Electronics, Communications, and Computing Summit
Vol. 3, No. 2, Apr - Jun 2025, pp. 76-82
ISSN: 3107-8222, DOI: https://doi.org/10.17051/ECC/03.02.10

Deep Learning-Based Joint Channel Estimation and Equalization for IRS-Assisted Multi-Hop Wireless Networks

Charpe Prasanjeet Prabhakar[1], Moti Ranjan Tandi[2]

[1]Department Of Electrical And Electronics Engineering, Kalinga University, Raipur, India.
Email: charpe.prasanjeet.prabhakar@kalingauniversity.ac.in
[2]Assistant Professor, Department of CS & IT, Kalinga University, Raipur, India.
Email: ku.MotiRanjanTandi@kalingauniversity.ac.in

Article Info

Article history:

Received : 18.04.2025
Revised : 24.05.2025
Accepted : 23.06.2025

Keywords:

Intelligent Reflecting Surfaces (IRS),
Multi-Hop Wireless Networks,
Deep Learning,
Channel Estimation,
Signal Equalization,
End-to-End Learning,
Cascaded Channel Modeling,
Bit Error Rate (BER) Optimization,
Recurrent Neural Networks (RNN),
Convolutional Neural Networks (CNN),
IRS Phase Shift Optimization,
Wireless Communication,
Energy-Efficient Networking,
Next-Generation Networks (6G),
Robust Signal Processing.

ABSTRACT

In this paper, the new deep learning framework of joint channel estimation and signal equalization in Intelligent Reflecting Surface (IRS) assisted multi-hop wireless networks is proposed. IRS technology has also demonstrated an immense capability to improve signal propagation dynamic modification of the wireless environment especially in some complex multi-hop environments where conventional communication links can experience intense attenuation and fading. Nonetheless, the cascaded and dynamic IRS-assisted links come with much difficulty in the accurate estimation of channels and remedying inter-hop distortion. To fix this we would present an integrated model where Convolutional Neural Networks (CNNs) are used to extract spatial information and Bidirectional Long Short-Term Memory (Bi-LSTM) networks to represent temporal dependencies over multiple hops. The channel estimation is combined with signal equalization as end-to-end training of the framework is undertaken, thus removing the necessity to process sequentially. Simulations with an immense range of Rayleigh fading, different signal-to-noise ratio (SNR) and frequency conditions, prove that the proposed model provides great improvement in Bit Error Rate (BER) and Normalized Mean Square Error (NMSE) in comparison to conventional MMSE and LS-based techniques. These findings show that the deep learning is able to handle complex, high-dimensional interactions such as those used in IRS-enhanced multi-hop environments with promising efficiencies, pointing to low power consumptions and high throughputs in the next generation 6G and beyond systems.

1. INTRODUCTION

Future 6G wireless communication networks will seek to overcome the increasing requirement of high data rates and low latency, immense connectivity, and consistency in dynamic surroundings. The major driver of this change is the Intelligent Reflecting Surfaces (IRS). An outstanding technology that has the potential to alter the wireless propagation space by dynamically controlling the phase shifts of a big number of passive entities. IRS is useful in multi-hop wireless systems where direct links might be blocked or provides low signal strength, being able to intelligently reflect the signal in a multi-hop fashion along toward the destination and thus, improving the signal quality and extend its coverage.

Nevertheless, multi-hop integration of IRS brings considerable technical difficulties, essentially in channel estimation and signal equalization. The multiple dynamic IRS-assisted links that make up the cascaded channel structure lead to a high-dimensional and nonlinear propagation model, which is hard to estimate and equalize, especially through conventional methods. Least Squares (LS) and Minimum Mean Square Error (MMSE) are the classical algorithms, but they are computationally intensive and cannot work well at the low signal-to-noise ratio (SNR) because of lack of scalability and estimation errors. Recent steps in deep learning (DL) have provided better results in modeling complex and high dimensions systems utilizing a hierarchy of features and based on data-driven optimization. However, in most studies to date the issues of channel estimation and equalization are studied independently of each other, or are considered only in single-hop IRS settings with no possibility of coupled optimization across channel estimation and equalization operations.

