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Deep Learning Based Channel State Estimation and Signal Detection for Orthogonal Frequency Division Multiplexing Wireless Systems

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Abstract: Orthogonal Frequency Division Multiplexing (OFDM) remains the dominant waveform for broadband wireless systems such as Wi-Fi, LTE/5G NR variants, and IoT links. Accurate channel state information (CSI) and robust symbol detection are crucial for optimal OFDM receiver performance. In recent years, deep learning (DL) techniques both purely data driven and model-driven (hybrid) have shown significant potential in improving channel estimation (CE) and signal detection, especially under severe channel impairments, nonlinearities, and hardware imperfections. This paper presents a comprehensive review of the state of the art in deep-learning-based CSI estimation and signal detection for OFDM systems. It summarizes conventional estimation techniques (LS, MMSE), explains various DL architectures (CNNs, RNNs/LSTMs, Transformers, and unfolded networks), and examines model-driven hybrid approaches such as COMNET, CSNET, and unfolded DETNET-style frameworks. Additionally, it discusses commonly used datasets and evaluation metrics, compares reported performances, highlights practical deployment challenges (including computational complexity, generalization ability, dataset bias, and model interpretability), and outlines promising future research directions such as meta-learning, domain adaptation, lightweight inference, and end-to-end joint estimation–detection learning.

The review consolidates and analyses 25 representative references encompassing foundational studies, methodological papers, surveys, and recent advancements in this rapidly evolving research area.

Keywords*:* OFDM, Channel Estimation, Signal Detection, Deep Learning, CNN, RNN, Model-Driven Deep Learning, Unfolded Networks, MIMO

I. INTRODUCTION

Orthogonal Frequency Division Multiplexing (OFDM) divides a wideband channel into multiple narrowband subcarriers, simplifying equalization in frequency-selective fading channels. Receiver tasks include channel estimation (to compensate amplitude/phase on each subcarrier) and signal detection (to recover the transmitted symbols). Classical estimators such as Least Squares (LS) and Minimum Mean Square Error (MMSE) are widely used but have limitations under NON-IDEALITIES (fast time-variations, phase noise, carrier frequency offset (CFO), nonlinear power amplifiers, hardware impairments, and short pilot budgets). Deep learning (DL) promises to learn complex mappings from pilot/received patterns to CSI or symbol decisions without requiring exact channel models, and to exploit structure in time–frequency patterns. Interest in DL for physical-layer tasks rose sharply after pioneering surveys and demonstrations that communications can be reframed as learning tasks (autoencoder concept) and that learned components can surpass or complement conventional modules. This paper focuses specifically on DL methods for channel state estimation and signal detection in OFDM (single- and multi-antenna). We cover architectures, training strategies, representative algorithms, datasets, evaluation metrics, benefits and limitations, and research directions. Deep learning (DL) promises to learn complex nonlinear mappings and to exploit structure from data; early works showed DL-based OFDM receivers can implicitly learn CSI and directly detect symbols, matching or surpassing classical methods in certain operating regimes. This paradigm has since expanded to model-driven deep unfolding networks (which blend expert knowledge with learning) and specialized architectures for time-varying channels and MIMO-OFDM scenarios.

II. CONVENTIONAL CHANNEL ESTIMATION & DETECTION (BASELINE)

- LS Estimator**:** simple inversion at pilot subcarriers; interpolated across subcarriers/time. Low complexity but high MSE in noise.
- MMSE estimator: uses previous channel statistics along with observations to minimize MSE; needs to know the covariance of the channel and is more complicated.
- Detection: Zero Forcing (ZF), MMSE linear detectors, and maximum likelihood (ML) detection for small dimensions; in MIMO settings, sphere decoding provides near-ML performance but with high complexity.

