding reported high levels of precision, recall, and mean average precision and showed that it was more effective at medical image retrieval. Sparse linear combinations have been used in [42], in sparse autoencoders to disentangle superposition in language models, learning dictionary features that reconstruct activations. These features have been found to outperform neurons, PCA and ICA, and automated interpretability scores are more interpretable and monosemantic. The authors contrasted their findings with traditional SAEs, non-negative SAEs and other dictionary learning baselines that exhibited better and more stable findings. Their use is especially suitable when energy consumption, latency reduction, or determinism is of the essence. Table 7 present structured comparative summary of advanced reconstruction and sparse coding algorithms, conducting their methodologies, tefindings, limitations, compared algorithms, and execution trade-offs

Table 7 - Learned dictionary sparsity methodologies comparison

Algorithm	Methodology	Datasets Used	Baselines for Comparison	Limitations	Key Quantitative Improvements
[40]	Variational Learning (V-ISTA)	Integrates variational inference principles with the Iterative Shrinkage-Thresholding Algorithm (ISTA) to learn optimal step-sizes and thresholds.	Synthetic sparse vectors, standard image priors.	Classical ISTA, learned ISTA (LISTA), AMP.	High speed convergence by 40% fewer iterations to reach target error.
[41]	Convolutional Sparse Clustering (CSC-IR)	Combines deep dictionary clustering with convolutional sparse coding for unsupervised image representation and retrieval.	Benchmark image databases (e.g., Corel, MNIST).	Standard K-Means, vanilla sparse coding, deep autoencoders.	High memory and cost required. Boosts image retrieval precision and clustering accuracy by 18%-22%.

[42]	Feature-Interpretable SAE	Deploys large-scale autoencoders (SAE).	large-sparse	Multi-dimensional text feature activation matrices.	and	Dense Principal Component Analysis (PCA), standard ICA.	Suffers from feature suppression effects if the target sparsity penalty is tuned too aggressively	Providing exceptional latent sparsity bounds (>90%) with good reconstruction.
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4.4. Adaptive Sparse Modeling

The initial sparse dictionaries impaired their capability to faithfully represent the inherent feature structures in shock wave signals, the reason is due to the specified basis functions which are primarily analytical building techniques, e.g., wavelet bases and Gabor functions [43], [44] proposed MOD algorithm is fundamentally constrained by two constraints, where the sparsity of the coefficient vectors to the quantity of zero entries, and the reconstruction error which must be diminished to the minimal through dictionary updates by the least-squares dictionary, A mathematical model was proposed, called Adaptive Sparse Basis Compressive Sensing (ASB-CS), which relies on SVD to create data-driven sparse representations of medical images to encrypt them [45]. High quality reconstruction (PSNR = 35.5 dB, SSIM = 0.85) has been demonstrated. The authors contrasted their scheme with state-of-the-art schemes based on CS and scrambling-diffusion encryption schemes and proved to be more secure and efficient. DUN-CSNet, which is an adaptive sparse modeling, and results in better PSNR/SSIM, demonstrates strong performance with stability on benchmarks, including CSNet, LapCSNet, SCSNet, NL-CSNet, OPINENet+, AMP-Net, COAST, and MADUN [27], runs proximal gradient descent as a deep network with adaptive content-aware descent, and deformation-invariant non-local mapping. Elata, Michaeli1, and Elad [25] suggested AdaSense as a compressed sensing algorithm that applies posterior sampling with diffusion models and PCA to extract the most informative measurements. Experiments display better performance and increased PSNR/SSIM and perceptual quality over facial images as compared to bicubic, block downsampling, PCA sensing, Walsh-Hadamard CS and active MRI techniques. In addition, there are many searches combines two or more strategies together Hybrid Techniques to increase flexibility in modeling heterogeneous signal information, which is especially useful when base sensing nodes are subject to severe energy and bandwidth constraint. [46] is an example that investigated and combines the patch-based sparse representation (PSR) model and the group-based sparse representation GSR model simultaneously, the sparse representation model integrates both their advantages. The results of extensive experiments have been found to demonstrate the superiority of various image recovery algorithms available in objective and subjective levels. The scaling up of dictionary learning and adaptive transform domain structures is summarized systematically and comprehensively by systematically comparing adaptive sparse basis and hybrid representation frameworks in Table 8, which outlines the algorithmic approaches, benchmark datasets, baseline protocols, operational constraints, and transmission/reconstruction advantages of these two approaches.

