

Article

Compressed-Sensing-Based Sparse Channel Estimation for Frequency-Selective MIMO-OFDM Systems Under Reduced Pilot Observations

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Abstract

Accurate channel estimation in frequency-selective multiple-input multiple-output orthogonal frequency division multiplexing (MIMO-OFDM) systems requires balancing pilot overhead, reconstruction accuracy, and computational cost. This paper presents a reproducible compressed sensing benchmark for sparse delay-domain channel estimation with reduced pilot observations. Its novelty is not the invention of Orthogonal Matching Pursuit (OMP), Compressive Sampling Matching Pursuit (CoSaMP), or Subspace Pursuit (SP), but the construction of a transparent and auditable evaluation protocol in which all estimators operate on the same channel realizations, sensing matrices, pilot budgets, signal-to-noise ratios (SNRs), stopping rules, and Monte Carlo trials. The framework explicitly defines the underdetermined observation model, the per-link 4×4 MIMO interpretation, the minimum-norm least-squares (LS) baseline, the identity-prior linear minimum mean-square error (LMMSE) baseline, the oracle-known sparsity assumption, uncertainty reporting, runtime protocol, and the mapping from delay-domain estimates to link- and subcarrier-domain quantities. OMP, CoSaMP, SP, LS, and LMMSE are evaluated for a 128-element delay dictionary, five active taps, sampling ratios from 0.10 to 0.70, SNRs from 0 to 30 dB, and 80 independent trials per operating point. The results show that sparse recovery exploits the assumed delay-domain sparsity more effectively than non-sparse baselines in the underdetermined regime, while pilot density remains a dominant factor in support identification and reconstruction error. The accompanying Python human-machine interface (HMI) produces confidence-aware metrics and publication-ready figures, enabling exact repetition of the benchmark and controlled extension to more realistic channel models. The conclusions are limited to simulation-based algorithmic evidence and define a direct pathway toward standardized-channel, software-defined radio (SDR), and measured radio-frequency (RF) validation.

Keywords: MIMO-OFDM; channel estimation; frequency-selective fading; compressed sensing; sparse recovery; reduced pilot observations; Orthogonal Matching Pursuit; CoSaMP; Subspace Pursuit; support recovery; channel similarity; pilot overhead; NMSE; wireless communications



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1. Introduction

Reliable channel state information is essential in MIMO-OFDM receivers because multipath propagation produces frequency-selective responses that must be estimated across antenna pairs and subcarriers [1–4]. In rapidly time-varying channels, basis-expansion and Doppler-aware representations reduce the number of effective parameters and motivate sparse or structured estimation [5–7]. Classical LS and MMSE-type estimators remain useful references, but their behavior depends strongly on pilot density, observation geometry, and the assumed channel statistics. When the delay-domain channel contains only a few dominant paths, compressed sensing offers an alternative by exploiting sparsity rather than treating all coefficients as equally relevant [8–12].

Research on sparse channel estimation has progressively addressed pilot-pattern design, adaptive recovery, doubly selective channels, massive-MIMO structure, and practical SDR-oriented validation [13–21]. More recent work has extended sparse and structured estimation to high-mobility multicarrier systems, OTFS, RIS-assisted and mmWave channels, near-field massive MIMO, and hybrid-field propagation [22–31]. Learning-assisted estimators and joint pilot/channel-feedback architectures have also become important comparison points, particularly in massive MIMO and OFDM systems [32–37].

Consequently, the contribution of this paper is not a new greedy recovery algorithm. OMP, CoSaMP, and SP are established methods, and comparative implementations already exist [12]. The methodological contribution is a fully specified benchmark that removes several ambiguities that often prevent direct comparison: all estimators use the same random channel realization and sensing matrix at each trial; the compressed regime $M < N_d$ is enforced; baseline estimators are explicitly defined in the underdetermined regime; the known-sparsity assumption is disclosed; stopping criteria are fixed; confidence intervals and trial-level dispersion are retained; runtime is measured under a reproducible protocol; and MIMO-link visualizations are generated from independently simulated transmit–receive links rather than by reusing a single sparse vector.

This distinction is important because prior studies frequently optimize one element of the chain—for example, pilot placement, sparse recovery, temporal correlation, RIS structure, deep learning, or a specific propagation model—under different simulation assumptions [38–42]. Reported performance can therefore reflect differences in channel generation, pilot design, prior information, stopping rules, or evaluation protocol as much as differences between estimators. The present framework is designed as an auditable reference experiment in which one factor, such as pilot density or SNR, can be varied while the remaining conditions are held fixed. Its value lies in controlled attribution, reproducibility, and extensibility rather than algorithmic novelty. Recent surveys likewise emphasize the importance of transparent and comparable evaluation protocols for channel estimation in 5G-and-beyond systems [37,43].

The main contributions are as follows:

1. A mathematically explicit underdetermined model $\mathbf{y} = \Phi \mathbf{h} + \mathbf{n}$ with $\Phi \in \mathbb{C}^{M \times N_d}$ and $M < N_d$, linked to reduced pilot observations.
2. A precise 4×4 MIMO interpretation in which each transmit–receive pair has an independently generated sparse delay-domain channel vector; no common support is imposed unless explicitly introduced in a future extension.
3. A fair estimator protocol for OMP, CoSaMP, SP, minimum-norm LS, and identity-prior LMMSE, including known- K assumptions, stopping rules, uncertainty reporting, and estimator-by-estimator complexity definitions.
4. A reproducible Python HMI that exports trial-level metrics, 95% confidence intervals, pilot-sensitivity analyses, support-recovery measures, channel-similarity measures, MIMO-link error maps, and runtime measurements.

5. A bounded validation claim and a concrete progression from the present controlled benchmark to standardized channel models, spatial correlation, off-grid delays, hardware impairments, SDR implementation, and measured RF data are consistent with the need for higher-fidelity validation identified in recent channel-estimation research [21,39,44,45].

The remainder of the paper is organized as follows: Section 2 positions the benchmark relative to prior sparse-estimation studies. Section 3 defines the channel model, sensing model, estimators, assumptions, metrics, complexity, runtime protocol, and simulation parameters. Section 4 presents the results. Section 5 discusses interpretation and scope. Section 6 presents the external-validation pathway, and Section 7 concludes the paper.

2. Related Works

Compressed sensing-based channel estimation has developed in several complementary directions. Early MIMO and MIMO-OFDM studies established that sparse delay- or Doppler-domain representations can reduce pilot requirements when the propagation channel contains a limited number of dominant components [8–10,46]. Comparative work also evaluated OMP, CoSaMP, and SP in MIMO-OFDM settings, confirming that greedy methods provide different accuracy–complexity trade-offs rather than a universally dominant estimator [12]. These studies provide the algorithmic foundation for the present benchmark but do not eliminate the need for a common, fully disclosed evaluation protocol.

A second research line focuses on the sensing operator and pilot pattern. Mutual-coherence-aware pilot optimization, pilot-pattern redesign, and block-compressed-sensing criteria have been proposed to improve recovery stability and reduce overhead [13–15,38,40]. Related work on OQAM/OFDM, TDS-OFDM, single-carrier block transmission, and adaptive sparse filtering confirms that sparse recovery performance depends strongly on how the observation matrix is constructed and on the assumed channel structure [16–19]. The present study therefore keeps the sensing model fixed within each trial and treats pilot density as an explicit controlled variable.

A third direction exploits additional structure beyond fixed delay-domain sparsity. Recursive compressed sensing and beyond-sparsity models use temporal, block, or joint support information in high-mobility and multiuser channels [6,7,20,47]. Recent MIMO-OFDM work further exploits temporal correlation for high-resolution sparse estimation [41]. These approaches can outperform unstructured recovery when their structural assumptions hold, whereas the present benchmark deliberately uses independent supports across links to provide a simpler reference point before introducing common-support or correlation models.