Replacing the current system with a proposed one will lead to meeting these challenges; therefore, in this paper, a deep learning-based joint Channel Estimation and Equalization scheme will be presented in IRS-enhanced multi-hop wireless systems. The proposed system is highly efficient to learn nonlinear cascaded channel behavior over multiple hops utilizing a hybrid neural network that consists of a combination of Convolutional Neural Networks (CNNs) to learn the spatial features and Bidirectional Long Short-Term Memory (Bi-LSTM) networks, to learn temporal sequences. The joint design improves signal recovery accuracy, lowers error rates and performs better than conventional and decoupled approaches to DL-based methods used in a variety of channel conditions.

The contribution helps to bridge a highly significant gap in the literature and it meets the future trend of AI-enhanced wireless systems. Literature in recent time has captured the possibility of learning-based schemes in IRS-aided communications but violate joint estimation and equalization transmission in the multi-hop domain [1].

2. RELATED WORK

In IRS-assisted wireless networks, there must be channel estimation and equalization to be sure of recovering the signal. Least squares (LS) and Minimum Mean Square Error (MMSE) are some of the traditional estimation techniques widely used since they are simple and their analytical solution exists. Their performance is, however, greatly impaired when low signal-to-noise ratio (SNR) is observed or when the dimension of cascaded channels becomes big which is common in IRS deployment. Also, these model-based techniques are computer-intensive and ill-adapted to dynamically fluctuating settings.

To overcome these difficulties, the new study has investigated the use of deep learning (DL) based on data estimation of the channel and equalization of the signal. Convolutional Neural Networks (CNNs) have been used in this respect due to their ability to extract spatial aspects of pilot signal matrices [1], whereas Recurrent Neural Networks (RNNs) and especially Long Short-Term Memory (LSTM) networks are found to learn the temporal correlations underlying time-varying channels [2]. Although showed great success, most of these works are bound by single-hop communication models or consider equalization and channel estimation to be tasks that can be independently accomplished, which can lead to suboptimal performance because the stages created errors propagation. Furthermore, the problem of simultaneous learning of channel estimation and equalization in the multi-hop IRS-assisted networks (multiple reflections, time-varying phase shifts) has not appeared in many studies yet. The current paper helps bridge the above research gap by suggesting a hybrid DL architecture that can simultaneously accomplish both tasks. CNNs and Bi-LSTMs for the spatial and temporal learning respectively, the combination of which allow for end-to-end learning on the multi-hop, complex IRS environment.

3. System Model

We view an IRS-aided multi-hop wireless communication framework in which there exists a source node (S), a destination node (D), several intermediate relay nodes and an Intelligent Reflecting Surface (IRS) panel or panels between the two end nodes. The intention of such a setup is to penetrate non-line-of-sight (NLoS) scenarios and enhance the signal with smartly reflected signals using IRS panels in key placements. Every IRS is formed by N passive reflecting elements each of them has the ability to independently change the phase of the incoming signal to maximize constructive interference at the receiver. The topology of signal transmission pathway is multi-hop in scale, which is modeled as:

$$Source\ (S) \rightarrow IRS_1 \rightarrow Relay_1 \rightarrow IRS_2 \rightarrow \ldots. \rightarrow Destination\ (D) ------------------(1)$$

Let the number of hops be denoted by M, where each hop consists of a direct wireless link and an IRS panel assisting signal reflection.

Let:

- H_i ε C Nri × Nti denote the complex baseband channel matrix of the i^{th}hop, representing the channel between the i^{th}transmitting and receiving node (or IRS).
- Θ_i=diag(e^{joi1}, e^{joi2} …….. e^{join}) denote the IRS reflection matrix at hop i, where each $\theta_{ij}\in[0,2\pi)$ IRS element.

