Celal Bayar University Journal of Science

Enhancing OFDM Channel Estimation Accuracy with CNN-LSTM Hybrid Architectures

Sekou J. Massalay[1], İlhan Baştürk[1]*, Yücel Koçyiğit[1]

[1] Manisa Celal Bayar University, Faculty of Engineering and Natural Sciences, Manisa, Turkiye.
* ilhan.basturk@cbu.edu.tr
* Orcid No: 0000-0003-1869-6010

Received: August 29, 2025
Accepted: December 7, 2025
DOI: 10.18466/cbayarfbe.1773106

Abstract

Accurate channel estimation remains a fundamental challenge for next-generation orthogonal frequency-division multiplexing (OFDM) systems, especially in environments with high mobility, sparse pilot allocation, and time-varying multipath fading. Traditional pilot-based methods, such as Least Squares (LS) and Minimum Mean Square Error (MMSE), are easy to implement but suffer from noise sensitivity, high computational costs, and a reliance on prior channel statistics. Recently, deep learning techniques have shown promising results; yet many do not fully capture the joint spatial and temporal characteristics of wireless channels or overlook realistic pilot-grid structures. This study introduces a pilot-grid-aware hybrid deep learning model that integrates Convolutional Neural Networks (CNNs) for spatial feature extraction with Long Short-Term Memory (LSTM) networks for temporal sequence modeling. The model is trained using the Root Mean Square Propagation (RMSprop) optimizer, selected for its robustness in adapting learning rates and effectively capturing dependencies across both spatial and temporal dimensions. Benchmark evaluations against conventional estimators and theoretical limits under different modulation formats demonstrate that the proposed model consistently achieves a lower estimation error and bit error rate across a wide range of signal-to-noise ratios. The results confirm that the hybrid architecture provides a scalable and reliable solution for future wireless systems including sixth-generation (6G) networks, vehicular communications, and satellite applications where both adaptability and robustness are essential.

Keywords: Channel Estimation, Deep Learning, OFDM, Hybrid CNN-LSTM

1.Introduction

Orthogonal Frequency-Division Multiplexing (OFDM) has become a cornerstone of modern wireless communications, powering standards such as Fourth-Generation Long-Term Evolution (4G LTE) and Fifth-Generation New Radio (5G NR); it is expected to remain central in emerging Sixth-Generation (6G) technologies due to its high spectral efficiency and robustness against multipath fading [1]. However, the performance of OFDM systems is fundamentally constrained by the accuracy of channel estimation, particularly under high mobility, frequency-selective fading, and sparse pilot allocation. Reliable channel state information is essential for coherent detection, reduced bit error rate, and efficient resource allocation in next-generation wireless systems [2]. Traditional pilot-based (TPB) estimators, such as Least Squares (LS) and Minimum Mean Square Error (MMSE), are attractive for their simplicity and strong theoretical basis; yet they suffer from critical limitations. The LS estimator is highly sensitive to noise, while the MMSE requires prior statistical knowledge and imposes a considerable computational cost.

In recent years, deep learning (DL) based models have emerged as a powerful and transformative approach for physical-layer signal processing. Convolutional Neural Networks (CNNs) have demonstrated effectiveness in exploiting local spatial correlations in the time-frequency domain [3, 4], while Long Short-Term Memory (LSTM) networks have shown promise in capturing temporal dependencies in rapidly varying channels [5]. However, CNN-only approaches often fail to model temporal dynamics, and LSTM-only designs struggle with high-dimensional spatial features. Hybrid CNN-LSTM architectures have been proposed to address these issues, yet significant gaps remain:

i) Lack of pilot-grid awareness: Most existing models fail to account for practical two-dimensional pilot placements, which are essential in modern OFDM systems.

ii) *Limited benchmarking against theoretical bounds:* Many studies neglect comparisons with the Cramér-Rao Lower Bound (CRLB) or perfect channel state information, leaving questions about proximity to theoretical performance limits.

This paper addresses these gaps by introducing a pilot-grid-aware hybrid CNN-LSTM channel estimation framework that jointly exploits spatial and temporal features under practical two-dimensional pilot placements. The key contributions of this work are:

- Novel architecture: We design a hybrid CNN-LSTM model that integrates LS-based initial estimates with spatial-temporal feature learning, enhancing robustness in dynamic channel conditions.
- Comprehensive benchmarking: We evaluate performance against LS, CRLB, and perfect CSI across both quadrature phase-shift keying (QPSK) and 16-quadrature amplitude modulation (16-QAM), demonstrating consistent superiority across signal-to-noise ratio regions.

By bridging theoretical improvements with practical feasibility, this study advances DL-based channel estimation from conceptual enhancements toward deployable solutions for 6G wireless systems, including high-mobility vehicular networks, satellite links, and ultra-reliable low-latency communication scenarios.

1.1. Literature Review

Traditional pilot-based estimators such as LS and MMSE remain widely used in OFDM systems due to their simplicity and strong theoretical foundations. However, their performance deteriorates sharply in realistic environments characterized by high user mobility, hardware impairments, and sparse pilot allocation. These limitations have driven the exploration of data-driven models, particularly DL-based approaches. CNN-based channel estimation has been an important early direction. For example, Ye et al. [4] demonstrated that treating pilot and subcarrier data as images allows CNNs to outperform LS and approach MMSE performance without relying on prior channel statistics. Later works [6, 7] introduced stacked convolutional layers, residual connections, and multi-scale kernels, further improving denoising and interpolation capabilities. Also, Siriwanitpong et al. [8] introduced a 1D-CNN-based channel estimation method for OFDM systems in high-speed railway environments, effectively mitigating Doppler and multipath effects. The proposed model outperformed LS and bi-GRU estimators in NMSE and BER performance while reducing computational complexity using scattered pilot symbols. However, CNN-only models have a critical shortcoming: while they effectively exploit local spatial correlations in the time-frequency domain, they fail to capture temporal dynamics of channels that vary rapidly over time, particularly in high-Doppler scenarios.