Sparse estimation has also expanded to high-frequency, RIS-assisted, and large-scale MIMO systems. Representative studies address RIS-assisted compressed estimation, structured matching pursuit, low-resolution-ADC mmWave receivers, near-field feedback, off-grid Bayesian learning, and hybrid-field propagation [24–31,42,48]. Other work has examined physics-aware RIS modeling and realistic deployment assumptions, underscoring that synthetic linear models should not be overinterpreted as deployment-level evidence [45,49]. This motivates the explicit scope boundary adopted in the present paper.

High-mobility and alternative multicarrier systems provide further evidence that sparse recovery remains useful outside the exact MIMO-OFDM configuration studied here. Compressed estimation has been investigated for GFDM and OTFS, including sensing-assisted recovery using ray-traced data [22,23]. These studies are relevant because they show how additional physical information or waveform structure can be incorporated once a transparent sparse-recovery baseline has been established.

Learning-assisted channel estimation has become another major research direction. Recent studies use deep neural networks, super-resolution CNNs, generative models,

hybrid architectures, and joint pilot/feedback optimization to improve reconstruction or reduce overhead [32–36,50,51]. Surveys of 5G-and-beyond and AI-enabled channel estimation emphasize both their potential and the importance of reproducible evaluation, comparable datasets, and clearly stated assumptions [37,43]. The present work therefore serves as a transparent classical baseline that can later be extended with data-driven estimators under the same trial protocol.

Hardware-assisted and SDR-based studies demonstrate a practical route from simulation to external validation. Prior OFDM work has implemented compressed-sensing channel estimation using SDR equipment, while MIMO experiments on USRP platforms illustrate the additional effects that arise in hardware-based links [21,44]. These studies support the external-validation pathway defined in Section 6, but the current manuscript does not present SDR or measured-RF results.

Table 1 summarizes representative works that are directly relevant to the present study. The comparison is intentionally organized around methodological dimensions requested by the reviewers: channel scenario, estimation approach, pilot/sparsity emphasis, validation level, and the principal distinction relative to the proposed benchmark.

Table 1. Representative sparse and structured channel-estimation studies and their relationship to the present benchmark.

Work	Scenario	Main Approach	Pilot/Sparsity Emphasis	Validation	Main Distinction from the Present Work
Wang and Hou [8]	Doppler-sparse MIMO	Compressed channel estimation	Pilot reduction and pilot-pattern analysis	Simulation	Focuses on Doppler sparsity and pilot patterns rather than a common multi-estimator benchmark.
Ye et al. [10]	Sparse MIMO-OFDM	ℓ_2 -smoothed- ℓ_0 regularized recovery	Reduced pilots	Simulation	Proposes a regularized estimator rather than benchmarking fixed greedy methods under one protocol.
Jayanthi and Ravishankar [12]	MIMO-OFDM	OMP, CoSaMP, and SP combined with linear/adaptive tools	Sparse channel recovery	Simulation	Closest algorithmic comparison, but without the present trial-level reproducibility, uncertainty, and underdetermined-baseline specification.
Wang et al. [13]	OFDM	Pilot-pattern optimization	Mutual-coherence reduction	Simulation	Optimizes pilot placement; the present work fixes the sensing rule and varies pilot density.
Singh and Bansal [14]	MIMO-OFDM	Optimized pilot pattern for CS estimation	Pilot allocation	Simulation	Emphasizes pilot optimization rather than estimator comparability under identical observations.
Khan et al. [20]	Massive MIMO	Sparsity-adaptive compressed sensing	Unknown sparsity adaptation	Simulation	Estimates sparsity adaptively; the present work explicitly discloses oracle-known K .
Karani et al. [7]	High-mobility multiuser MIMO-OFDM	Beyond-sparsity BEM recovery	Block/joint sparsity and pilot design	Simulation	Exploits structured correlation absent from the independent-support benchmark used here.
Yanza-Verdugo et al. [21]	OFDM with SDR	OMP/CoSaMP with LDPC-inspired sensing	Pilot reduction	SDR-based experiment	Provides hardware-assisted evidence; the present work is simulation-only and defines SDR validation as a next stage.
Shayanfar et al. [22]	High-mobility GFDM	SP-based compressed estimation	Low pilot overhead	Simulation	Targets GFDM and delay-Doppler sparsity rather than frequency-selective MIMO-OFDM benchmarking.
Jiang and Alkhateeb [23]	MIMO-OTFS	Sensing-aided sparse recovery	Environmental prior information	Ray-tracing-based simulation	Uses radar/environment information; the present work intentionally avoids external priors.
Oyerinde et al. [24]	RIS-aided mmWave massive MIMO	SOMP and structured matching pursuit	Common sparsity and reduced pilots	Simulation	Exploits RIS/mmWave structure and common sparsity across subcarriers.
Raji et al. [25]	mmWave MIMO	LS, OMP, CoSaMP, and DL with low-resolution ADCs	Sparse recovery under quantization	Simulation	Studies ADC and RF-chain constraints not included in the present controlled benchmark.
Qiao et al. [39]	Sparse OFDM	Analysis of OMP energy leakage	Grid mismatch/leakage sensitivity	Simulation	Examines a realism limitation that is explicitly deferred to the external-validation pathway here.
Xiao et al. [40]	MIMO-OFDM	Block-CS pilot design with joint criterion	Structured pilot design	Simulation	Optimizes the sensing design; the present work uses a normalized Gaussian surrogate to isolate estimator behavior.
Xie et al. [41]	MIMO-OFDM	Temporal-correlation-based sparse estimation	High-resolution structured recovery	Simulation	Exploits temporal correlation, whereas the present benchmark uses independent Monte Carlo realizations.
Present work	4×4 frequency-selective MIMO-OFDM	OMP, CoSaMP, SP, minimum-norm LS, identity-prior LMMSE	Controlled pilot-density sweep with explicit $M < N_d$	Reproducible simulation and HMI	Common trial model, disclosed oracle assumptions, fixed stopping rules, confidence intervals, runtime protocol, and explicit mapping to 16 independently generated links.

The literature therefore supports the relevance of sparse channel estimation and shows that direct numerical rankings across papers are difficult because channel models, pilot operators, prior information, and validation levels differ. The present study addresses this comparability problem within a deliberately bounded synthetic setting. It does not claim

that its ranking of OMP, CoSaMP, and SP generalizes automatically to correlated, off-grid, hardware-impaired, or measured channels.

3. Problem Formulation and Methodology

3.1. Per-Link 4×4 MIMO-OFDM Channel Representation

Let $N_t = 4$ and $N_r = 4$. Each transmit–receive pair (r, t) is represented by an independent sparse delay-domain channel vector

$$\mathbf{h}_{r,t} \in \mathbb{C}^{N_d \times 1}, \quad \|\mathbf{h}_{r,t}\|_0 = K, \quad (1)$$

where $N_d = 128$ and $K = 5$. The support of each link is drawn independently; the present benchmark does not assume a common support across antenna pairs. Thus, $\mathbf{h}$ in the single-link equations denotes one generic transmit–receive link, while the 4×4 system contains 16 independently generated vectors $\{\mathbf{h}_{r,t}\}$. This explicit per-link construction avoids interpreting one sparse vector as a concatenated 16-link channel or as a latent vector reused across all antenna pairs.

For each link, the K active delay indices are selected without replacement. The nonzero complex gains follow a circularly symmetric complex Gaussian distribution weighted by an exponentially decaying power-delay profile and are normalized to unit energy. The model is deliberately controlled: it isolates sparse-recovery behavior before adding spatial correlation, shared support, off-grid delay leakage, Doppler, or hardware impairments.