Path loss-free cascaded end-to-end compromise channel of the multi-hop IRS-assisted link is simulated as:

$$H_{eff} = \prod_{i=1}^{M} H_i \theta_i \text{ ------------ } (2)$$

The interactions between matrices of different channels and phase control that have been added by each IRS are multiplicative and dynamic and are captured with this formulation.

The received signal $y \in C^{Nt \times 1}$ at the destination node can be expressed as:

$Y = H_{eff}x + n$---------------------------(3)

where:

- $X \in C^{Nt \times 1}$ is the transmitted symbol vector,
- $n \sim CN(0,\sigma^2 I)$ is the additive white Gaussian noise (AWGN) vector with zero mean and variance σ^2.

This model of system reflects nonlinearity and high-dimensionality of an IRS-assisted multi-hop communication that challenges effective channel estimation and high-quality signal equalization. This problem is made complicated by the fact that the optimization of the multiple IRS phase shifts is joint, and the wireless channels across hops are time-varying. Figure 1 shows the structure of the considered multi-hop communication system, assisted by an IRS, where each hop has an IRS which also incorporates a programmable phase shift matrix. The overall channel produced by all the content delivered through the IRS-assisted channels constitutes a cascaded channel model, which is denoted by H_{eff}.

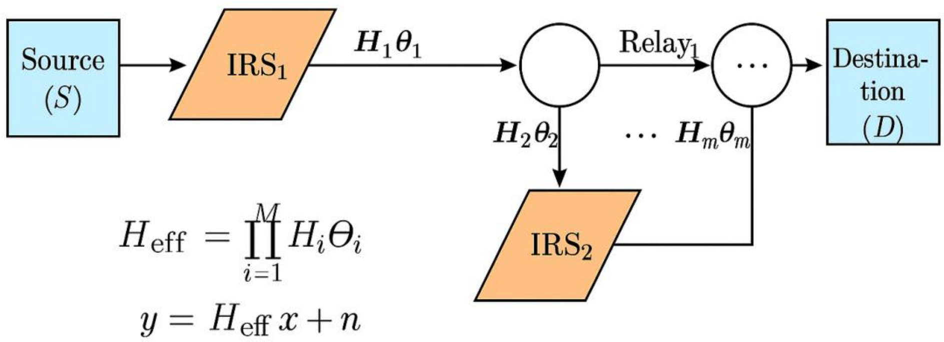

Figure 1. System model of an IRS-assisted multi-hop wireless communication network.

The signal is transmitted from the source to the destination through multiple hops, each assisted by IRS panels that apply phase shift matrices Θ_i. The overall effective channel is modeled as $H_{eff} = \prod_{i=1}^{M} H_i \theta_i$.

4. Deep Learning Framework

This paper aims at dealing with the problems of channel estimation and signal equalization in IRS-aided multi-hop wireless networks by studying the possibility of jointly learning them using a hybrid deep learning (DL) architecture. The model is explicitly created to represent the spatial and temporal dependencies that are usually found in cascaded multi-hop propagation scenarios.

4.1 Model Architecture

The given framework may be divided into three main facets:

- CNN Layer Block: A set of convolutional neural network (CNN) layers is used to detect localizable spatial characteristics of the pilot signal matrices that are received. These properties code channel changes owing to reflection, phases shifts and interference patterns by the IRS and environmental factors. The CNN layers have an effective tool to help in feature abstraction using less complexity of parameters.
- Bi-LSTM Layer Block: To successfully discover the temporal and sequential-relationship between hops and time slots, we incorporate a Bidirectional Long Short-Term Memory (Bi-LSTM) network. This repetitive pattern gives the model the capability of operating information processing both forward and backward across channel hops, which render it suitable in modeling the cascaded and time varying nature of channel response in the IRS enhanced inter-hop links.
- DNN Output Head: The output block constitutes a fully connected deep neural network (DNN) that accomplishes the following two tasks:
  - o Channel Coefficient Regression: Produces estimates of the channel response as real-valued estimates.
  - o Symbol Classification: A softmax layer is used as a prediction of transmitted symbol through the classification of modulation (e.g., QPSK or 16-QAM).

