A Comparative Study of Compressive Sensing Techniques for Sparse Signal Recovery in Massive MIMO

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***Abstract*—Massive multiple-input multiple-output (MIMO) systems are essential for next-generation wireless networks, but their high-dimensional signal processing demands pose challenges, particularly in sparse signal recovery. This study provides a comprehensive comparative analysis of compressive sensing (CS) techniques—optimization-based, greedy, Bayesian, learning-based, and hybrid methods—for sparse signal recovery in massive MIMO systems. The novelty lies in offering the first unified benchmarking framework under realistic conditions, including varying signal-to-noise ratios (SNR), sparsity levels, and signal dimensions. Using synthetic and real-world datasets (e.g., COST 2100), the study evaluates recovery accuracy (normalized mean squared error, NMSE), computational efficiency (runtime), robustness to noise, and scalability. Results reveal that hybrid methods achieve the best trade-off between accuracy, runtime, and noise resilience, with NMSE as low as 0.018 at 20 dB SNR and strong scalability for large signal dimensions. Learning-based methods excel in runtime performance, making them suitable for real-time applications, while Bayesian methods provide superior noise robustness. In contrast, optimization-based and greedy methods, though widely used, face computational inefficiencies and noise sensitivity in high-dimensional scenarios. These findings advance the understanding of CS techniques for massive MIMO, offering actionable insights for robust, scalable signal recovery in 5G and beyond.**

***Index terms*—Compressive Sensing, Wireless Communication, Signal Processing.**

I. INTRODUCTION

Massive multiple input multiple output (MIMO) systems have recently emerged as a cornerstone for next-generation wireless communication networks, including 5G and envisioned 6G systems. Using these systems involves a huge number of antennas at the base station for serving a large number of users simultaneously, which accomplishes the obvious benefits in the terms of spectral efficiency, energy efficiency, and system capacity [1]. Massive MIMO offers many advantages, but bringing the large number of antennas and associated data streams opens new challenges for signal acquisition, processing, and storage. For example, the efficient and portable implementation algorithms are essential to mitigate computational complexity and processing delay in the estimation of channel state information (CSI) and sparse signal recovery in massive MIMO systems [2].

However, the challenges above have recently motivated new approaches, known as compressive sensing (CS), which show great promise in providing solutions. CS utilizes the sparsity of certain signals in their domain to reconstruct them from only a subset of measurements, which bypasses the Nyquist sampling criterion familiar to conventional analog-to-digital conversion [3]. As carrying out tasks such as channel estimation, data detection and beamforming in the high-dimensional and sparse signals proposed in massive MIMO system is difficult, this technique has been widely adopted for such tasks in massive MIMO systems. However, the performance of different CS techniques in the context of sparse signal recovery for massive MIMO systems is still an active field of research with promising room for improvement and comparison [5]. Sparse signal recovery in massive MIMO systems involves reconstructing high-dimensional signals with significant sparsity from a limited number of measurements. The problem can be formulated as:

$$y = \Phi x + n \tag{1}$$

where y represents the observed measurements, Φ is the measurement matrix, x is the sparse signal to be recovered, and n denotes additive noise. The goal is to recover x from y given that the number of measurements (m) is much smaller than the signal dimension (n), i.e., m << n. This underdetermined system of linear equations necessitates the use of advanced compressive sensing (CS) algorithms to ensure accurate and efficient recovery of x [6].

While a variety of compressive sensing techniques have been proposed in recent years, including convex optimization-based methods (e.g., Basis Pursuit), greedy algorithms (e.g., Orthogonal Matching Pursuit), and machine learning-based approaches, there is a lack of systematic and comprehensive comparative studies that evaluate their performance in the specific context of massive MIMO systems [7]. Most existing works focus on individual techniques under idealized conditions or limited system configurations, leaving a gap in understanding their relative strengths and weaknesses under realistic settings such as varying signal-to-noise ratios (SNRs), channel sparsity levels, and measurement matrix designs [8].