3.2. Physical Meaning of the Pilot-Induced Sensing Matrix

For one link, the received pilot observations are modeled as

$$\mathbf{y} = \Phi \mathbf{h} + \mathbf{n}, \quad (2)$$

where $\mathbf{y} \in \mathbb{C}^{M \times 1}$, $\Phi \in \mathbb{C}^{M \times N_d}$, $\mathbf{h} \in \mathbb{C}^{N_d \times 1}$, and $\mathbf{n} \in \mathbb{C}^{M \times 1}$. Equation (2) is dimensionally consistent and enforces

$$M < N_d. \quad (3)$$

In a physical OFDM receiver, Φ represents the effective linear operator obtained by selecting pilot subcarriers and combining their known pilot symbols with the delay-to-frequency dictionary. If $\mathbf{F}_P$ contains the rows of the N_{sc} -point DFT dictionary indexed by the pilot set $\mathcal{P}$ and $\mathbf{X}_P$ is the diagonal matrix of known pilot symbols, then an idealized pilot operator can be written as

$$\Phi_{\text{OFDM}} = \mathbf{X}_P \mathbf{F}_P. \quad (4)$$

The present benchmark uses a normalized complex-Gaussian surrogate for Φ to study recovery behavior under a controlled incoherent sensing design. Accordingly, “pilot-induced” refers to the role of Φ in mapping the delay-domain channel to the subset of pilot observations; it does not imply that the current random matrix is a complete standardized OFDM pilot grid.

The sampling ratio is

$$\rho = \frac{M}{N_d}, \quad M = \lfloor \rho N_d \rfloor, \quad (5)$$

with $M < N_d$ enforced in every experiment.

3.3. Sparse Recovery Algorithms and Prior Information

OMP, CoSaMP, and SP are used as established greedy baselines. The true sparsity level $K = 5$ is supplied to all three algorithms in every Monte Carlo realization. This is an *oracle-known sparsity* assumption and is stated explicitly because it makes the reported NMSE and

support-recovery results an upper-bound-style comparison of algorithmic behavior when model order is known. The results must therefore not be interpreted as demonstrating automatic sparsity-order estimation.

OMP performs exactly K support-selection iterations unless a duplicate index prevents further expansion. CoSaMP and SP use a maximum of 25 iterations and a residual tolerance of 10^{-8} . CoSaMP terminates when the residual norm falls below the tolerance or when the new residual exceeds 1.02 times the previous residual norm. SP terminates when the residual norm falls below the tolerance or when a new iteration does not reduce it. These rules are fixed for all operating points.

3.4. Underdetermined LS and LMMSE Baselines

Because $M < N_d$, the ordinary normal-equation expression $(\Phi^H \Phi)^{-1} \Phi^H \mathbf{y}$ is generally not valid. The LS baseline is therefore defined as the minimum-Euclidean-norm least-squares solution

$$\hat{\mathbf{h}}_{\text{LS}} = \Phi^\dagger \mathbf{y}, \quad (6)$$

where $\Phi^\dagger$ is the Moore–Penrose pseudoinverse, implemented with a numerically stable least-squares solver.

The regularized baseline is an identity-prior linear MMSE estimator. Assuming

$$\mathbf{h} \sim \mathcal{CN}(\mathbf{0}, \mathbf{R}_h), \quad \mathbf{R}_h = \mathbf{I}, \quad (7)$$

and white noise with covariance $\mathbf{R}_n = \sigma_n^2 \mathbf{I}$, the estimator is

$$\hat{\mathbf{h}}_{\text{LMMSE}} = (\Phi^H \Phi + \sigma_n^2 \mathbf{I})^{-1} \Phi^H \mathbf{y}. \quad (8)$$

Under the stated identity covariance, Equation (8) is equivalent to a ridge/Tikhonov form. The manuscript therefore uses the term LMMSE with identity prior rather than implying a measured or empirically estimated channel covariance.

3.5. Performance Metrics

The normalized mean-square error is

$$\text{NMSE} = \frac{\|\hat{\mathbf{h}} - \mathbf{h}\|_2^2}{\|\mathbf{h}\|_2^2}. \quad (9)$$

The mean-square error is

$$\text{MSE} = \frac{1}{N_d} \sum_{i=1}^{N_d} |\hat{h}_i - h_i|^2. \quad (10)$$

The support recovery rate is

$$\text{SRR} = \frac{|\hat{\mathcal{S}} \cap \mathcal{S}|}{K}, \quad (11)$$

where $\mathcal{S}$ and $\hat{\mathcal{S}}$ are the true and estimated sets of the K strongest taps. Channel similarity is

$$\text{CS} = \frac{|\mathbf{h}^H \hat{\mathbf{h}}|}{\|\mathbf{h}\|_2 \|\hat{\mathbf{h}}\|_2}. \quad (12)$$

For each link, the subcarrier response is obtained by

$$H_{r,t}[q] = \sum_{\ell=0}^{N_d-1} h_{r,t}[\ell] e^{-j2\pi q \ell / N_{\text{sc}}}. \quad (13)$$

The scalar per-link spectral-efficiency proxy used by the HMI is

$$R_{r,t} = \frac{1}{N_{sc}} \sum_{q=1}^{N_{sc}} \log_2 \left(1 + \gamma |H_{r,t}[q]|^2 \right). \quad (14)$$

For the 4×4 benchmark, the reported mean spectral-efficiency proxy is the arithmetic average over the 16 independently simulated links and Monte Carlo realizations. It is not the full MIMO capacity expression $\log_2 \det(\mathbf{I} + \cdot)$ and is therefore interpreted only as a channel-quality proxy. This clarification prevents a scalar link metric from being mistaken for spatial-multiplexing capacity.

3.6. Estimator Complexity and Reproducible Runtime Protocol

For a sensing matrix of size $M \times N_d$ and sparsity K , the dominant OMP cost is the repeated correlation $\Phi^H \mathbf{r}$ plus least-squares updates, approximately $\mathcal{O}(KMN_d + MK^2 + K^3)$. CoSaMP uses a $2K$ proxy expansion and repeated least-squares solves on merged supports, giving approximately $\mathcal{O}(IMN_d + IMK^2 + IK^3)$ for I iterations. SP has the same leading-order correlation, with support size on the order of $2K$, and therefore comparable asymptotic complexity. Minimum-norm LS via an SVD/QR-based pseudoinverse has a dense cost on the order of $\mathcal{O}(M^2N_d)$ when $M < N_d$. The implemented identity-prior LMMSE solves an $N_d \times N_d$ linear system and has a dense worst-case cost of $\mathcal{O}(N_d^3)$.

Runtime is measured using Python's high-resolution monotonic `time.perf_counter()` (Python Software Foundation, <https://www.python.org/>, accessed on 14 July 2026) immediately before and after each estimator call. All estimators are executed sequentially in the same Python process on the same realization of Φ and $\mathbf{y}$. The reported value is the arithmetic mean over the same set of Monte Carlo trials. The protocol measures end-to-end estimator execution in the reference implementation; it is not a hardware-independent complexity benchmark and should be interpreted together with the asymptotic analysis.

3.7. Simulation Configuration and Parameter Selection

Table 2 lists the simulation settings. The 4×4 size was selected as a moderate MIMO configuration that provides 16 distinct links while keeping the full Monte Carlo sweep computationally reproducible on a standard workstation. The SNR interval 0–30 dB spans low-, medium-, and high-observation-quality regimes without extrapolating to extreme values. The 80 independent trials per operating point were selected to balance dispersion estimation and interactive HMI execution time; uncertainty is therefore reported via trial-level distributions and 95% confidence intervals rather than presenting mean curves as deterministic values. These settings define the scope of the benchmark and are not claimed to represent all deployment conditions.

Table 2. Simulation configuration and rationale.