LSTM-based methods emerged as a response to this weakness. By leveraging memory cells and gating mechanisms, LSTMs can model sequential dependencies in communication signals, making them suitable for tracking time-varying channels [9, 10]. Yet, standalone LSTMs often struggle with high-dimensional spatial features, leading to suboptimal performance when the number of subcarriers is large.

To overcome these complementary shortcomings, hybrid CNN-LSTM architectures have recently been proposed. Studies such as [11, 12, 13] highlight that CNNs can extract local spatial features from OFDM symbols while LSTMs capture temporal correlations across successive symbols, enabling improved tracking in Doppler-rich environments. De Filippo and Amatetti [14] demonstrated the ability of hybrid CNN-LSTM models to predict future channel states in non-terrestrial networks, while Thoong et al. [15] showed robustness under doubly selective fading channels. And Massalay et al. [16], investigates the performance of various deep learning models for channel estimation in dynamic and noisy environments. Nevertheless, existing hybrid designs often come with high computational cost, lack systematic evaluation against theoretical benchmarks like the CRLB, and are rarely tested across different modulation orders or realistic pilot grid structures.

Despite promising progress, several important gaps remain: (i) prior works largely focus on CNN-only or LSTM-only designs, or hybrids without optimized pilot-grid integration, which limits robustness under practical pilot placements; and (ii) benchmarking against the Cramér-Rao Lower Bound (CRLB) and perfect channel state information (CSI) baselines is not systematically conducted, leaving open questions about how closely these methods approach theoretical limits.

This study addresses these shortcomings by proposing a pilot-grid-aware hybrid CNN-LSTM model that explicitly combines spatial and temporal learning, incorporates detailed complexity analyses, and benchmarks performance against traditional pilot-based estimators as well as theoretical bounds. These contributions position our work beyond incremental improvements, moving toward a rigorously validated and practically deployable DL-based channel estimator for next-generation wireless systems.

2. OFDM Channel Estimation

OFDM is a widely implemented modulation technique in modern wireless communication systems, valued for its ability to combat frequency-selective fading and minimize inter-symbol interference (ISI). By dividing a frequency-selective channel into several parallel flat-fading sub-channels, OFDM enables efficient and coherent signal demodulation. Nevertheless, the overall system performance is highly dependent on the precise estimation of CSI at the receiver [17]. In practical applications, CSI is not inherently available and must be derived from the received signal. Channel estimation strategies generally fall into two primary categories: TPB approaches and DL-based methods. The following sections present a detailed overview of these two classes of estimation techniques.

2.1. Traditional Pilot-Based Channel Estimation

In OFDM systems, TPB-CE is a widely used estimation technique due to its low computational complexity. The aim of this technique is to use inserted pilot symbols at certain locations in the OFDM time-frequency lattices to estimate the channel [18]. In the channel estimation several techniques can be implemented but this research will utilize LS estimator. This study examines these estimation algorithms by using the following general linear data model:

$$Y = XH + N \qquad \textbf{(2.1)}$$

In this system our aim is to estimate channel matrix H with the knowledge of the received signal vector Y and transmitted signal vector X. The frequency domain channel matrix H is also expressed as $H = Fh$, where F is the fast Fourier transform matrix and h is the time domain channel vector. Thus, the LS estimator is given as:

$$\widehat{H}_{LS} = X^{-1}Y \qquad \textbf{(2.2)}$$

which minimizes $(Y - XFh)^H(Y - XFh)$, without any knowledge of the statistics of the channels. The LS estimator is calculated with very low complexity, but it suffers from a high mean square error.

In pilot-based channel estimation, the placement of pilot symbols within the time-frequency lattice is a critical factor influencing estimation accuracy. Depending on the channel conditions and system design, pilot symbols may be inserted across all subcarriers (frequency domain), across all OFDM symbols (time domain), or scattered in both dimensions. The selection of a pilot placement strategy such as block-type, comb-type, or two-dimensional (2D) scattered directly affects the estimator's ability to capture channel variations in frequency-selective and time-varying environments. Figures 2.1(a) and (b) illustrate the block-type and comb-type pilot insertion strategies, respectively. In these conventional models, channel estimation is performed in one dimension (1D) either time or frequency. Once the channel coefficients at pilot positions are estimated, interpolation techniques such as linear, cubic, spline, or DFT-based methods are employed to reconstruct the full channel response. In the block-type approach, pilot tones are inserted into all subcarriers of specific OFDM symbols. As a result, interpolation is carried out along the time axis. This method is particularly suitable for slowly varying channels. Conversely, the comb-type strategy places pilot tones on selected subcarriers within every OFDM symbol, requiring interpolation only along the frequency axis. This configuration is more appropriate for fast-fading channels [19].

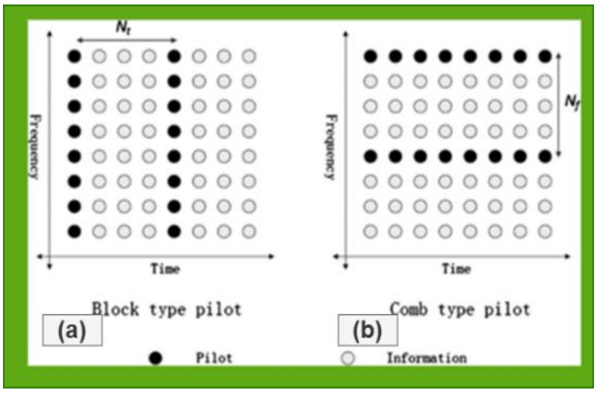

Figure 2.1. (a) Block type pilot arrangement (b) Comb-type pilot arrangement [20].