III. WHY DEEP LEARNING FOR OFDM CE & DETECTION?

Key drivers:

- Model mismatch & NON-IDEALITIES: Real channels and RF front-ends create distortions that are not fully captured in standard linear models, and DL can learn the residuals. [1]
- Exploiting structure: Time–frequency CSI forms images convolutional layers can exploit local correlations. [2]
- Joint tasks & end-to-end optimization: DL enables joint learning of estimation, detection, and even pilot placement, potentially improving global performance. [1]
- Unfolding existing algorithms: Iterative algorithms (e.g., gradient descent, expectation propagation) can be unfolded into NN layers for faster learned convergence (Det Net, learned ISTA/AMP families). The conceptual foundation for DL at the physical layer and for specific receiver modules these are important context for the field. [3]

IV. CATEGORIES OF DEEP LEARNING APPROACHES

We classify methods into three broad families:

- Pure data-driven (black-box) approaches. These treat CE/detection as regression/classification. Examples: deep MLPs that take received pilots/time–Frequency maps and output CSI CNNs treating CSI as 2-D images; RNN/LSTMs for time-varying channels. Advantages flexible disadvantages need large “LABELED” datasets, limited interpretability. [1]

- Model-driven (hybrid) approaches. Combine domain knowledge with learning. Examples: COMNET and CSNET (DL modules combined with MMSE/LMMSE or known signal processing blocks) and unfolded networks where iterations of an algorithm become NN layers with learned parameters. These often achieve robust performance and reduced training data needs. [4]

- End-to-end learning (autoencoder) approaches. Jointly learn transmitter and receiver mappings to optimize end-to-end error rates. Useful for discovering unconventional modulation or coding challenging for regulatory and interoperability reasons. [3]

V. ARCHITECTURES & REPRESENTATIVE METHODS

- CNN-based Channel Estimation: Treats pilot-scattered channel matrices as images; applies super-resolution or denoising CNNs to interpolate CSI CNNs (SR-based), showing improved MSE over LS/MMSE under pilot sparsity. [2]
- RNN / LSTM for Time-Varying Channels: LSTMs capture temporal correlation for channels varying over OFDM symbols. They can predict CSI for future OFDM symbols (channel prediction) and improve robustness under Doppler. [5]
- Unfolded / Learned Iterative Detectors: DETNET (unfolded projected-gradient descent) for MIMO detection is an influential example; it converts iterations into NN layers and learns parameters to accelerate convergence and improve BER. Variants adapt to OFDM MIMO settings COMNET / CSNET (Model-Driven Receiver) COMNET splits the receiver into an initial conventional estimator (e.g., LS/MMSE) followed by learned refinement networks. CSNET extends this idea to CE + SD modules with coupling between them. These hybrid models often outperform purely data-driven methods while retaining interpretability.
- Transformers & Attention: Transformers (self-attention) can capture global dependencies across subcarriers/time. Recent research applies attention layers for joint channel estimation and detection, particularly beneficial when long-range correlations exist (e.g., correlated scattering).
- Auto encoder & End-to-end: Design combined transmitter/receiver neural network optimizing end-to-end reconstruction. While promising, these approaches face challenges in standard compliance and generalization to unseen channels.

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VI. DATASETS, TRAINING & EVALUATION PROTOCOLS

Datasets & Simulation Environments: Most work uses Datasets & Simulation Environments: Most work uses synthetic channels: Rayleigh/ Rician fading, Jakes' Doppler models, ETSI/ 3GPP standardized channel models (EPA/ETU/ETRA/ITU-e.g., 3GPP SCM/TDL models), and measured channel traces where available. For MIMO and massive MIMO experiments, realistic correlation models and antenna arrays are used. Some papers release code/datasets; however, the lack of standardized public benchmarks is a challenge for fair comparison.

VII. SIMULATION RESULTS

He proposed DL-GRU-based CSE outperforms all other estimators in the simulated scenario with 64 pilots and no cyclic prefix (CP), as illustrated in Fig. 8. The results also show that the BILSTM model achieves performance comparable to that of the MMSE estimator. In contrast, the LS estimator continues to exhibit the poorest performance among all compared methods. These observations are consistent with the findings reported in "Deep Learning-Based Channel Estimation in OFDM Systems for Time-Varying Rayleigh Fading Channels" [7].