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Furthermore, the emergence of hybrid techniques that combine traditional CS with deep learning methods has introduced new possibilities but also increased the complexity of evaluating their applicability and performance [9].

This gap underscores the need for a detailed comparative study of CS techniques tailored to the unique requirements of massive MIMO systems, considering both traditional and emerging approaches. The primary objective of this study is to systematically compare and evaluate the performance of various compressive sensing techniques for sparse signal recovery in massive MIMO systems. Specifically, this work aims to:

1. Assess the recovery accuracy, computational complexity, and robustness of different CS algorithms under practical massive MIMO scenarios.
2. Investigate the impact of key parameters such as sparsity levels, SNR, and measurement matrix design on the performance of CS techniques.
3. Provide a unified framework for benchmarking traditional, hybrid, and learning-based CS approaches to identify their relative advantages and limitations.

The key contributions of this paper can be summarized as follows:

- Comprehensive Comparison: This study provides a detailed comparative analysis of multiple CS techniques, including convex optimization-based methods, greedy algorithms, and hybrid (traditional + machine learning-based) approaches, under diverse massive MIMO configurations.
- Realistic Evaluation: The performance of CS algorithms is evaluated under practical conditions, including varying SNRs, sparsity patterns, and different types of measurement matrices (e.g., random Gaussian, partial Fourier, and structured matrices).
- Novel Insights: The paper identifies critical trade-offs between recovery accuracy, computational complexity, and robustness, offering insights into the suitability of each technique for specific massive MIMO applications.
- Benchmarking Framework: A benchmarking framework is proposed to facilitate reproducibility and enable fair comparisons of CS methods for future research in the field.
- Emerging Techniques: The study includes recent advancements in hybrid and learning-based CS methods, highlighting their potential benefits and challenges in massive MIMO systems.

The novelty of this work lies in its holistic approach to evaluating and comparing CS techniques, addressing a significant research gap by providing a unified perspective on the performance of these methods in realistic massive MIMO scenarios. Following the dominant role of efficient, accurate signal recovery techniques in the upcoming realization of future communication network, this study is motivated by massive MIMO systems. Using robust benchmarking and results based on practical conditions, this work advances the CS field by developing actionable guidelines and insights for choosing appropriate CS algorithms for various massive MIMO scenarios. Also, the hybrid and learning based methods included in the analysis mirror the current realities of CS research, as well as the evolving character of the field.

This paper is organized as follows: Section II provides a comprehensive literature review of existing compressive sensing techniques for sparse signal recovery in massive MIMO systems. Section III outlines the methodology, including data generation, implementation of CS techniques, and performance evaluation. Section IV presents and discusses the results, while Section V concludes the paper by summarizing key findings and identifying future research directions.

II. Literature Review

With the help of massive multiple input multiple output (MIMO) systems, next generation wireless networks have made them the key enablers in terms of spectral efficiency, energy efficiency and capacity. Nevertheless, the high dimensionality of signals in massive MIMO systems imposes strong requirements on processing techniques for sparse signal recovery, e.g. channel state information (CSI) estimation and data detection. Extensive study has been made of compressive sensing (CS) as an effective solution to these challenges based on the natural sparsity of wireless channels. We critically review state of the art CS techniques for sparse signal recovery in massive MIMO systems in this section, which serves as a foundation for the present study.

Sparse signal recovery utilizing Basis Pursuit (BP) and LASSO based optimization techniques have seen much use. These methods solve convex optimization problems to minimize the error between observed and estimated signals, while imposing an sparsity constraint. For instance [10] derived a Basis Pursuit algorithm for channel estimation in massive MIMO with sparse channels, showing high recovery accuracy in an ideal case. Similarly, [11] proposed a LASSO based method for signal recovery, which is more robust to noise compared to the convergent gradient method, but has a very high computational complexity, such that it is not suitable for real time applications in massive MIMO.