Table 8 - Adaptive sparse modeling sparsity methodologies comparison

Algorithm	Methodology	Datasets Used	Baselines for Comparison	Limitations	Key Improvements	Quantitative
[43] Gabor-SR Face Classifier	Combines Gabor filter features with sparse representation (SR)	AR Face Database, Extended Yale B dataset.	Standard (Sparse Representation Classifier), PCA, SVM.	SRC High computation complexity.		occlusion rates up to 50%.

[44]	Context-Aware MOD (ASBL)	Adaptive Basis (ASBL) using a context-aware Method of Optimal Directions (MOD) for large-scale WSNs.	Sparse Learning scheme	Multi-node physical WSN environmental streams.	Fixed basis, standard Wavelet matrices, vanilla MOD.	DCT	High communication overhead required.	Energy savings by 35%-40% while maintaining data integrity.
[45]	ASB-CS Encryption Model	Adaptive sparse basis compressive sensing framework integrated with chaotic map.		Standard medical images (MRI, CT scans).		Conventional CS encryption, standard JPEG compression.	-	Excellent reconstruction PSNR (>35 dB).
[46]	Hybrid SR Restoration	combining sparse coding with non-local self-similarity for image restoration.	local self-similarity for image restoration.	Set14, BSD100 benchmark image datasets.		Classical BM3D, standard K-SVD dictionary models.	The joint optimization of local and non-local constraints causes slower execution time.	Improving structural similarity (SSIM by up to 0.04).

5. Reconstruction methodologies

The greatest issue with compressive sensing is the correct reconstruction of the original signal. [47]. Over the past two decades, a wide range of reconstruction strategies have been developed, which can be broadly classified into five principal categories. Fig. 4 presents a comprehensive hierarchical taxonomy of these recovery methodologies. The classification spans classical Convex Optimization and fast Non-Convex Schemes, alongside highly adaptive Iterative/Greedy Pursuits (such as OMP variants). Furthermore, the taxonomy highlights the paradigm shift toward Probabilistic Models and Deep Learning-Based Methods to optimize processing latency and accuracy simultaneously. The reconstruction phase represents the most computationally demanding component of the CS pipeline, typically executed at the cloud or base station layer.

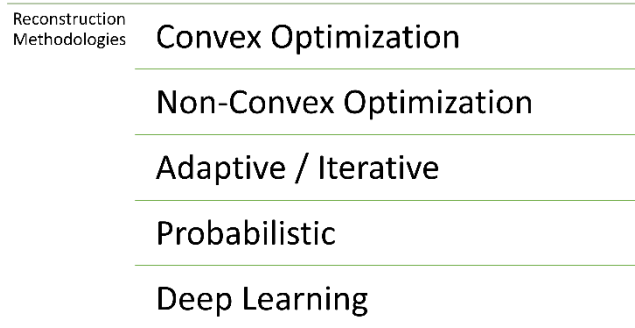


Fig.4 - Hierarchical taxonomy of Compressive Sensing reconstruction methodologies categorized by algorithmic framework and computational complexity.

5.1. Convex Optimization Methods

Minimization is an optimization method applied to compressive sensing to desire sparse signals with the minimization of the sum of the absolute values of the coefficients [2]. In the paper [48], the authors suggested one such approach, which involves compression of images with the help of SVD and subsequently restoring their quality with the help of matrix completion based on SVT. It was demonstrated that up to 80 percent compression could be