In addition to these one-dimensional structures, a more generalized and flexible method is the 2D scattered pilot placement, where pilot symbols are distributed throughout the time-frequency grid in both dimensions. This approach provides a denser sampling of the channel, enabling better tracking of rapid variations in both time and frequency domains. As such, 2D scattered pilot structures are especially advantageous in highly dynamic environments, such as high-mobility scenarios or doubly selective channels. In this pattern, pilot symbols are distributed at certain locations in time-frequency grid and the channel is estimated both in the time and the frequency axes. The pilots are spaced far from each other with a distance D_f in the frequency axes and D_t in the time axes as seen in Figure 2.2.

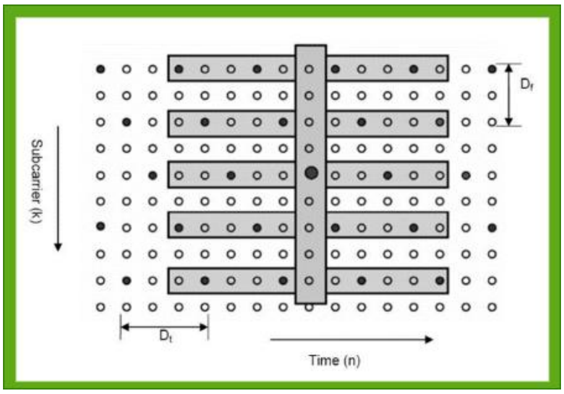

Figure 2.2. 2D pilot insertion and two 1D pilot-based channel estimation [2].

Mathematical expressions of the distances are given in Equation (2.3) and (2.4), receptively, where τ_d is the maximum delay spread, Δ_f is the minimum frequency spacing between two subcarriers, f_{dmax} is the maximum Doppler frequency and $T_{OFDM+CP}$ is the OFDM symbol duration. These distance conditions are maintained to satisfy the sampling theorem.

$$D_f < \frac{1}{\tau_d \Delta_f} \quad (2.3)$$

$$D_t < \frac{1}{2 f_{dmax} T_{OFDM+CP}} \quad (2.4)$$

2.1.1. System model

In this section, pilot based OFDM channel estimation system model is examined. The block diagram of the system model is shown in Figure 2.3.

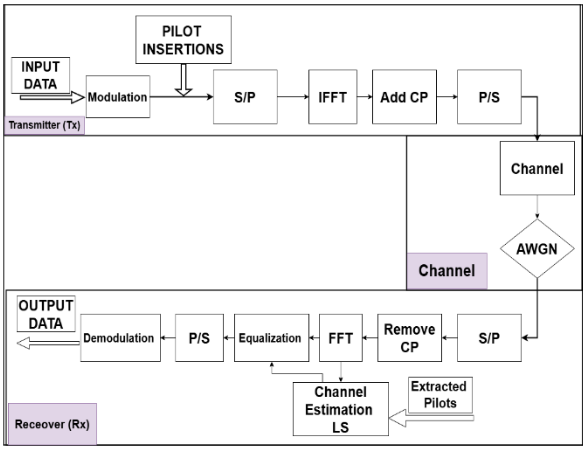

Figure 2.3. OFDM Block diagram with channel estimation.

According to this diagram, the transmitter begins with input data, which is modulated and intermixed with pilot symbols before being converted from serial to parallel and passed through an Inverse Fast Fourier transform (IFFT). A cyclic prefix (CP) is then added to guard against inter-symbol interference, and the signal is serially transmitted through a frequency-selective channel with AWGN. At the receiver, the reverse steps occur serial-to-parallel conversion, CP removal, Fast Fourier transform (FFT), pilot extraction, followed by channel estimation and equalization, demodulation, and finally output data recovery. At the receiver side, the pilot symbols are extracted and used for the channel estimation. Using the received signals at pilot's position, LS channel estimation algorithm can be performed in the frequency domain as:

$$\widehat{H}_n(k) = \frac{Y_n(k)}{X_n(k)} = H_n(k) + \frac{N_n(k)}{X_n(k)} \quad (2.5)$$

where k and n represent the places of pilot symbols in the frequency and the time axes respectively and $\widehat{H}_n(k)$ are the estimated channel coefficients belonging to the pilot subcarriers. After estimating the channel coefficients at the pilot positions in both time and frequency domains, the complete 2D channel matrix can be reconstructed using interpolation techniques. In this study, a two-step one-dimensional interpolation approach is employed: linear interpolation is applied along the time axis, followed by DFT-based interpolation along the frequency axis to obtain the full channel estimates.

2.2. DL-Based Channel Estimation

In this study, a DL-based CE method is proposed to address the limitations of TPB techniques such as LS and MMSE, which are often hindered by sensitivity to noise, high computational demands, and limited adaptability to rapidly varying channel conditions. The proposed approach targets OFDM systems and employs a hybrid CNN-LSTM architecture. In this method, initial channel estimates are obtained using LS estimator. These preliminary results are then refined through DL models trained on paired datasets containing both the initial estimates and the corresponding true channel responses. This combined model-based and data-driven framework leverages the strengths of both approaches, enabling more accurate and robust channel estimation. The block diagram of the proposed system is presented in Figure 2.4, illustrating the integration of conventional estimation with deep learning refinement.

