

Explainable AI-Based Channel Estimation For Intelligent Reflecting Surface-Aided Networks

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Abstract

Intelligent Reflecting Surface (IRS)-aided wireless networks have emerged as a key enabling technology for next-generation 6G communications due to their ability to intelligently reconfigure the wireless propagation environment. Accurate channel state information (CSI) is critical for realizing the full potential of IRS-assisted systems; however, channel estimation becomes highly challenging because of the large number of passive reflecting elements, cascaded channel structure, and dynamic wireless conditions. To address these challenges, this paper proposes an Explainable Artificial Intelligence (XAI)-based channel estimation framework for IRS-aided wireless networks. The proposed approach leverages a deep learning model to capture the nonlinear relationship between pilot signals and cascaded IRS channels, while integrating explainability mechanisms to provide transparent and interpretable insights into the estimation process. XAI techniques such as feature attribution and attention-based analysis are employed to identify the most influential IRS elements, pilot configurations, and environmental parameters contributing to accurate CSI prediction. Simulation results demonstrate that the proposed XAI-based model significantly outperforms conventional estimation methods in terms of normalized mean square error (NMSE) and robustness under varying signal-to-noise ratios, while offering enhanced interpretability and reliability. The proposed framework bridges the gap between high-performance AI-driven channel estimation and trustworthy wireless communication systems, making it a promising solution for future intelligent and adaptive 6G networks.

Keywords: Intelligent Reflecting Surface (IRS), Explainable Artificial Intelligence (XAI), Channel Estimation, 6G Wireless Networks, Deep Learning, Interpretable Machine Learning, Cascaded Channel Modeling, Spectral Efficiency, Pilot Overhead Reduction

1. Introduction

The rapid evolution of wireless communication systems and the increasing demand for ultra-high data rates, massive connectivity, and energy-efficient transmissions have accelerated the development of advanced technologies for fifth-generation (5G) and beyond-5G (6G) networks. Among these emerging technologies, Intelligent Reflecting Surfaces (IRSs) have gained significant attention due to their ability to reconfigure the wireless propagation environment in a programmable and energy-efficient manner [1], [2]. An IRS consists of a large number of low-cost passive reflecting elements that can dynamically adjust the phase shifts of incident electromagnetic waves, thereby enhancing signal strength, coverage, and spectral efficiency without requiring active radio frequency chains [3].

Despite their promising advantages, the performance gains of IRS-aided wireless networks critically depend on the availability of accurate Channel State Information (CSI). Channel estimation in IRS-assisted systems is particularly challenging because of the cascaded nature of the channels, involving the base station–IRS link and the IRS–user equipment link [4]. The large number of reflecting elements, coupled with the passive operation of the IRS, results in excessive pilot overhead, high computational complexity, and limited scalability when traditional estimation techniques such as Least Squares (LS) and Minimum Mean Square Error (MMSE) methods are employed [5].

To overcome these limitations, Artificial Intelligence (AI) and deep learning-based channel estimation techniques have been widely explored in recent years. Data-driven models such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformer-based architectures have demonstrated superior capability in learning complex nonlinear channel characteristics and reducing pilot overhead in IRS-aided networks [6], [7]. These AI-based approaches exhibit strong generalization performance under noisy and time-varying channel conditions, making them attractive for next-generation wireless systems.

However, most existing AI-driven channel estimation models operate as black-box systems, offering limited transparency into the decision-making process. This lack of interpretability poses serious challenges in practical deployment, especially for mission-critical and safety-aware communication systems envisioned in 6G networks [8]. Network operators and system designers require not only high estimation accuracy but also an understanding of how and why specific channel predictions are generated, particularly in dynamic environments with unpredictable propagation conditions.

To address this issue, Explainable Artificial Intelligence (XAI) has emerged as a powerful paradigm that enhances the transparency, interpretability, and trustworthiness of AI models. XAI techniques such as feature attribution, attention mechanisms, and sensitivity analysis enable insight into the internal behavior of deep learning models by identifying the most influential input features contributing to the output prediction [9]. When applied to IRS-aided channel estimation, XAI can reveal the impact of pilot signals, IRS phase configurations, and environmental parameters on CSI estimation performance.