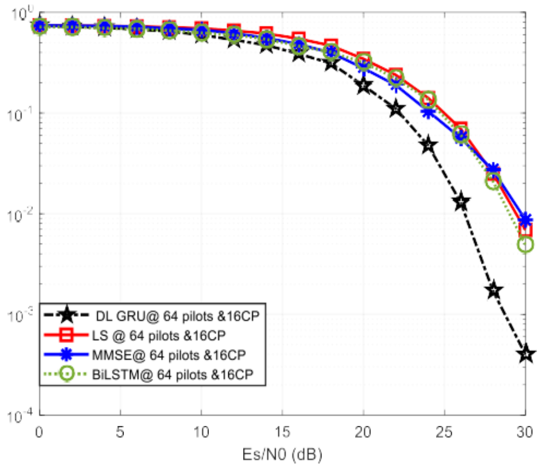

Fig. 6. SER performance curves of the proposed DL GRU model and the different estimators with 64 pilots and a CP length of 16 using the Adam optimizer and cross-entropy loss function [1]

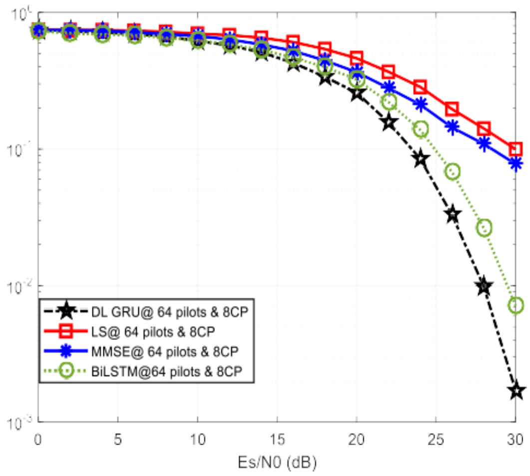

Fig. 7. SER performance curves of the proposed DL GRU model and the different estimators with 64 pilots and a CP length of 8 using the Adam optimizer and cross-entropy loss function.

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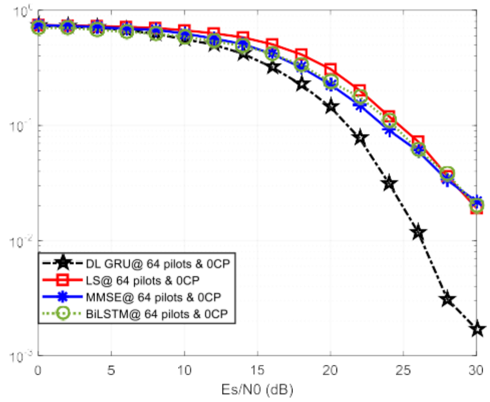

Fig. 8. SER performance curves of the proposed DL GRU model and the different estimators with 64 pilots and without CP using the Adam optimizer and cross-entropy loss function.

It is evident from Figures 6, 7, and 8 that the LS estimator consistently exhibits the worst SER performance in all cases because its estimation method does not rely on any prior knowledge of channel statistics. In contrast, the MMSE estimator utilizes the mean and covariance matrices (second-order channel statistics), resulting in better performance than its LS counterpart.

In all scenarios, the SER performance of the proposed DL-GRU-based CSE is superior to that of the two traditional methods and the DL-BILSTM model presented in [21, 22]. This demonstrates the effectiveness of the proposed DL-GRU structure in jointly estimating the channel state and detecting transmitted symbols. The GRU layer architecture allows it to retain previously processed information more efficiently than the DL-BILSTM model, leading to improved accuracy. Furthermore, these results confirm the robustness of the proposed DL-GRU structure, even with short or no cyclic prefix (CP).

Figure 9 illustrates the performance of the different estimation methods when the number of pilots is limited to 8 and the CP length is 16. As shown, the proposed DL-GRU-based CSE significantly outperforms the other estimators, starting from an SNR of 7 DB. Both LS and MMSE estimators fail to efficiently estimate the channel information under these conditions.

