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Adaptive machine learning-enhanced channel estimation for RIS-assisted mmWave systems: a hybrid approach

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Abstract
This paper introduces a novel approach to channel estimation in reconfigurable intelligent surface (RIS)-assisted millimeter-wave (mmWave) systems, leveraging machine learning to enhance traditional compressive sensing methods. In mmWave communication, the rapidly changing channel conditions and inherent signal sparsity present significant challenges for accurate channel estimation. To address these challenges, we propose a hybrid model that combines deep learning with compressive sensing, enabling adaptive and efficient channel estimation. The deep learning component applies a convolutional neural network (CNN) to interpret and predict complex channel dynamics based on previous data, and the compressive sensing approach takes advantage of the sparsity of mmWave channels to minimize pilot overhead. By incorporating these approaches, our system dynamically adjusts to diverse channel conditions, improving channel estimation accuracy and minimizing computing complexity. Extensive simulations demonstrate that the proposed method surpasses conventional estimating methods, such as orthogonal matching pursuit (OMP), in terms of normalized mean square error (NMSE) and adaptability to non-ideal conditions.

Keywords Machine learning · Channel estimation · Reconfigurable intelligent surface (RIS) · Millimeter-Wave (mmWave) systems · Compressive sensing · Convolutional neural networks (CNN) · Sparse channel estimation · Adaptive beamforming · Hybrid model · Normalized mean square error (NMSE) · Next-generation wireless communication · Pilot overhead reduction · Signal processing · Non-ideal conditions

1 Introduction

The rapid advancement of wireless communication technologies has substantially boosted the demand for higher data rates and more reliable communication methods. Millimeter-wave (mmWave) technology has emerged as a

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prominent candidate to fulfill these requirements owing to its capacity to provide significant bandwidth and facilitate high data rates [1, 2]. mmWave systems perform at frequencies often exceeding 24 GHz, enabling much broader bandwidths compared to conventional sub-6 GHz systems. Nonetheless, these higher frequencies provide additional obstacles, including increasing path loss, vulnerability to blockages, and restricted scattering abilities [1, 3, 4]. These difficulties require sophisticated approaches to guarantee reliable and efficient communication in mmWave systems.

The introduction of reconfigurable intelligent surfaces (RIS) has emerged as a transformational technology to tackle these difficulties, enhancing wireless communication via the adaptive control of electromagnetic fields in the surrounding atmosphere [3, 5, 6]. A Reconfigurable Intelligent Surface (RIS) generally consists of several passive reflecting elements that may be digitally adjusted to modify the phase of incoming waves, thereby enhancing signal strength and coverage by guiding the waves toward the designated receiver [4, 5]. The capacity to influence the conditions for propagation makes RIS an attractive strategy for mitigating the substantial path loss and obstacles caused by the mmWave frequencies.

In RIS-assisted mmWave systems, accurate channel estimate is essential for optimizing beamforming and improving overall system performance. Beamforming is a crucial approach in mmWave systems that compresses transmission power in designated directions to enhance signal strength and minimize interference [2, 7]. Accurate knowledge of channel state information (CSI) is a requirement for successful beamforming. Conventional channel estimating approaches often use compressive sensing (CS) methods, capitalizing on the underlying sparsity of mmWave channels to minimize the required pilot signals and the corresponding computing complexity [8–10]. Compressive sensing utilizes the natural sparsity of mmWave channels in the angular domain, promoting rapidly channel recovery with a reduced number of measures [11, 12].

In spite of the advantages of compressive sensing, these techniques frequently presume prior knowledge of the channel's sparsity level, which is challenging to acquire in real-world situations where channel conditions can vary instantly due to mobility of users, environmental circumstances, and hardware impairments [10, 12, 13]. Furthermore, conventional CS-based methodologies may lack resilience under non-ideal circumstances, such as noise and interference, which often occur in practical applications [13–15]. Recent research has investigated the use of machine learning (ML) methods, especially deep learning, to enhance channel estimation by using previous data and adjusting to dynamic channel conditions [8, 16–18].