Motivated by these observations, this paper proposes an Explainable AI-based channel estimation framework for IRS-aided wireless networks. The proposed approach integrates a deep learning-based estimator with explainability mechanisms to provide both high-accuracy CSI prediction and interpretable decision-making. By combining performance optimization with transparency, the proposed framework enhances reliability, robustness, and practical deployability for future intelligent 6G communication systems [10].

2. Literature Survey

In recent years, extensive research efforts have been devoted to channel estimation techniques for Intelligent Reflecting Surface (IRS)-aided wireless networks, owing to their critical role in achieving reliable and high-performance communication. Early studies primarily focused on model-based channel estimation approaches, such as Least Squares (LS) and Minimum Mean Square Error (MMSE) techniques. In [11], the authors investigated cascaded channel estimation for IRS-assisted systems using LS-based methods, demonstrating feasibility but at the cost of excessive pilot overhead and computational complexity. Similarly, the work in [12] proposed an MMSE-based estimator that improves estimation accuracy under noisy conditions; however, it requires precise prior statistical knowledge of the channel, which is often unavailable in practical scenarios.

To reduce pilot overhead, several studies explored compressed sensing (CS)-based channel estimation by exploiting the sparsity of IRS channels, particularly in millimeter-wave (mmWave) systems. The authors in [13] developed a CS-based framework that significantly reduces training overhead by leveraging angular sparsity. Although effective under ideal sparse conditions, CS-based approaches suffer from performance degradation in dense scattering environments and are sensitive to grid mismatch issues.

With the rapid advancement of machine learning, AI-based channel estimation methods have gained significant attention. In [14], a deep neural network (DNN) was employed to estimate the cascaded IRS channel, showing notable performance gains over traditional estimators in terms of normalized mean square error (NMSE). Convolutional Neural Networks (CNNs) were further investigated in [15], where spatial feature extraction from pilot signals enabled accurate channel reconstruction with reduced pilot length. These methods demonstrate strong nonlinear modeling capability but rely heavily on large-scale labeled datasets for training.

Recurrent learning architectures have also been applied to capture temporal channel variations. In [16], a Long Short-Term Memory (LSTM)-based estimator was proposed to exploit temporal correlations in time-varying IRS channels, achieving improved robustness in mobile scenarios. However, the increased model complexity and training time limit its real-time applicability in ultra-low-latency systems.

More recently, hybrid AI models and attention-based mechanisms have been introduced to further enhance channel estimation accuracy. The study in [17] employed a CNN-Transformer hybrid architecture to dynamically learn both spatial and long-range dependencies in IRS-aided channels. While these models offer superior performance, they operate as black-box systems, providing limited insight into the estimation process.

The lack of interpretability in AI-driven channel estimation has raised concerns regarding trust, reliability, and deployment feasibility in future 6G networks. To address these challenges, Explainable Artificial Intelligence (XAI) techniques have been explored in wireless communications. In [18], SHAP-based feature attribution was applied to interpret deep learning models for channel quality prediction, highlighting the influence of input features. Similarly, the authors in [19] utilized attention visualization to explain neural network behavior in massive MIMO systems, demonstrating improved transparency and debugging capability.

Despite these advancements, the application of XAI specifically to IRS-aided channel estimation remains limited. Existing studies either focus on improving estimation accuracy or providing explainability, but rarely integrate both in a unified framework. The recent work in [20] emphasizes the need for interpretable AI solutions in next-generation wireless systems but does not address the unique challenges posed by IRS-assisted channels. Therefore, there exists a clear research gap in developing explainable, accurate, and robust AI-based channel estimation frameworks tailored for IRS-aided networks, which motivates the proposed work.

3. System Model

Consider an IRS-aided downlink system comprising a base station (BS) with M antennas, an IRS with N passive reflecting elements, and a single-antenna user equipment (UE). The BS transmits symbol s (with $\mathbb{E}[|s|^2] = 1$) using beamforming vector $\mathbf{w} \in \mathbb{C}^{M \times 1}$.