When the CP length decreases to 8, as shown in Figure 10, the proposed DL-GRU estimator continues to deliver the best performance among all compared methods. In contrast, the SER curves of the traditional MMSE and LS estimators saturate at SNR values exceeding 10 DB.

Finally, in the simulation scenario with 8 pilots and no CP (Figure 11), the DL-GRU-based CSE still achieves the best SER performance compared to its counterparts. Additionally, the DL-BILSTM model performs similarly to the MMSE estimator, while the LS estimator once again provides the poorest performance.

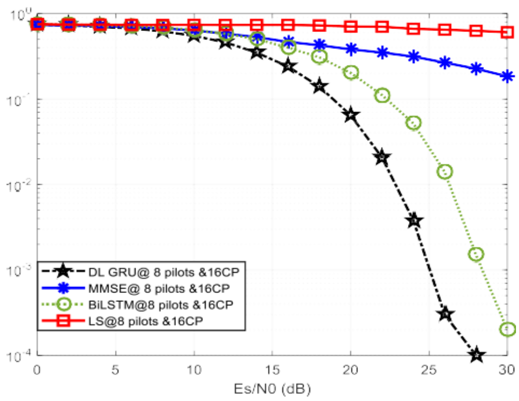

Fig. 9. SER performance curves of the proposed DL GRU model and the different estimators with 8 pilots and a CP length of 16 using the Adam optimizer and cross-entropy loss function.

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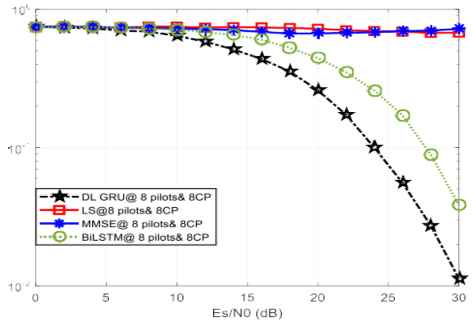

Fig. 10. SER performance curves of the proposed DL GRU model and the different estimators with 8 pilots and a CP length of 8 using the Adam optimizer and cross-entropy loss function.

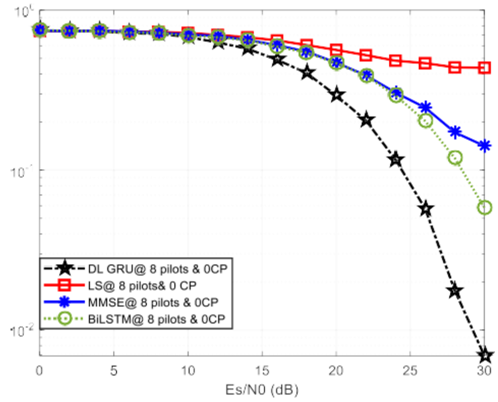

Fig. 11. SER performance curves of the proposed DL GRU model and the different estimators with 8 pilots and without CP using the Adam optimizer and cross-entropy loss function.

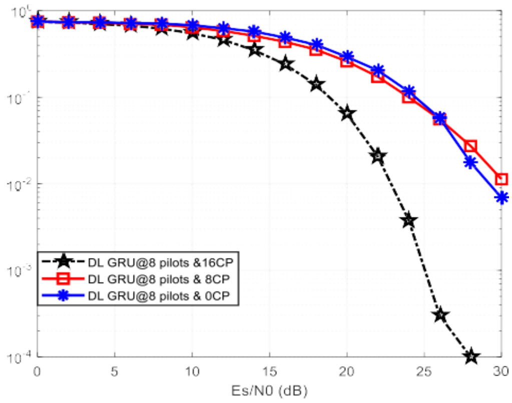

Fig. 12. SER performance of the proposed DL GRU framework at 8 pilots and CP lengths of 16, 8, and zero using the Adam optimizer and cross-entropy loss function

The performance of the proposed DL-GRU-based CSE with 8 pilots and different CP lengths (16, 8, and 0) is summarized in Fig. 12. At low SNR values, it can be observed that the proposed DL-GRU architecture with short or no CP achieves similar performance over the SNR range of 0–8 DB. Furthermore, the DL-GRU model with CP exhibits fewer variations across the SNR range (8–14 dB) compared to its counterpart without CP.