Machine learning, particularly deep learning models such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), has demonstrated considerable potential in identifying intricate patterns and correlations in data, leaving it an efficient tool for channel estimation in wireless communication systems. These models are able to identify the fundamental distribution of channel states from massive datasets, allowing for more precise predictions of the Channel State Information (CSI) compared to conventional approaches that depend on heuristic assumptions [19, 20]. The combination of machine learning with traditional compressive sensing methods to exploit both the learning abilities of ML and the sparsity of mmWave channels remains inadequately investigated [5, 21].

A notable shortage has been identified in the literature about the development of hybrid models that integrate machine learning with compressive sensing for RIS-assisted mmWave systems. Although ML-based algorithms may adjust to fluctuating channel conditions and provide precise predictions, they do not naturally use the sparsity of mmWave channels as effectively as CS techniques [8, 16, 17, 22]. In contrast, CS approaches, while efficient in sparse settings, do not possess the flexibility of ML models in dynamic and complicated situations [10–12]. A hybrid strategy that combines machine learning with conventional signal processing could offer a more reliable and efficient solution for channel prediction in RIS-assisted mmWave systems, using the advantages of both methodologies to address their respective limitations.

The significance of creating a hybrid methodology is essential, considering the growing complexity of wireless settings and the demand for more adaptable and effective channel estimate methodologies. The integration of machine learning's predictive capabilities with the sparsity-utilizing features of compressive sensing enables enhanced channel estimation with reduced pilot overhead and computational complexity, while also exhibiting resilience to non-ideal conditions [16, 19, 23]. This methodology enhances the state-of-the-art in channel estimation for RIS-assisted mmWave systems [12, 24, 25]. However, this paper proposes an adaptive machine learning-enhanced channel estimation method for RIS-assisted mmWave systems. The main contributions of this work are as follows: we develop a hybrid model that integrates deep learning with compressive sensing, leveraging both the data-driven capabilities of neural networks and the inherent sparsity of mmWave channels to enhance channel estimation accuracy and reduce pilot overhead. Additionally, we introduce a novel sparsity-adaptive matching pursuit (SAMP) method that dynamically adjusts to the channel's sparsity level, eliminating the need for prior knowledge and enhancing robustness to varying channel conditions

[19, 23]. Extensive simulations demonstrate the proposed method's superior performance over traditional estimation techniques, such as orthogonal matching pursuit (OMP), in terms of normalized mean square error (NMSE) and adaptability to non-ideal conditions [16, 17, 22].

Throughout this paper, several symbols are used to describe the mathematical models and algorithms. Specifically, H represents the channel matrix, G denotes the RIS-assisted channel gain, N is the number of antennas, and M is the number of RIS elements. The received signal is denoted by y, and the transmitted signal by x. The RIS phase shift matrix is represented by $\mathbf{\Theta}$, while σ^2 refers to the noise variance. The beamforming matrix is denoted by $\mathbf{W}$, and $\hat{H}$ indicates the estimated channel matrix. The signal-to-noise ratio (SNR) is represented by γ, the sparsity level of the channel by L, the pilot matrix by $\mathbf{\Phi}$, and the training duration by T. Lastly, $\mathcal{L}$ denotes the loss function, and $\mathbf{h}$ represents the channel vector.

The rest of the paper is organized as follows. In Section II, we review related work on channel estimation techniques for RIS-assisted mmWave systems and the application of machine learning in this domain. Section III presents the system model and problem formulation, outlining the assumptions and methodologies used in our study. In Section IV, we introduce the proposed hybrid channel estimation method and discuss its implementation in detail. Section V provides simulation results and a comprehensive performance analysis, demonstrating the effectiveness of our approach under various conditions. Finally, Section VI concludes the paper and suggests directions for future research.

2 Related work

The problem of channel estimation in reconfigurable intelligent surface (RIS)-assisted millimeter-wave (mmWave) systems has garnered significant attention in recent years due to its potential to enhance wireless communication by intelligently manipulating the propagation environment. Several research efforts have explored various techniques for efficient channel estimation in these systems.