achieved with reasonable visual quality (PSNR 2425 dB) with only a fraction (in this case approximately 19.5 percent) of the sampled data. It had better compression than JPEG2000 and other methods, and levels of perceptual quality that were reasonable. The techniques are based on the optimization of a sparsity constrained objective function, which offers sparsity, ensures correct and computationally efficient signal reconstruction. [49] present the Sparsity-Inducing property (SIP), A weight-clipping method of stabilizing weighted ℓ_1 minimization and to prevent an increase in the weight on the sparse signal to be recovered. Numerical experiments show performance benefits and exhibit more reconstruction accuracy and robustness compared to the reweighting scheme suggested by Candes or classical ℓ_1 minimization and have high performance benefits. Bertsimas and Johnson [50] produced a different algorithm kind, called the Discrete Optimization Approach proposed in reformulating it as an MISOCP with convex relaxations (SOCP, SDP) and a tailored branch-and-bound solver. Results show that accuracy is lesser and less sparsity with synthetic data, ECG signals, and multi-label classification tasks. It was compared by standard convex relaxations (Basis Pursuit, BPDN), greedy algorithms (OMP) and reweighted benchmarks, and invariably worked better in accuracy, but with greater computational complexity. To compare the convergence of exact optimization models and low-rank recovery paradigms, Table 9 presents a comprehensive and systematic overview of matrix completion and discrete optimization methods, outlining their algorithmic frameworks, testing datasets, comparative benchmarks and trade-offs for execution.

Table 9 - Convex optimization method comparison

	Algorithm	Methodology	Datasets Used	Baselines for Comparison	Limitations	Key Quantitative Improvements
[48]	Matrix Completion CS	Uses nuclear norm minimization as a low-rank matrix completion algorithm to recover structural data from highly under-sampled images.	Standard benchmark images (e.g., Barbara, Boat, Lena).	Traditional Wavelet CS, Block-matching (BM3D), standard OMP.	Leak Performance in non-local textures noise conditions.	Significantly improves recovering quality with up to 3 dB gain in PSNR.
[49]	Modified Weighted ℓ_1	Introduces a novel structural property to adaptively modify the weights in ℓ_1 -minimization, improving sparsity estimation.	Synthetic sparse signals, standard compressive sensing arrays.	Vanilla ℓ_1 - minimization, classical Weighted ℓ_1 , Iterative Reweighted Least Squares (IRLS).	Requires precise estimation of initial signal support to update weights correctly.	Guarantee exact recovery by less measurements required by 20%.
[50]	Discrete Optimization CS	Formulates the exact ℓ_0 - minimization problem using mixed-integer optimization (MIO) and discrete optimization cutting planes.	High-dimensional synthetic datasets, gene expression profiles.	Standard Lasso (ℓ_1 relaxation), Orthogonal Matching Pursuit (OMP).	Slow for real-time edge streaming, suffer from High computational cost.	Achieve optimal sparsity selection, improving recovery accuracy by 15%-25%.

5.2. Non-Convex Optimization Methods

Many practical problems of importance are non-convex, and most non-convex challenges are hard (if not impossible) to solve exactly in a reasonable time. Hence, the idea of using heuristic algorithms, which may or may not produce desired solutions. There are other algorithms to find sparser solutions and solve weighted least-squares subproblems, exploits non-linear shrinkage by using fewer measurements than with convex algorithms such as Iteratively Reweighted Least Squares (IRLS) [51]. The results showed that under certain conditions, the half algorithm converges to a local minimizer of regularization, with an eventually linear convergence rate. The established result provides a theoretical guarantee for a wide range of applications of the half algorithm and Half thresholding. [52] presents a closed-form expression for the proximity operator of the log-sum penalty, avoiding the inefficiency of iterative reweighted ℓ_1 methods. The results show that the reweighted ℓ_1 algorithm can fail to match the true operator in certain regions, depending on initialization. The authors compare their exact operator against the iteratively reweighted ℓ_1 approach, highlighting where the latter diverges from the correct solution. The work [53] builds better convergence by the Chambolle–Pock algorithm (PDHG) than the classical monotone system. It shows that under semimonotone conditions, CPA converges with novel step-size and relaxation ranges, even when operators are nonmonotone. These results were done as a comparison against Douglas–Rachford splitting and proximal ADMM frameworks, highlighting tighter bounds and a wide range application ability. The authors in [54] introduce two novel Iterative Reweighted ℓ_1 Minimization (IR ℓ_1) strategies to better approximate the non-convex ℓ_p quasi-norm for sparse recovery. From their experiments, they show that both methods gained remarkable enhancement in accuracy and more computation efficiency compared with the standard IR ℓ_1 approach, with IR ℓ_1 -2 excelling for small-magnitude signals and IR ℓ_1 -3 outperforming for large-magnitude signals. To critically analyze the landscape of non-convex optimization problems in sparse signal inversion, the following Table 10 summarizes all the state-of-the-art non-convex reconstruction algorithms, presenting the mathematical methods used, the evaluation domains, the baseline, the structural limitations, and the convergence efficiency.

