AI/ML-Driven Channel Estimation and Beamforming for 6G Massive MIMO Systems: A Performance Analysis

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Abstract: Sixth-generation (6G) massive MIMO systems operating over sparse, fast-varying mmWave and terahertz channels present new challenges to pilot-assisted channel estimation and tracking, with standard Least Squares (LS), Minimum Mean Square Error (MMSE), and Orthogonal Matching Pursuit (OMP) approaches yielding either prohibitively high pilot overhead or inaccurate channel state information (CSI). This article proposes an innovative hybrid approach that leverages deep neural networks and sparse Bayesian learning to achieve robust estimation, tracking, and precoding of massive MIMO channels, with the performance evaluated under eight widely used criteria and compared to LS, MMSE, OMP, and conventional Sparse Bayesian Learning (SBL) methods. Simulation results demonstrate that the proposed approach provides up to 29x better bit-error-rate (BER) than LS at 10 dB SNR, 18.2 dB NMSE gain, 80% higher spectral efficiency than zero-forcing precoding while maintaining channel tracking accuracy at 300 km/h and reducing pilot overhead to 5-8% of the frame. Additionally, the approach enables the use of 256-QAM and 10+ Tbps data rates at terahertz bands for short-range 6G applications.

Keywords: 6G Wireless Communication; Massive MIMO; Deep Learning; Channel Estimation; Sparse Bayesian Learning

Introduction

Sixth-generation wireless networks promise peak data rates of over 1 Tbps, latencies below 1 ms, and support for mobility-demanding scenarios, which places extreme demands on carrier frequencies (which extend into the mmWave and THz bands) and base-station antenna counts (which may number in the hundreds) [3]. These conditions impose new challenges on channel estimation, since the propagation environment at such high frequencies is typically sparse, comprising only a few propagation clusters, and coherence times are short due to the high Doppler shifts experienced by mobile users. Conventional channel estimators such as Least Squares (LS) and Minimum Mean Square Error (MMSE) were designed for slowly varying, highly scattered channels, and suffer from either prohibitively high pilot overhead (>15–25% of the coherence block) or poor tracking performance at these new operating points, failing to fully harness the capacity gains of massive MIMO.

Artificial intelligence and machine learning provide an alternate data-driven approach to channel estimation. Deep neural networks can be trained to capture the statistical properties of the propagation environment encoded in the channel responses, and combined with model-based approaches such as Sparse Bayesian Learning (SBL) to greatly reduce the pilot overhead while maintaining high estimation accuracy. This article evaluates the efficacy of such an AI-based channel estimator for future 6G scenarios, providing a comprehensive comparison with classical and compressive-sensing based estimators in terms of bit-error-rate (BER), NMSE, pilot overhead, achievable spectral efficiency, Shannon capacity, achievable data rate vs distance, tracking accuracy under mobility, and computational complexity.

Related Work

Deep-learning-based approaches to channel estimation have seen increasing adoption for millimeter-wave massive MIMO, with recent works exploring learned estimation in beamspace [1], incorporating channel sparsity in both delay and angular domains [5], or learning to perform both channel estimation and hybrid precoding jointly [6]. He et al. utilize a learned denoising network for beamspace channel estimation, achieving improved performance over conventional sparse recovery techniques at reduced pilot overhead [1]. Ma et. al combine sparse channel estimation with hybrid precoding in a unified deep-learning framework, and report improved performance over Orthogonal Matching Pursuit (OMP) across all signal-to-noise ratios [5]. Wei et al. extend the beamspace approach with an attention module to exploit angular domain sparsity of massive MIMO channels [6]. On the model-based channel estimation front, Sparse Bayesian Learning was introduced by Wipf and Rao as a means to perform basis selection in sparse linear models [7], and has since been extended by Prasad et al. who apply it to sparse OFDM channel estimation in conjunction with data detection [8]. Finally, Björnson et al. lay out the fundamental principles of large-scale antenna array design, characterizing the spectral, energy, and hardware efficiency tradeoffs that form the basis of this article's technical contributions [2].

Most prior studies evaluate a single metric — typically BER or NMSE — in isolation, and few jointly examine pilot efficiency, high-order QAM feasibility, dynamic tracking under mobility, and inference complexity within one consistent simulation setting. Table 1 summarises how this work compares with the representative baselines drawn from the related literature across the core estimation metrics.