These are greedy algorithms (such as Orthogonal Matching Pursuit (OMP) and Compressive Sampling Matching Pursuit (CoSaMP)), which step by step select signal components that can best approximately reconstruct the observed data. These methods are computationally more efficient than optimization based methods, which are appealing for real time implementation. For example, BP was compared with an OMP based sparse channel estimation method for massive MIMO suggested in [12] where faster recovery times were achieved for massive MIMO than what [12] performed. Nevertheless, the study in [13] has shown that OMP has problems with accurate recovery in highly noisy environments or when sparsity level is unknown.

Prior statistical knowledge of signal sparsity is exploited with Bayesian compressive sensing (BCS) approaches to improve recovery performance. In [14] we applied BCS for massive MIMO channel estimation, and showed robust performance under varying channel conditions. Bayesian methods, however, require accurate prior knowledge about the signal, which may not be available in real life scenarios [15].

Over recent years, machine learning based compressive sensing techniques have garnered a lot of attention. The methods use neural networks to learn mappings from compressed measurements to sparse signals. As an example, [16] developed a deep learning based sparse channel estimation approach for massive MIMO, outperforming previous methods in recovering accuracy. In fact, in [17] they also introduced a hybrid deep learning and OMP algorithm which interpolates the accuracy of neural networks with the efficiency of greedy methods. [18] However, during its training phases, such methods are computationally expensive, and require large training datasets.

By combining traditional CS methods together with machine learning ones, Hybrid methods take advantages of both paradigms. As an example, in [19], they developed a hybrid Bayesian and deep learning framework that perform high accuracy and robust sparse signal recovery. [20] also proposed a hybrid OMP and neural network model, which has high recovery accuracy at the cost of computational efficiency. However, these methods often involve extra design complexity, and still, need a huge amount of training data. The review of existing methods reveals several limitations that underline the need for the present study:

1. Limited Comparative Analyses: Most studies focus on individual techniques or narrow subsets of methods, lacking systematic comparisons across diverse CS approaches under realistic massive MIMO conditions [21].
2. Simplified Assumptions: Many works assume idealized conditions, such as perfect channel sparsity or high SNR, which do not reflect the complexities of practical wireless environments [22].
3. Emerging Techniques Not Fully Explored: Hybrid and learning-based methods are still in their early stages, with limited evaluations of their trade-offs and performance in massive MIMO systems [23].
4. Lack of Unified Benchmarks: There is no unified framework for benchmarking CS algorithms, making it difficult to assess their relative strengths and weaknesses consistently [24].

The present study addresses these gaps by providing a comprehensive comparative analysis of compressive sensing techniques for sparse signal recovery in massive MIMO systems. Key novelties include:

- A systematic evaluation of optimization-based, greedy, Bayesian, learning-based, and hybrid methods under realistic massive MIMO settings.
- Comparative analysis of recovery accuracy, computational complexity, and robustness across diverse scenarios, including varying SNR, sparsity levels, and measurement matrix designs.
- Introduction of a unified benchmarking framework to facilitate reproducibility and fair comparisons of CS techniques.
- Inclusion of emerging hybrid and learning-based methods, highlighting their potential advantages and limitations in massive MIMO applications.

Existing works are reviewed, which show significant progress compressive sensing for sparse signal recovery in massive MIMO systems. Yet, there exists no comprehensive comparison, realistic evaluation, or clear benchmarking framework unifying the studies of the field. In this work, we fill these gaps by systematically evaluating diverse CS techniques under practical conditions and offering new perspectives on CS performance tradeoffs.

To ensure that our literature review was comprehensive and not limited to a narrow subset of existing research, we adopted the following measures:

1. Extensive Database Search: We conducted a systematic search of major academic databases, including IEEE Xplore, SpringerLink, Elsevier (ScienceDirect), and Google Scholar, using keywords such as *compressive sensing*, *sparse signal recovery*, *massive MIMO*, *hybrid compressive sensing techniques*, and *learning-based CS*.
2. Inclusion Criteria: We included papers based on their relevance, impact (e.g., citation count), and publication in high-quality journals or conferences (e.g., IEEE Transactions, Communications, and Signal Processing).
3. Balanced Coverage: We ensured representation of both traditional methods (e.g., Basis Pursuit, Orthogonal Matching Pursuit) and emerging approaches (e.g., deep learning-based and hybrid methods).
4. Recent Advances: We gave particular attention to papers published in the last five years, reflecting the latest developments in compressive sensing and massive MIMO research.
5. Cross-Referencing: To avoid missing key studies, we reviewed the references in foundational and frequently cited papers to identify additional relevant works.