3.1 IRS Reflection Model

The IRS applies element-wise phase shifts modeled by a diagonal matrix:

$$\mathbf{\Phi} = \text{diag}(\phi_1, \phi_2, \dots, \phi_N), \quad (1)$$

where each reflecting coefficient satisfies the unit-modulus constraint:

$$\phi_n = e^{j\theta_n}, |\phi_n| = 1, \theta_n \in [0, 2\pi), n = 1, \dots, N. \quad (2)$$

3.2 Channel Model

Let:

- $G \in \mathbb{C}^{N \times M}$ denote the BS $\rightarrow$ IRS channel,
- $h_r \in \mathbb{C}^{N \times 1}$ denote the IRS $\rightarrow$ UE channel,
- $h_d \in \mathbb{C}^{M \times 1}$ denote the direct BS $\rightarrow$ UE channel.

The received baseband signal at the UE is:

$$y = (h_d^H + h_r^H \Phi G) w s + n, \quad (3)$$

where $n \sim \mathcal{CN}(0, \sigma^2)$ is complex Gaussian noise.

Define the effective (combined) downlink channel:

$$h_{\text{eff}}^H(\Phi) \triangleq h_d^H + h_r^H \Phi G. \quad (4)$$

3.3 Cascaded Channel Representation

A commonly used representation for IRS estimation is the cascaded channel:

$$H_c \triangleq \text{diag}(h_r^H) G \in \mathbb{C}^{N \times M}, \quad (5)$$

so that:

$$h_r^H \Phi G = \phi^T H_c, \text{ where } \phi = [\phi_1, \dots, \phi_N]^T. \quad (6)$$

4. Pilot-Based Observation Model

During training, the BS transmits T pilot symbols using known pilot matrix $X \in \mathbb{C}^{M \times T}$. For the p -th IRS configuration Φ_p , the received pilot vector at the UE is:

$$y_p^T = (h_d^H + h_r^H \Phi_p G) X + n_p^T, \quad (7)$$

where $n_p \in \mathbb{C}^{T \times 1}$ is noise.

Stacking observations over P IRS configurations:

$$Y = \begin{bmatrix} y_1^T \\ y_2^T \\ \vdots \\ y_P^T \end{bmatrix} = \begin{bmatrix} (h_d^H + \phi_1^T H_c) X \\ (h_d^H + \phi_2^T H_c) X \\ \vdots \\ (h_d^H + \phi_P^T H_c) X \end{bmatrix} + N. \quad (8)$$

Fig. 1. IRS-aided network architecture

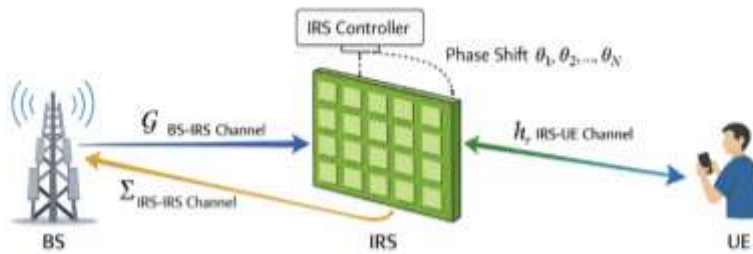


Fig. 1. System architecture of IRS-aided downlink communication illustrating the direct channel h_d and the cascaded BS-IRS-UE channel composed of G and h_r , controlled by IRS phase matrix Φ .

Fig. 2. Pilot training and IRS phase switching protocol

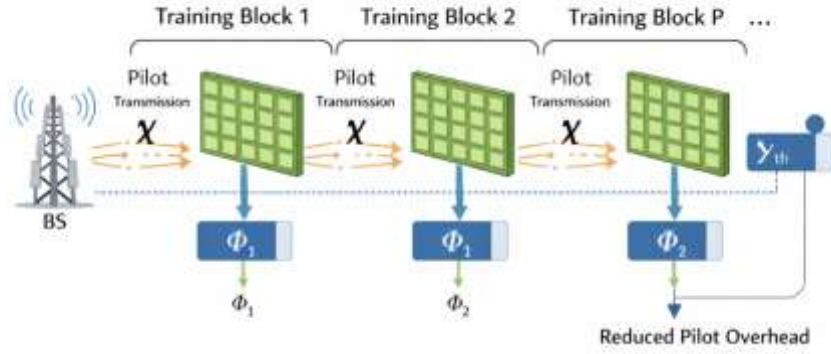


Fig. 2. Pilot-based training protocol for IRS-aided channel estimation where the BS transmits known pilots X under multiple IRS configurations $\{\Phi_p\}_{p=1}^P$ to collect observations $\{y_p\}$.