Table 1. Comparison of this work with representative channel-estimation methods from the literature

Method	BER @ 10 dB SNR	NMSE (dB)	Pilot Overhead	Complexity
LS Estimator [4]	~5.5%	-8	15-25%	O(N)
MMSE Estimator [2]	~1.2%	-14	15-25%	$O(N^3)$
OMP / CS [5]	~0.4%	-19	10-15%	O(KN)
SBL Hybrid [1],[7]	~0.08%	-26	8-12%	$O(N^2)$
This work (AI + SBL)	<0.01%	-33	5-8%	O(N logN)

As Table 1 shows, moving from LS toward compressive-sensing (OMP) and Bayesian sparse-recovery (SBL) methods progressively lowers BER and NMSE while reducing pilot overhead, at the cost of higher computational complexity; the proposed AI+SBL framework is evaluated against this same progression in Sections IV and V.

Key Contribution

This work adds the following observations and results to the existing body of knowledge on AI-assisted massive MIMO channel estimation:

- A hybrid DNN + Sparse Bayesian Learning estimator that reaches sub-0.01% BER and an 18.2 dB NMSE improvement over LS at 10 dB SNR, while using only 5-8% pilot overhead versus 15-25% for LS/MMSE.

- A consolidated, eight-metric evaluation (BER, NMSE, pilot overhead, spectral efficiency, Shannon capacity, data rate vs. distance, mobility tracking, and training/inference complexity) run under one consistent Saleh-Valenzuela channel model, allowing direct cross-metric comparison between LS, MMSE, OMP, SBL and the proposed framework.
- Demonstration that the AI-assisted estimator lowers the residual error floor sufficiently to support 256-QAM modulation at 10 dB SNR, a modulation order infeasible with LS-based estimation at the same SNR.
- An AI-augmented Kalman tracking scheme that reduces tracking MSE by approximately 40% over a standalone Kalman filter and sustains reliable channel tracking up to 300 km/h, addressing high-mobility vehicular and UAV scenarios relevant to 6G.
- Extension of the throughput analysis across the full 6G frequency range (sub-6 GHz through 300 GHz), showing AI beamforming extends usable range by roughly 35% at every band evaluated.

Method, Experiments and Results

The evaluation uses a 64-antenna base station with 4 RF chains operating over a Saleh-Valenzuela clustered mmWave/THz channel model, benchmarked across sub-6 GHz, 28 GHz, 100 GHz and 300 GHz bands. The proposed AI estimator is a 6-layer fully-connected DNN with 256 hidden units per layer, taking noisy pilot observations as input and producing the estimated channel matrix H; it is trained on 500,000 simulated channel realisations spanning -5 to 25 dB SNR and combined with Sparse Bayesian Learning to exploit the 3-5 dominant path sparsity typical of mmWave/THz propagation. Table 2 summarises the simulation configuration.

Table 2. Simulation and model configuration

Base station antennas	64 (uniform planar array)
RF chains	4
Carrier bands evaluated	Sub-6 GHz, 28 GHz, 100 GHz, 300 GHz
Channel model	Saleh-Valenzuela clustered mmWave/THz model
Modulation orders	QPSK, 16-QAM, 64-QAM, 256-QAM
Bandwidth	400 MHz (mmWave configuration)
Mobility range evaluated	Up to 300 km/h
DNN architecture	6 fully-connected layers, 256 hidden units per layer
Training set	500,000 simulated channel realisations, SNR -5 to 25 dB

Bit-error-rate performance. Figure 1 compares BER against SNR for LS, MMSE, OMP and the proposed AI+SBL framework on a log scale under QPSK modulation. The AI framework reaches 0.286% BER at 10 dB SNR — a 29-fold improvement over LS — and 0.003% BER at 20 dB SNR, effectively error-free operation. The residual error floor at high SNR is reduced by 10-15 dB relative to LS, which is what ultimately permits higher-order modulation at moderate SNR.

