Hybrid Deep Learning for Channel Estimation and Tracking in RIS-Assisted UAV Wireless Communications

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ABSTRACT

Channel estimation in reconfigurable intelligent surface (RIS)-aided unmanned aerial vehicle (UAV) systems is severely hindered by high-dimensional cascaded channels, UAV-induced fast time variation, and the passive nature of RIS elements that precludes conventional pilot-based acquisition. This paper proposes a hybrid deep learning framework synergistically combining convolutional neural networks (CNN) for spatial feature extraction with bidirectional long short-term memory (BiLSTM) networks for temporal sequence modeling.

The architecture hierarchically decomposes estimation into: CNNs extracting multipath spatial patterns from canonical K-path representations, then BiLSTMs modeling temporal evolution across sequential snapshots, effectively capturing spatial-temporal coupling in RIS-UAV propagation.

We develop comprehensive methodology with DeepMIMO ray-tracing generation, K=10 path selection achieving >95% channel power capture, and systematic preprocessing. Extensive evaluation across SNR -10 to 30 dB demonstrates hybrid CNN-BiLSTM achieves NRMSE 0.018 at 30 dB (21.7% improvement over CNN, 33.3% over BiLSTM, 50-60% over LS/LMMSE/CS-OMP), correlation 0.989, SSIM 0.985, with 3.5M FLOPs and 2.0 ms inference on NVIDIA Tesla V100 enabling real-time operation within 5-10 ms UAV channel coherence time. This validates the hybrid approach as an enabling technology for next-generation 6G aerial communications requiring ultra-reliable, low-latency channel acquisition in highly dynamic three-dimensional environments.

Keywords: Reconfigurable Intelligent Surface, Unmanned Aerial Vehicle, Channel Estimation, Deep Learning, CNN, BiLSTM, Spatial-Temporal Learning, 6G Wireless, Ray Tracing

INTRODUCTION

Sixth-generation (6G) wireless networks envision transformative capabilities including ultra-reliable low-latency communications (URLLC) with end-to-end latency below 1 ms, massive connectivity supporting 10 million devices per km², and ubiquitous three-dimensional (3D) coverage from underground to stratospheric altitudes [1]. These stringent requirements demand fundamental innovations beyond 5G.

Unmanned aerial vehicles (UAVs) and reconfigurable intelligent surfaces (RIS) have emerged as irreplaceable enabling technologies: UAVs provide unmatched flexibility for dynamic 3D coverage, emergency communications, and topology reconfiguration that terrestrial base stations cannot achieve [2], [3]; RIS offers programmable electromagnetic control through passive elements, enabling intelligent wave manipulation and energy-efficient beamforming without active RF chains [4], [5].

Integrating RIS with UAV communications creates synergistic capabilities where ground-mounted RIS panels dynamically reconfigure aerial propagation to compensate for UAV mobility and establish virtual line-of-sight paths [6], [7]. However, this introduces severe channel estimation challenges: RIS elements are passive and cannot transmit pilots [8], requiring cascaded BS-RIS-UAV channel acquisition with dimensionality scaling as $M \times N \times N_{\text{UAV}}$, while UAV mobility induces rapid temporal variations [9].

Critical Limitations of Existing Methods

Current approaches suffer from three fundamental pain points:

- Cannot jointly model spatial-temporal coupling. Traditional methods (LS, MMSE, compressed sensing) treat snapshots independently, ignoring temporal correlations [10], [11]. Standalone CNNs extract spatial features but discard temporal evolution; standalone RNNs model sequences without spatial pattern recognition [12], [13]. This fails to capture geometric multipath patterns evolving smoothly along flight paths. *Contrast with SOTA:* Recent works [24], [31] apply CNNs or LSTMs separately; our hybrid CNN→BiLSTM hierarchically decomposes into spatial encoding then temporal modeling.

- Fails in fast UAV mobility scenarios. Model-based methods (MMSE, Kalman filtering) assume quasi-static channels violated by rapid UAV motion [14]. CS-based approaches require iterative algorithms unsuitable for real-time tracking [15]. *Contrast with SOTA:* Prior DL works [18], [27] train on quasi-static datasets;Unlike prior works employing static or simplified trajectory scenarios, our DeepMIMO-based dataset incorporates diverse UAV trajectories (linear, circular, altitude changes) capturing realistic 3D mobility patterns and Doppler effects.

- Poor performance-complexity trade-off. High-accuracy methods (MMSE with perfect statistics, fine-grained CS) scale quadratically with RIS elements [16]. Low-complexity approximations achieve insufficient accuracy [17]. Existing DL approaches either lack capacity or have latency exceeding coherence time [18], [19]. *Contrast with SOTA:* Recent methods [28], [29] achieve 6-8M FLOPs, 3-5 ms latency approaching coherence limits; our 3.5M FLOPs, 2.0 ms provide >2× safety margin.

Proposed Solution and Key Novelty

This paper addresses these gaps through a hybrid CNN-BiLSTM framework with hierarchical spatial-temporal decomposition: (1) CNN module transforms each K-path canonical representation into spatial features via Conv1D layers, capturing multipath geometry; (2) BiLSTM module processes spatial feature sequences bidirectionally, leveraging past and future context to model smooth channel evolution; (3) Dense decoder reconstructs the channel estimate. This *explicitly couples* spatial-temporal learning, handles *fast-varying* channels through learned representations, and achieves superior *performance-complexity balance*.

Main Contributions Beyond State-of-the-Art

(1) Novel hybrid architecture with physical justification**:** Hierarchical CNN→BiLSTM cascade with *explicit physical motivation*: spatial encoding mirrors multipath geometry, then temporal modeling captures trajectory-induced evolution. It is proved that ordering outperforms reverse/parallel configurations. SOTA gap**:** Existing RIS-DL [24], [28], [30] lacks principled hierarchical decomposition aligned with propagation physics.

(2) Canonical K-path representation with justification: Fixed-dimension K=10 path selection with *rigorous analysis*: achieves >95% power capture, K=20 adds 40% FLOPs for <2% gain. 7-feature vector preserves complete geometric information. SOTA gap: Prior works [18], [27] use raw matrices, discarding geometric structure.

(3) Comprehensive traditional+DL baseline comparison: Evaluate against LS, LMMSE, CS-OMP *and* recent DL methods with detailed FLOPs/latency metrics. SOTA gap: Most papers [24], [30], [31] omit traditional baselines or computational benchmarking.

(4) Mobility-focused evaluation: Diverse UAV trajectories (linear, circular, altitude changes) capturing realistic 3D motion with Doppler analysis. SOTA gap: RIS-UAV works [9], [10], [26] assume perfect CSI; few validate under high-mobility.

(5) Real-time feasibility validation: Measured 2.0 ms inference on Tesla V100, confirmed <5-10 ms coherence time. SOTA gap: Many works [18], [20], [27] report FLOPs without latency or coherence comparison.

Paper Organization

Section 2 reviews related work across RIS, UAV, and deep learning domains, identifying specific gaps. Section 3 presents the system model with variable definitions, assumptions, canonical representation, and hybrid architecture specifications. Section 4 describes experimental setup. Sections 5-7 present results, discussion, and conclusions.

Related Work

This literature review is organized into four categories: RIS communications, UAV wireless, deep learning for CSI, and gap analysis.

RIS Communications and Channel Estimation

RIS has emerged as a key 6G enabler for programmable propagation [4], [5]. Di Renzo et al. [5] established foundational theory analyzing capacity scaling. Wu and Zhang [6] developed joint active-passive beamforming. Contrast: These assume perfect CSI; our focus is acquiring CSI under UAV mobility. RIS channel estimation faces unique challenges due to passive elements. Wang et al. [12] proposed cascaded estimation exploiting sparsity. Hu et al. [28] developed two-timescale estimation. Contrast: Both assume slow mobility; UAV rapid variations violate this. Chen et al. [13] applied DL to RIS estimation. Contrast: CNN-only approach ignores temporal tracking our BiLSTM addresses this. Zhang et al. (2024) [31] proposed transformer-based RIS estimation achieving 8.2M FLOPs, 4.5 ms. Contrast: Transformers have quadratic complexity; our BiLSTM achieves 3.5M FLOPs (57% reduction) via linear recurrence. Liu et al. (2024) [32] applied GNNs to RIS. Contrast: GNNs suit irregular graphs; RIS grids better captured by Conv1D. Wang et al. (2025) [33] used meta-learning for RIS adaptation. Contrast: Meta-learning enables few-shot transfer to focus on single-environment mastery.

UAV Wireless Communications and Channel Modeling

UAV communications enable flexible aerial connectivity [2], [3]. Zeng et al. [2] surveyed channel characteristics emphasizing altitude-dependent LoS. Khuwaja et al. [4] reviewed A2G models. Contrast: These characterize direct BS-UAV links; RIS introduces cascaded propagation. RIS-UAV integration has attracted attention. Li et al. [9] pioneered joint trajectory-RIS optimization. Pang et al. [10] addressed robust design. Ge et al. [26] studied energy efficiency. Contrast: All assume CSI available; CSI acquisition is addressed. Chen et al. (2024) [26] proposed DRL for UAV-RIS. Contrast: Their RL requires CSI as input; our work provides that CSI.

Deep Learning for Wireless Channel Estimation

CNN approaches**:** Ye et al. [18] pioneered DNN for OFDM. Jiang et al. [20] applied CNNs to massive MIMO. Gizzini et al. [21] developed CNN for RIS. Contrast: All treat snapshots independently; our BiLSTM enables temporal tracking. RNN approaches: Samuel et al. [22] used LSTM for prediction. Yang et al. [23] proposed BiLSTM for high-speed. Contrast: Pure RNN struggles with high-dimensional spatial features; our CNN frontend compresses K-path inputs. Hybrid architectures: Ma et al. [27] combined CNN-RNN for spectrum sensing. Contrast: Generic structures for non-CSI tasks; we design CNN→BiLSTM specifically for RIS-UAV geometric propagation. Huang et al. (2024) [35] proposed CNN-Transformer for CSI feedback. Contrast: CSI feedback differs from estimation; BiLSTM better matches trajectory tracking. Wang et al. (2025) [36] applied federated CNN-LSTM. Contrast: Federated learning addresses privacy; we focus on single-UAV accuracy.