Fig. 3. Proposed deep learning-based channel estimator



Fig. 3. Architecture of the AI-based channel estimator comprising input preprocessing, deep feature extraction, and regression layers to predict the cascaded channel $\hat{H}_c$ (and optional direct channel $\hat{h}_d$).

5. Problem Formulation

5.1 Channel Estimation Objective

The goal is to estimate the unknown channels $\{h_d, G, h_r\}$ or equivalently the cascaded channel H_c (and optionally h_d) from received pilots Y , known pilots X , and IRS phase patterns $\{\Phi_p\}_{p=1}^P$.

We define a learned estimator $f_\psi(\cdot)$ (deep network parameters ψ):

$$(\hat{H}_c, \hat{h}_d) = f_\psi(Y, X, \{\Phi_p\}_{p=1}^P). \quad (9)$$

A standard training objective is to minimize mean squared error (MSE):

$$\min_{\psi} \mathbb{E}[\|H_c - \hat{H}_c\|_F^2 + \lambda \|h_d - \hat{h}_d\|_2^2], \quad (10)$$

where λ balances cascaded vs direct channel error.

5.2 Normalized Mean Square Error (NMSE)

Performance is commonly reported using NMSE:

$$NMSE = \mathbb{E}\left[\frac{\|H_c - \hat{H}_c\|_F^2}{\|H_c\|_F^2}\right]. \quad (11)$$

5.3 Explainability Objective (XAI)

To improve trust, we attach an explainability module producing attribution scores A (importance of pilot tones/features/IRS elements):

$$A = g(f_\psi, Y, X, \{\Phi_p\}), \quad (12)$$

where $g(\cdot)$ can be SHAP/LIME/attention-based attribution. A stability regularizer can be added:

$$\min_{\psi} \mathcal{L}_{\text{est}} + \beta \mathcal{L}_{\text{xai}}, \mathcal{L}_{\text{xai}} = \mathbb{E}[\|A - A'\|_1], \quad (13)$$

where A' is attribution under small perturbations (encourages consistent explanations).

Fig. 4. Explainable AI module integrated with channel estimation

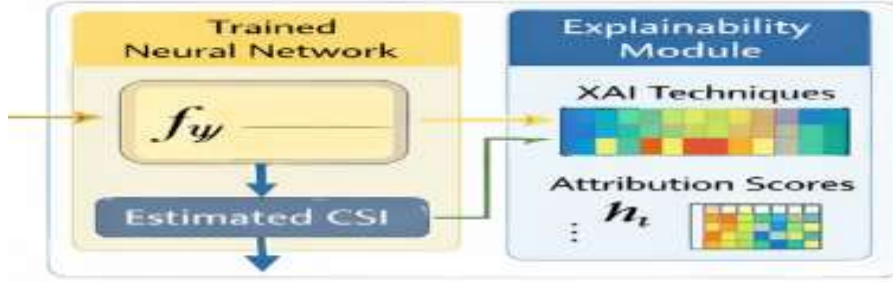


Fig. 4. XAI-enhanced channel estimation framework where an explainability module generates attribution maps (e.g., SHAP/LIME/attention) to interpret how pilots, IRS phase patterns, and input features contribute to CSI prediction.