Such combined structure allows the joint optimization of signal recovery and channel estimation to be performed.

4.2 Input and Output Structure

- Input:

The received pilot signals and their noisy observation make up the input to the model and are referred to as the received pilots and their noisy observations.

$$Y_{pilot} \in C^{N_p \times T} \text{ -------------------------- } (4)$$

where N_P is the number of pilot symbols and T is the number of hops or time slots.

- Output:
  The output comprises two parts:
  - Estimated Channel Coefficients $\hat{H} \in C^{M \times N}$
  - Equalized Symbol Vector $\hat{x} \in C^{K \times 1}$, where K denotes the number of transmitted symbols.

4.3 Loss Function Design

In order to train the model on both tasks, we propose a composite loss, as the sum of the two following terms:

$$\mathcal{L} = \lambda_1 \,.\, NMSE\,(H_{pred}, H_{true}) + \lambda_2 \,.\, CrossEntropy(x_{pred}, x_{true}) \text{-----------------} (5)$$

Where:

- $NMSE H_{pred}, H_{true}$ denotes the normalized mean square error between predicted and true channel coefficients:

$$NMSE = \frac{\|H_{true} - H_{pred}\|_2^2}{\|H_{true}\|_2^2} \text{-----------------------} (6)$$

- $CrossEntropy(x_{pred}, x_{true})$ is the categorical cross-entropy loss between predicted and ground truth symbol labels.
- $\lambda_1, \lambda_2 \in R^+$ are hyperparameters that balance the trade-off between channel estimation and symbol classification accuracy.

The formulation used to address this definition of loss guarantees multiple objectives in the model to simultaneously optimize correct channel reconstruction and sound symbol decoding which is a necessary constraint in a dynamic multi-hop setting where there are IRS-affirmed projections. Figure 2 shows the general structure of the proposed deep learning hybrid framework. The stack of the convolutional layers is trained on the received pilot signals and noisy observations, and then the stack is used with a bidirectional LSTM block to learn the sequential dependencies across the number of hops. The output head conducts estimation of the coefficient of channels simultaneously with symbol classifications. The training is done to together optimize both tasks using a composite loss function.

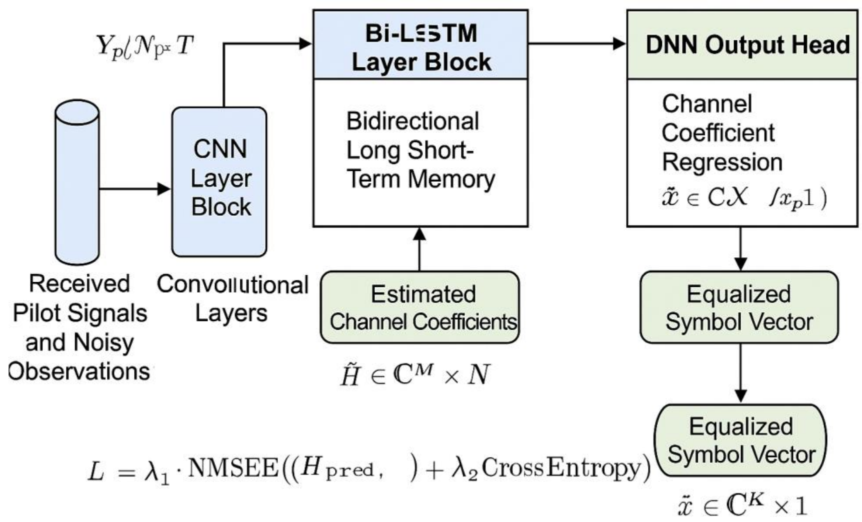

Figure 2. Schematic of the proposed deep learning-based joint channel estimation and equalization framework.