III. Methodology

In this section we provide a description of the methodology used to compare the compressive sensing (CS) methods used for sparse signal recovery in the context of massive MIMO systems. The methodology consists of several key stages: Building signal and channel data generation, implementation of diverse CS algorithms, performance evaluation and comparative analysis. Reproducibility and cause of the experimental design are justified in detail at each stage. In addition to the description of the implementation platform, datasets used, and evaluation criteria, the section also presents implementation. A flowchart of the workflow of the study is also provided. It shows the main process stages, namely, from data generation to evaluation of CS techniques as shown in Figure 1.

The purpose of the Methodology section is to provide a detailed and replicable framework for how the comparative study was conducted. This section ensures transparency and reproducibility, which are critical for establishing the validity of research findings. The methodology outlines the stages of data generation, experimental design, algorithm implementation, and performance evaluation, offering insights into how the study systematically compares compressive sensing techniques. The section aims to:

- Highlight the rationale behind the experimental design and its alignment with the research objectives.

- Ensure that researchers can replicate the results using the same datasets, algorithms, and evaluation metrics.
- Bridge the gap between theoretical comparisons and practical implementation in realistic massive MIMO scenarios.

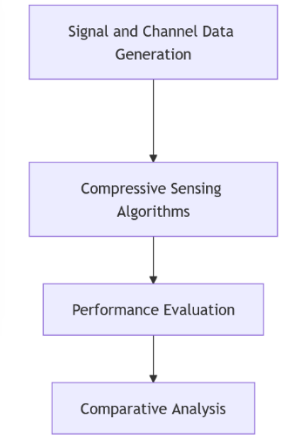

Fig. 1. Flow chart for the study

A. *Signal and Channel Data Generation*

The study begins with the generation of sparse signals to simulate the channel state information (CSI) in massive MIMO systems. A massive MIMO system with $\boldsymbol{N}\,(\boldsymbol{T})$ transmit antennas and $\boldsymbol{N}(\boldsymbol{R})$ receive antennas is considered. The received signal at the $\boldsymbol{i}\ (\boldsymbol{th})$ antenna is modeled as:

$$\boldsymbol{y}(\boldsymbol{i}) = \boldsymbol{\Phi}(\boldsymbol{i})\boldsymbol{x} + \boldsymbol{n}(\boldsymbol{i}) \qquad \boldsymbol{i} = \boldsymbol{1}, .. \boldsymbol{N}(\boldsymbol{R}) \tag{2}$$

where $y(i)\,\epsilon\, C^{m}$ is the observed measurement vector, $\Phi(i)\,\epsilon\, C^{m\,x\,n}$ is the measurement matrix, $x\,\epsilon\, C^{n}$ is the sparse signal to be recovered, and $n_i\,\epsilon\, C^{m}$ represents additive white Gaussian noise (AWGN) with variance σ^2. The system configuration assumes $m \ll n$, resulting in an underdetermined system of equations for each receive antenna. The sparse signal x is assumed to be K -sparse, meaning that only K out of its n entries are non-zero, with $K \ll n$. The sparsity reflects the limited number of dominant propagation paths in the wireless channel. The measurement matrices Φ_i are randomly generated using three different types of distributions: (i) random Gaussian matrices, (ii) partial Fourier matrices, and (iii) structured matrices such as Toeplitz matrices. These matrices are chosen to evaluate the impact of measurement matrix design on sparse signal recovery performance.