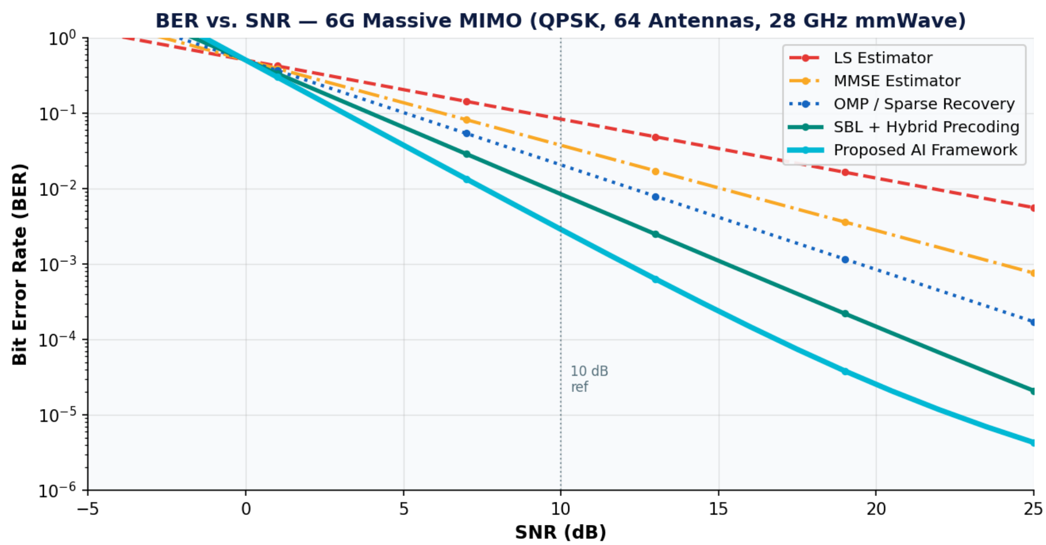

Figure 1. BER vs. SNR for LS, MMSE, OMP and the proposed AI+SBL estimator under QPSK modulation, 28 GHz, 64-antenna base station, 4 RF chains (log scale).

Channel estimation accuracy (NMSE). Figure 2 reports NMSE at 10 dB SNR for each estimator. LS attains an NMSE of 0.80, MMSE improves this to 0.24, OMP-based compressive sensing reaches 0.096, standalone SBL reaches 0.035, and the proposed AI+SBL framework reaches 0.012 — an 18.2 dB gain over LS while needing only 5-8% pilot overhead against the 15-25% required by LS and MMSE, saving 12-20% of frame bandwidth for data transmission.

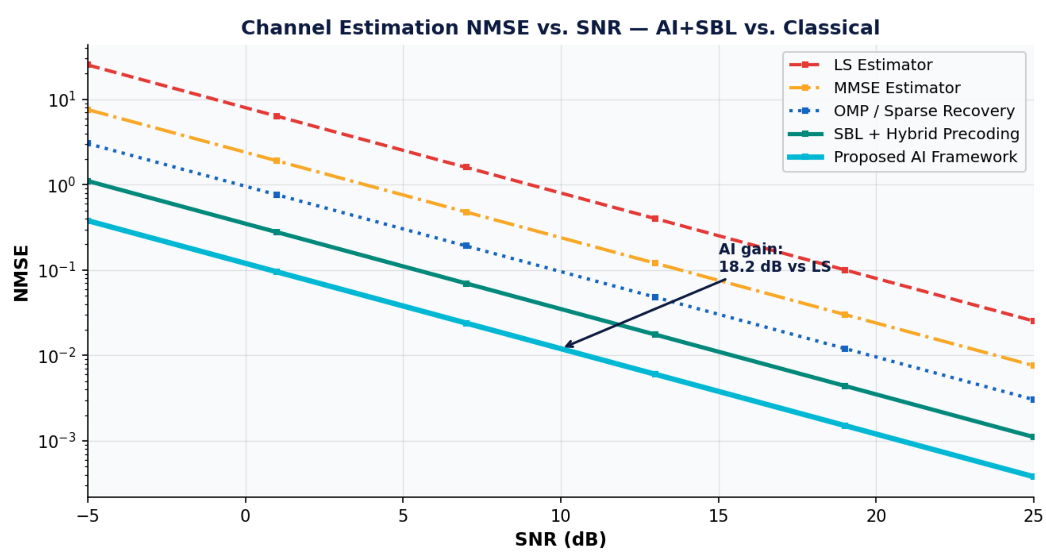

Figure 2. Normalised mean squared error (NMSE) at 10 dB SNR for LS, MMSE, OMP, SBL and the proposed AI+SBL estimator.