The loss function plays a crucial role in developing and enhancing the performance of deep learning algorithms. A lower loss function value corresponds to better overall performance. In general, a deep learning model is trained using an optimizer that minimizes the loss function by computing the error between the expected and predicted outputs of the CSE. In the proposed DL-GRU model, three loss functions are utilized in the classification layer to evaluate and optimize network performance.

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The Adam optimization algorithm is employed to train the proposed DL-GRU network, with different loss functions applied in the final layer to determine the most efficient and robust version of the proposed DL-GRU-based CSE/SD model.

Figure 13 shows that with 8 pilots, a CP length of 16, and Adam optimization, the proposed DL-GRU structure with a cross-entropy-based classification layer achieves performance comparable to that of the SSE- and MAE-based classification layer models at low SNR ranges (0–10 dB) and (0–7 dB), respectively. Beyond these SNR values, the proposed DL-GRU model with the cross-entropy-based classification layer outperforms both SSE- and MAE-based models, whereas the MAE-based model exhibits the lowest performance.

When the CP length decreases to 8, as illustrated in Fig. 14, the proposed DL-GRU structure with the SSE-based classification layer demonstrates superior performance, while the cross-entropy model still outperforms the MAE-based model. In the simulation scenario with 8 pilots and no CP, the proposed DL GRU model with cross-entropy-, SSE-, and MAE based classification layers exhibits comparable performance across the SNR range of 0–20 dB, as shown in Fig. 15. Beyond this range, the cross entropy-based model achieves better performance than the SSE and MAE models.

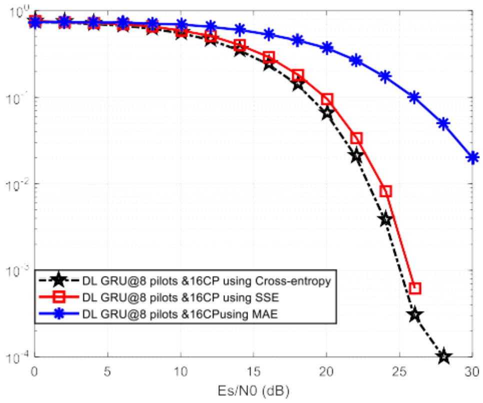

Fig. 13. SER performance of the proposed DL GRU model at 8 pilots and a CP length of 16 by using the Adam optimizer and various loss functions.

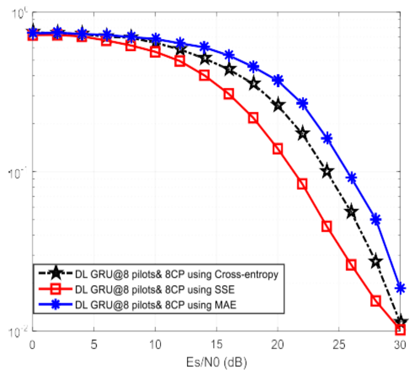

Fig. 14. SER performance of the proposed DL GRU model at 8 pilots and a CP length of 8 by using the Adam optimizer and various loss functions.