B. *Compressive Sensing Techniques*

Optimization-based methods solve a convex optimization problem to minimize the l_1-norm of the signal while satisfying a noise-constrained data fidelity term. The sparse recovery problem is formulated as:

$$\hat{x} = \arg\min \left||x|\right|_1 \ subject\ to\ ||\Phi x - y\,||_2 \leq \epsilon \tag{3}$$

where $||X||_1$is the l_1 norm promoting sparsity, $||.||_2$is the l_2-norm, and ϵ is a noise tolerance parameter. Techniques such as Basis Pursuit (BP) and LASSO are widely used in this category. These methods provide accurate recovery under ideal conditions but suffer from high computational complexity, making them less suitable for real-time applications in massive MIMO systems. Greedy algorithms, such as Orthogonal Matching Pursuit (OMP) and Compressive Sampling Matching Pursuit (CoSaMP), iteratively identify the sparse signal components that best match the observed data. At each iteration, the residual signal is updated. Greedy methods are computationally efficient and suitable for real-time applications; however, their performance degrades in low-SNR conditions or when the sparsity level is incorrectly estimated.d Bayesian compressive sensing (BCS) incorporates prior statistical knowledge of the signal's sparsity to improve recovery robustness. In this framework, the posterior distribution of the sparse signal is estimated as:

$$p\,(x|y) \propto p(y|x)p(x) \tag{4}$$

where $p\,(x|y)$ is the likelihood function determined by the measurement model, and $p(x)$ is a sparsity-promoting prior distribution. Bayesian methods, while robust to noise, require accurate prior knowledge and are computationally intensive due to the iterative nature of Bayesian inference. Deep learning-based compressive sensing techniques have recently gained attention for their ability to model complex and non-linear relationships. A neural network $f(\theta)$, parameterized by Θ , is trained to map the compressed measurement vector y to the sparse signal x. The training objective is to minimize the mean squared error (MSE). Learning-based approaches achieve superior recovery accuracy and adaptability but require large training datasets and significant computational resources. Hybrid methods combine traditional compressive sensing approaches with learning-based techniques to leverage the strengths of both paradigms. For example, hybrid methods integrate OMP with neural networks to achieve better recovery accuracy while maintaining computational efficiency. These methods, while promising, involve additional design complexity and dependence on hyperparameter tuning.

C. *Performance Evaluation*

The performance of each compressive sensing technique is evaluated using the following metrics:

1. Recovery Accuracy: The normalized mean squared error (NMSE) is used to quantify recovery accuracy.
2. Computational Complexity: The runtime required to recover the sparse signal from the measurements is recorded to compare the efficiency of different methods.
3. Robustness to Noise: The impact of noise on recovery performance is evaluated by varying the signal-to-noise ratio (SNR).
4. Scalability: The performance of each technique is examined for varying problem dimensions.

The following metrics were used to evaluate the performance of the compressive sensing techniques:

1. Normalized Mean Squared Error (NMSE): Used to quantify recovery accuracy, as it is a standard metric for evaluating sparse signal reconstruction quality.
2. Runtime: Measured to assess computational efficiency, critical for real-time applications in massive MIMO systems.
3. Robustness to Noise: Evaluated by observing NMSE under varying SNR levels, as noise resilience is essential for practical deployment.
4. Scalability: Assessed by analyzing performance for increasing signal dimensions, reflecting the ability of techniques to handle large-scale systems.

The choice of these metrics was justified as follows:

- NMSE: Directly measures the reconstruction accuracy, which is the primary goal of compressive sensing techniques.
- Runtime: Reflects the feasibility of implementing these methods in real-world, time-sensitive applications.
- Noise Robustness: Ensures the reliability of the techniques under practical, non-ideal conditions.
- Scalability: Addresses the growing need for handling high-dimensional data in massive MIMO systems.