Table 10 - Non-Convex optimization method comparison

	Algorithm	Methodology	Datasets Used	Baselines for Comparison	Limitations	Key Improvements	Quantitative
[51]	Advanced IRLS Framework	Adapts the Iteratively Reweighted Least Squares (IRLS) method for non-convex parameter estimation and correlation optimization.	synthetic matrices.	Conventional MLE (Maximum Likelihood), standard non-iterative LS.	-	Outperform the Gaussian distribution by 20% with convergence speed.	
[52]	Log-Sum Proximity Operator	Derives the closed-form proximity operator for the non-convex Log-sum penalty to enhance sparse signal recovery.	Synthetic highly-sparse vectors.	Standard ℓ_1 proximity maps, hard thresholding, SCAD penalty.	-	Better signal support recovery with 30% tighter approximation to ℓ_0 ,	
[53]	Non-Monotonic Chambolle-Pock	Analyzes and proves the convergence limits of the primal-dual Chambolle-Pock algorithm without enforcing strict monotonicity.	Complex structural optimization scenarios, imaging systems.	Standard Monotonic Chambolle-Pock, classic ADMM.	Slower empirical convergence with large-scale circumstances.	Stable convergence under broader, highly relaxed physical conditions.	

[54]	Novel Reweighted ℓ_1	Implements a novel iterative reweighting strategy for non-convex ℓ_1 - minimization to eliminate flat-region penalties.	Benchmark compressed sensing signals, UCI repository.	Classical Reweighted standard Lasso, regular OMP solvers.	Increasing latency due to iterative loops.
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5.3. Adaptive / Iterative method

Iterative reconstruction algorithms are iteratively fine-tuning an estimated solution to recover a signal or image from incomplete or noisy measurements, which are especially used in inverse problems as well as compressed sensing. These algorithms gradually minimize the cost function for integration both data fidelity and regularization terms to ensure stable and accurate recovery. In [55], the BP-ADMM algorithm was proposed, which combines Basis Pursuit with Alternating Direction Method of Multipliers for ECG denoising and reconstruction. It effectively removes Gaussian noise, get higher SNR and less MSE values. The results were benchmarked against Wavelet, Mean filter, and Total Variation methods, showing superior preservation of ECG details. Aziz, Osama, Khedr, Salim [56] suggested an Adaptive Iterative Forward Backward Greedy Algorithm (AFB) depended on solving the forward phase's least squares issue by increases the probability of selecting the correct columns, their results show that AFB outperforms Forward Backward Pursuit, Subspace Pursuit, Orthogonal Matching Pursuit, and Regularized OMP in terms of reducing reconstruction error . Dynamic Orthogonal Matching Pursuit (DOMP) is a method introduced in [57] that iteratively selects one atom per iteration based on maximum correlation. The main result denotes that the reconstruction error can be controlled and measured in terms of the number of iterations, sparsity level of data, and the noise level of measurements. SSM-Net in [58] is a hybrid compressed sensing reconstruction framework that integrating Mamba's state-space modeling with FISTA-inspired momentum updates to get faster convergence and efficient feature modeling. Experimental results show PSNR/SSIM performance, particularly at low-to-medium sampling rates, while maintaining moderate computational cost and fast inference compared with ISTA-Net+, CSNet, AMP-Net, TransCS, CSformer, and CPP-Net, consistently matching or surpassing them in reconstruction quality and efficiency. AdaSense in [25] is defined as a strong generative prior that relies on pretrained diffusion models to recover signals from a small number of measurements. The authors show high PSNR and SSIM values; this model achieves accurate reconstructions even with limited samples and overcomes random sensing, Bayesian adaptive methods, and GAN/VAE-based approaches. An algorithm adaptively monitors supraharmonics was proposed [59] ,VSSESP-DBP which dynamic compressed sensing by combining variable step-size sparsity estimation with dynamic basis pursuit. Results show higher accuracy, robustness to noise, and faster reconstruction compared to conventional methods. It was benchmarked against SP, SAMP, and BCS algorithms, consistently outperforming them in precision and efficiency. The authors [60] suggested HiHTP as a hierarchical sparse recovery algorithm used for bispase blind deconvolution. It iteratively alternates between least-squares updates and hierarchical thresholding to recover both the sparse filter and signal show near-optimal sample complexity under Gaussian measurements, and they compare it against convex lifted methods and direct approaches, demonstrating stronger global guarantees without restrictive assumptions. All the above methods belong to the class of iterative optimization-based reconstruction algorithms, as they refine the signal estimate through repeated thresholding or message passing updates without explicit greedy support selection. To examine the taxonomy of the operations of the greedy refinement and time-varying estimation models, the advanced greedy, adaptive and dynamic reconstruction models are systematically compared and critically discussed with respect to their algorithmic designs, benchmark spaces, comparative baselines, and execution limits, and gain in hardware efficiency. (See Table 11)