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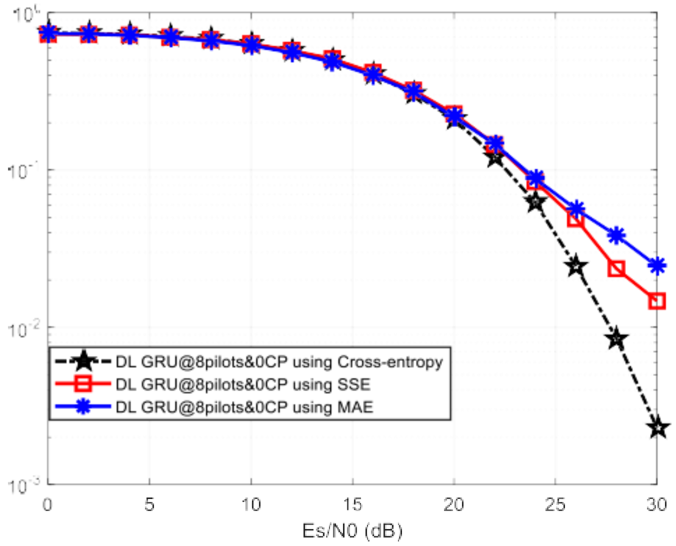

Fig. 15. SER performance of the proposed DL GRU model at 8 pilots and without CP using the Adam optimizer and various loss functions.

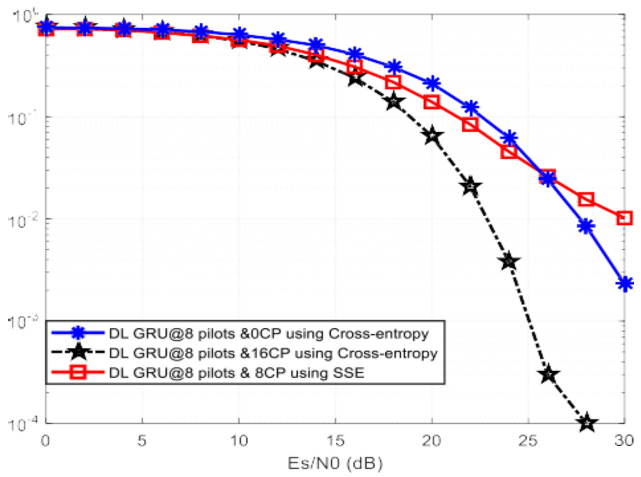

Fig. 16. SER performance comparison of the best GRU-based DL model with a limited number of pilots (8 pilots) using different lengths of CP and various loss functions.

VIII. FUTURE DIRECTIONS

1. Meta-learning and Domain Adaptation. Models that quickly adapt to new channels with few samples mitigate retraining costs. (Few-shot or meta-trained CE/detectors.)
2. Self-supervised & Unsupervised Learning. Exploit received data without explicit CSI labels using consistency losses, pilot masking, or generative models.
3. Lightweight Architectures & Quantization. Design compressed NNs (pruning, quantization, knowledge distillation) for real-time baseband deployment.
4. Joint Pilot Design & Learning. Learn pilot placement and resource allocation jointly with CE/detection networks for sample-efficient signalling.

30

5. Hybrid Model-Data Methods & Uncertainty Quantification. Combine physics-based priors with learning and provide reliability/confidence outputs (crucial for safety).
6. Benchmarks & Open Datasets. Community efforts to create standardized OFDM CE/detection benchmarks (various SNRs, Dopplers, hardware impairments) will enable fair comparisons.

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IX. CONCLUSION

The deep learning (DL) architecture based on gated recurrent unit (GRU) neural networks has been proposed for channel state estimation (CSE) and signal detection (SD) applications. The proposed deep learning neural network (DLNN) operates in an end-to-end manner, jointly performing CSE and SD tasks in orthogonal frequency division multiplexing (OFDM) wireless communication systems. The proposed DL GRU framework is trained offline using received OFDM signals that have been subjected to various channel impairments before being deployed online to extract or recover the transmitted data symbols. Extensive simulations have been conducted to evaluate the performance of the proposed DL GRU structure and to demonstrate its efficiency for CSE and SD functions when compared with conventional LS and MMSE estimation methods, as well as the DL-based BILSTM model. Moreover, the simulation results highlight the importance of exploring different loss functions to obtain the most effective configuration of the proposed DL GRU framework. For future work, the proposed DL GRU based CSE/SD model will be extended to more complex system configurations, such as multiple-input multiple-output (MIMO) environments.

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