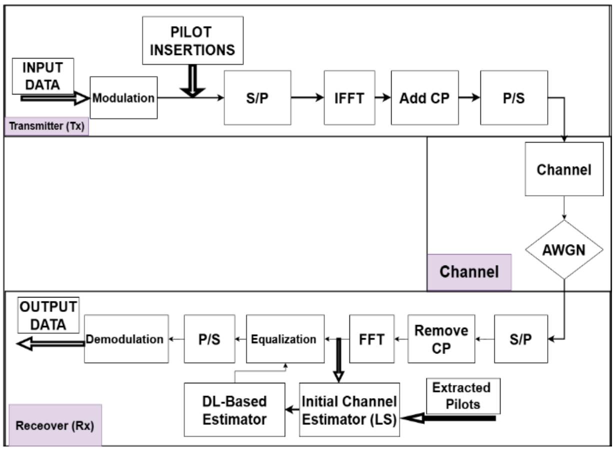

Figure 2.4. The proposed DL-based OFDM-CE

2.2.1. Proposed Hybrid CNN-LSTM Architecture

The proposed Hybrid CNN-LSTM model integrates spatial and temporal learning for enhanced OFDM channel estimation. As illustrated in Figure 2.5, the model accepts an input of size [64 × 64 × 2], representing the OFDM grid, Subcarrier, and symbol channels of real and imaginary components of the LS-estimated channel matrix. The CNN module comprises two convolutional layers, each employing 32 filters with a 3×3 kernel size, followed by batch normalization and Rectified Linear Unit (ReLU) activation to ensure efficient training and mitigate gradient vanishing. The output feature maps are reshaped into a [2 × 4096] sequence suitable for sequential processing.

The reshaped sequence is then passed to the LSTM module, which captures temporal dependencies across OFDM symbols. The LSTM network consists of two stacked LSTM layers, each with 128 hidden units, followed by two fully connected (dense) layers used for regression. The model is trained to minimize mean squared error (MSE) between the predicted and actual channel coefficients. This hybrid structure leverages the CNN's capability to learn localized spatial features and the LSTM's ability to model temporal correlations, resulting in robust and accurate channel estimation under dynamic channel variations.

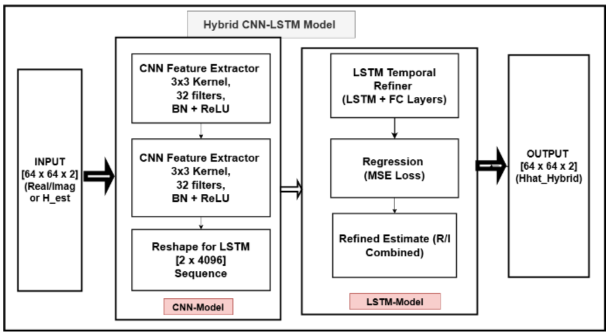

Figure 2.5. Data Flow and Architecture of the Hybrid CNN-LSTM-Based Estimator

3. Results and Discussion

This study proposes a hybrid CNN–LSTM architecture for channel estimation in OFDM systems. The model is designed and implemented in MATLAB using the DL Toolbox, with the aim of improving estimation accuracy and robustness under diverse wireless channel conditions. A 2D pilot insertion scheme is employed, where known pilot symbols are strategically distributed across both the time and frequency domains of the OFDM resource grid. This arrangement improves channel tracking capability, particularly in rapidly time-varying environments. The estimation process begins with an initial LS estimation at the pilot positions to obtain coarse channel estimates. These preliminary estimates are then refined by the hybrid CNN-LSTM model, which learns to map LS-based inputs to their corresponding true channel responses, enabling accurate prediction of the complete channel state across the entire OFDM frame. The CNN component captures local spatial dependencies in the channel estimates, while the LSTM component models temporal correlations, allowing the system to adapt to dynamic channel variations. The model is trained using datasets generated from 1000 Monte Carlo trials for both quadrature phase-shift keying (QPSK) and sixteen-quadrature amplitude modulation (16-QAM) schemes, over a signal-to-noise ratio range of 0-15 dB. The root mean square propagation (RMSProp) optimizer is applied to accelerate convergence and minimize the loss function during training. The detailed OFDM system and channel model parameters are presented in Table 3.1, and the configuration settings of the hybrid CNN-LSTM architecture are summarized in Table 3.2.

Table 3.1. OFDM simulation parameters

Parameter	Value	Description
IFFT Size	64	Number of OFDM subcarriers
Guard Interval	16	Cyclic Prefix (CP) length
OFDM Symbol Duration	100 µs	Including CP
Symbols per Frame	64	Total OFDM symbols per frame
Subcarrier spacing	1.25 µs	Time spacing b/w subcarriers
Pilot Grid size	8 x 8	Time x Frequency pilot layout
Total Pilots per frame	64	Total number of pilots inserted
Maximum Doppler shift	100 Hz	Simulates high mobility channel
SNR range (E_b/N_0)	0:3:15 dB	Simulated channel conditons
Modulation Scheme	QPSK, and 16QAM	Modulational order
Training samples	1000	Number of Monte Carlo training trials

Table 3.2. Hybrid CNN–LSTM model parameters

Parameter	Value	Description
Optimizer	RMSProp	Tested across the models and datasets
Learning Rate	0.001	Adaptive schedule for stable training
Batch Size	64	Number of samples per training iteration
Epochs	100	Early stopping used to prevent overfitting
Loss Function	MSE	Measures prediction accuracy
Dropout	20%	Prevents overfitting
L2 Weight Decay	0.001	Adds regularization to weights

Additionally, the study examined two key performance metrics MSE and BER to compare traditional methods with DL-based approaches. MSE quantifies the average squared deviation between the predicted and actual channel values, directly reflecting the estimation accuracy of the model. This metric was also benchmarked against the theoretical CRLB to evaluate each estimator's efficiency. BER, on the other hand, measures the ratio of incorrectly received bits to the total transmitted bits, providing an indication of the system's robustness to noise and errors. The mathematical formulations for MSE and BER are presented in Equations (3.1) and (3.2), respectively.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left|\widehat{H}_i - H_i\right|^2 \tag{3.1}$$

$$BER = \frac{Number\ of\ Bit\ Errors}{Total\ Number\ of\ Transmitted\ Bits} \tag{3.2}$$