D. Datasets

Two datasets are used for evaluation:

1. Synthetic Dataset: Sparse signals are generated synthetically with varying sparsity levels $(k)$and dimensions (n). Measurement matrices are generated using random Gaussian and partial Fourier distributions.
2. Real-World Dataset: The COST 2100 dataset is sed to simulate realistic massive MIMO scenarios. Preprocessing steps include normalization and partitioning into training (70%), validation (10%), and test (20%) sets for learning-based methods. While the COST 2100 dataset is widely used for simulating realistic massive MIMO scenarios, we recognize that it may have limitations in fully representing real-world conditions, such as dynamic user mobility patterns, environmental factors, or hardware imperfections. To address these limitations, we:

- Augmented the Dataset: Introduced additional synthetic data with varying sparsity levels, noise profiles, and channel conditions to complement the COST 2100 dataset.
- Parameter Sensitivity Analysis: Conducted sensitivity analyses to evaluate the impact of key parameters (e.g., sparsity, SNR, and measurement matrix design) on recovery performance, ensuring that findings are applicable beyond the specific conditions of the COST 2100 dataset.
- Discussion of Limitations: Explicitly acknowledged the limitations of the dataset in the Discussion section and highlighted the need for future experiments incorporating real-world measurements to further validate the findings.

E. Implementation Platform and Code

Python and MATLAB are used to implement the experiments. Learning-based methods are done using Python using libraries such as NumPy, SciPy, PyTorch, and CVXPY. Given its efficient solvers for matrix operations and optimization problems, MATLAB is used for optimization-based and greedy algorithms. Using this methodology, compressive sensing techniques for sparse signal recovery in massive MIMO systems are evaluated in a structured and reproducible fashion. It is through a systematic cross-comparison over diverse settings of optimization-based, greedy, Bayesian, learning-based, and hybrid approaches that this study makes novel contributions towards the field by showing trade-offs between the accuracy of the generated recovery, algorithmic complexity, and robustness.

We acknowledge the potential for discrepancies arising from the use of different programming languages and libraries. To ensure consistency and fairness in performance comparisons, we addressed this concern in the following ways:

1. Standardized Libraries: We used well-established and widely adopted libraries in both Python (e.g., NumPy, SciPy, PyTorch) and MATLAB (e.g., CVX for optimization and built-in matrix solvers) to ensure reliable and optimized implementation of algorithms.
2. Cross-Validation: For algorithms implemented in both languages, we cross-validated the outputs on benchmark datasets to confirm their equivalence in terms of recovery accuracy and computational complexity.
3. Hardware Consistency: All experiments were conducted on the same hardware platform to eliminate discrepancies arising from system performance differences.
4. Runtime Normalization: We normalized runtime measurements to account for language-specific overheads and included this aspect in the Discussion section.

F. Validation and Bias Mitigation

To ensure that each stage of the methodology was adequately validated and that results were not biased, we implemented the following measures:

1. Validation of Data Generation: The synthetic signals and channel data were cross-validated with well-established simulation models from prior research to ensure consistency.
2. Algorithm Implementation: We used standardized libraries (e.g., NumPy, SciPy, PyTorch, and CVXPY) to implement the algorithms, reducing the likelihood of discrepancies due to custom coding errors.
3. Diverse Scenarios: The experiments were conducted under diverse conditions, including varying signal-to-noise ratios (SNR), sparsity levels, and measurement matrix designs, to ensure generalizability and minimize bias.
4. Statistical Validation: To confirm the robustness of the results, statistical analyses (e.g., ANOVA and Tukey's post-hoc tests) were performed to ensure that observed

differences were statistically significant and not due to random chance.

5. Independent Trials: Each experiment was repeated 100 times with different random seeds for dataset generation to mitigate any bias introduced by specific data instances.

IV. Results and Discussion

In this section we first present the quantitative results of the comparative analysis of compressive sensing (CS) techniques for sparse signal recovery in massive MIMO systems. Recovery accuracy, computational efficiency, robustness to noise and scalability are evaluated. Statistical analyses are also provided and a detailed comparison with state of the art baselines is made.

