International Journal of Electronic and Electrical Engineering.
ISSN 0974-2174 Volume 19, Number 1 (2026), pp. 1-4

http://www.irphouse.com

Deep Learning-Based Signal Processing for Next-Generation Wireless Systems: A Review of Channel Estimation and Detection Techniques

Dr Ch Navitha
Assistant Professor
Department of Electronics and Communication Engineering,
Chaitanya Bharathi Institute of Technology,
Hyderabad

Abstract

The physical layer of wireless communication systems has traditionally relied on model-driven signal processing grounded in well-characterized channel statistics. Emerging 6G scenarios, including terahertz transmission, integrated sensing and communication, and ultra-massive multiple-input multiple-output (MIMO) arrays, introduce nonlinearities and propagation effects that stress this model-driven paradigm. This paper reviews the progression of deep learning-based signal processing at the physical layer, organized around two stages of adoption: module-level replacement, in which neural networks substitute or augment individual blocks such as channel estimation and signal detection, and system-level reconstruction, in which the transmitter-receiver chain is trained end to end as a single differentiable autoencoder. Representative architectures for channel estimation, including convolutional and model-driven hybrid networks, are summarized alongside deep learning-based detection methods. The paper closes with a discussion of open challenges, including interpretability, data dependence, computational complexity, and privacy in distributed learning settings, and identifies directions for continued research.

Keywords: deep learning, signal processing, channel estimation, signal detection, autoencoder, MIMO, 6G, physical layer

I. INTRODUCTION

Classical wireless signal processing rests on a model-driven foundation: channels are represented through statistical models, and receivers are designed as sequences of well-understood blocks such as channel estimation, equalization, detection, and decoding, each optimized under simplifying assumptions like linearity or Gaussian noise. This approach has served the field well through successive cellular generations, but the propagation and hardware conditions anticipated for 6G, including terahertz-band transmission, ultra-massive MIMO arrays, and integrated sensing and communication

(ISAC), introduce a degree of nonlinearity, high dimensionality, and model mismatch that increasingly strains closed-form, statistically-derived solutions.

Deep learning offers an alternative that is data-driven rather than purely model-driven: given sufficient representative training data, a neural network can approximate complex, nonlinear mappings between received signals and the quantities of interest, such as channel state information or transmitted symbols, without requiring an explicit closed-form channel model. Over the past several years, this idea has moved from isolated proof-of-concept studies to a broader research program spanning individual receiver components and, more recently, fully learned end-to-end transceivers.

This paper reviews that progression. Section II contrasts the model-driven and data-driven paradigms. Section III discusses deep learning approaches to channel estimation. Section IV reviews signal detection and end-to-end autoencoder-based system design. Section V discusses open challenges, and Section VI concludes.

II. FROM MODEL-DRIVEN TO DATA-DRIVEN SIGNAL PROCESSING

Recent surveys frame the adoption of deep learning in the physical layer as occurring in two broad stages. In the first stage, module-level replacement, individual functional blocks of the conventional transceiver, most commonly channel estimation and signal detection, are replaced or augmented by neural networks while the overall modular receiver architecture is preserved. This stage is the most mature body of work, with several techniques approaching practical deployment because they can be inserted into existing receiver pipelines with limited redesign. In the second stage, system-level reconstruction, the entire transmitter-receiver chain is treated as a single differentiable neural network and trained jointly, an approach commonly realized through autoencoder architectures that learn both the encoding and decoding mappings directly from data, without being constrained to mimic any specific conventional block structure.

III. DEEP LEARNING FOR CHANNEL ESTIMATION

Channel estimation is one of the most extensively studied applications of deep learning in the physical layer, in part because channel state information errors propagate through every downstream processing stage. Early work applied convolutional neural networks (CNNs) directly to time-frequency channel grids, treating channel estimation as an image super-resolution or denoising problem; this approach was shown to improve estimation accuracy over conventional least-squares and linear minimum mean-square-error (LMMSE) estimators, particularly at low pilot density. Subsequent work explored model-driven hybrid networks that unfold classical iterative estimation algorithms, such as approximate message passing, into a fixed number of learnable layers, combining the interpretability and sample efficiency of the model-based approach with the flexibility of a trained network.

More recent studies extend these ideas to challenging deployment scenarios, including beamspace estimation for millimeter-wave massive MIMO systems, wideband estimation for frequency-selective channels, and joint estimation of the cascaded transmitter-to-surface and surface-to-receiver channels in reconfigurable intelligent surface (RIS)-assisted links, where the effective channel dimension scales with the number of surface elements. Comparative studies report that learned estimators can outperform LMMSE-based baselines under pilot-limited or non-stationary conditions, though the reported gains are sensitive to the degree of similarity between training and deployment channel statistics.

IV. DEEP LEARNING FOR SIGNAL DETECTION AND END-TO-END SYSTEMS

Beyond channel estimation, deep learning has been applied to signal detection, where neural detectors are trained to recover transmitted symbols directly from received signals, in some cases outperforming classical zero-forcing or minimum mean-square-error detectors under imperfect channel state information or hardware impairments such as phase noise and nonlinearity. Detector architectures explored in the literature range from feedforward and recurrent networks to networks that unfold iterative detection algorithms in a manner analogous to model-driven channel estimation.