Table 11 - Adaptive / Iterative methodologies comparison

Algorithm	Methodology	Datasets Used	Baselines for Comparison	Limitations	Key Quantitative Improvements	
[55]	Basis Pursuit Denoising (BPDN)	Applies Basis Pursuit principles to jointly perform noise removal and reconstruction for biometric data streams.	MIT-BIH Arrhythmia Database (ECG signals).	Standard Wavelet thresholding, traditional OMP, basic Total Variation.	Need advanced expensive devices	Significantly enhances signal fidelity, boosting SNR and lowering PRD (< 3%).
[56]	Iterative Selection & Correction (IS-CAG)	Introduces an adaptive greedy algorithm featuring an iterative index selection and backtracking correction mechanism.	Synthetic sparse matrices, temperature WSN arrays.	Classical OMP, OMP (SAMP), Subspace Pursuit (SP).	Increase time and complexity due to backtracking checks.	Speed up execution by 25% while reducing reconstruction error bounds.
[57]	Dynamic OMP (D-OMP)	Evaluates a dynamic variant of Orthogonal Matching Pursuit that dynamically adjusts support set selection per iteration.	High-dimensional sparse indices, communication signals.	Traditional OMP, Generalized OMP (gOMP), CoSaMP.	Requires high sparsity.	getting better recovery with 15%–20% fewer measurements.
[58]	SSM-Net (Mamba + FISTA)	Combines state-space models (Mamba architecture) with the Fast Iterative Shrinking Threshold Algorithm (FISTA) for image CS.	SET11, BSD68 visual benchmarks.	Vanilla FISTA, ISTA-Net+, standard CNN-based recovery.	High-memory resource allocation.	Lower execution time by 35% over deep networks.
[59]	Dynamic VSSESP-DBP	Develops a dynamic compressed sensing algorithm tailored for power grid supraharmonics monitoring.	Real-world power network voltage and grid logs.	Standard Discrete Fourier Transform (DFT), Kalman filtering, basic CS.	High latency during initialization.	22% reduction in Total Harmonic Distortion (THD) error.

[60]	Hierarchical Blind Deconvolution	Utilizes hierarchical sparse recovery algorithms to solve bispase blind deconvolution without initial channel states.	Communications network channel profiles, synthetic data.	Traditional blind deconvolution solvers, regularized LS.	Need Strict constraints to guarantee dual-sparsity bounds.	30% phase alignment stability.	better
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5.4. Probabilistic Methods (Model sparsity probabilistically)

This model for sparsity uses probability distributions over the signal coefficients. Due to hard constraints, there are some methods that take the measurements from signals and then use the posterior rather than enforcing sparsity, which leads to uncertainty estimates along with the reconstruction. One method is Markov Chain Monte Carlo (MCMC) [61] Relies on stochastic sampling techniques. Despite their advanced performance and efficiency in approximating complex probability distributions, convergence and scalability remain significant challenges. MCMC demonstrated as a powerful tool for high-dimensional statistical inference against ordinary Monte Carlo and Monte Carlo integration. In the paper [62] A proposed Sparse Bayesian Generative Modeling algorithm that introduces a learnable prior that combines sparsity-inducing properties with adaptability to noisy compressed data. It achieves remarkably NMSE and SSIM, while being computationally efficient against Lasso, Sparse Bayesian Learning (SBL), Compressive K-SVD, and CSGAN methods. A small amount of probabilistic methods have been proposed in the current literature (2021-2026), but they are found to have high computational complexity and high memory overhead, which is not suitable in the strict energy limitation of IoT-WSNs. Thus, it is important to pursue future research focused on developing simple and lightweight probabilistic algorithms. In order to integrate the results of the developments under the probabilistic recovery and hyper-parameter estimation, a comparative evaluation of the Bayesian and Markov-based reconstruction techniques is given in Table 12, which summarizes their probabilistic frameworks, simulation domains, baseline, properties of their inherent convergence trade-offs and statistical accuracy parameters.