2.1 Techniques for channel estimation in RIS-assisted mmWave systems

Conventional channel estimating strategies in RIS-assisted mmWave systems frequently employ compressive sensing (CS) methods to leverage the natural sparsity of mmWave channels [8–10]. These strategies reduce the total number of pilot signals needed, thus lowering overhead and computational complexity. Elbir and Coleri [8] introduced a sparse channel estimation framework using deep learning-based compressive sensing, which surpasses conventional CS approaches in accuracy and efficiency.

Nevertheless, CS-based methodologies often presume prior knowledge of the channel's sparsity, which is not always possible in dynamic circumstances [10–12]. To mitigate this restriction, many scholars have proposed methodologies that do not depend on exact sparsity data. Cai et al. [26] developed a channel estimate method that utilizes the low-rank characteristic of the cascaded channel matrix, therefore eliminating the need for precise sparsity information.

Recent advancements in millimeter-wave (mmWave) massive multiple-input multiple-output (MIMO) systems have underscored the importance of efficient channel estimation techniques to enhance communication reliability and resource allocation. Among these techniques, tensor modeling has emerged as a promising approach to address the high-dimensional challenges inherent in mmWave channels. For instance, a unified tensor-based framework for joint channel and target parameter estimation in integrated sensing and communication systems is presented in [27], highlighting the potential of combining sensing and communication functionalities. Similarly, tensor decomposition methods have been effectively applied to channel estimation in hybrid mmWave massive MIMO systems operating under high-mobility scenarios, offering robust solutions for dynamic environments [28]. Furthermore, tensor-based approaches have been utilized in Terahertz systems for target sensing, demonstrating their capability to enhance channel training and estimation in massive MIMO deployments [29]. These studies underscore the growing significance of tensor modeling in tackling the complexities of mmWave massive MIMO systems, complementing other methodologies such as deep learning and compressive sensing.

An alternative strategy is to employ hybrid analog-digital beamforming to reduce the dimensionality of the channel estimation problem, thus decreasing the pilot overhead [2]. Hybrid beamforming methodologies segregate the channel estimation procedure between analog and digital domains, significantly reducing the computational complexity caused by massive antenna arrays in mmWave systems.

2.2 Applications of machine learning in channel estimation

Applications of machine learning (ML), especially deep learning, in channel estimation have gained attention owing to their capacity to recognize complex structures from data and adjust to variable channel conditions [16–18]. Machine learning methodologies have shown enhanced efficacy related to conventional procedures by using large data sets and solid computational environments. Taha et al. [16] presented a deep learning framework for rapid channel estimation in beamspace mmWave massive

MIMO systems. Their methodology use a convolutional neural network (CNN) to predict channel states, significantly decreasing the estimate duration related to conventional approaches. Zhou et al. [17] introduced a machine learning-based beam training technique for RIS-assisted mmWave systems, enhancing beam alignment precision and minimizing training overhead. Recent studies have investigated this integration, aiming to combine the adaptability of ML models with the sparsity-exploiting capabilities of CS techniques [19, 22]. This hybrid approach has the potential to offer more robust and efficient solutions for channel estimation in RIS-assisted mmWave systems [18, 30].

In summary, while substantial advancements have been achieved in channel estimate methodologies for RIS-assisted mmWave systems, several problems remain. Conventional compressive sensing methods need exact knowledge of the channel's sparsity, whereas machine learning approaches, despite their efficacy, have not been completely incorporated with compressive sensing techniques. Hybrid methodologies integrating machine learning with CS are developing as a potential avenue, providing a balance between flexibility and computing efficiency. As the field continues to evolve, these innovative techniques will play a crucial role in advancing the performance and capabilities of next-generation wireless communication systems.

3 System model and problem formulation

A block diagram illustrating the RIS-assisted mmWave system model, including key components like the transmitter, RIS, and receiver, has been depicted in Fig. 1.