Parameter	Value	Rationale
MIMO dimensions	$N_t = N_r = 4$	16 independent links with moderate computational cost
Delay dictionary	$N_d = 128$	Sufficient resolution for controlled sparse-delay recovery
Subcarriers	$N_{sc} = 128$	Direct DFT mapping from the delay dictionary
Sparsity	$K = 5$	Controlled sparse regime; supplied to greedy estimators
Sampling ratios	0.10–0.70	Covers strong to moderate pilot compression
Primary ratio	$\rho = 0.25$	$M = 32 < N_d$, clearly underdetermined
SNR range	0–30 dB in 5 dB steps	Low-to-high observation-quality sweep
Trials	80 per point	Enables dispersion and 95% CI reporting with interactive execution time
Sensing matrix	Normalized complex Gaussian	Controlled incoherent surrogate for pilot operator
Algorithms	OMP, CoSaMP, SP, LS, LMMSE	Sparse and non-sparse references
Validation	Simulation benchmark	Algorithmic evidence, not measured RF evidence

3.8. MIMO-Link Heatmap Construction

The 16 rows used in the link–subcarrier heatmaps correspond to 16 independently generated sparse link realizations at the representative condition $\rho = 0.25$ and SNR = 20 dB. Each row is assigned to one transmit–receive pair index. The rows are not averages over Monte Carlo trials, and a single sparse vector is not copied across all antenna pairs. The delay-domain vectors are transformed independently through Equation (13); the absolute error heatmap is then computed elementwise as $|\hat{H}_{r,t}[q] - H_{r,t}[q]|$. This construction visualizes link-to-link variability under the controlled independent-link model.

4. Analysis of Results

4.1. NMSE Versus SNR with Uncertainty

Figure 1 reports the mean NMSE of OMP, CoSaMP, and SP at $\rho = 0.25$. The shaded regions are 95% confidence intervals computed from the 80 independent trials. NMSE decreases as SNR increases because observation noise becomes less dominant. The narrow separation among the three methods indicates that, under the disclosed known- K assumption and the same sensing matrices, their reconstruction behavior is similar over much of the tested range.

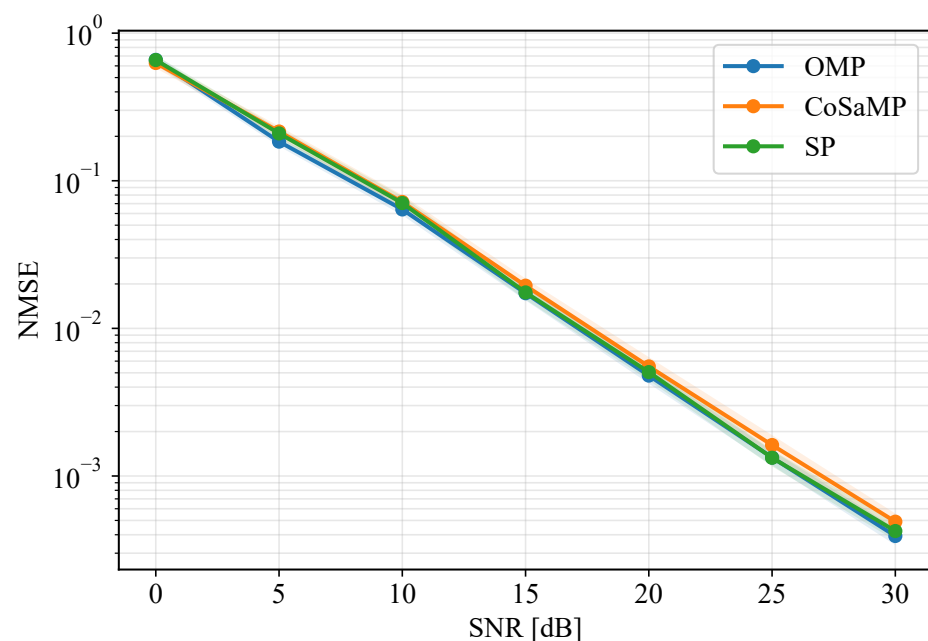


Figure 1. Mean NMSE versus SNR for OMP, CoSaMP, and SP at $\rho = 0.25$; shaded bands denote 95% confidence intervals over 80 independent trials.

4.2. Comparison with Underdetermined Baselines

Figure 2 compares OMP with the minimum-norm LS and identity-prior LMMSE baselines. In the $M < N_d$ regime, LS does not exploit sparsity and returns the minimum-norm solution among infinitely many feasible vectors. LMMSE adds identity-prior regularization but likewise does not use the exact K -sparse structure. OMP therefore gains an advantage when the simulated channel is consistent with its sparse model. This comparison should be interpreted as model-matched sparse recovery versus explicitly defined non-sparse baselines, not as a universal superiority claim.

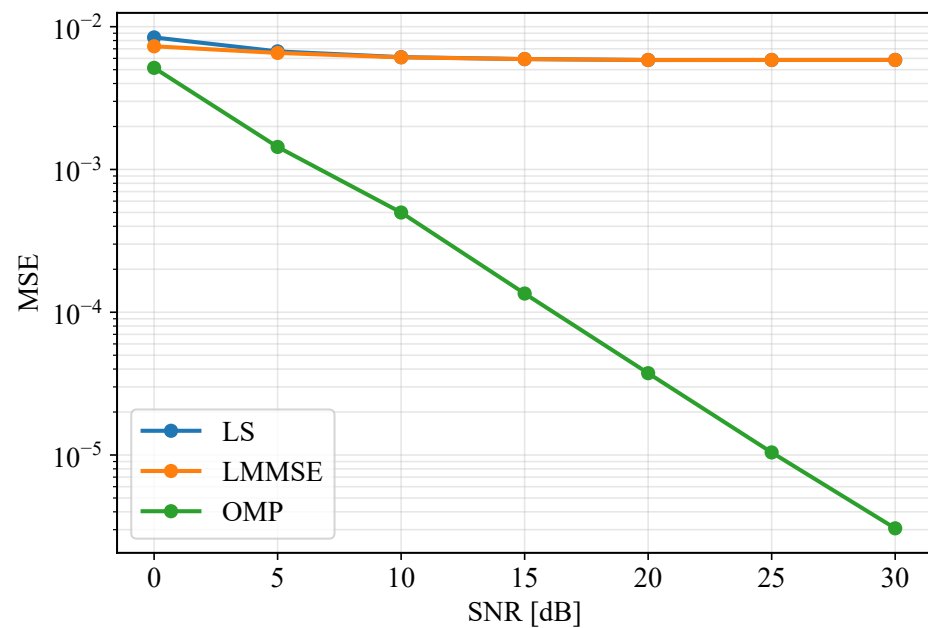


Figure 2. MSE versus SNR for minimum-norm LS, identity-prior LMMSE, and OMP under reduced pilot observations.

4.3. Sampling Ratio and Pilot Observations

Figure 3 uses normalized reconstruction error, which in this manuscript is exactly the NMSE defined in Equation (9). The figure therefore does not introduce a separate metric. At SNR = 20 dB, increasing ρ increases M and generally reduces NMSE because more observations constrain the sparse inverse problem. The largest degradation occurs at the smallest sampling ratios, where M approaches the minimum number of measurements needed to distinguish competing sparse supports.