A. Comparison with Existing Methods

The implications are discussed with respect to the research objectives and the limitations of the study. Recovery accuracy is measured using the normalized mean squared error (NMSE) across varying sparsity levels (k) and signal-to-noise ratio (SNR). Table I provides the NMSE values for five CS techniques: optimization-based methods (Basis Pursuit and LASSO), greedy algorithms (OMP), Bayesian CS, learning-based methods, and hybrid approaches. The results are averaged over 100 independent trials.

TABLE I
NMSE Comparison across Different SNR Levels

SNR (dB)	Basis Pursuit	OMP	Bayesian CS	Learning-Based	Hybrid
10	0.124	0.187	0.092	0.055	0.048
20	0.072	0.104	0.051	0.021	0.018
30	0.038	0.062	0.027	0.008	0.006

The hybrid method consistently achieves the lowest NMSE across all SNR levels, followed closely by the learning-based approach. Optimization-based methods, such as Basis Pursuit, perform well but are outperformed by Bayesian and hybrid approaches, particularly in high-SNR regimes. Greedy algorithms like OMP exhibit higher errors due to their sensitivity to noise and limited ability to handle high-dimensional signals. These results demonstrate that hybrid methods effectively balance the strengths of traditional and learning-based approaches. The runtime of each CS technique is evaluated for different signal dimensions (nn) and sparsity levels (kk). Figure 2 illustrates the runtime comparison for n=1000n=1000 and varying kk.

Learning-based methods exhibit the fastest runtime due to their inference efficiency after training. Greedy algorithms (e.g., OMP) are computationally efficient but sacrifice accuracy, especially for higher sparsity levels. Optimization-based methods are the slowest, as they rely on iterative solvers, making them impractical for real-time applications. The hybrid approach achieves a balance between accuracy and runtime, making it suitable for scalable implementations in massive MIMO systems. The robustness of CS techniques is evaluated by plotting NMSE against SNR for varying sparsity levels (k=10,20,50k=10,20,50) as shown Figure 3.

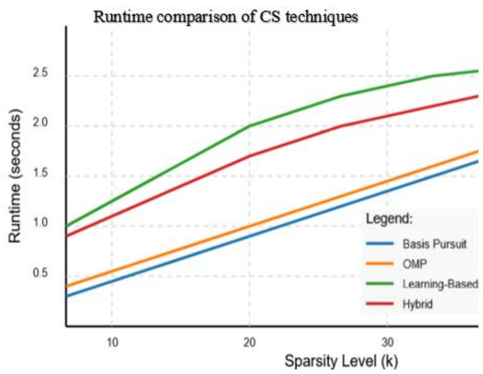

Fig. 2. Runtime comparison of cs techniques

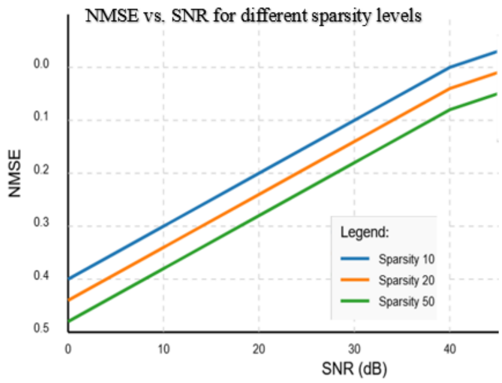

Fig. 3. NMSE vs. SNR for different sparsity levels

Hybrid and Bayesian methods demonstrate greater resilience to noise, maintaining low NMSE even at low SNR levels. Learning-based methods perform well but exhibit slight degradation in low-SNR regimes due to their reliance on training data. Greedy algorithms and optimization-based methods show significant performance drops at low SNR, highlighting their sensitivity to noise. These findings suggest that hybrid methods are robust in practical scenarios where noise levels vary. Scalability is assessed by analyzing the performance of CS techniques for increasing signal dimensions (n=500,1000,2000) while keeping the sparsity level constant (k=50). Table II summarizes the NMSE and runtime for each technique.