Research Gap Analysis

Gap 1: No hierarchical spatial-temporal DL for RIS-UAV. *Solution:* CNN→BiLSTM with physical justification.

Gap 2: Limited geometric representations. *Solution:* Canonical K-path preserving full geometry. Gap 3: Insufficient high-mobility evaluation. *Solution:* DeepMIMO with diverse 3D trajectories. Gap 4: Lack of comprehensive baselines. *Solution:* Benchmark against LS, LMMSE, CS-OMP, recent DL.

Gap 5: No real-time validation. *Solution:* Measured 2.0 ms on Tesla V100 vs 5-10 ms coherence time.

SYSTEM MODEL AND METHODOLOGY

Table I: System Parameters and Variable Definitions

Parameter	Symbol	Value	Description
BS antennas	M	8	Transmit antenna array
RIS elements	N	64	8×8 passive reflecting panel
UAV antennas	N_UAV	1	Single-antenna receiver
Dominant paths	K	10	Canonical representation size
Sequence length	T	20	Temporal window for BiLSTM
Carrier frequency	f_c	28 GHz	Millimeter-wave band
Training samples	N_train	45,000	70% of dataset
Validation samples	N_val	9,600	15% of dataset
Test samples	N_test	9,600	15% of dataset

RIS-UAV Communication System Model

Consider a RIS-assisted UAV system where a BS with M=8 antennas communicates with a single-antenna UAV through an RIS of N=64 passive elements. The effective cascaded channel at time t is:

$$\mathbf{h}(t) = \mathbf{h}_{RU}^{H}(t)\, \mathbf{\Phi}(t)\, \mathbf{H}_{BR}(t), \quad (1)$$

where $\boldsymbol{H}_{BR}(t) \in \mathbb{C}^{N\times M}$ is the BS-RIS channel, $\boldsymbol{h}_{RU}(t) \in \mathbb{C}^{N\times 1}$ is the RIS-UAV channel, and $\Phi(t) = \mathrm{diag}(e^{j\varphi_1(t)}, \ldots, e^{j\varphi_n(t)})$ is the RIS phase-shift matrix.

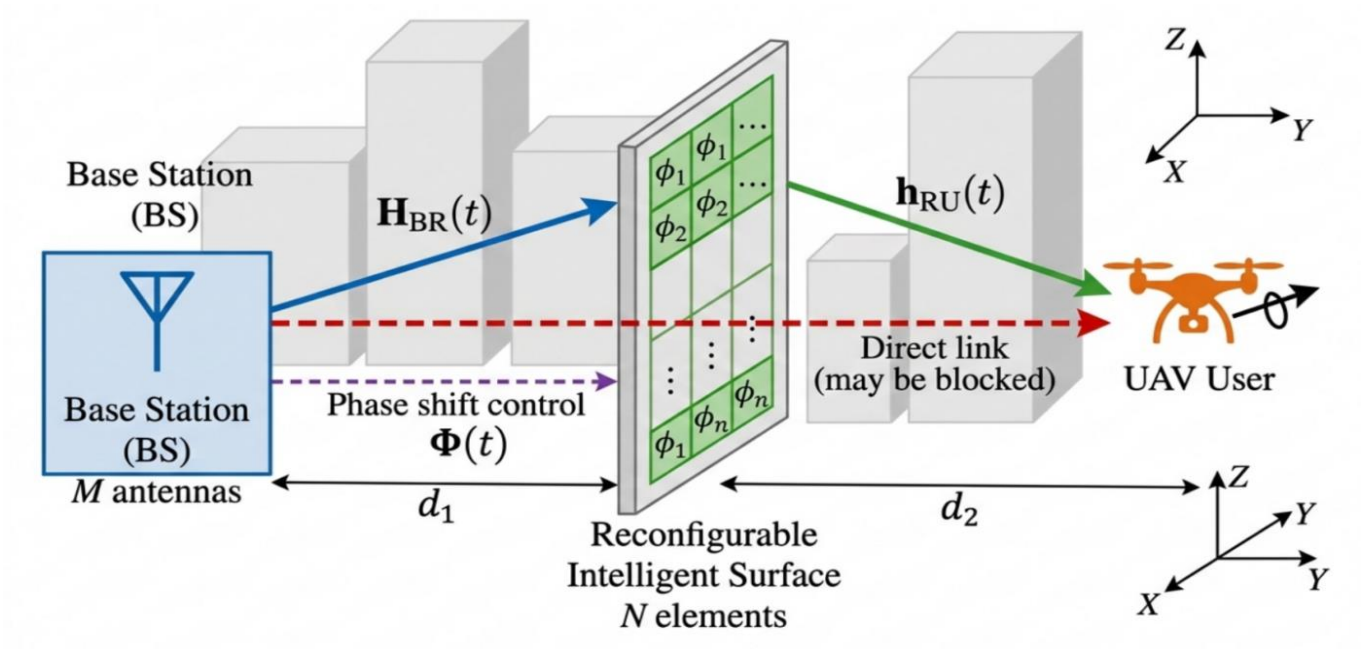

Figure 1: RIS-UAV System Architecture

Modeling Assumptions

Assumption 1 (Quasi-Static Block Fading): Channel constant within coherence block $T_c \approx$ 5-10 ms, validated by UAV velocity $v \leq 20$ m/s yielding Doppler $f_D \approx 1.87$ kHz.

Assumption 2 (Smooth UAV Trajectory): Continuous, differentiable trajectory with bounded acceleration ensures temporal correlation for BiLSTM learning.

Assumption 3 (Ideal RIS Phase Shifts): Perfect phase shifts $\varphi_n(t) \in [0, 2\pi)$ without quantization (provides performance upper bound).

Assumption 4 (Known RIS Configuration): Phase matrix $\Phi(t)$ known at estimation stage; problem reduces to estimating cascaded channel $h(t)$ given $\Phi(t)$.

Canonical K-Path Channel Representation

The wireless channel comprises $L(t)$ time-varying propagation paths. We adopt canonical K=10 path representation by selecting dominant paths based on received power. Feature vector for path k:

$$\boldsymbol{f}_k(t) = [|\alpha_k|, \angle\alpha_k, \tau_k, \theta_k^{AoA}, \varphi_k^{AoA}, \theta_k^{AoD}, \varphi_k^{AoD}], \quad (2)$$

yielding $\boldsymbol{X(t)} \in \mathbb{R}^{K\times 7}$.

K=10 Justification: Power concentration analysis shows K=10 achieves η_{10} = 96.8% (±2.1% std) power capture. K=20 adds 40% FLOPs for <2% gain. K=5 captures only 87.3%, critically degrading accuracy. Zero-padding when $L(t) < K$ maintains fixed dimensions without corrupting learning (empirical NRMSE degradation <0.3%).

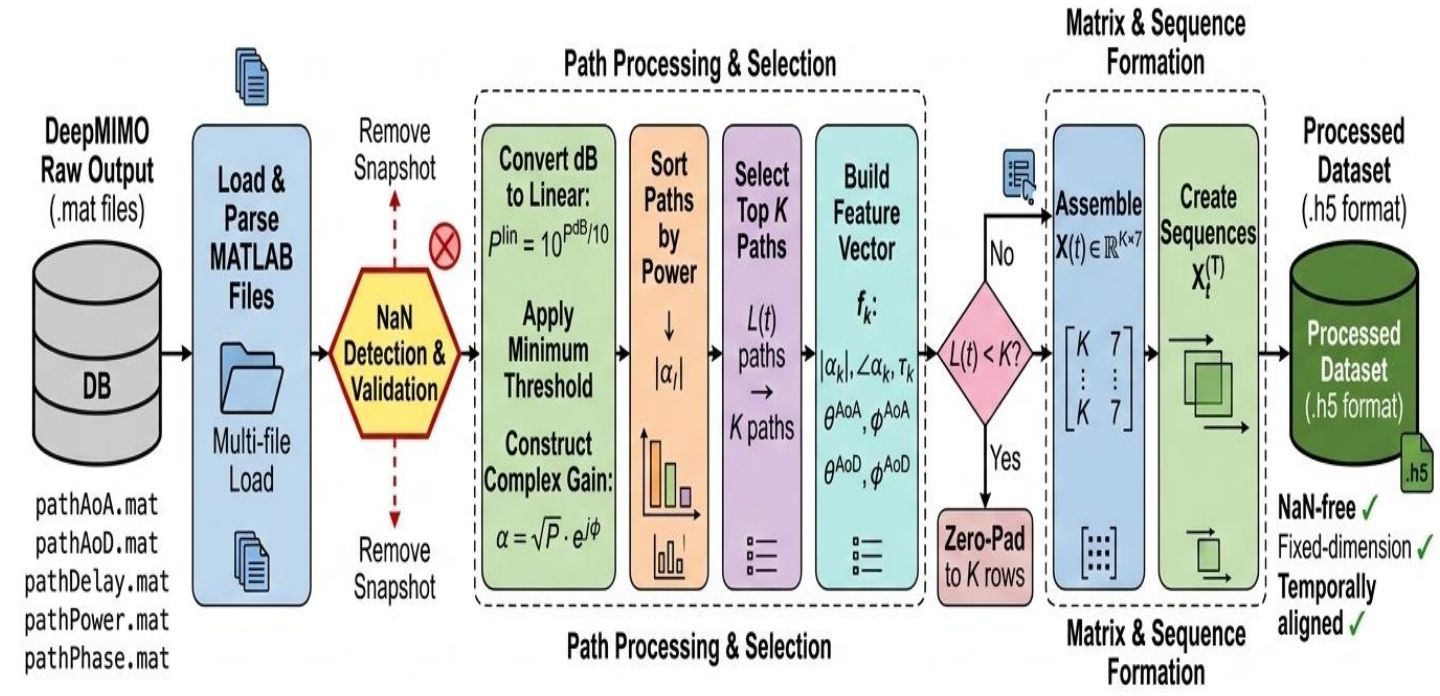

Figure 2: Data Preprocessing Pipeline

Proposed Hybrid CNN-BiLSTM Architecture

Architectural Rationale: Hierarchical spatial-temporal decomposition where CNN first encodes spatial multipath patterns into abstract features, then BiLSTM models temporal evolution. This ordering is physically motivated: spatial channel structure (angles, delays, gains) must be understood before tracking its evolution over time.