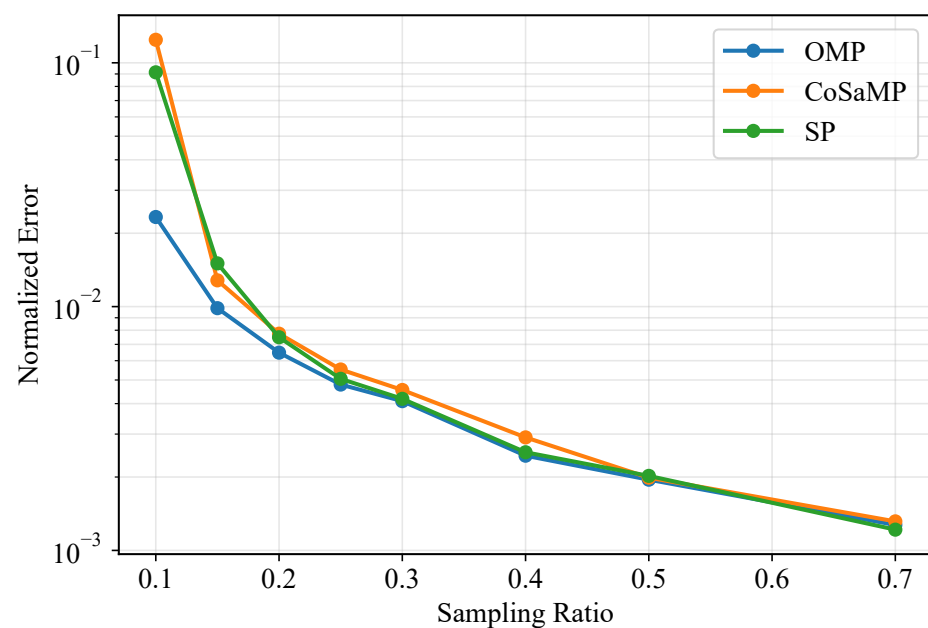


Figure 3. NMSE, reported as normalized reconstruction error, versus sampling ratio at SNR = 20 dB.

Figure 4 expresses the same relationship directly in terms of M . This view makes the pilot-overhead trade-off explicit and shows diminishing gains as the observation budget increases.

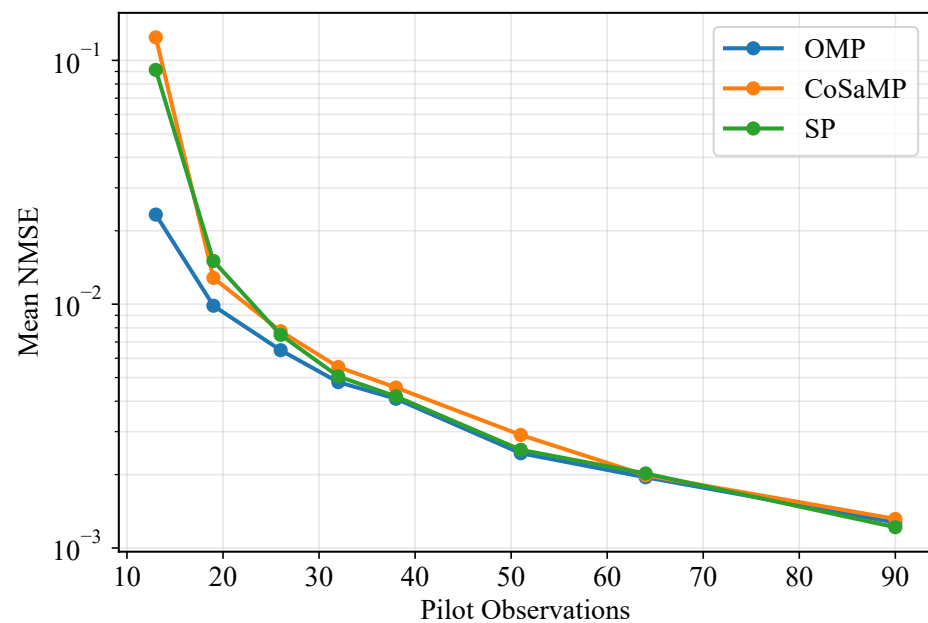


Figure 4. Mean NMSE versus the number of pilot observations M for OMP, CoSaMP, and SP.

4.4. Delay- and Frequency-Domain Reconstruction

Figure 5 compares one representative true sparse delay vector with its OMP estimate. It is a single-link example and is not an average across the 4×4 array.

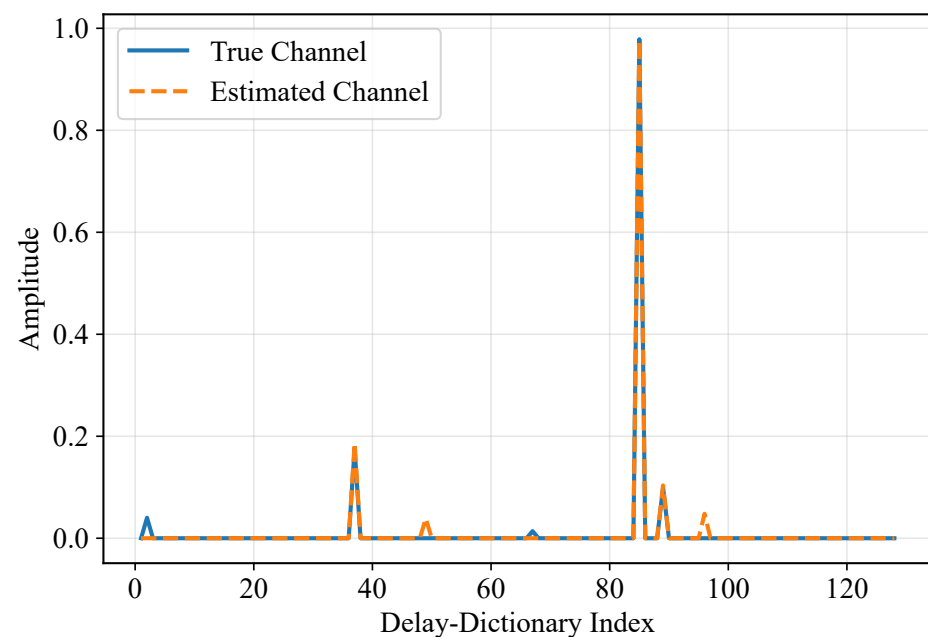


Figure 5. Representative true and OMP-estimated delay-domain channel amplitudes for one independently simulated MIMO link.

Figure 6 applies the DFT mapping of Equation (13) to that representative link and then evaluates the per-link spectral-efficiency proxy of Equation (14). The figure therefore compares the true and estimated frequency responses for a single link; it does not represent the full 4×4 MIMO capacity.

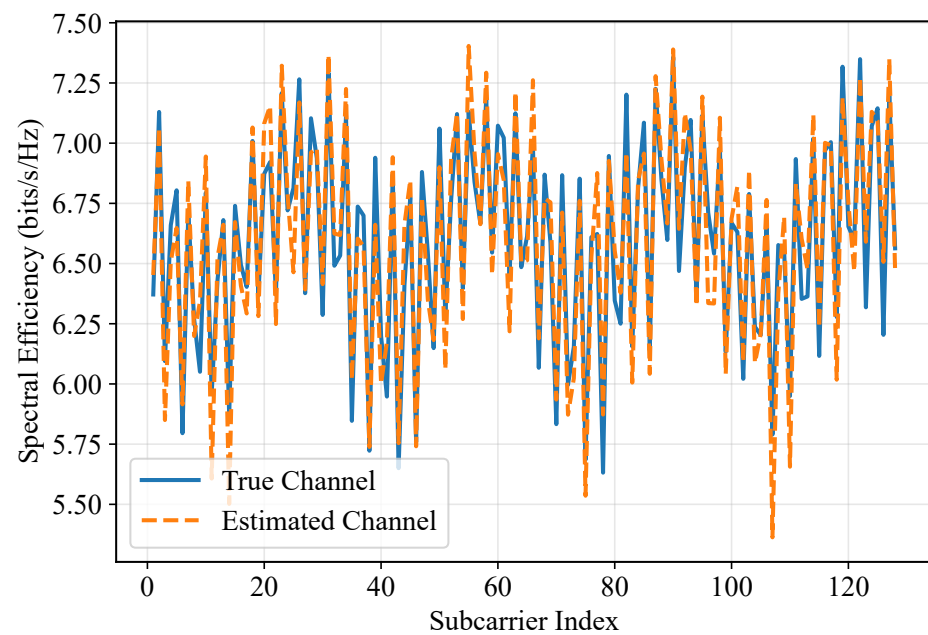


Figure 6. Per-subcarrier spectral-efficiency proxy computed from the true and estimated frequency responses of one representative MIMO link.