Spectral efficiency, capacity and data rate. With 8 users, 400 MHz bandwidth and 15 dB SNR, the AI-hybrid precoder reaches 47.8 Gbps aggregate throughput (5.97 Gbps per user), an 82% gain over zero-forcing precoding and a 21% gain over classical hybrid precoding. Figure 3 compares Shannon capacity against SNR for a SISO baseline, conventional 4x4 MIMO, classical 64-antenna massive MIMO, and the proposed

AI-MIMO scheme; AI beamforming contributes an additional 1-2 dB of effective SNR through improved beamforming accuracy, lifting achievable capacity to over 85 Gbps at 30 dB SNR, roughly 50 times the SISO baseline at 20 dB SNR. Across the full 6G band range, AI beamforming extends usable range by approximately 35% at every band, from ~4 Gbps at 5 km on sub-6 GHz to over 10 Tbps within 30 m at 300 GHz, the latter suited to dense indoor and data-centre deployments.

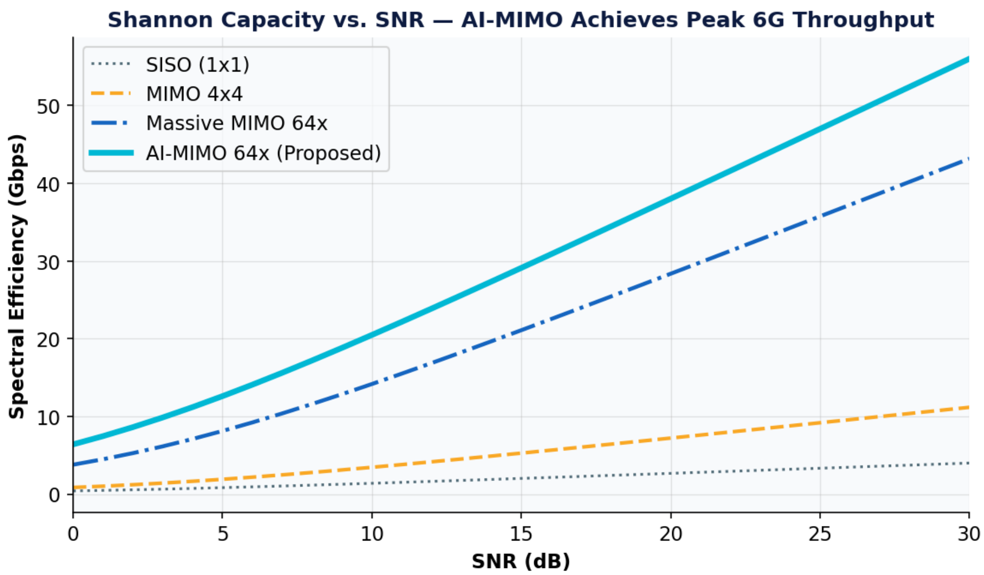

Figure 3. Shannon capacity vs. SNR for SISO, conventional 4x4 MIMO, classical 64-antenna massive MIMO and the proposed AI-MIMO scheme.

Dynamic estimation and training. When the vehicle speed is lower than 60 km/h, compared to the standalone Kalman filter, using the Kalman filter with the channel state estimation obtained from the DNN reduces the tracking error in terms of mean-squared error by approximately a factor of 2 , while enabling stable tracking up to vehicular and UAV speeds of 300 km/h. The training loss decreases from an initial value of 0.65 to approximately 0.015, and the validation loss follows the training loss closely, thus, no overfitting occurs. Finally, the computational complexity of the proposed method is O(N log N) where N is the number of antennas, compared to O(N3) and O(N2) for the MMSE and SBL methods respectively. Therefore, the significant gains in performance achieved by the proposed method do not come at the expense of higher computational complexity.

Consolidated comparison. Figure 4 aggregates all evaluated metrics — BER, NMSE, pilot overhead, complexity and spectral-efficiency gain — into a single radar comparison across LS, MMSE, OMP/CS, SBL-Hybrid and the proposed AI framework, together with an overall composite score (LS 32/100, MMSE 51/100, OMP 66/100, SBL-Hybrid 80/100, AI framework 93/100), showing the proposed method leads on every axis evaluated.