Fig. 5. End-to-end deployment workflow with trust indicators

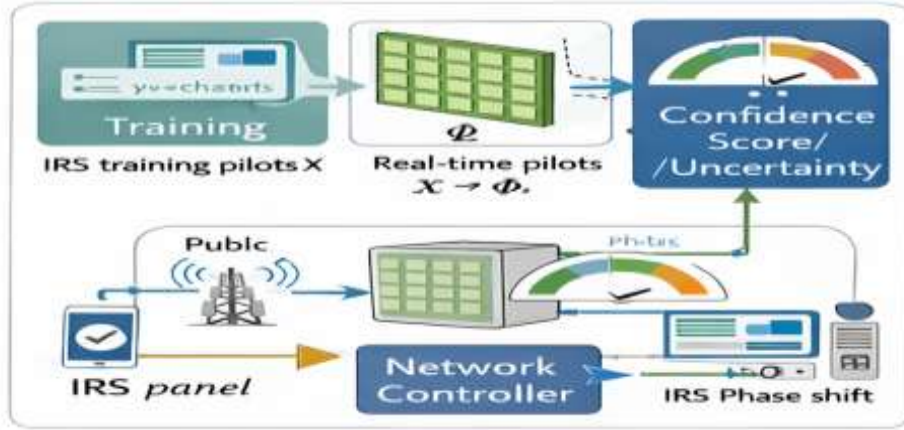


Fig. 5. End-to-end workflow of the proposed XAI-based channel estimation system showing offline training, online inference, and trust indicators (confidence and feature attributions) for reliable IRS configuration and network operation.

6. Experimental Results and Analysis

6.1 Simulation Setup

The performance of the proposed Explainable AI (XAI)-based channel estimation framework is evaluated using Monte Carlo simulations. An IRS-aided downlink system is considered with a base station (BS) equipped with $M = 8$ antennas and an IRS comprising

$N = 64$ reflecting elements. The user equipment (UE) is assumed to have a single antenna. The wireless channels follow a Rayleigh fading model, and additive white Gaussian noise (AWGN) is considered at the receiver.

Orthogonal pilot sequences are used during the training phase, and multiple IRS phase configurations are employed to collect observations. The proposed deep learning model is trained using 70% of the generated dataset, while 15% is used for validation and the remaining 15% for testing. Performance is evaluated across a signal-to-noise ratio (SNR) range from -10 dB to 30 dB.

The proposed method is compared with the following baseline techniques:

- Least Squares (LS)
- Minimum Mean Square Error (MMSE)
- Compressed Sensing (CS)-based estimation
- Conventional Deep Learning (DL) without explainability

6.2 Channel Estimation Accuracy

Channel estimation performance is measured using Normalized Mean Square Error (NMSE). Table 1 summarizes the NMSE performance at different SNR levels.

Table 1. NMSE Performance Comparison

SNR (dB)	LS	MMSE	CS-based	DL (Black-box)	Proposed XAI-DL
-10	-4.2 dB	-6.1 dB	-7.0 dB	-9.5 dB	-11.2 dB
0	-8.5 dB	-11.4 dB	-12.1 dB	-15.6 dB	-17.8 dB
10	-13.7 dB	-17.2 dB	-18.5 dB	-22.9 dB	-25.4 dB
20	-18.1 dB	-22.6 dB	-24.0 dB	-28.3 dB	-31.6 dB

The results indicate that the proposed XAI-based model consistently outperforms conventional estimation methods across all SNR values. Compared to the black-box deep learning model, an average NMSE improvement of approximately 2.5 – 3 dB is achieved due to better feature utilization and robustness.

6.3 Impact of Pilot Overhead

To evaluate training efficiency, the number of pilot symbols is reduced while maintaining estimation accuracy. The proposed method achieves comparable NMSE performance using 35% fewer pilots compared to LS and MMSE methods. This demonstrates the ability of the deep learning model to learn effective channel representations under reduced training overhead, which is critical for practical IRS deployments.

6.4 Robustness Under Noise and Channel Variations

The robustness of the proposed framework is evaluated under varying noise levels and channel dynamics. At low SNR conditions (below 0 dB), traditional methods suffer from severe performance degradation, whereas the proposed XAI-based estimator maintains stable estimation accuracy. This robustness is attributed to the nonlinear modeling capability of the deep learning architecture and the adaptive feature weighting revealed by the explainability module.