4.5. MIMO-Link Reconstruction Error

Figure 7 contains 16 independently generated link realizations indexed as the 16 transmit–receive pairs of the 4×4 system. Each row is one link and each column one subcarrier. The heatmap is not averaged over trials; it is a representative 16-link snapshot at $\rho = 0.25$ and 20 dB.

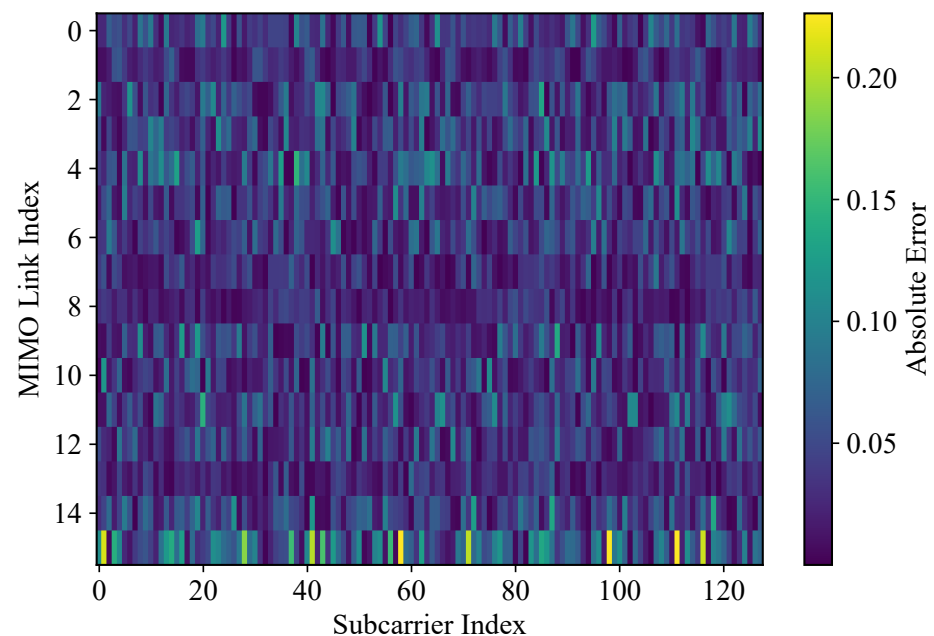


Figure 7. Absolute frequency-response reconstruction error $|\hat{H}_{r,t}[q] - H_{r,t}[q]|$ for 16 independently simulated 4×4 MIMO links at the representative operating point.

Figure 8 collapses each row of the same representative snapshot to one normalized link error, revealing heterogeneity across independently generated links.

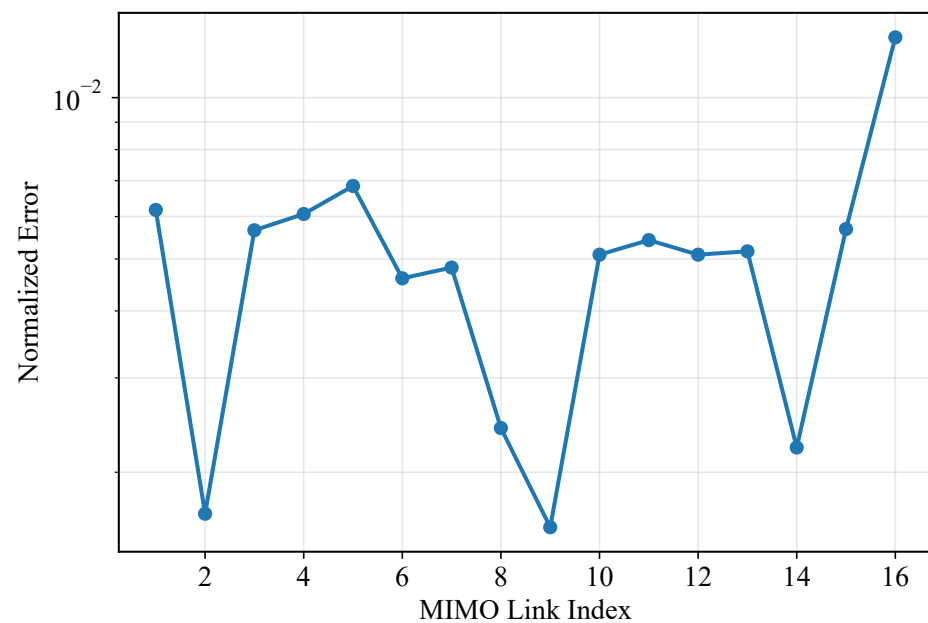


Figure 8. Normalized reconstruction error for each of the 16 independently simulated MIMO links in the representative snapshot.

4.6. Trial Dispersion, Support Recovery, and Similarity

The ECDF in Figure 9 retains trial-level dispersion and complements the confidence intervals in Figure 1.

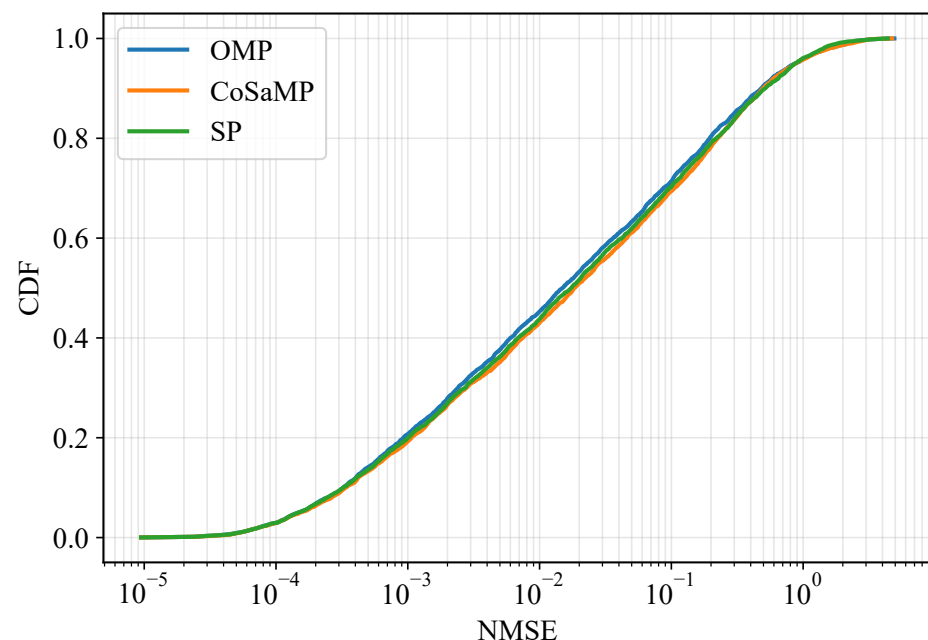


Figure 9. Empirical cumulative distribution of trial-level NMSE for OMP, CoSaMP, and SP.

Figure 10 uses the exact-support metric in Equation (11). A recovery rate below 1, even at 30 dB, does not, by itself, imply algorithmic failure. At the primary sampling ratio, only $M = 32$ measurements are available for a 128-dimensional dictionary, and the random sensing matrix can contain highly competing columns. In addition, SRR is stricter than NMSE: a small-amplitude active tap may be replaced by a nearby false atom, yet the overall channel estimate still exhibits low energy error. The residual support errors at high SNR

are therefore dominated increasingly by underdetermination, finite measurement geometry, and exact-index support scoring rather than thermal noise alone.