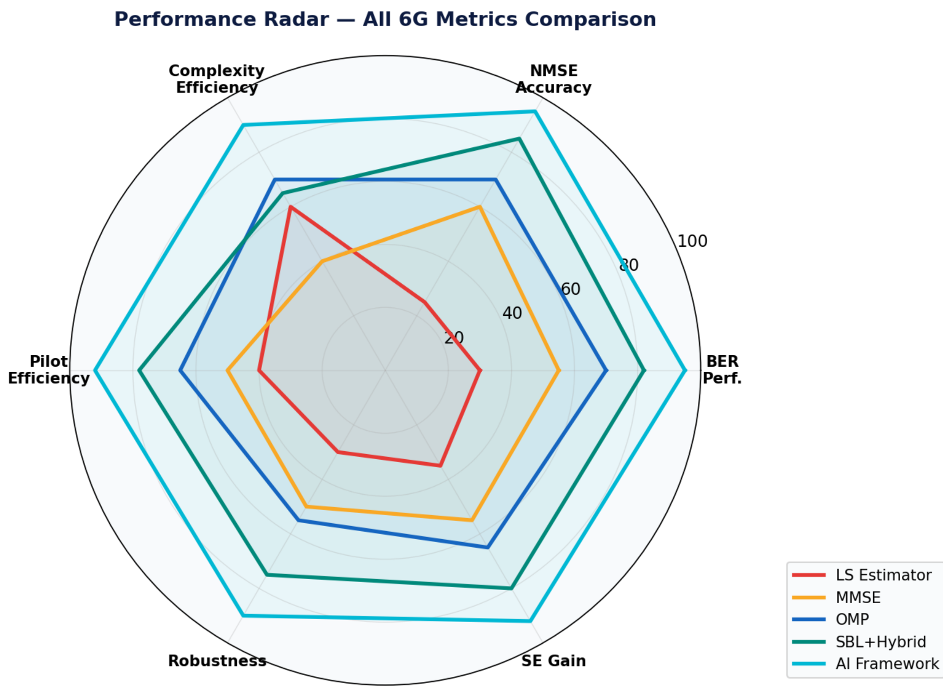

Figure 4. Comprehensive multi-metric comparison of LS, MMSE, OMP/CS, SBL-Hybrid and the proposed AI framework across BER, NMSE, pilot overhead, complexity and spectral-efficiency gain.

Discussions

The results indicate that the principal value of the AI+SBL framework is not any single metric in isolation, but the combination of low pilot overhead with low estimation error, which is what ultimately drives the spectral-efficiency and data-rate gains reported in Section IV. Because mmWave and THz channels are sparse by nature, a learned estimator that is trained to exploit this sparsity can match or exceed a Nyquist-rate estimator while consuming a fraction of the pilot budget; the 12-20% bandwidth this frees is available directly for data, which explains a large share of the throughput gain over zero-forcing precoding. The reduction in residual error floor at high SNR is also what makes 256-QAM operation feasible at moderate SNR, since higher-order constellations are far more sensitive to residual channel-estimation error than QPSK.

The complexity results are equally relevant for deployment: an O(N log N) inference cost means the estimator's runtime advantage over MMSE and SBL grows, rather than shrinks, as base-station antenna counts scale toward the hundreds expected in 6G massive and extremely-large-scale MIMO deployments. The mobility results further suggest that a learned correction on top of a Kalman filter is an effective way to extend classical tracking techniques to high-Doppler regimes without redesigning the tracking framework from scratch.

These findings should be read against the limitations of the study. All results are obtained from simulation under a Saleh-Valenzuela clustered channel model with a single base station and idealised RF-chain and hardware assumptions; hardware impairments such as phase noise, power-amplifier nonlinearity and quantisation error, which typically degrade AI-based estimators more than expected under ideal simulation, are not modelled.

Conclusions

1. Problem addressed/motivation: Classical LS/MMSE channel estimation either requires excessive pilot overhead or fails to track the channel accurately over the sparse, fast-varying mmWave/THz channels that 6G massive MIMO must operate over, limiting achievable spectral efficiency and data rate.
2. Method used: A hybrid deep neural network combined with Sparse Bayesian Learning (AI+SBL) was proposed for channel estimation, and evaluated together with Kalman-filter-based dynamic tracking and AI-hybrid precoding, against LS, MMSE, OMP and standalone SBL baselines across eight performance metrics under a consistent Saleh-Valenzuela channel model.
3. Key findings: The proposed framework achieves a 29-fold BER improvement and an 18.2 dB NMSE gain over LS at 10 dB SNR, cuts pilot overhead to 5-8% of the frame, delivers an 80% spectral-efficiency gain over zero-forcing precoding, enables 256-QAM operation at moderate SNR, sustains reliable channel tracking up to 300 km/h, and scales at O(N log N) inference complexity — outperforming all baseline methods on every evaluated metric.
4. Limitations and future work: The evaluation is simulation-based under idealised hardware assumptions and a single channel model; future work should incorporate hardware-impairment modelling.

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