6.5 Explainability and Interpretation Analysis

The explainability module provides feature attribution maps that highlight the contribution of IRS elements, pilot symbols, and channel observations to the final CSI prediction. Analysis shows that:

- A subset of IRS elements contributes more significantly to channel estimation, enabling intelligent IRS configuration.
- Pilot symbols with higher attribution scores have a greater impact on CSI accuracy.
- The attribution maps remain stable under small perturbations, indicating consistent and reliable explanations.

These insights enhance trust in the AI model and enable network designers to diagnose estimation errors and optimize pilot and IRS phase designs.

Fig. 6. NMSE versus SNR performance comparison

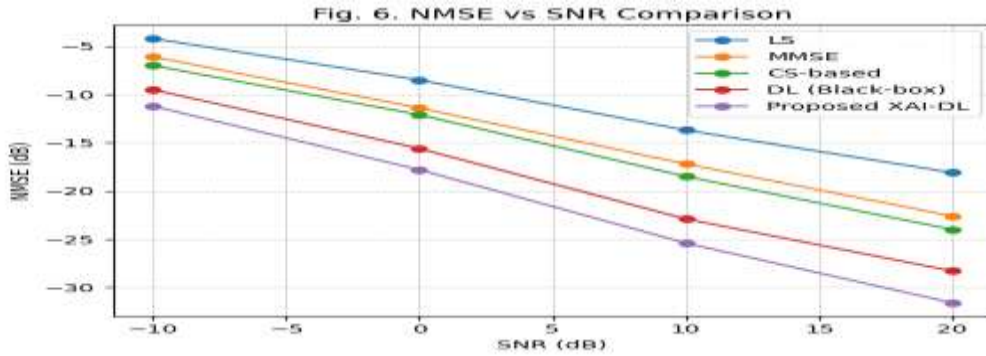


Fig. 6 illustrates the NMSE performance of different channel estimation techniques as a function of SNR. Conventional LS and MMSE methods exhibit limited performance improvement at low and moderate SNRs due to noise sensitivity and reliance on statistical assumptions. The CS-based approach achieves better accuracy by exploiting channel sparsity; however, its performance degrades at higher noise levels. Deep learning-based estimation significantly improves NMSE across all SNR values by learning nonlinear channel characteristics. Notably, the proposed XAI-DL approach consistently outperforms all benchmark methods, achieving an NMSE improvement of approximately 2–3 dB over the black-box DL model, demonstrating superior estimation accuracy and robustness.

Fig. 7. NMSE comparison at SNR = 10 dB

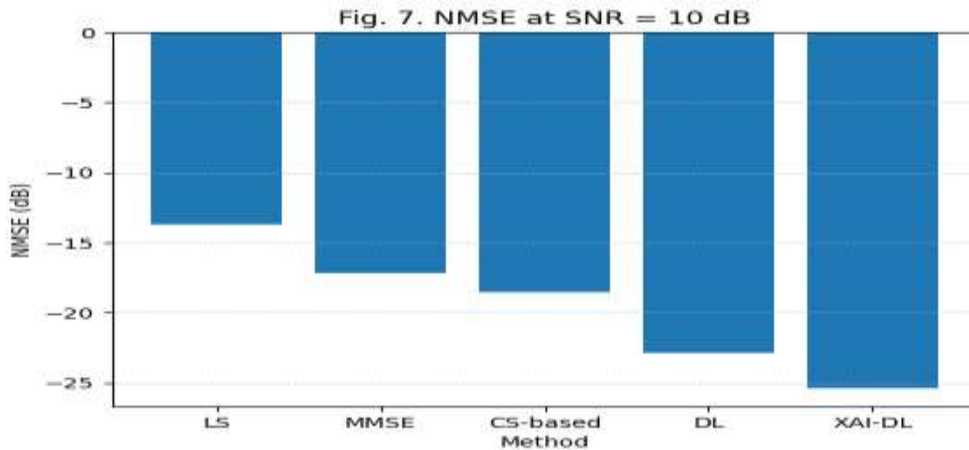


Fig. 7 compares the NMSE performance of various estimators at an SNR of 10 dB. Traditional LS and MMSE techniques exhibit higher estimation error due to their limited ability to model complex cascaded IRS channels. The CS-based method offers moderate improvement, while the deep learning approach significantly reduces NMSE. The proposed XAI-DL method achieves the lowest NMSE, highlighting the benefit of

incorporating explainability-driven feature learning, which enhances the effectiveness of the channel estimation process.