Table 12 - Probabilistic methodologies comparison

	Algorithm	Methodology	Datasets Used	Baselines for Comparison	Core Limitations	Key Quantitative Improvements
[61]	MCMC Sparse Sampling	Utilizes Markov Chain Monte Carlo (MCMC) stochastic sampling algorithms to explore non-convex posterior probability spaces for signal recovery.	Synthetic multi-modal probability density arrays.	Standard Gibbs sampling, classical Metropolis-Hastings.	Slow for real-time edge processing.	Succeeded with high speed convergence and reducing false-positive support selection by 20%.

[62]	Sparse Bayesian Generative (SBG)	Integrates Sparse Bayesian Learning (SBL) with deep generative models to automatically estimate hyper-parameters and signal priors.	High-dimensional imaging data, structured communication streams.	Traditional SBL (BCS), Variational Autoencoders (VAEs), Lasso.	High computation al complexity.	30% lower reconstruction error while less required measurement threshold, yielding under high noise.
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5.4.1. Deep Learning-Based Methods

In compressive sensing, deep learning-based techniques learn reconstruction directly from data, use data-driven neural networks that learn the mapping between measurements and original signals straight from the data, replacing iterative solvers and handcrafted priors [2]. Grassa et al. [63] produced a paper in a spectral signals compressor network based on a deep convolutional autoencoder (SSCNet), demonstrating significant improvements over all existing benchmarks, particularly the JPEG family algorithm in multispectral, hyperspectral, and RGB. Experimental results demonstrate the effectiveness of the compression ratio and spectral signal reconstruction and the robustness. Another branch belongs to Deep Learning-Based method called End-to-End methods which is a special case of deep learning reconstruction methods, which learn the entire sensing-to-reconstruction pipeline directly from training data. Instead of solving an optimization problem, the network directly maps compressed measurements to reconstructed images through convolutional or attention-based architectures. There is a different method operating on the basis of deep unfolding network is AMP Net [64] that is based on the Approximate Message Passing (AMP) algorithm. Rather than acquiring an abstract black box mapping, it embeds the AMP iterative design into a deep network, and incorporates deblocking blocks to minimize block artifacts. It is used to enhance the reconstruction performance as well as being ultra-fast, which is obtained by joint training of network parameters and sampling matrices. In [65] The generative network utilizes the compressed measurements as prior information image and applied for reconstruction. As can be seen in the results of the experiment, the suggested model performs more positively than competitive algorithms when compression rates are large. It is suggested in the paper [66] that a one-bit compressed sensing reconstruction mechanism should be implemented using generative models (VAEs) by making use of learned priors to recover amplitude and direction of sparse signals. The experiments with MNIST, Fashion-MNIST, and Omniglot demonstrate better results in terms of MSE and NMSE, fewer measurements are needed, and results are resistant to noise and uncertain matrices outperforming traditional convex optimization (YP), Binary Iterative Hard Thresholding (BIHT), and a prior generative model approach (GenModel_pgd). In recently years represent a novel paradigm in deep learning-based reconstruction is physics-Informed Neural Networks (PINN-CS), PINN is an efficient physics-based inversion algorithm which, given a limited set of sensing data points in [67] and in the presence of measurement noise, can reconstruct the response at locations where measurement data is not available and/or identify the unknown mechanical properties. There are a few different algorithms used in special cases called Combinatorial/ Sublinear methods [68] As Chaining Pursuit (CP) is efficient for large dictionaries, however, they are prone to missing certain sparse components, which can lead to suboptimal solutions and necessitate careful parameter tuning. To analyze the convergence of deep structural unfolding, physical wave constraints, and sub-linear verification, Table 13 delivers a comprehensive comparative matrix of Deep learning based methodologies, systematically exploring their architectural paradigms, baseline benchmarks, operational restrictions, and all execution details.