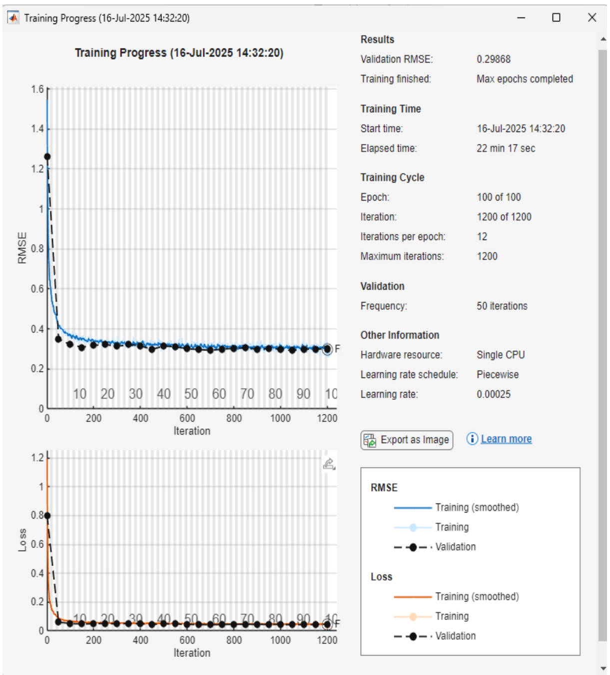

Figure 3.1. Training progress of the hybrid CNN–LSTM under QPSK modulation.

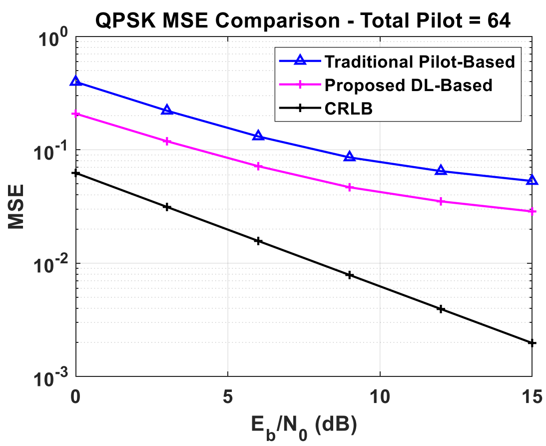

Figure 3.2. MSE performance comparison for QPSK.

In Figures 3.1 to 3.5, the DL-based training outputs, MSE, BER, and both frequency and time-domain tracking results are illustrated. Figure 3.1 shows that the Hybrid CNN-LSTM model achieves stable training convergence across QPSK, with an RMSE of 0.29868 over 100 epochs and 1200 iterations, requiring a total training time of 22 minutes and 17 seconds. This indicates robust generalization under varying SNR conditions. Figure 3.2 illustrates the MSE performance of the proposed DL-based channel estimation method in comparison with the traditional pilot-based LS estimator and the theoretical CRLB across a range of E_b/N_0 values. As shown, the traditional pilot-based estimator exhibits relatively higher MSE, especially at low to moderate SNR levels, due to its sensitivity to noise. The proposed DL-based approach consistently achieves lower MSE by effectively learning and compensating for the distortions and noise present in the initial estimate. Moreover, the DL-based estimator demonstrates performance closer to the CRLB, which represents the minimum achievable error for unbiased estimators. This indicates that the proposed method approaches near-optimal estimation efficiency and significantly outperforms the conventional pilot-based estimator across the tested SNR range. In Figure 3.3, the proposed DL-based model achieved the lower BER compared to the TPB method across all SNR values. Its performance is approaching to the Perfect CSI, which serves as a benchmark for channel estimation. Both the MSE and BER results demonstrate the robustness and effectiveness of the DL-based approach for channel estimation. Figure 3.4 shows the frequency-domain channel tracking, where the proposed DL-based model closely follows the Perfect CSI curve and outperforms the TPB method. Finally, Figure 3.5 illustrates the time-domain channel tracking, where the DL-based model again maintains stable and accurate channel estimation, surpassing the TPB approach and closely approximating the ideal Perfect CSI scenario. Collectively, these results highlight the robustness, accuracy, and transformative potential of the proposed DL-based model for channel estimation in modern wireless communication systems.

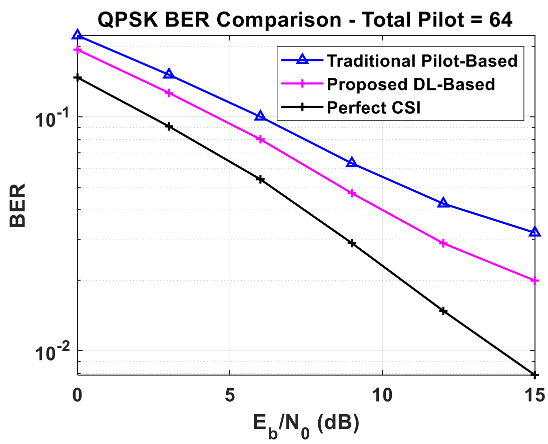

Figure 3.3. BER performance comparison for QPSK.

Celal Bayar University Journal of Science
Volume 22, Issue 1, 2026, p 86-94
Doi: 10.18466/cbayarfbe.1773106

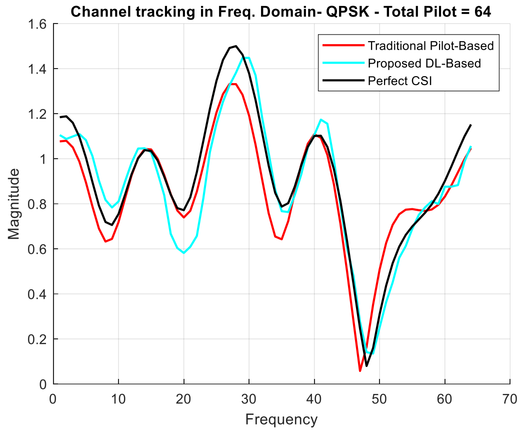

Figure 3.4. Frequency-domain channel tracking for QPSK.