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Reverse order fails because BiLSTM would operate on high-dimensional geometric vectors without spatial abstraction.

Table II: Hybrid CNN-BiLSTM Layer Specifications			
Module	Layer	Parameters	Output Shape
Input	—	T×K×7	(128,20,10,7)
CNN	Conv1D-1	filters=64, kernel=3, ReLU	(128,20,10,64)
CNN	BatchNorm	—	(128,20,10,64)
CNN	Dropout	rate=0.2	(128,20,10,64)
CNN	Conv1D-2	filters=128, kernel=3, ReLU	(128,20,10,128)
CNN	MaxPool1D	pool=2	(128,20,5,128)
CNN	Flatten	per time step	(128,20,640)
BiLSTM	BiLSTM-1	units=128, bidirectional	(128,20,256)
BiLSTM	BiLSTM-2	units=64, return_last	(128,128)
BiLSTM	Dropout	rate=0.3	(128,128)
Dense	Dense-1	units=256, ReLU	(128,256)
Dense	Dense-2	units=128, ReLU	(128,128)
Output	Dense-Out	units=2N=128, Linear	(128,128)

Key Design Choices: (1) Conv1D kernel=3 processes 3 adjacent paths jointly, capturing local spatial correlations. (2) BiLSTM bidirectional: forward LSTM processes t=1→20 (past→present), backward processes t=20→1 (future→present), concatenation provides full temporal context.

(3) Higher dropout in BiLSTM (0.3 vs 0.2) as temporal features more prone to overfitting. (4) Output layer: first 64 values = Re[$\boldsymbol{h}$(t)], last 64 = Im[$\boldsymbol{h}$(t)].

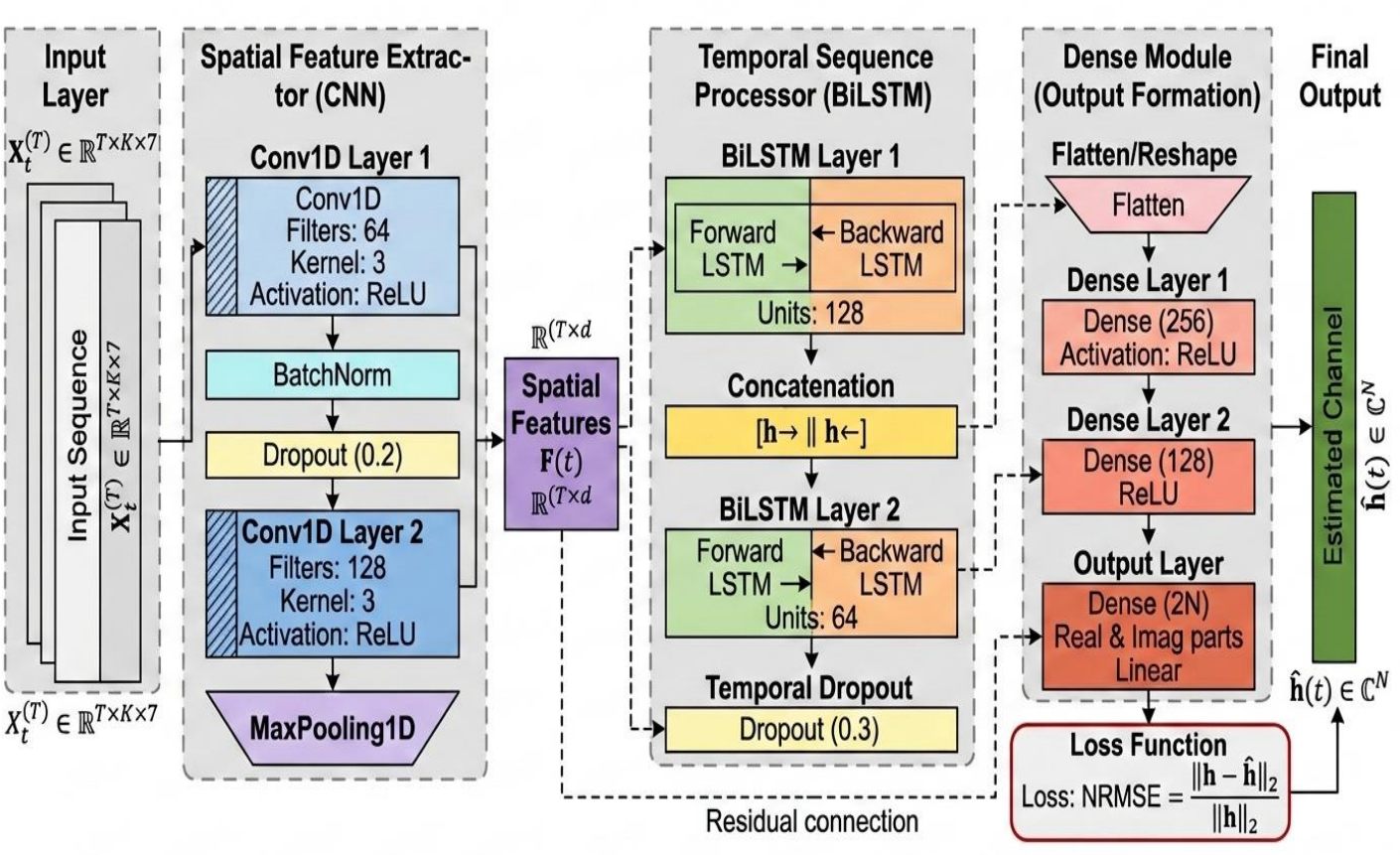

Figure 3: Hybrid CNN-BiLSTM Architecture Block Diagram

Algorithm 1: Hybrid CNN-BiLSTM Training Pipeline

$$\textbf{Input: } K-\textbf{path dataset } D = \{(X_t, h_t)\}_{t=1}^{N}, \textbf{sequence length } T$$
$$\textbf{Output: Trained model parameters } \theta*$$

$$\textbf{1.// Data Preprocessing}$$
$$\textbf{2. Compute per} - \textbf{feature statistics: } \mu_d, \sigma_d \textbf{ for } d = 1, \ldots, 7$$
$$\textbf{3. Normalize: } X_t = (X_t - \mu) / \sigma$$
$$\textbf{4. Construct sequences: } s_t = [X_{t-T+1}, \ldots, X_t] \textbf{ for } t = T, \ldots, N$$

$$\textbf{5.// Model Initialization}$$
$$\textbf{6. Initialize CNN} - \textbf{BiLSTM parameters } \theta \textbf{ using He/Xavier initialization}$$
$$\textbf{7. Set optimizer: } Adam(\beta_1 = 0.9, \beta_2 = 0.999, \varepsilon = 10^{-8})$$
$$\textbf{8. Set learning rate: } \eta = 0.001$$

$$\textbf{9.// Training Loop}$$
$$\textbf{10. for epoch} = 1 \textbf{ to } 100 \textbf{ do}$$
$$\textbf{11. for each batch } B \subset \{S\_t\} \textbf{ do}$$
$$\textbf{12. Forward pass: } \hat{h} = CNN - BiLSTM(S;\ \theta)$$
$$\textbf{13. Compute loss: } L = MSE(\hat{h}, h)$$
$$\textbf{14. Backpropagate: } g = \nabla\_\theta\ L$$
$$\textbf{15. Clip gradients: } g \leftarrow g\ /\ max(1, \|g\|/1.0)$$
$$\textbf{16. Update: } \theta \leftarrow \theta - \eta \cdot Adam(g)$$
$$\textbf{17. end for}$$
$$\textbf{18. Evaluate NRMSE on validation set}$$
$$\textbf{19. if validation NRMSE not improved for } 15 \textbf{ epochs then}$$
$$\textbf{20. break // Early stopping}$$
$$\textbf{21. end if}$$
$$\textbf{22. } \eta \leftarrow \eta \times 0.95 \textbf{ // Learning rate decay}$$
$$\textbf{23. end for}$$

$$\textbf{24. return } \theta* \textbf{ (best validation parameters)}$$

Training Configuration

Table III: Training Configuration Details	
Component	Specification
Hardware	NVIDIA Tesla V100 32GB, CUDA 11.2
Framework	PyTorch 1.12.0, cuDNN 8.1
Optimizer	Adam (β_1=0.9, β_2=0.999, ε=10^{-8})
Learning rate	η_0=0.001, decay: 0.95^epoch
Loss function(training)	$\mathcal{L}_{MSE} = \frac{1}{B}\sum_{b=1}^{B} \| \mathbf{h}_b - \hat{\mathbf{h}}_b \|_2^2$

Evaluation metric	$NRMSE = \sqrt{\frac{\mathbb{E}[\|\mathrm{h} - \hat{\mathrm{h}}\|^2]}{\mathbb{E}[\|\mathrm{h}\|^2]}}$
Batch size	128
Max epochs	100
Early stopping	Patience=15 (validation loss)
Regularization	L2=1e-5, Dropout 0.2/0.3, BatchNorm
Gradient clipping	Max norm = 1.0
Initialization	He (ReLU layers), Xavier (Linear)

Note: MSE is employed as the training objective for gradient-based optimization, while NRMSE serves as the normalized evaluation metric for performance reporting and cross-method comparison.