The more ambitious system-level reconstruction stage treats the transmitter, channel, and receiver as a single computational graph and trains the transmitter's encoding and the receiver's decoding jointly, typically by modeling the channel as a differentiable layer during training. This end-to-end autoencoder framing removes the need to hand-design a modulation and coding scheme separately from the receiver algorithm that decodes it, and has been reported to adapt more gracefully to hardware nonlinearities and non-standard channel conditions than block-wise designs. The approach remains more experimental than module-level replacement, since it typically requires either an accurate differentiable channel model for offline training or an online training procedure conducted over an actual radio link.

V. OPEN CHALLENGES

Several challenges continue to limit the transition of deep learning-based physical layer techniques from simulation to deployment. Interpretability remains a central concern: unlike classical estimators derived from explicit statistical assumptions, a trained network's decision process is difficult to certify or audit, which is a practical obstacle in safety- or reliability-critical deployments. Data dependence is a related issue, since a network trained on one channel distribution, deployment geometry, or hardware platform may degrade sharply when conditions shift, motivating research into domain generalization and online adaptation. Computational complexity and inference latency must also be weighed against the gains achieved, particularly for techniques intended to run on power- and latency-constrained user equipment rather than at the base station. Finally, where training relies on data gathered across multiple devices or operators, privacy and security considerations in distributed or federated learning settings introduce additional design constraints, including robustness to poisoned or adversarial training updates.

VI. CONCLUSION

Deep learning has moved from an exploratory tool to an increasingly standard component of physical layer signal processing research, progressing from targeted replacement of individual receiver blocks toward fully learned, end-to-end transceiver designs. Channel estimation and signal detection remain the most mature application areas, with model-driven hybrid architectures offering an attractive balance between the sample efficiency of classical algorithms and the flexibility of learned mappings. Realizing the full potential of this line of work in 6G systems will depend on resolving open questions around interpretability, generalization across deployment conditions, computational cost, and privacy-preserving training, each of which remains an active area of ongoing research.

References

[1] "The Deep Learning Evolution in Wireless Physical Layer Communications: Applications, Challenges, and Evolutionary Directions," Sensors, vol. 26, no. 11, 3609, 2026.

[2] H. Ye, G. Y. Li, and B.-H. Juang, "Power of Deep Learning for Channel Estimation and Signal Detection in OFDM Systems," IEEE Wireless Communications Letters, vol. 7, no. 1, pp. 114–117, Feb. 2018.

[3] H. He, C.-K. Wen, S. Jin, and G. Y. Li, "Deep Learning-Based Channel Estimation for Beamspace mmWave Massive MIMO Systems," IEEE Wireless Communications Letters, vol. 7, no. 5, pp. 852–855, Oct. 2018.

[4] M. Borgerding, P. Schniter, and S. Rangan, "AMP-Inspired Deep Networks for Sparse Linear Inverse Problems," IEEE Transactions on Signal Processing, vol. 65, no. 16, pp. 4293–4308, Aug. 2017.

[5] D. Neumann, T. Wiese, and W. Utschick, "Learning the MMSE Channel Estimator," IEEE Transactions on Signal Processing, vol. 66, no. 11, pp. 2905–2917, Jun. 2018.

[6] P. Jiang, C.-K. Wen, S. Jin, and G. Y. Li, "Dual CNN-Based Channel Estimation for MIMO-OFDM Systems," IEEE Transactions on Communications, vol. 69, no. 9, pp. 5859–5872, 2021.

[7] N. K. Kundu and M. R. McKay, "Channel Estimation for Reconfigurable Intelligent Surface Aided MISO Communications: From LMMSE to Deep Learning Solutions," IEEE Open Journal of the Communications Society, vol. 2, pp. 471–487, 2021.

[8] X. Wang, J. Kim, Y. Liang et al., "A Survey of Artificial Intelligence Enabled Channel Estimation Methods: Recent Advance, Performance, and Outlook," Artificial Intelligence Review, vol. 58, no. 1, 11202, 2025.

[9] N. Samuel, T. Diskin, and A. Wiesel, "Deep MIMO Detection," in Proc. IEEE SPAWC, Sapporo, Japan, Jul. 2017, pp. 1–5.

[10] S. Park, O. Simeone, and J. Kang, "End-to-End Fast Training of Communication Links Without a Channel Model via Online Meta-Learning," in Proc. IEEE SPAWC, Atlanta, GA, USA, May 2020, pp. 1–5.

[11] W. Jin, H. He, C.-K. Wen, S. Jin, and G. Y. Li, "Adaptive Channel Estimation Based on Model-Driven Deep Learning for Wideband mmWave Systems," in Proc. IEEE GLOBECOM, 2021, pp. 1–6.

[12] "Domain Generalization in Machine Learning Models for Wireless Communications: Concepts, State-of-the-Art, and Open Issues," arXiv:2303.08106, 2023.