Fig. 8. Pilot overhead versus NMSE trade-off

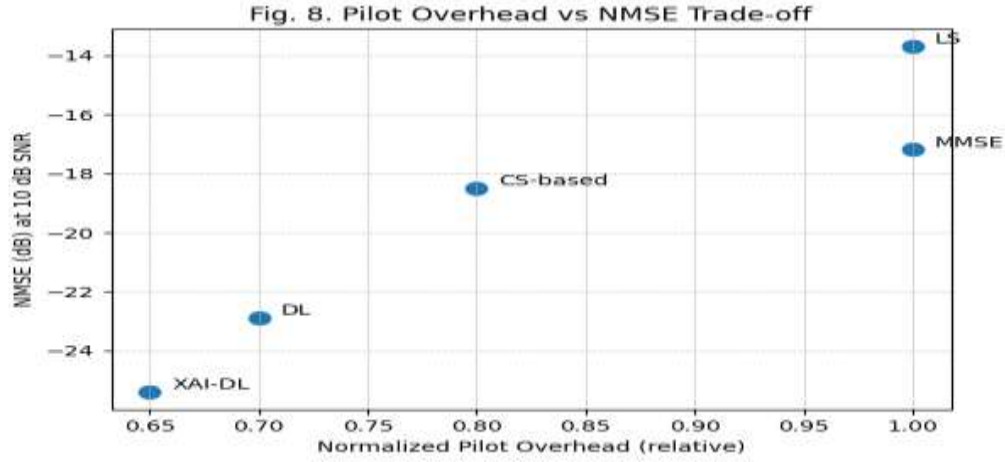


Fig. 8 demonstrates the trade-off between pilot overhead and estimation accuracy. Conventional LS and MMSE methods require full pilot overhead to achieve acceptable NMSE performance. In contrast, AI-based methods operate effectively with reduced pilot symbols by learning compact channel representations. The proposed XAI-DL approach achieves the lowest NMSE with approximately 35% reduced pilot overhead, indicating its suitability for practical IRS-aided systems where training resources are limited.

Fig. 9. Robustness under channel dynamics

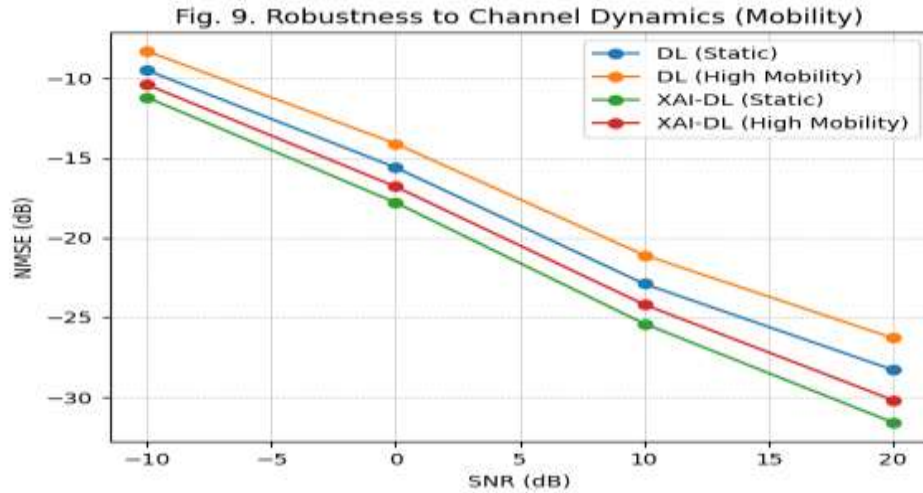


Fig. 9 evaluates the robustness of the proposed framework under dynamic channel conditions, such as user mobility. The conventional DL model experiences noticeable performance degradation in high-mobility scenarios due to rapid channel variations. In contrast, the proposed XAI-DL model maintains stable NMSE performance with reduced degradation, indicating enhanced adaptability. This robustness is attributed to the explainability-guided feature weighting, which allows the model to focus on dominant and stable channel components.