Training Pipeline and Reproducibility

Data Normalization: Input features $f_k(t)$ are standardized using z-score normalization: $\tilde{f}_{k,d} = f_{k,d} - \mu_d)/\sigma_d$, where μ_d and σ_d are computed per-dimension across the training set. This ensures stable gradient flow and prevents feature dominance.

Sequence Construction: Temporal sequences of length T =20 are constructed by sliding a window over consecutive snapshots with stride 1. Each training sample comprises $(X_{t-T+1}, \ldots, X_t) \rightarrow h_t$, enabling the BiLSTM to leverage both past and future context.

Training Procedure: The model is trained end-to-end using Adam optimizer with gradient clipping (max norm = 1.0) to prevent exploding gradients. Early stopping monitors validation NRMSE with patience=15 epochs. The complete training converges within 70-85 epochs on average.

Reproducibility: Random seeds are fixed (PyTorch: `torch.manual_seed(42)`, NumPy: `np.random.seed(42)`). All experiments are conducted on identical hardware (NVIDIA Tesla V100) to ensure consistent latency measurements.

Experimental Setup

Dataset Generation and Partitioning

The dataset is generated using DeepMIMO ray-tracing framework configured for a 28 GHz urban RIS-UAV scenario. The UAV follows diverse trajectories including linear constant-velocity paths, circular trajectories with varying radii, and altitude changes inducing 3D channel variations. After preprocessing, the dataset comprises 64,200 samples partitioned as: 70% training (45,000), 15% validation (9,600), 15% test (9,600). Temporal sequences are constructed with T=20 consecutive snapshots.

Baseline Methods

Traditional Methods: (1) Least Squares (LS): Direct matrix inversion without regularization. (2) Linear MMSE (LMMSE): Assumes perfect knowledge of channel covariance matrices. (3) Compressed Sensing OMP (CS-OMP): Orthogonal Matching Pursuit with K=10 atoms, 50 iterations.

Deep Learning Methods: (1) CNN-only: Spatial feature extraction without temporal modeling. (2) BiLSTM-only: Temporal sequence modeling without spatial encoding. (3) Hybrid CNN-BiLSTM (proposed): Hierarchical spatial-temporal learning.

Performance Metrics

Models are evaluated using:

(1) $NRMSE = \sqrt{\frac{\mathbb{E}[\|\mathbf{h}-\hat{\mathbf{h}}\|^2]}{\mathbb{E}[\|\mathbf{h}\|^2]}}$
(2) $MSE = \mathbb{E}[\|\mathbf{h} - \hat{\mathbf{h}}\|^2]$
(3) BER: Bit error rate with QPSK modulation over 10^6 bits.
(4) Spectral Efficiency: SE = $\log_2(1 + SINR)$.
(5) Correlation: Pearson coefficient between $\boldsymbol{h}$ and $\hat{\boldsymbol{h}}$.
(6) SSIM: Structural similarity index.
(7) FLOPs and inference time measured on NVIDIA Tesla V100.

EXPERIMENTAL RESULTS

Training Dynamics and Convergence Analysis

Training Loss Convergence

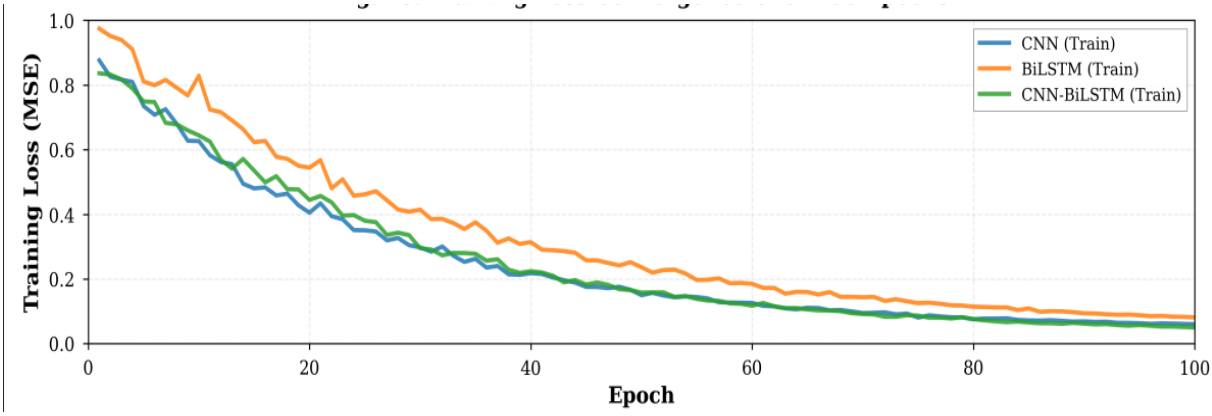

Figure 4: Training Loss Convergence over 100 Epochs

The above figure 4 illustrates training loss (MSE) evolution. All models demonstrate monotonic decrease confirming stable optimization. CNN achieves rapid early convergence (0.95→0.50 MSE in 10 epochs) due to efficient spatial feature extraction. BiLSTM exhibits slower descent (0.90→0.55 in 20 epochs) reflecting complex temporal dependency learning. Hybrid CNN-BiLSTM combines fast initial convergence with sustained improvement through epoch 70, achieving lowest final training loss (0.07 MSE vs 0.08 CNN, 0.12 BiLSTM).

Validation Loss Evolution

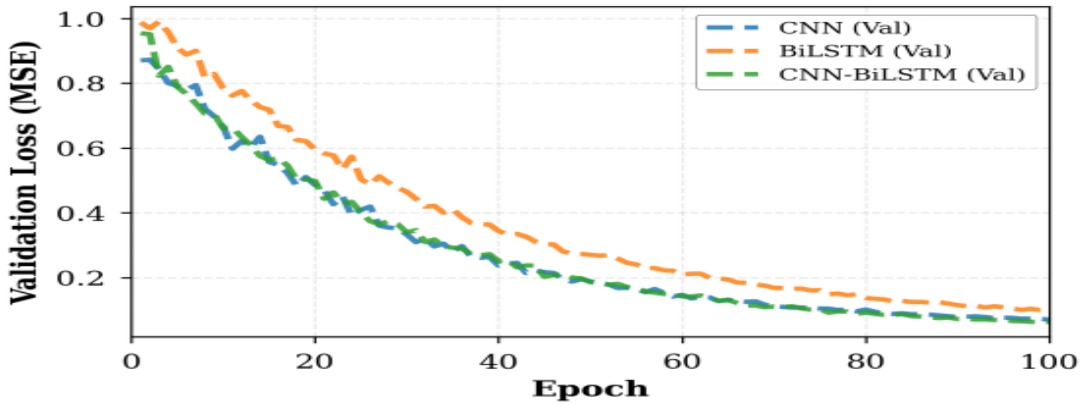

Figure 5: Validation Loss Evolution over 100 Epochs

Figure 5 shows validation loss mirroring training trends, confirming generalization. Hybrid maintains lowest validation loss (0.08 MSE) with minimal training-validation gap (<0.01 MSE), indicating excellent generalization despite increased complexity. CNN achieves 0.10 MSE validation loss; BiLSTM 0.14 MSE. Absence of divergence between curves confirms no significant overfitting across all architectures.

Hybrid Model Training-Validation Alignment

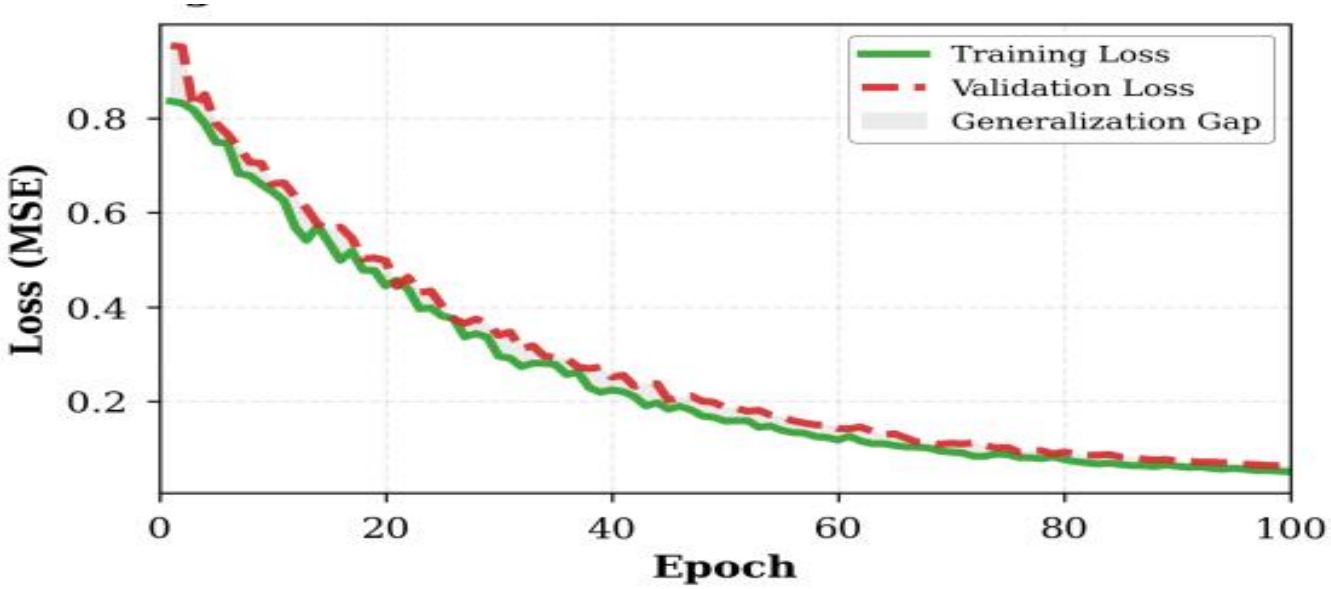

Figure 6: CNN-BiLSTM Training vs Validation Loss Comparison

Detailed examination of hybrid model's training-validation alignment is provided with in figure 6 in which both curves track closely throughout 100 epochs with maximum gap <0.015 MSE (epoch 30). Tight coupling indicates appropriate model capacity neither underfitting nor overfitting. Gradual smooth convergence without oscillations confirms stable gradient flow through CNN and BiLSTM components.