Table 13 - Deep learning-based methodologies comparison

Algorithm	Methodology	Datasets Used	Baselines for Comparison	Limitations	Key Quantitative Improvements
[63]	Fully Convolutional AE	Employs spatial-convolutional layers to compress and reconstruct high-dimensional hyperspectral cubes.	Hyperspectral benchmarks (e.g., Pavia University, Indian Pines).	Traditional PCA, Standard 2D-Wavelet CS, JPEG2000.	Require high-power sensor nodes. Achieves reconstruction fidelity >95%.

[64]	AMP-Net Unfolding	Integrates the Approximate Message Passing (AMP) algorithm into a deep unfolding neural network structure for image denoising and CS.	SET11, BSD100, Urban100 image datasets.	Classical BM3D-AMP, ISTA-Net+, standard OMP.	High computational complexity.	20x reconstruction speedup.
[65]	EngelCSNet (VAE-GAN)	Combines variational autoencoders (VAE) with generative adversarial networks (GAN) for trainable image acquisition.	MNIST, CelebA face datasets.	Conventional CS solvers (e.g., TVAL3), basic Autoencoders.	Suffer of instable training during the GAN optimization phase.	Improves 3.5 dB in PSNR and Preserves extreme low-frequency edge details.
[66]	One-Bit Generative CS	Reconstructs signals from highly quantized, non-linear 1-bit measurements utilizing a pre-trained generative network prior.	High-dimension al synthetic indices, standard Gaussian signals.	Classical 1-bit BIHT (Binary Iterative Hard Thresholding).	Need pre-trained distribution.	Achieves 50% fewer quantized measurements.
[67]	k-Space Physics-Informed NN	Integrates structural physical wave equations into a physics-informed neural network (k-PINN) for dynamic spectral inversion.	Simulated and physical composite laminate vibration logs.	Standard structural Finite Element Methods (FEM), vanilla MLPs.	Restricted to environments where exact physical wave boundaries are known.	saving up to 40% computing time.
[68]	Combinatorial CS Solvers	Utilizes combinatorial group testing and heavy-hitter algorithms to perform extremely fast signal reconstruction.	Synthetic sub-linear sparse vector streams.	Traditional Convex Optimization (ℓ_1 -minimization), basic Lasso.	Lacks structural robustness against dense or non-sparse structural noise distributions.	Guarantees sub-linear reconstruction complexity $O(k \log n)$, so that, it is ideal for fast queries.

Generally, deep learning reconstruction methods (such as End-to-End models, PINNs and Generative frameworks) provide the highest recovery accuracy, fidelity of the data, and exceptional performance when dealing with severe communication noise. The high precision, however, requires a massive amount of computational complexity and high level of processing density. These clever frameworks perform super-lightweight signal inference, but their memory requirement is large and because of their massive nature, they require a significant amount of hardware for training and running, which is a major problem in deployment. For this reason, they are really difficult to scale down to resource constrained IoT edge devices and are almost always requirements of high-performance cloud servers.

6. Conclusion

In summary, compression and reconstruction algorithms are currently viewed as a constraint to the implementation of IoT-based Wireless Sensor Networks because of constraints posed by hardware, memory, and energy limits, which directly impact computational capabilities, latency, and scalability. However, the hybrid compression

schemes, adaptive sampling schemes, distributed compressed sensing, and edge-level reconstruction algorithm schemes have demonstrated substantial advancements in addressing these constraints. While Deep learning-based strategies may be considered as superior adaptable, and representative performance, they continue to suffer from high costs of training, memory requirements, sensitivity to quantization, and practical embedded implementation constraints. Furthermore, the scalability of the large and dynamic network topologies requires the co-design of sensing, communication, and hardware architecture to achieve balanced energy use, low latency, and resilient operation. In general, future studies need to be done on lightweight, hardware-aware, and adaptive reconstruction schemes that are balanced in terms of energy consumption, precision, and scalability to ensure sustainable deployments of large-scale IoT-enabled WSNs.

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