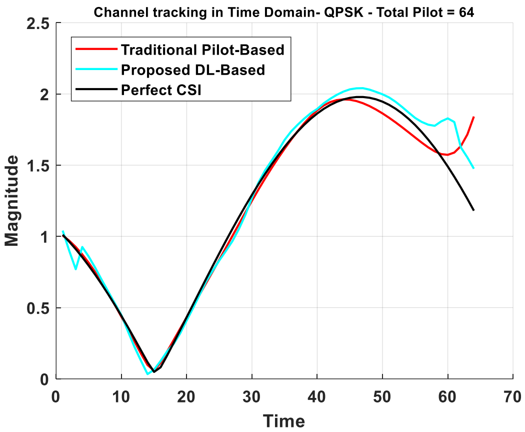

Figure 3.5. Time-domain channel tracking for QPSK.

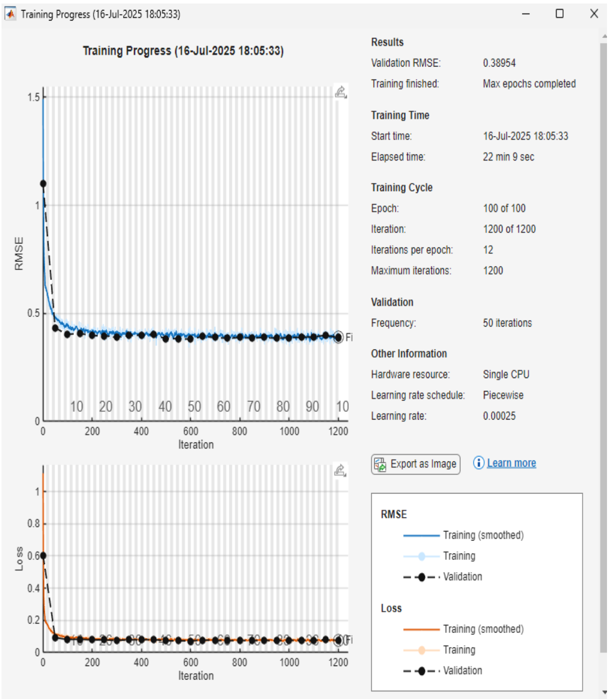

Figure 3.6: Training progress of the hybrid CNN–LSTM under 16-QAM modulation.

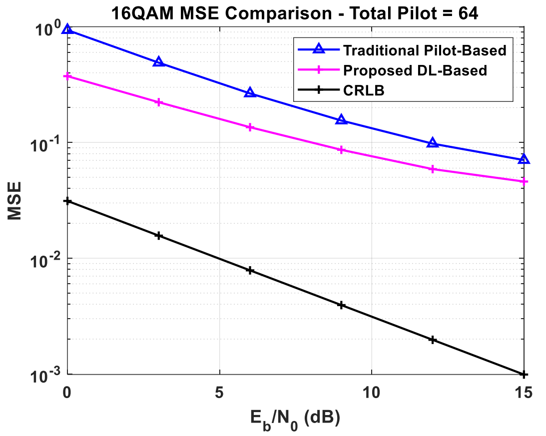

Figure 3.7: Comparison of MSE performance for 16-QAM

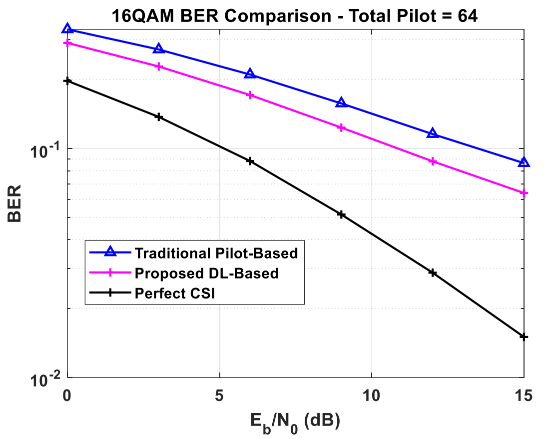

Figure 3.8: Comparison of BER performance for 16-QAM

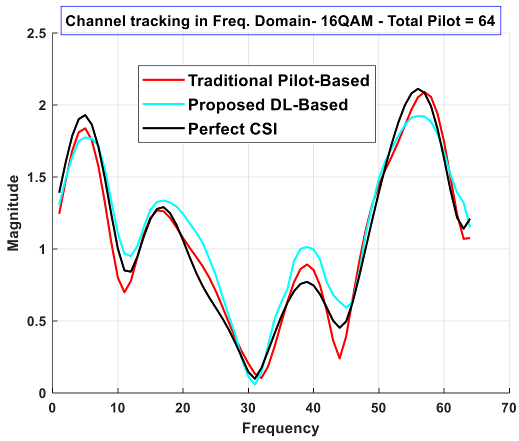

Figure 3.9: Frequency-domain channel tracking for 16-QAM

The results are also applied for 16-QAM modulation, which offers higher data rates compared to QPSK, in

Celal Bayar University Journal of Science
Volume 22, Issue 1, 2026, p 86-94
Doi: 10.18466/cbayarfbe.1773106