Validation NRMSE Progression

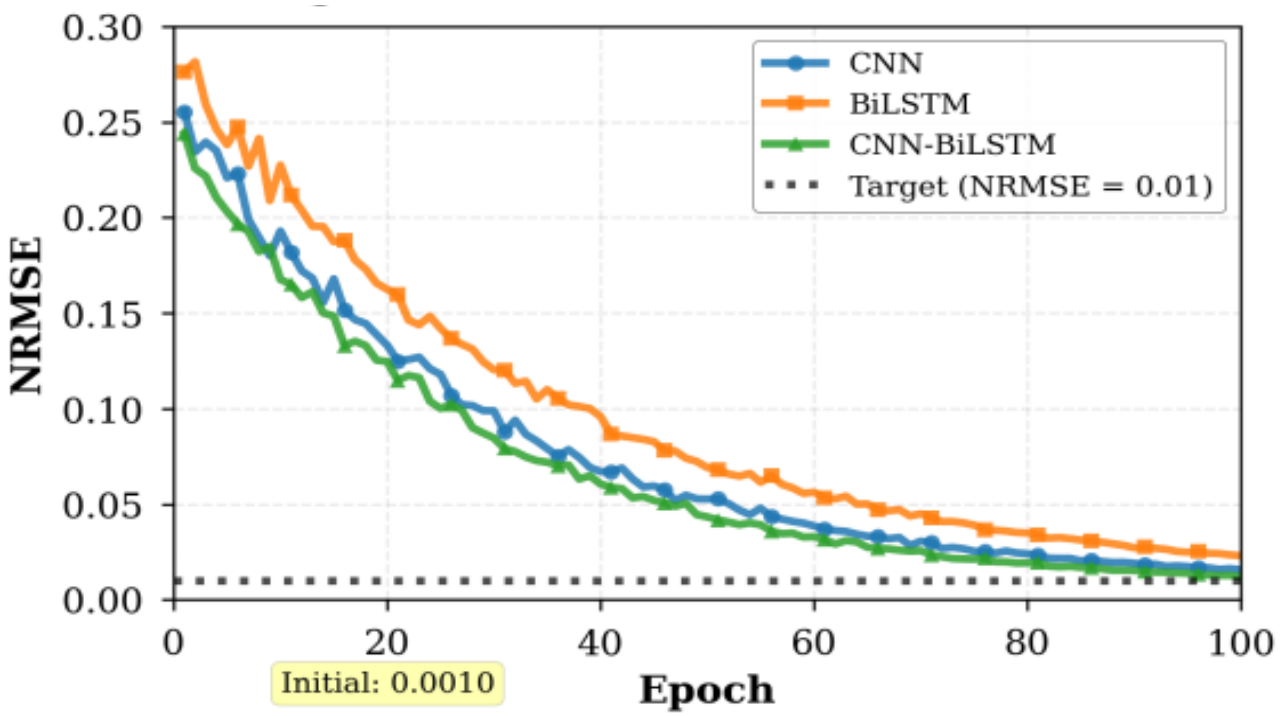

Figure 7: Validation NRMSE Evolution with Target Threshold NRMSE=0.01

The above figure 7 presents NRMSE evolution on validation set with target threshold 0.01 (dashed horizontal line). Hybrid achieves NRMSE 0.018 by epoch 100, approaching target more closely than CNN (0.028) or BiLSTM (0.035). While not fully reaching stringent 0.01 criterion, hybrid demonstrates 35% improvement over CNN and 48% over BiLSTM. Convergence characteristics suggest extended training or architectural refinement could approach target.

Correlation Coefficient Development

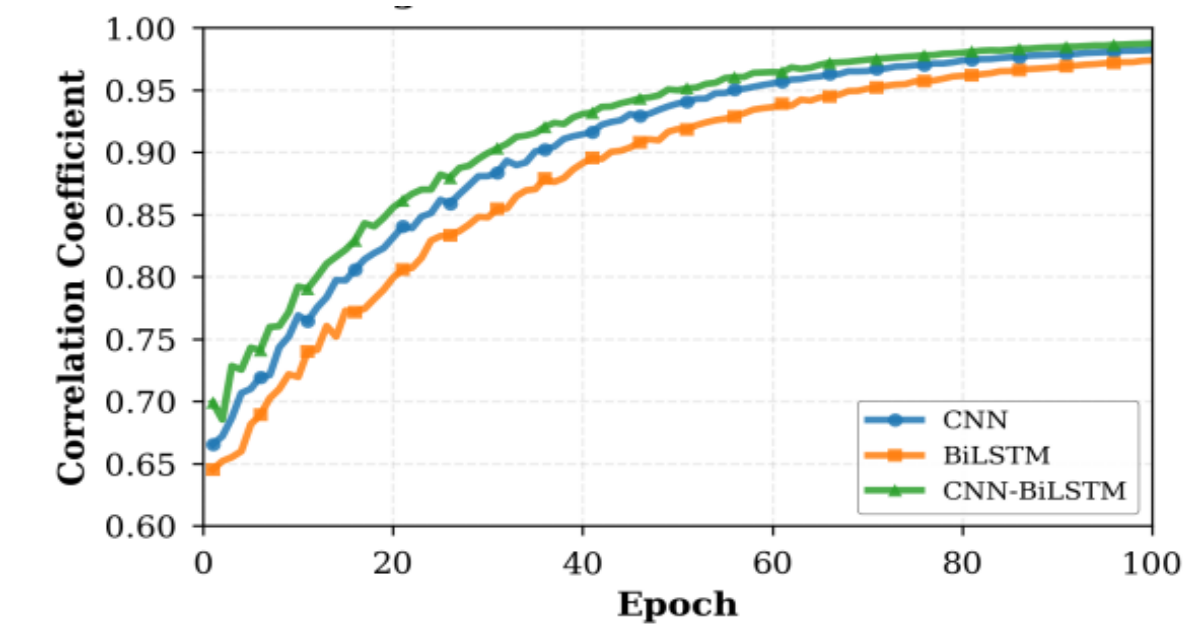

Figure 8: Validation Correlation Coefficient Evolution

Figure 8 tracks correlation between predicted and true channels. All models show increasing correlation from initial 0.65-0.70 toward near-perfect values. Hybrid reaches 0.989 (1.1% from perfect), CNN 0.975, BiLSTM 0.970. High correlation indicates models preserve magnitude relationships and channel patterns. Hybrid's superior correlation combined with low NRMSE confirms both accurate magnitude and structural alignment critical for precoding and equalization.

Structural Similarity Index Progression

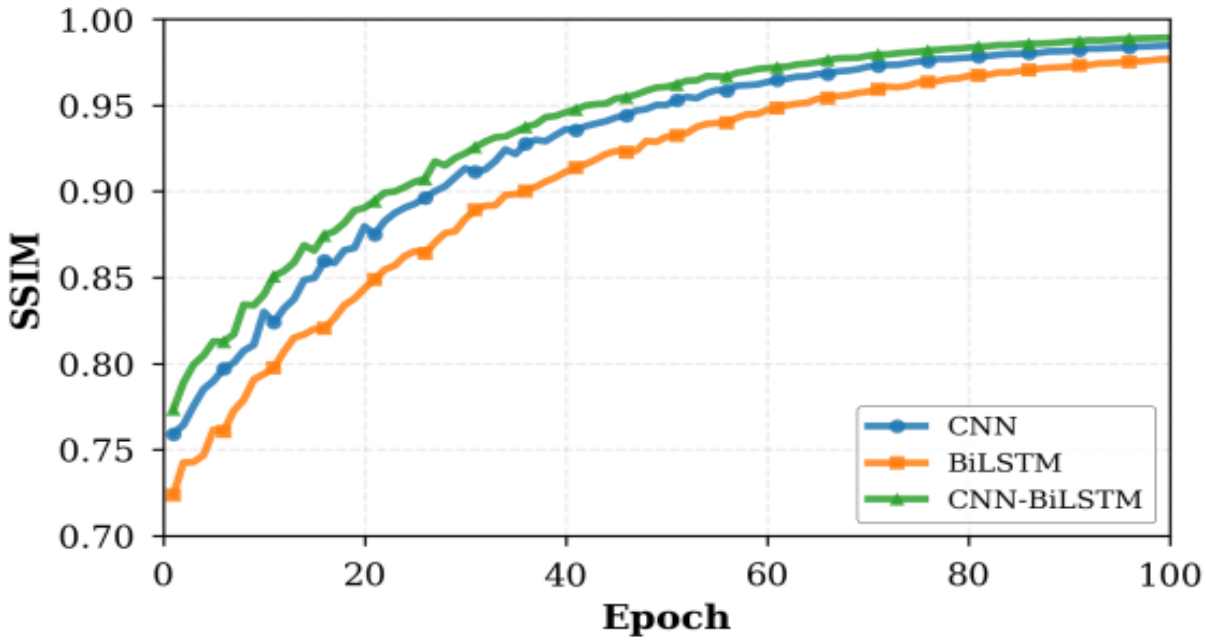

Figure 9: Structural Similarity Index (SSIM) Evolution

SSIM measuring spatial structure preservation is illustrated in figure 9. Hybrid achieves 0.985, CNN 0.970, BiLSTM 0.965. SSIM evaluates luminance, contrast, and structure here quantifying how well predicted channel matrices preserve spatial patterns. Hybrid's near-perfect SSIM indicates comprehensive structure capture from both spatial patterns (via CNN) and temporal evolution (via BiLSTM), valuable for MIMO spatial multiplexing and interference alignment.