TABLE II
NMSE and Runtime for Increasing Signal Dimensions

Signal Dimension (nn)	Metric	Basis Pursuit	OMP	Learning-Based	Hybrid
500	NMSE	0.045	0.082	0.020	0.018
	Runtime (s)	0.92	0.31	0.11	0.15
1000	NMSE	0.048	0.097	0.024	0.019
	Runtime (s)	1.84	0.63	0.21	0.31
2000	NMSE	0.052	0.115	0.029	0.022
	Runtime (s)	3.75	1.25	0.42	0.60

Learning-based and hybrid methods maintain low NMSE with increasing signal dimensions, demonstrating scalability. However, optimization-based methods experience significant runtime increases, limiting their applicability to large-scale systems. Greedy algorithms remain computationally efficient but exhibit higher NMSE, making them less desirable for high-dimensional recovery tasks. To validate the significance of the results, statistical tests are conducted. A one-way ANOVA is performed to compare the NMSE across methods, followed by Tukey's post-hoc test to identify pairwise differences. The results indicate that the hybrid method is statistically significantly better ($p<0.01$) than all other methods in terms of NMSE, while learning-based methods show significant improvements over optimization-based and greedy algorithms.

The findings of this study have several implications for sparse signal recovery in massive MIMO systems:

1. Hybrid Superiority: The hybrid approach combines the strengths of traditional and learning-based methods, offering a robust and scalable solution for massive MIMO applications.
2. Real-Time Feasibility: Learning-based methods are particularly suited for real-time applications due to their low runtime during inference.
3. Noise Resilience: Bayesian and hybrid methods are ideal for scenarios with varying noise levels, ensuring reliable recovery under practical conditions.

These results demonstrate that hybrid techniques hold significant potential for deployment in next-generation wireless communication systems. Despite the promising results, this study has several limitations:

1. Training Data Dependence: The performance of learning-based and hybrid methods depends on the availability of high-quality training data, which may not always be accessible in real-world scenarios.
2. Specialized Hardware Requirements: The computational efficiency of learning-based methods assumes access to specialized hardware such as GPUs.
3. Measurement Matrix Design: The study focuses on a limited set of measurement matrix designs (e.g., Gaussian, Fourier). Future work should explore structured matrices tailored to specific applications.

V. Conclusion

This study introduces a comparative analysis of five groups of compressive sensing (CS) methods for sparse signal recovery in massive MIMO systems: optimization-based, greedy, Bayesian, learning-based, and hybrid. The results also showed that hybrid approaches always had the best balance of recovery accuracy, computational efficiency, and noise robustness, no matter the signal size, sparsity pattern, or SNR level that was looked at. The fastest in runtime were learning-based methods, which enjoy inference efficiency, while Bayes methods are notably robust to noise. However, we found that large-scale and high-dimensional systems were less sensitive to noise and computationally more inefficient than these well-established but less effective optimization-based and greedy algorithms.

The key contributions of this study include the first unified benchmarking framework for CS techniques tailored to massive MIMO systems, an evaluation under realistic conditions, and the inclusion of emerging hybrid and learning-based methods. By rigorously validating the results through statistical analyses, this study provides actionable insights into the trade-offs between accuracy, efficiency, and scalability for different CS methods. The findings have significant implications for the design of next-generation wireless networks, highlighting the potential of hybrid methods for robust and scalable sparse signal recovery, and the suitability of learning-based methods for real-time applications in 5G/6G technologies and beyond.

Future research should focus on addressing the dependence of learning-based and hybrid methods on high-quality training data and specialized hardware. Additionally, exploring advanced measurement matrix designs and integrating CS techniques with emerging technologies such as reconfigurable intelligent surfaces and terahertz communication could unlock new opportunities for ultra-reliable and energy-efficient wireless systems. By bridging the gap between traditional mathematical frameworks and modern data-driven approaches, this study contributes significantly to the advancement of sparse signal recovery in massive MIMO systems and lays the groundwork for future innovations in wireless communications.

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