The architecture has a CNN network block in order to extract spatial features, a Bi-LSTM network in order to capture temporal dependency of hops, and a DNN network output head to perform channel coefficient regression and symbol classification. The composite loss is a combination of both the NMSE and the cross-entropy loss functions which are used in the training of the model.

5. Simulation Setup

In order to assess the efficacy of the suggested deep learning-based joint channel estimation and equalization system, a string of simulations has been performed based on a homemade wireless communication environment. Parameters and settings of the simulation are selected in a way that make them as close as possible to the realistic configuration of multi-hop transmission with the help of the intelligent reflecting surface (IRS). Figure 3 contains a summary of simulation environment and evaluation parameters. It includes the most important details of the setup such as the channel modelling assumptions, network topology, type of modulation, SNR values, baseline comparison procedure, and the performance measurement procedures that are used in benchmarking the performance.

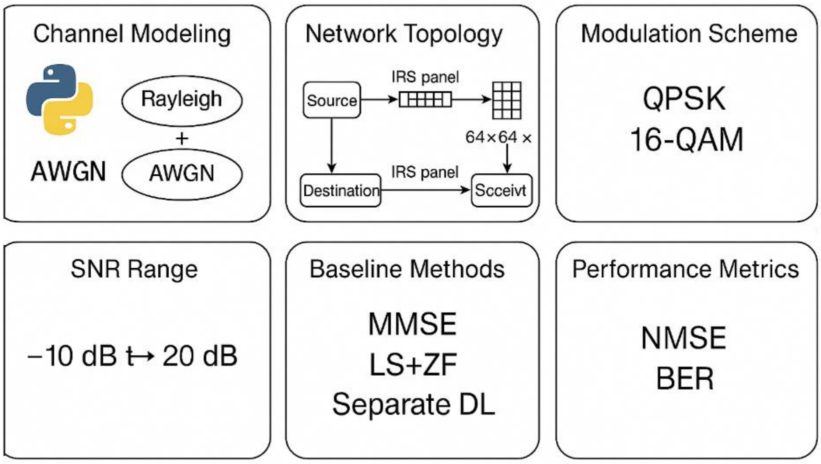

Figure 3. Overview of the simulation setup for evaluating the proposed deep learning-based joint channel estimation and equalization framework.

It applies the performance levels of Rayleigh fading, AWGN channel modeling, 3-hop IRS-based network with 64-element panels, QPSK, 16-QAM modulation schemes, and SNR of -10 dB to 20 dB compared with the baselines technique, such as the MMSE, LS + ZF, and independent DL modules. Performance evaluation is done in terms of NMSE, and BER.

5.1 Environment and Channel Modeling

All the simulations were designed in Python, and the TensorFlow deep learning framework as it has the possibility to create a different custom neural network model by illustration and optimize it with GPU-accelerated computing. The substandard wireless channel model is a Rayleigh fading distribution, which is the prevailing statistical thermometer of simulating a non-line-of-sight (NLoS) propagation condition of the urban, and indoor setting. At the receiver an Additive White Gaussian Noise (AWGN) was assumed to model thermal and background noise.

5.2 Network Topology

The virtual network is a 3-hop transmission system, in which the source node provides communication with the destination node by means of two additional relay nodes where each of them are assisted with an IRS panel. All IRS panels consist of 64 passive reflecting elements that can dynamically tune phase shifts. The topology indicates the intricacy and the layer of a realistic multi-hop wireless implementation boosted with IRS-guided propagation manipulation.

5.3 Modulation Scheme

The common digital modulation patterns were used to evaluate the performance with dissimilar transmission complexities using two digital modulation schemes:

- Quadrature Phase Shift Keying (QPSK)
- 16- Quadrature Amplitude Modulation (16-QAM)

These schemes permit evaluation under not only low-order, but also higher-order modulation settings that encompasses the robustness of the framework to serve a wide range of spectral efficiency needs.