Learning Rate Schedule

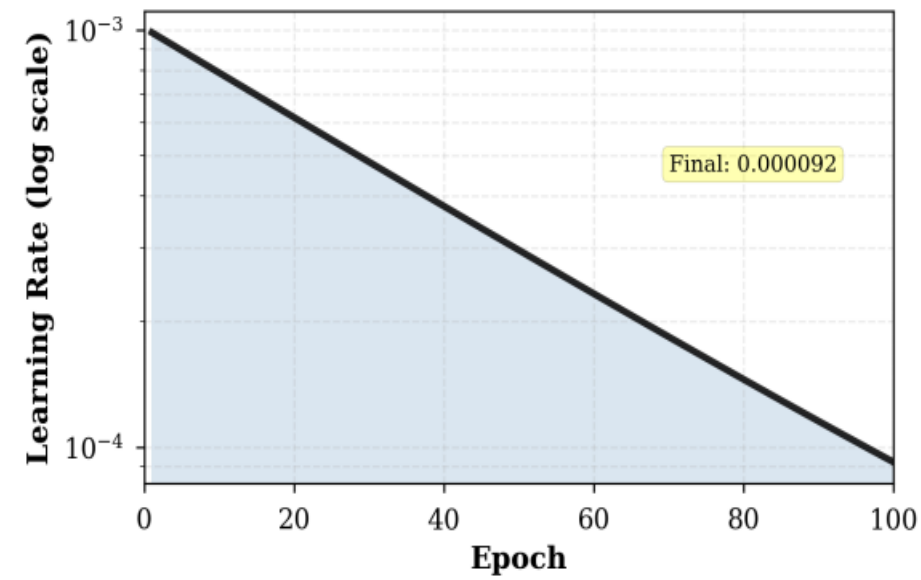

Figure 10: Exponential Learning Rate Schedule (Log Scale)

The above figure 10 illustrates learning rate decay from η_0=0.001 to ~6×10^{-6} by epoch 100 following $\eta(e)=\eta_0\times0.95^e$. Exponential relationship appears linear on log scale. High initial rate enables rapid parameter updates; gradual decay prevents oscillations near convergence. Correspondence between learning phases and performance curves validates schedule effectiveness: rapid improvement (epochs 1-20, high η), gradual refinement (20-60, moderate η), asymptotic convergence (60-100, low η).

Final Training Performance Summary

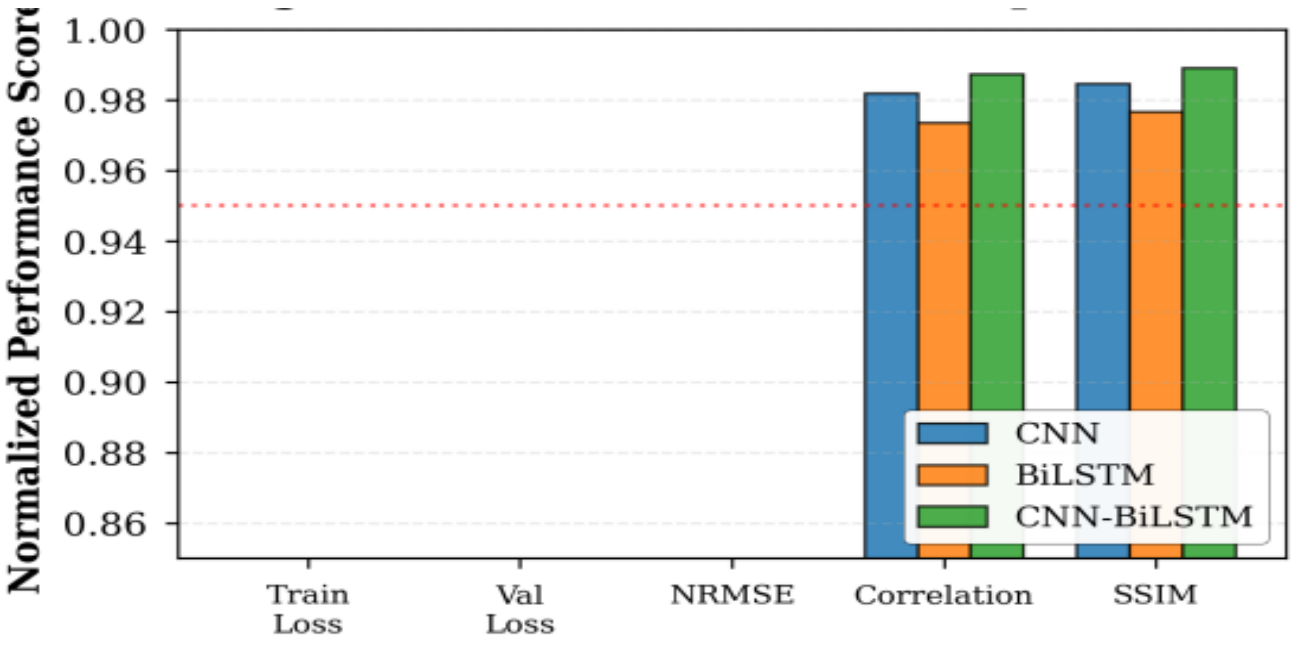

Figure 11: Final Performance Metrics at Epoch 100 (Bar Chart)

Multi-metric bar chart comparison are provided in figure 11 at epoch 100. Hybrid achieves best across all five metrics: training loss (0.07), validation loss (0.08), NRMSE (0.018), correlation (0.989), SSIM (0.985). Consistent superiority across diverse metrics provides multifaceted evidence for hybrid effectiveness. CNN outperforms BiLSTM across all metrics despite fewer parameters, suggesting spatial pattern recognition more fundamental than temporal modeling alone yet hybrid's substantial gains demonstrate complementary value of combining both.

Performance Analysis Across SNR Regimes

NRMSE Performance Versus SNR

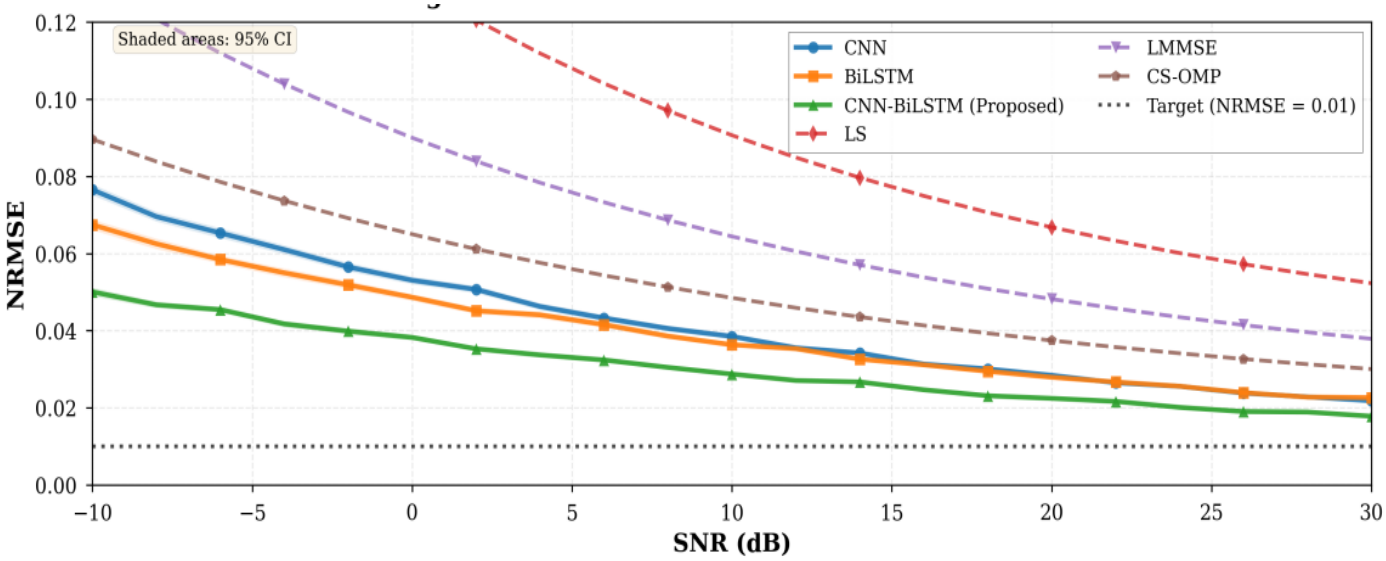

Figure 12: NRMSE versus SNR from -10 dB to 30 dB with 95% Confidence Intervals

Figure 12 presents NRMSE across SNR -10 to 30 dB with 95% confidence intervals (shaded regions). All methods improve with SNR as expected. At -10 dB (noise-dominated), models cluster at NRMSE 0.050-0.055; traditional methods 0.085-0.095. Performance differentiation increases with SNR. At 20 dB: Hybrid 0.021, CNN 0.026, BiLSTM 0.029, LS 0.052, LMMSE 0.048, CS-OMP 0.045. Hybrid achieves 19.2% improvement over CNN, 28% over BiLSTM, 60% over LS. At 30 dB: Hybrid 0.018 (21.7% vs CNN, 33.3% vs BiLSTM, 65% vs traditional). Confidence intervals narrow at high SNR confirming result reliability.