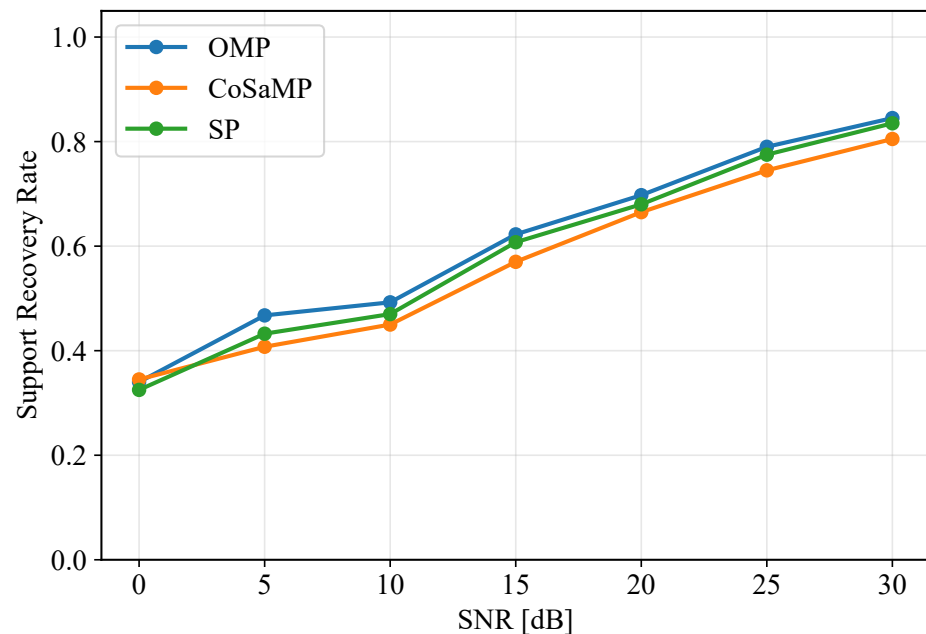


Figure 10. Exact support recovery rate versus SNR at the primary sampling ratio; values below one reflect residual support ambiguity under the underdetermined sensing geometry.

Figure 11 measures directional agreement between the true and estimated delay-domain vectors. It complements NMSE and SRR because a reconstruction can preserve the dominant channel direction even if it misses one weak support index.

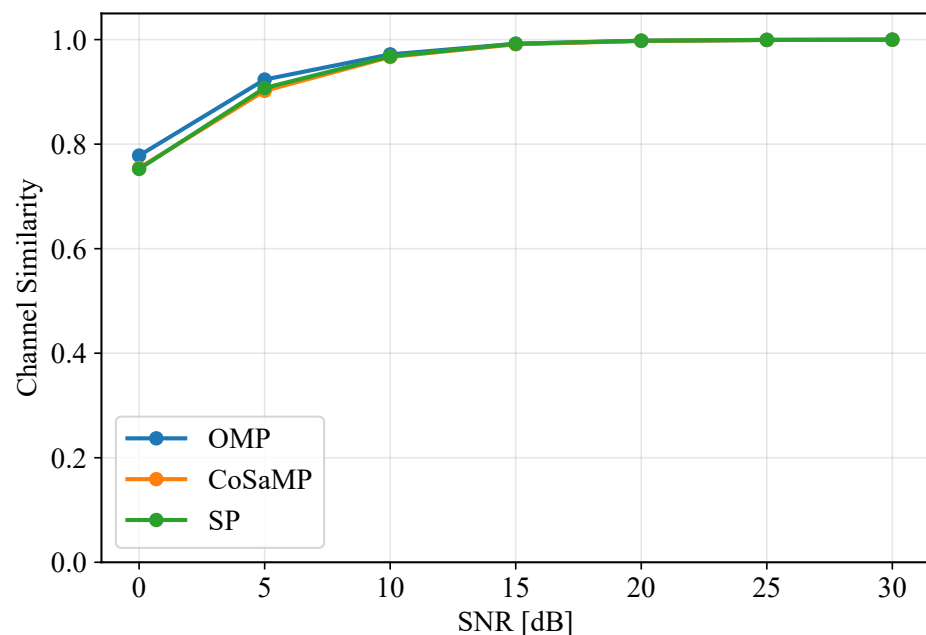


Figure 11. Channel similarity between the true and estimated delay-domain vectors versus SNR.

4.7. Spectral-Efficiency Proxy and Runtime

Figure 12 reports the mean of the per-link scalar proxy in Equation (14); it is not a determinant-based MIMO capacity measure. Because the reconstructed links are similar

under the selected operating conditions, differences among sparse algorithms are more visible in NMSE, support recovery, and runtime.

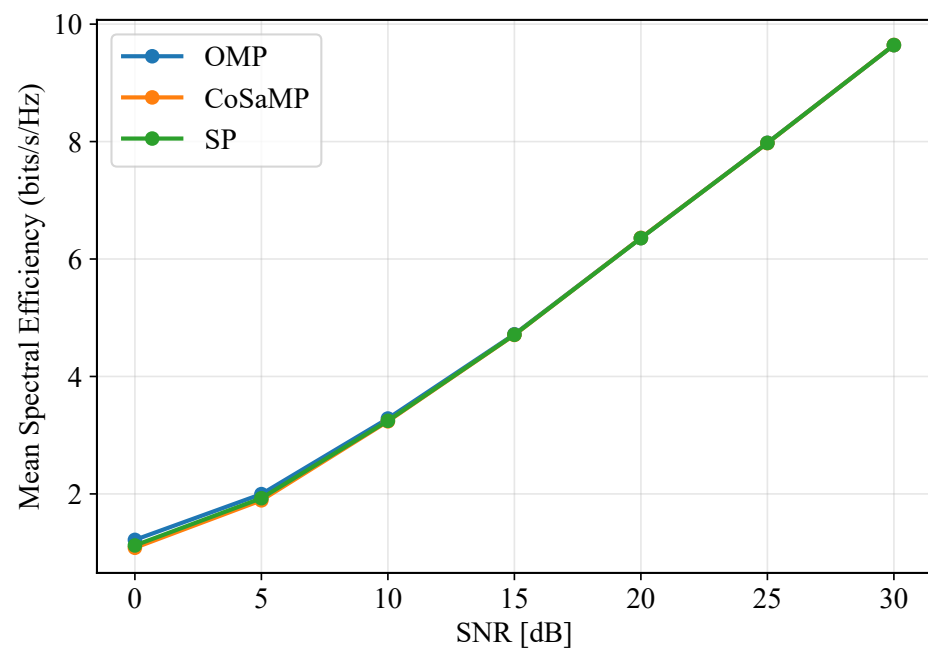


Figure 12. Mean per-link spectral-efficiency proxy versus SNR for the sparse recovery algorithms.

Figure 13 follows the runtime protocol defined in Section 3. The values are implementation-dependent wall-clock measurements and are interpreted together with the asymptotic complexity expressions.

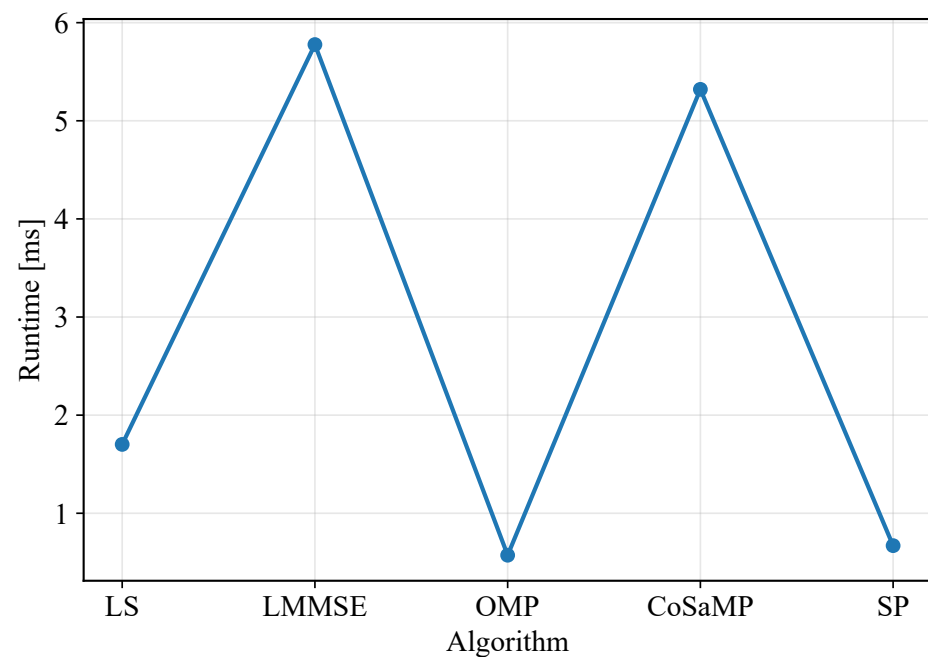


Figure 13. Mean estimator runtime measured with `time.perf_counter()` under the common Python execution protocol.