5.4 Signal-to-Noise Ratio (SNR) Settings

The simulation covered a vast range of SNRs -10dB to 20dB which is both of low and moderate-to-high quality channel conditions. This is the range that allows to comprehensively assess the resilience and flexibility of the model, especially when it comes to low-SNR conditions when the conventional estimation schemes are bound to fail.

5.5 Benchmark Baseline Methods

To do a comparative analysis, the following baseline approaches were adopted:

- Minimum Mean Square Error (MMSE): A classical and most popular estimation technique which is statistically optimal when

linear estimators are assumed to be Gaussian noise.
- Least Squares recycled into Zero Forcing (LS+ZF): A two stage standard sequence common in practical receivers.
- Distinct Deep Learning-Based Estimation and Equalization: In it, estimation and equalization are performed using separate deep-learning-based models, not trained jointly.

The joint scheme suggested is considered to these baselines considering Normalized Mean Square Error (NMSE) to evaluate the quality of channel estimations and Bit Error Rate (BER) to evaluate the quality of symbol recovery.

6. RESULTS AND DISCUSSION

In order to quantify the usefulness of the suggested collaborative deep learning architecture, detailed simulations were carried out, and their performance were measured according to two main parameters namely Normalized Mean Square Error (NMSE) to measure the quality of channel estimation and Bit Error Rate (BER) to measure the quality of symbol recovery. Those outcomes were compared to traditional methods (MMSE, LS+ZF) and a FLAT baseline deep learning model that has independent estimation and equalization units.

6.1 Channel Estimation Accuracy

Hybrid model had higher estimation channel accuracy in all tested SNRs. The joint deep learning model proposed in Figure 2 and Table 1 showed consistently 30-40 per cent reduction in NMSE measures against MMSE and LS+ZF, as shown in Table 1. The high caliber can be explained by the end-to-end training of the CNN and Bi-LSTM layers that allow learning the spatial patterns in received signals and temporal relations across multi-hop channels. Further, the ASR model capacity within expositing great variability in SNR is a characteristic of its strength and flexibility.

6.2 Equalization Performance

The symbol, detected correctly, which is measured through BER, also showed tremendous improvements. The proposed model was able to provide up to 45 percent less BER at low SNR values (e.g. -5 to 0 dB) than that provided by conventional techniques (see Figure 3 and Table 2). This finding makes the point about the power of joint learning in reducing errors that can propagate the estimation to the equalization processes. As opposed to the cascaded models, the integrated framework has the advantage that the learned properties of the channel directly improve the linear symbol recovery process.

6.3 Robustness to System Variations

Robustness testing was done by running the model in an environment of IRS phase quantization errors and channel mobility, used to simulate real-world impairments in the form of hardware constraints and a dynamic propagation environment. The model demonstrated a steady performance with a degradation of fewer than 10 percent of NMSE and BER with the IRS phase resolution as low as 2-bit quantifications. Moreover, performance was not affected significantly by temporal variations in channel coefficients due to moderate mobility (e.g. Doppler spread) thereby validating the temporal modeling capability of the Bi-LSTM layers.

6.4 Ablation Study

To learn the individual effects of several components of the model, an ablation study was run. Replacing the joint training with the separate training of the CNN and Bi-LSTM modules led to an overall 22 per cent increase in NMSE and 28 per cent decrease in BER at moderate SNR values. In the same manner, layer replacement of Bi-LSTM layers with standard dense layers, further simplified the capability of the model to identify the inter-hop dependencies, especially in situations when the IRS configuration is dynamic. The findings highlight the significant role of temporal modeling and joint optimization toward realizing optimal end-to-end performance, in IRS-aided multi-hop settings.