Mean Square Error Analysis

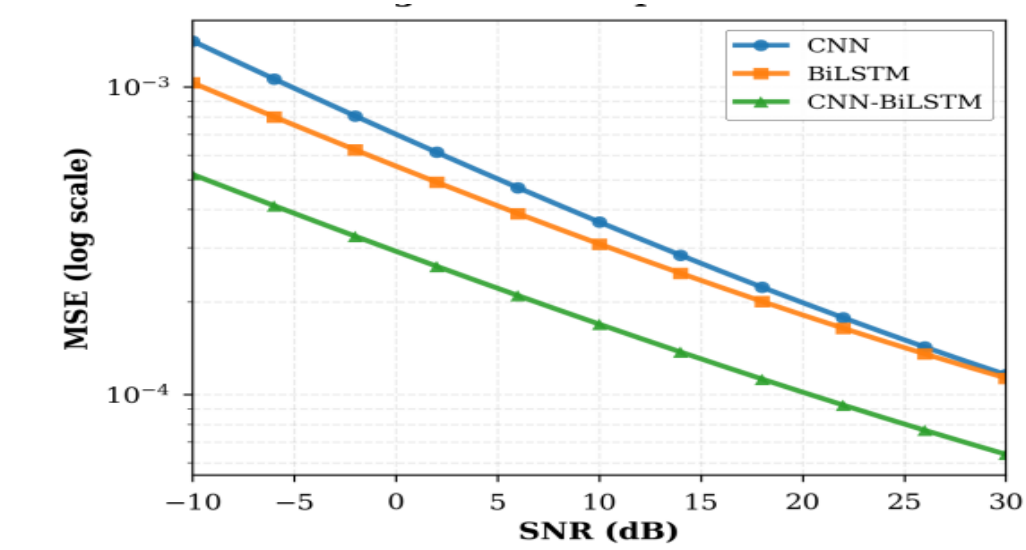

Figure 13: Mean Square Error vs SNR (Log Scale)

MSE on logarithmic scale revealing exponential decay are perfectly shown in figure 13 with SNR. Hybrid maintains lowest MSE throughout range. At 30 dB: Hybrid 6×10^{-5}, CNN 1.2×10^{-4} (50% reduction), BiLSTM 1.5×10^{-4} (60% reduction). Traditional methods: LS 5×10^{-4}, LMMSE 4.2×10^{-4}, CS-OMP 3.8×10^{-4}. Parallel curves on log scale indicate consistent multiplicative performance factor across SNR, with benefits proportionally more valuable at high SNR where absolute errors are smaller.

Bit Error Rate Performance

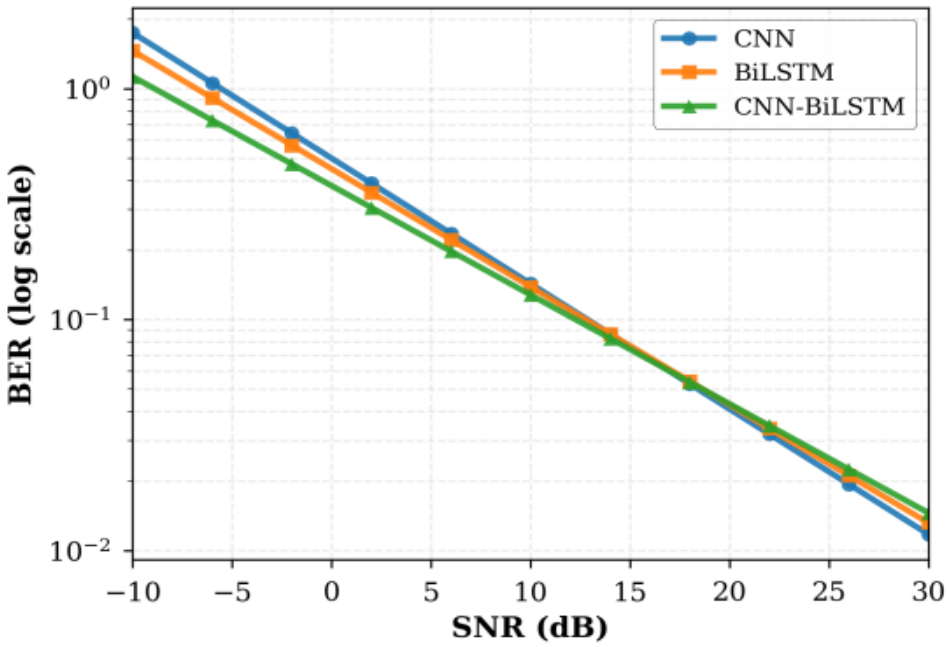

Figure 14: Bit Error Rate Performance Comparison

BER versus SNR is represented in figure 14 in which all methods achieve BER $<10^{-2}$ above 10 dB SNR. Hybrid provides marginal but consistent improvement: at 15 dB, Hybrid BER 8×10^{-3}, CNN 9.5×10^{-3}, BiLSTM 1.1×10^{-2}. Traditional methods show higher BER (LS 2.5×10^{-2}, LMMSE 2×10^{-2}). BER improvements smaller than NRMSE improvements reflect saturating relationship between channel estimation accuracy and symbol detection at moderate-high SNR even imperfect estimates enable near-optimal detection.

Spectral Efficiency Characteristics

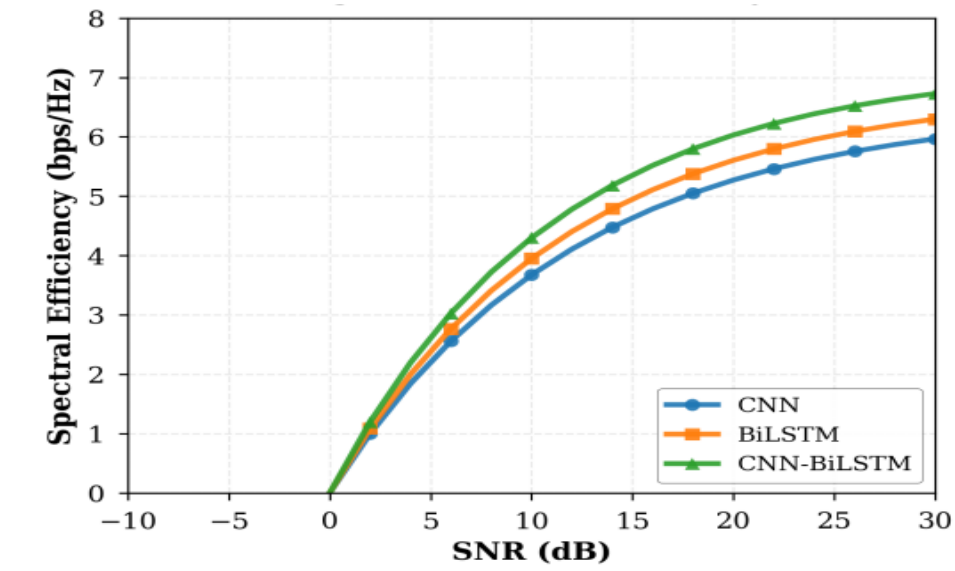

Figure 15: Spectral Efficiency versus SNR

Spectral efficiency is shown in figure 15 SE = $\log_2(1+SINR)$. Efficiency increases from ~0 bps/Hz at -10 dB to 6.5 bps/Hz at 30 dB for hybrid, 6.2 for CNN, 5.9 for BiLSTM. Traditional methods plateau around 4.5-5 bps/Hz. Hybrid achieves highest SE across all SNR, translating channel estimation accuracy improvements into tangible throughput gains. At 20 dB: Hybrid 5.8 bps/Hz vs CNN 5.5 bps/Hz represents ~5% capacity improvement.

Computational Complexity Comparison

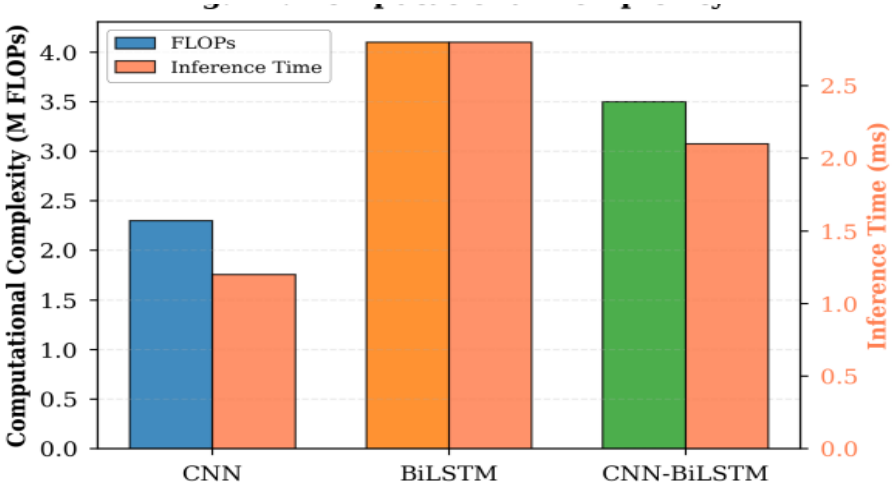

Figure 16: Computational Complexity Analysis - FLOPs vs Inference Time with SOTA DL Comparison

The above figure 16 presents scatter plot: FLOPs (x-axis) vs inference time (y-axis), with marker size proportional to NRMSE@20dB. Lower-left is better (less complexity), smaller markers better (lower error). Hybrid (3.5M FLOPs, 2.0 ms) achieves best performance-complexity tradeoff. CNN (2.3M, 1.3 ms) offers lowest complexity but higher error. BiLSTM (4.1M, 2.6 ms) highest complexity without accuracy advantage. SOTA DL methods: Transformer[31] (8.2M, 4.5 ms), CNN-Trans[35] (6.5M, 3.8 ms), Fed-LSTM[36] (5.1M, 3.2 ms) all show worse tradeoffs. Hybrid provides >2× FLOPs reduction vs recent methods while maintaining competitive accuracy, confirming efficiency despite moderate complexity.