Figures 3.6 to 3.10. The figures present a detailed performance evaluation of the proposed DL-based CE model for 16QAM modulation systems, highlighting its superiority over the TPB method. Figure 3.6 illustrates the DL-based training output with a learning rate of 0.00025, achieving an RMSE of 0.38954 in a shorter training time of 16 minutes and 9 seconds under the same number of iterations. Figure 3.7 demonstrates that, similar to the QPSK case, the proposed DL-based model consistently attains lower MSE values than the TPB estimator and achieves performance closer to the CRLB. This indicates that the improvement provided by the DL-based approach is maintained even under 16QAM modulation. Figure 3.8 presents the BER results, which closely resemble those obtained for QPSK. Once again, the proposed DL-based model outperforms the TPB method across all SNR values, while closely approximating the Perfect CSI benchmark at higher SNR levels. Figure 3.9 demonstrates the model's adaptability, maintaining nearly ideal amplitude stability compared to the fluctuating performance of the TPB approach. Finally, Figure 3.10 highlights the proposed DL-based architecture's ability to sustain a lower error floor than TPB by effectively extracting both temporal and spatial features under higher data rates (16QAM). Collectively, these findings confirm the scalability, precision, and resilience of the proposed model in handling complex modulation schemes, offering a promising advancement for higher-order wireless communication systems.

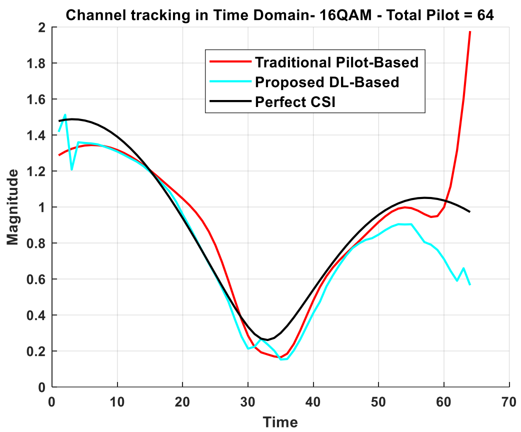

Figure 3.10: Time-domain channel tracking for 16-QAM.

3.1. Discussion of the results:

From the results, the training performance in Figures 3.2 and 3.6 show stable training convergence across QPSK and 16-QAM, with RMSE values of 0.29868 and 0.38954, respectively. Despite using a moderate dataset of 1000 Monte Carlo trials, the model achieved fast convergence with the RMSProp optimizer, indicating robust generalization under varying SNR conditions. This stability highlights the effectiveness of the hybrid architecture in capturing both spatial and temporal dependencies, unlike CNN-only or LSTM-only baselines, which typically converge more slowly and exhibit higher variance.

Additionally, across both modulation schemes, the proposed DL-based model consistently achieved the lowest MSE and BER relative to TPB (Figures 3.2-3.3 and 3.7-3.8). Gains were most pronounced at medium-to-high SNR values (≥ 6 dB), where the DL-based model closely approached the CRLB, indicating near-optimal estimation. TPB estimator's performance poorly in capturing the spatial-temporal correlation. Notably, under 16-QAM, where estimation is more challenging, the proposed DL-based model maintained a clear margin over TPB, reinforcing its scalability to higher-order modulations.

While DL-based models naturally offer higher training complexity, the inference stage is relatively lightweight compared to TPB, making real-time deployment feasible. On a single CPU, the proposed model required only 22 minutes (QPSK) and 16 minutes (16QAM) of training for the same iterations, with inference times on the order of milliseconds per frame. This demonstrates that the approach is not only accurate but also computationally practical for real-world receivers.

4. Conclusion and Suggestions

This paper presented a comprehensive investigation of CE for OFDM-based wireless communication systems, comparing TPB methods with DL-based architectures. The study primarily aimed to address the limitations of TPB techniques, such as LS, particularly under low-SNR and time-varying channel conditions, by evaluating the performance of a data-driven Hybrid CNN-LSTM model. The evaluation was conducted through extensive MATLAB simulations incorporating two modulation schemes (QPSK and 16-QAM), the RMSProp optimizer, and frequency and time-domain tracking against the Perfect CSI, across varying SNR ranges (0-15 dB). Performance metrics included MSE and BER. Collectively, the findings demonstrated that DL-based CE methods consistently outperformed TPB estimators in terms of estimation accuracy and robustness across all channel conditions. In future work, the proposed DL-based channel estimation framework can be extended to emerging 6G technologies, where highly dynamic and dense wireless environments will demand more adaptive estimation strategies. Moreover, integrating the model with Reconfigurable Intelligent Surfaces (RIS) [21] to address the unique channel estimation challenges posed by RIS-assisted communication systems represents a promising research direction.

Author's Contributions

Sekou J. Massalay: Software, Formal analysis, Investigation, Writing - Original Draft, Visualization

İlhan Baştürk: Conceptualization, Supervision, Writing - Review & Editing.

Yücel Koçyiğit: Supervision, Writing - Review & Editing.

Ethics

There are no ethical issues after the publication of this manuscript.