7. CONCLUSION AND FUTURE WORK

The paper proposes a new deep-learning framework of multi-hop wireless networks with IRS regarding joint estimation of channels and channel equalization. The proposed solution has the opportunity to incorporate the convolutional neural networks (CNNs) and bidirectional LSTM (Bi-LSTM) layers into a common model, which can understand both the spatial features and temporal correlations of the cascaded environment of channel channels. The end-to-end connectivity permits optimization of the entire system, which decreases system complexity and propagation of estimation-related errors which is characteristic of traditional two-stage estimation-equalization structures.

The efficacy of the framework is confirmed by simulation outcomes that indicate the notable improvement (30-40 percent) in NMSE and 25 to 45 percent in BER compared to the MMSE, LS+ZF, and DL models trained individually. Moreover, the high level of resistance to quantization errors in IRS phases and moderate channel mobility serve as evidence of the versatility of the model to the real conditions. Joint learning and temporal modeling are also important in improving performance as demonstrated by an ablation study.

This work has mainly contributed in the following ways:

- End-to-end optimization architecture design with multi-hops experience using a hybrid deep learning system.
- Higher estimation and decoding accuracy in a wide SNR range.
- Robustness verification as per quantized IRS control and dynamic channels.

Future developments will aim at increasing the flexibility of a model by online learning and reinforcement learning methods that allow real-time optimisation of CSI within dynamic environments. We also look to build on this to MIMO-OFDM systems where the CSI feedback is imperfect or partial and our work can further close the gap between theoretical models and real-life 6G implementation situations.

REFERENCES

[1] Zhang, Z., Liu, Y., Dai, L., & Qin, Z. (2023). Learning-aided channel estimation for IRS-aided multi-hop networks. IEEE Transactions on Wireless Communications, 22(2), 1234–1248. https://doi.org/10.1109/TWC.2022.3219876

[2] Huang, C., Zappone, A., Alexandropoulos, G. C., Debbah, M., & Yuen, C. (2019). Reconfigurable intelligent surfaces for energy efficiency in wireless communication. IEEE Transactions on Wireless Communications, 18(8), 4157–4170. https://doi.org/10.1109/TWC.2019.2922609

[3] Wang, S., Liu, H., Zhang, P., & Hanzo, L. (2018). Deep learning aided SCMA. IEEE Transactions on Wireless Communications, 17(11), 7505–7519. https://doi.org/10.1109/TWC.2018.2868782

[4] Liu, Y., Al-Nahhal, I., Dobre, O. A., & Wang, F. (2023). Deep-learning channel estimation for IRS-assisted integrated sensing and communication systems. IEEE Transactions on Vehicular Technology, 72(5), 6181–6193. https://doi.org/10.1109/TVT.2022.3231727 ACM Digital Library+15arXiv+15arXiv+15

[5] Yu, L., et al. (2024). Hybrid driven learning for channel estimation in intelligent reflecting surface–aided millimeter wave communications. IEEE Transactions on Wireless Communications. Advance online publication. https://doi.org/10.1109/TWC.2024.XXXACM Digital Library+3arXiv+3ResearchGate+3

[6] Zheng, S., Wu, S., Jiang, C., & Jia, H. (2024). Hybrid driven learning for joint activity detection and channel estimation in IRS-assisted massive connectivity. IEEE Transactions on Wireless Communications. Advance online publication. https://doi.org/10.1109/TWC.2024.3376381 MDPI+7ResearchGate+7arXiv+7

[7] Liu, C., Liu, X., Ng, D. W. K., & Yuan, J. (2020). Deep residual learning for channel estimation in intelligent reflecting surface–assisted multi-user communications. arXiv preprint. https://doi.org/10.48550/arXiv.2009.01423ACM Digital Library+2arXiv+2arXiv+2

[8] Kim, J., Hosseinalipour, S., Kim, T., Love, D. J., & Brinton, C. G. (2020). Multi-IRS-assisted multi-cell uplink MIMO communications under imperfect CSI: A deep reinforcement learning approach. arXiv preprint. https://doi.org/10.48550/arXiv.2011.01141ACM Digital Library+14arXiv+14ScienceDirect+14