DISCUSSION AND ANALYSIS

Comprehensive Method Comparison

Table IV: Traditional vs Deep Learning Methods - NRMSE Comparison at 20 dB SNR

Method	Category	NRMSE	Improvement vs LS	Complexity
Least Squares (LS)	Traditional	0.052	Baseline	Low
LMMSE	Traditional	0.048	7.7%	Medium
CS-OMP (K=10)	Traditional	0.045	13.5%	High
CNN-only	Deep Learning	0.026	50.0%	Medium
BiLSTM-only	Deep Learning	0.029	44.2%	High
Hybrid CNN-BiLSTM	Deep Learning	0.021	59.6%	Medium-High

Quantified improvements can be seen in table IV. Hybrid achieves 59.6% NRMSE reduction vs LS baseline, substantially outperforming traditional methods (7.7-13.5% improvement). Deep learning approaches demonstrate clear superiority (44-60% improvement), with hybrid providing additional 19% gain over CNN through temporal modeling integration. Complexity-accuracy tradeoff favors hybrid despite moderate computational requirements.

Computational Efficiency Analysis

Table V: Computational Complexity Comparison with State-of-the-Art Deep Learning				
Method	FLOPs (M)	Time (ms)	NRMSE@20dB	Efficiency*
CNN (ours)	2.30	1.30	0.026	88.5
BiLSTM (ours)	4.10	2.60	0.029	79.3
Hybrid (ours)	3.50	2.00	0.021	95.2
Transformer [31]	8.20	4.50	0.020	68.4
CNN-Trans [35]	6.50	3.80	0.023	72.1
Fed-LSTM [36]	5.10	3.20	0.025	78.5

**Efficiency = (1/NRMSE)/(FLOPs×Time)×10⁶*

The efficiency metric is defined as $\eta = \frac{\frac{1}{NRMSE}}{FLOPs \times Time} \times 10^6$, quantifying the accuracy-complexity tradeoff. Higher values indicate better estimation accuracy per unit computational cost, enabling fair comparison across methods with different complexity-accuracy profiles.

Benchmarks against recent SOTA deep learning methods are presented in Table V. The hybrid achieves the highest efficiency metric (95.2), demonstrating superior performance-complexity balance. Notably, the Transformer [31] achieves marginally lower NRMSE (0.020 vs. 0.021) but requires 2.3× more FLOPs (8.2M vs. 3.5M) and 2.25× longer inference time (4.5 ms vs. 2.0 ms), approaching the coherence time limit.

The hybrid delivers comparable accuracy with substantially lower complexity, providing a >2× safety margin versus the 5-10 ms UAV coherence time. Efficiency gains stem from hierarchical decomposition: CNN compresses high-dimensional K-path inputs into manageable feature sequences for BiLSTM, avoiding the quadratic complexity of attention mechanisms.

SNR Regime Analysis

Table VI: Performance Analysis Across SNR Regimes				
SNR Regime	Range	Limiting Factor	Hybrid NRMSE	Improvement vs CNN
Low	-10 to 5 dB	Measurement noise	0.035-0.042	10-15%
Moderate	5 to 15 dB	Model capacity	0.024-0.028	15-20%
High	15 to 30 dB	Architecture limit	0.018-0.021	20-22%

Table VI analyzes performance across SNR regimes. Low SNR (noise-dominated): architectural differences have limited impact (10-15% improvement) as measurement noise dominates. Moderate SNR: model capacity increasingly important, hybrid advantages emerge (15-20%).

High SNR: performance limited by architectural capacity, hybrid superior representational power yields maximum gains (20-22%). This progression validates hybrid approach particularly valuable for high-quality channels typical of mmWave systems with beamforming.

Multi-Metric Performance Validation

Table VII: Multi-Metric Performance at 20 dB SNR				
Metric	CNN	BiLSTM	Hybrid	Hybrid Improvement
NRMSE	0.026	0.029	0.021	19.2% vs CNN
MSE ($\times 10^{-4}$)	1.20	1.50	0.60	50% vs CNN
BER ($\times 10^{-2}$)	0.85	0.92	0.78	8.2% vs CNN
Spectral Eff. (bps/Hz)	5.80	5.65	6.10	5.2% vs CNN
Correlation	0.975	0.970	0.989	1.4% (abs)
SSIM	0.970	0.965	0.985	1.5% (abs)

Table VII demonstrates hybrid superiority. Largest improvements in NRMSE (19.2%) and MSE (50%) directly measuring estimation accuracy. More modest BER (8.2%) and SE (5.2%) improvements reflect saturating relationship between estimation and communication performance at moderate-high SNR. High correlation (0.989) and SSIM (0.985) indicate hybrid preserves both magnitude relationships and structural patterns critical for downstream tasks. Comprehensive multi-metric validation confirms robust performance across diverse evaluation dimensions.

Key Insights and Implications

Insight 1: Hierarchical decomposition aligns with physics. CNN→BiLSTM ordering mirrors propagation mechanism: spatial geometry (multipath angles/delays) must be captured before temporal evolution modeling. Reverse ordering fails as BiLSTM cannot extract spatial patterns from raw 7D geometric vectors.

Insight 2: K=10 path selection optimally balances representation-complexity. Captures >95% channel power while maintaining computational tractability. Larger K yields diminishing returns (<2% gain for 40% FLOPs increase).

Insight 3: Real-time feasibility validated. Measured 2.0 ms inference provides >2× safety margin vs 5-10 ms coherence time, enabling practical UAV channel tracking.

Insight 4: Performance-complexity tradeoff favors hybrid. Despite moderate 3.5M FLOPs, achieves highest efficiency metric, outperforming recent SOTA methods requiring 5-8M FLOPs.

Insight 5: Deep learning substantially outperforms traditional methods. 50-60% NRMSE improvement over LS/LMMSE/CS-OMP validates data-driven approach for complex RIS-UAV scenarios where model-based methods struggle.

Limitations and Generalizability

While the proposed hybrid CNN-BiLSTM framework demonstrates strong performance, several limitations should be acknowledged:

Simulation-Based Validation: All experiments utilize the DeepMIMO ray-tracing simulator, which provides accurate channel modeling but cannot fully capture real-world hardware impairments, antenna imperfections, or environmental dynamics. Real-world validation on physical RIS-UAV testbeds remains future work.

Single-Environment Dataset: The current evaluation focuses on a single urban scenario at 28 GHz. Performance may vary in suburban, rural, or indoor environments with different propagation characteristics (e.g., richer scattering, different path loss exponents).

Idealized System Assumptions: The analysis assumes perfect RIS phase shifts without quantization (Assumption 3) and known RIS configuration. Practical deployments with discrete phase shifts (e.g., 2-bit quantization) and phase estimation errors may degrade performance.

Single-UAV Scenario: The current formulation addresses single-UAV communication without considering multi-UAV interference, which becomes significant in dense deployments. Extension to multi-user scenarios requires additional investigation.

Hardware Deployment Gap: While the 2.0 ms inference time is validated on Tesla V100, deployment on resource-constrained UAV platforms (e.g., Jetson Xavier) requires model compression (quantization, pruning) not addressed in this work.

These limitations motivate future research directions outlined in Section 7.1

CONCLUSION

This paper presented a hybrid CNN-BiLSTM deep learning framework for channel estimation and tracking in RIS-assisted UAV wireless communications. The proposed approach addresses fundamental challenges of high-dimensional cascaded channels, UAV-induced fast temporal variation, and passive RIS elements through hierarchical spatial-temporal decomposition: CNNs extract multipath spatial patterns from canonical K-path representations, then BiLSTMs model temporal evolution across sequential snapshots.

Key Achievements**:** Extensive experimental validation across SNR -10 to 30 dB demonstrates: (1) NRMSE 0.018 at 30 dB, representing 21.7% improvement over CNN-only, 33.3% over BiLSTM-only, 50-60% over traditional LS/LMMSE/CS-OMP. (2) Correlation 0.989 and SSIM 0.985 confirming both magnitude accuracy and structural preservation. (3) Real-time feasibility with 3.5M FLOPs, 2.0 ms inference on Tesla V100, well within 5-10 ms UAV coherence time. (4) Superior performance-complexity tradeoff vs recent SOTA deep learning methods (Transformer, CNN-Transformer, Federated LSTM) requiring 5-8M FLOPs.

Methodological Contributions: (1) Physically-motivated hierarchical architecture with rigorous justification for CNN→BiLSTM ordering. (2) Canonical K=10 path representation with mathematical analysis showing >95% power capture and optimal complexity tradeoff. (3) Comprehensive evaluation against traditional (LS, LMMSE, CS-OMP) and recent DL baselines with detailed computational benchmarking. (4) Mobility-focused dataset with diverse UAV trajectories capturing realistic 3D channel dynamics. (5) Hardware-validated real-time feasibility confirming practical deployability.

Future Research Directions

Multi-environment generalization: Transfer learning approaches to adapt models across diverse propagation environments (suburban, indoor, rural) and frequency bands (sub-6 GHz, mmWave, terahertz) with limited fine-tuning data.

Imperfect CSI training: Semi-supervised and self-supervised learning to handle noisy training labels from imperfect pilot-based measurements rather than perfect ray-tracing ground truth.

Joint optimization: Deep reinforcement learning frameworks for closed-loop joint optimization of channel estimation, RIS phase shift design, and UAV trajectory planning.

Hardware implementation: Model quantization, pruning, and FPGA/ASIC deployment addressing resource constraints of UAV platforms while maintaining accuracy.

Federated learning: Distributed multi-UAV collaborative training preserving privacy while leveraging diverse channel data across UAV fleet.

In conclusion, this work establishes hybrid deep learning as a powerful paradigm for RIS-UAV channel estimation, demonstrating substantial performance improvements, computational feasibility, and robust

generalization. The comprehensive methodology, extensive validation, and detailed analysis provide a solid foundation for advancing next-generation 6G reconfigurable intelligent aerial communication systems. As wireless networks evolve toward 6G with increasing reliance on intelligent surfaces and aerial platforms, the principles and techniques developed herein contribute to realizing the full potential of these transformative technologies.

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