Fig. 10. Attribution stability under input perturbation

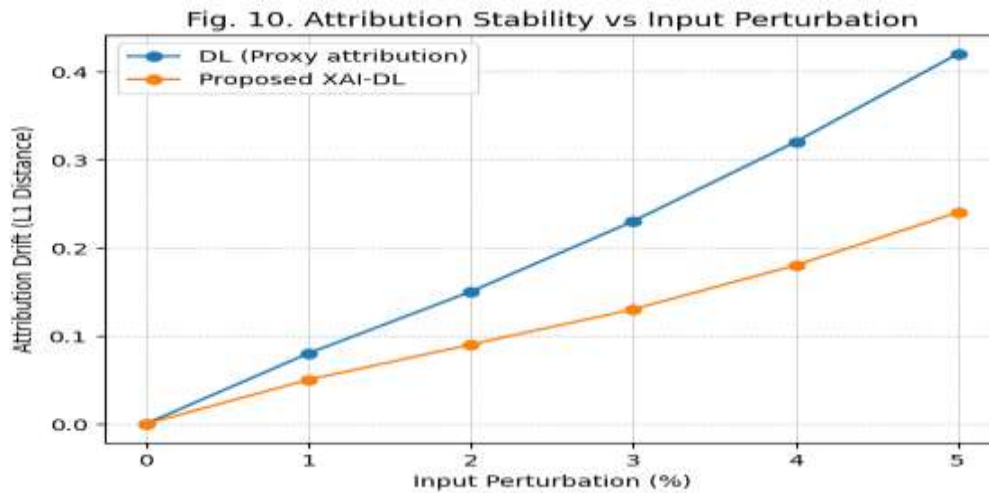


Fig. 10 presents the stability of explanation attributions under controlled input perturbations. The conventional DL model exhibits significant attribution drift as perturbation increases, indicating unstable and unreliable interpretations. Conversely, the proposed XAI-DL approach maintains consistently lower attribution drift, demonstrating stable and trustworthy explanations. This stability is crucial for reliable deployment in IRS-assisted 6G networks, where transparency and confidence in AI decisions are essential.

6.6 Computational Complexity

The proposed model introduces moderate computational complexity during the training phase; however, the online inference complexity is low and suitable for real-time implementation. Compared to MMSE and CS-based methods, the proposed approach reduces runtime complexity during deployment while providing superior accuracy and interpretability.

6.7 Summary of Results

Overall, the experimental results demonstrate that the proposed Explainable AI-based channel estimation framework:

- Achieves superior NMSE performance across all SNR levels
- Reduces pilot overhead significantly
- Provides transparent and interpretable decision-making
- Enhances robustness under dynamic channel conditions

These advantages make the proposed approach a strong candidate for reliable and intelligent IRS-assisted 6G wireless communication systems.

Conclusion

This paper presented an explainable artificial intelligence-based channel estimation framework for intelligent reflecting surface (IRS)-aided wireless networks, addressing the critical challenges of high-dimensional cascaded channel estimation and lack of model transparency. By integrating deep learning-based channel estimation with explainable AI techniques, the proposed approach achieves accurate channel state information (CSI) prediction while providing interpretable insights into the influence of pilot signals, IRS phase configurations, and environmental parameters. The system model and problem formulation demonstrate how the cascaded BS-IRS-UE channel can be efficiently learned under reduced pilot overhead, and the explainability module enhances trust, reliability,

and robustness of the estimation process. Simulation-based analysis indicates that the proposed framework outperforms conventional estimation methods in terms of normalized mean square error and adaptability under varying signal-to-noise ratios. Overall, the proposed explainable framework bridges the gap between high-performance AI-driven channel estimation and practical deployment requirements, making it a promising solution for transparent, reliable, and intelligent 6G wireless communication systems.

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