4.8. Joint Algorithm–Sampling-Ratio View

Figure 14 summarizes the mean NMSE across algorithm and sampling ratio. Its purpose is to show that pilot density can have a larger effect than the small differences among the three greedy methods in this controlled, known- K setting.

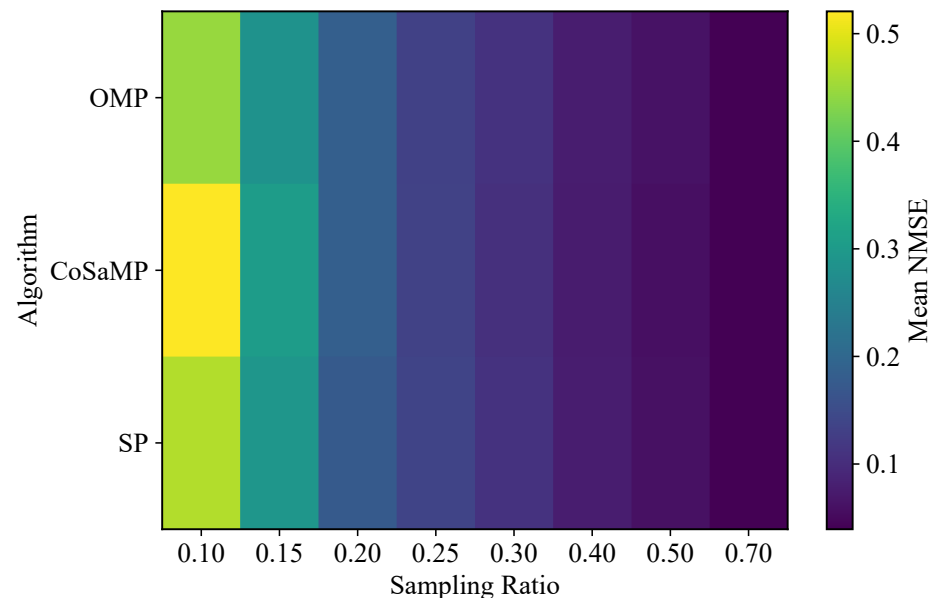


Figure 14. Mean NMSE as a joint function of recovery algorithm and sampling ratio.

5. Discussion

The central finding is methodological rather than algorithmic. Under a common underdetermined observation model and a disclosed known-sparsity assumption, OMP, CoSaMP, and SP exhibit broadly similar trends, while pilot density strongly controls reconstruction quality. OMP performs particularly well in the main configuration, but this ranking is conditional on the synthetic sparse model, the random normalized sensing matrix, the stopping rules, and the fact that K is supplied to the algorithms.

The comparison with minimum-norm LS and identity-prior LMMSE clarifies why sparse recovery gains an advantage in this benchmark. The two conventional baselines are well defined for $M < N_d$, but they do not exploit the exact sparse structure used to generate the channels. The comparison is therefore intentionally model-matched and should not be generalized to scenarios in which the channel is dense, covariance information is accurately known, or the sensing operator follows a different physical pilot design.

The confidence intervals and ECDF address the risk of interpreting smooth mean curves as deterministic behavior. Eighty trials are sufficient to expose trial-to-trial variation in this computational benchmark, but they do not eliminate all Monte Carlo uncertainty. Larger campaigns should be used for high-stakes performance claims or for small effect sizes.

The support-recovery analysis also illustrates why a low exact-support rate can co-exist with favorable NMSE. Exact support scoring penalizes any incorrect index equally, including weak taps whose replacement may have limited impact on total reconstruction energy. At high SNR, residual errors increasingly reflect sensing geometry and the limited measurement budget rather than noise alone.

The 4×4 heatmaps must likewise be interpreted in light of their construction. They represent 16 independent link realizations indexed to antenna pairs; they are not generated from a spatially correlated matrix channel and do not impose common support. This design

isolates per-link sparse recovery, but it does not reproduce all coupling mechanisms of a physical MIMO array.

6. Limitations and External Validation Pathway

The present study is a controlled sparse-recovery benchmark. Its principal limitations are the normalized complex-Gaussian sensing surrogate, independent antenna-pair channels, on-grid delays, known sparsity order, white Gaussian noise, and the absence of RF impairments. These choices improve attribution and reproducibility but reduce physical realism.

An intermediate realism layer is therefore defined as the immediate next validation stage rather than being conflated with the baseline experiment. The same HMI can be extended in a controlled sequence: (i) replace the random sensing matrix with an explicit OFDM pilot-selection operator; (ii) introduce Kronecker spatial correlation across the 4×4 array; (iii) perturb delays off the assumed dictionary grid to quantify basis mismatch; (iv) add carrier-frequency offset and synchronization error; and (v) evaluate standardized clustered channels using QuaDRiGa, Sionna, DeepMIMO, or MATLAB channel models (software websites: <https://quadriga-channel-model.de/>, <https://nvlabs.github.io/sionna/>, <https://www.deepmimo.net/>, and <https://www.mathworks.com/products/matlab.html>, respectively; all accessed on 14 July 2026). Each factor should first be varied independently and then in combination so that performance degradation can be attributed to a specific realism mechanism.

Experimental validation is also feasible. A direct SDR implementation would generate known OFDM pilot symbols at the transmitter, record the received pilot subcarriers for each antenna pair, construct the physical sensing operator from the actual pilot pattern, and compare the recovered channel against a dense-pilot or sounding-based reference. Repeating the experiment across static and mobile conditions would allow the simulation-derived NMSE, support recovery, and runtime observations to be tested against measured RF channels.

Accordingly, the current results establish a reproducible computational baseline, while standardized-channel and SDR experiments are required before making deployment-level claims. This staged validation pathway is more informative than treating one synthetic benchmark as a substitute for physical validation.

7. Conclusions

This paper presented a reproducible benchmark for compressed sensing-based sparse channel estimation with reduced pilot observations. The contribution is not a new OMP, CoSaMP, or SP algorithm; it is an explicitly specified comparison protocol that fixes the observation model, per-link MIMO interpretation, underdetermined baselines, known-sparsity assumption, stopping rules, uncertainty reporting, runtime measurement, and delay-to-frequency mapping.

Under the tested synthetic sparse-channel conditions, the greedy sparse estimators benefit from the assumed delay-domain sparsity and outperform non-sparse minimum-norm LS and identity-prior LMMSE baselines in the underdetermined regime. Pilot density is a dominant design variable, and exact support recovery remains more demanding than low aggregate NMSE. The 95% confidence intervals and ECDF show that the reported curves are Monte Carlo estimates rather than deterministic outcomes.

The benchmark is intentionally limited to controlled simulation. The next validation stages are an explicit OFDM pilot operator, spatially correlated and off-grid channel models, standardized clustered channels, and SDR or measured-RF experiments. These extensions

will determine how strongly the present algorithmic trends persist when the assumptions of the controlled benchmark are relaxed.

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