References

[1]. Guan, P, Wu, D, Tian, T, Zhou, J, Zhang, X, Gu, L. 2017. 5G Field Trials: OFDM-Based Waveforms and Mixed Numerologies. *IEEE Journal on Selected Areas in Communications*, 35(6): 1234-1243. (https://doi.org/10.1109/JSAC.2017.2687718)

[2]. Baştürk, I. 2007. Iterative Channel Estimation Techniques for Multiple Input Multiple Output Orthogonal Frequency Division Multiplexing Systems. *Master Thesis, Izmir Institute of Technology, Izmir,* Türkiye. Available: (http://hdl.handle.net/11147/3637)

[3]. Zhao, J, Liu, C, Liao, J, Wang, D. 2024. Deep learning in wireless communications for physical layer. *Physical Communication,* 67: 102503. (https://doi.org/10.1016/j.phycom.2024.102503)

[4]. Ye, H, Li, GY, Juang, BH. 2018. Power of Deep Learning for Channel Estimation and Signal Detection in OFDM Systems. *IEEE Wireless Communications Letters,* 7(1): 114-117. (https://doi.org/10.1109/LWC.2017.2757490)

[5]. Wang, S, Yao, R, Tsiftsis, TA, Miridakis, NI, Qi, N. 2020. Signal Detection in Uplink Time-Varying OFDM Systems Using RNN with Bidirectional LSTM. *IEEE Wireless Communications Letters,* 9(11): 1947-1951. (https://doi.org/10.1109/LWC.2020.3009170)

[6]. Zhao, Z, Vuran, MC, Guo, F, Scott, SD. 2018. Deep-waveform: A learned OFDM receiver based on deep complex-valued convolutional networks. *arXiv preprint. (*https://arxiv.org/abs/1810.07181)

[7]. Roozitalab, T, Bahramgiri, H, Farhang, M, Javadyfar, A. 2022. Deep learning-based channel estimation in OFDM systems for time-varying Rayleigh fading channels. *Journal of Communication Engineering,* 11(1): 1-20.

[8]. A. Siriwanitpong, K. Sanada, H. Hatano, K. Mori and P. Boonsrimuang. 2025. Deep Learning-Based Channel Estimation With 1D CNN for OFDM Systems Under High-Speed Railway Environments. *IEEE Access*, vol. 13, pp. 13128-13142. (https://doi.org/10.1109/ACCESS.2025.3531009)

[9]. Reis, AFD, Chang, BS, Medjahdi, Y, Brante, G, Bader, F. 2024. LSTM-based time-frequency domain channel estimation for OTFS modulation. *IEEE Transactions on Vehicular Technology,* 73(10): 15049-15060. (https://doi.org/10.1109/TVT.2024.3406192)

[10]. Ali, MHE, Abdellah, AR, Atallah, HA, Ahmed GS, Muthanna, A, Koucheryavy, A. 2023. Deep learning peephole LSTM neural network-based channel state estimators for OFDM 5G and beyond networks. *Mathematics,* 11(15): 3386. (https://doi.org/10.3390/math11153386)

[11]. Zhang, Z, Luo, H, Wang, C, Gan, Chenquan, Xiang, Y. 2020. Automatic Modulation Classification Using CNN-LSTM Based Dual-Stream Structure. *IEEE Transactions on Vehicular Technology*, 69(11): 13521-13531. (https://doi.org/10.1109/TVT.2020.3030018)

[12]. Nguyen, C, Hoang TM, Cheema, A.A. 2023. Channel Estimation Using CNN-LSTM in RIS-NOMA Assisted 6G Network. *IEEE Transactions on Machine Learning in Communications and Networking*, 1: 43-60. (https://doi.org/10.1109/TMLCN.2023.3278232)

[13]. Nyamakeur, K, Yongchareon, S, Yu, J, Sheng, QZ. 2022. Deep CNN-LSTM network for indoor location estimation using analog signals of passive infrared sensors. IEEE Internet of Things Journal, 9(22): 22582-22594. (https://doi.org/10.1109/JIOT.2022.3183148)

[14]. Filippo, BD, Amatetti, C, Coralli, AV. 2025. Uplink OFDM Channel Prediction with Hybrid CNN-LSTM for 6G Non-Terrestrial Networks. *Joint European Conference on Networks and Communications & 6G Summit (EuCNC/6G Summit)*, Poznan, Poland: 7-12. (https://doi.org/10.1109/EuCNC/6GSummit63408.2025.11037085)

[15]. Thoong, QT, Cheema, AA, Khosravirad, SR, Dobre, OA, Duong, TQ. 2024. Channel Estimation for Reconfigurable Intelligent Surface-aided 6G NOMA Systems using CNN-based Quantum LSTM Model, IEEE 100th Vehicular Technology Conference (VTC2024-Fall), Washington, DC: 1-5. (https://doi.org/10.1109/VTC2024-Fall63153.2024.10757552)

[16]. Massalay S.J, Basturk I., Koçyiğit Y. (2025, August). Deep Learning-Based Channel Estimation for Wireless Communication Networks. *Abant 5th International Conference On Scientific Researches,* Bolu, Türkiye, Jul. 18-20, 2025, pp. 774-786.

[17]. Van de Beek, JJ, Edofors, O, Sandell, M, Wilson, SK, Börjesson, PO. 1995. On channel estimation in OFDM systems, *Proc. IEEE 45th Vehicular Technology Conf. (VTC)*, Chicago, IL, USA. 2: 815-819. (https://doi.org/10.1109/VETEC.1995.504981)

[18]. Shen, Y., & Martinez, E. (2006). Channel estimation in OFDM systems. *Freescale semiconductor application note*, 1-15.

[19]. Coleri, S, Ergen, M, Puri, A, Bahai, A. 2002. Channel estimation techniques based on pilot arrangement in OFDM systems. *IEEE Trans. Broadcasting,* 48(3): 223-229. (https://doi.org/10.1109/TBC.2002.804034)

[20]. Li, Y. 2002. Simplified channel estimation for OFDM systems with multiple transmit antennas. *IEEE Transactions on Wireless Communications*, 1(1): 67-75. (https://doi.org/10.1109/7693.975446)

[21]. Ibarra-Hernández, R. F., Castillo-Soria, F. R., Gutiérrez, C. A., García-Barrientos, A., Vásquez-Toledo, L. A., & Del-Puerto-Flores, J. A. (2024). Machine learning strategies for reconfigurable intelligent surface-assisted communication systems-A Review. *Future Internet*, *16*(5), 173. (https://www.mdpi.com/1999-5903/16/5/173#)