We consider a reconfigurable intelligent surface (RIS)-assisted millimeter-wave (mmWave) downlink communication system, where the RIS is deployed to enhance data transmission from a base station (BS) equipped with N antennas to a single-antenna user. The RIS is modeled as a planar array consisting of M reflecting elements. The channel matrix from the BS to the RIS is denoted by $\boldsymbol{G} \in \mathbb{C}^{M \times N}$, and the channel vector from the RIS to the user is represented by $\boldsymbol{h}_r \in \mathbb{C}^{M \times 1}$. In this setup, we neglect the direct link between the BS and the user for simplicity, but it can be easily incorporated if needed. Each reflecting element of the RIS can adjust the incident signal's phase shift and amplitude through a sophisticated controller [31].

The phase shift matrix of the RIS is denoted as $\boldsymbol{\Phi} = \mathrm{diag}(\beta_1 e^{j\theta_1}, \beta_2 e^{j\theta_2}, \ldots, \beta_M e^{j\theta_M})$, where $\beta_m \in [0, 1]$ and $\theta_m \in [0, 2\pi]$ represent the amplitude reflection coefficient and the phase shift associated with the m-th passive element of the RIS, respectively. The received signal at the user at the l-th time instant can be expressed as:

$$y_l = \boldsymbol{h}_r^T \boldsymbol{\Phi}_l \boldsymbol{G} \boldsymbol{b}_l s_l + n_l, \tag{1}$$

where s_l denotes the transmitted symbol, $\boldsymbol{b}_l$ represents the beamforming vector at the BS, and n_l is the additive white Gaussian noise (AWGN) with zero mean and variance σ^2.

To simplify the model, we define the cascaded channel matrix $\boldsymbol{H} \triangleq \mathrm{diag}(\boldsymbol{h}_r^T)\boldsymbol{G} \in \mathbb{C}^{M \times N}$. Thus, the received signal in Eq. (1) can be rewritten as:

$$y_l = \boldsymbol{v}_l^T \boldsymbol{H} \boldsymbol{b}_l s_l + n_l, \tag{2}$$

where $\boldsymbol{v}_l \triangleq [e^{j\theta_1}, e^{j\theta_2}, \ldots, e^{j\theta_M}]^T \in \mathbb{C}^M$ represents the phase shift vector at the l-th time instant.

In mmWave systems, both the number of reflecting elements (M) at the RIS and the number of antennas (N) at the BS can be large. Studies have shown that mmWave channels typically exhibit sparse scattering characteristics in practical environments [32–38]. This sparsity can be exploited to reduce the training overhead required for channel estimation.

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4 Proposed hybrid channel estimation method

In this section, we introduce the proposed hybrid channel estimation method, which integrates machine learning with compressive sensing (CS) to enhance the accuracy and efficiency of channel estimation in reconfigurable intelligent surface (RIS)-assisted millimeter-wave (mmWave) systems. The proposed method leverages the data-driven capabilities of deep learning to predict channel states and the sparsity-exploiting features of CS to reduce pilot overhead and computational complexity.

4.1 Problem formulation

Given the system model described earlier, the primary objective is to estimate the cascaded channel matrix $\boldsymbol{H}_k$ for each user k from the received signal matrix $\boldsymbol{Y}_k$. The received signal model after Q pilot transmissions can be expressed as:

$$\boldsymbol{Y}_k = \boldsymbol{H}_k \boldsymbol{\Phi} + \boldsymbol{W}_k, \tag{3}$$

where $\boldsymbol{Y}_k \in \mathbb{C}^{N \times Q}$ is the overall measurement matrix, $\boldsymbol{\Phi} \in \mathbb{C}^{M \times Q}$ is the mixing matrix containing the phase shifts of the RIS elements over Q time slots, and $\boldsymbol{W}_k \in \mathbb{C}^{N \times Q}$ is the noise matrix.

To simplify the estimation process, we transform the received signal model into the angular domain. Let $\boldsymbol{U}_M$ and $\boldsymbol{U}_N$ be the unitary discrete Fourier transform (DFT) matrices for the RIS and BS, respectively. The angular cascaded channel matrix $\check{\boldsymbol{H}}_k$ is then given by:

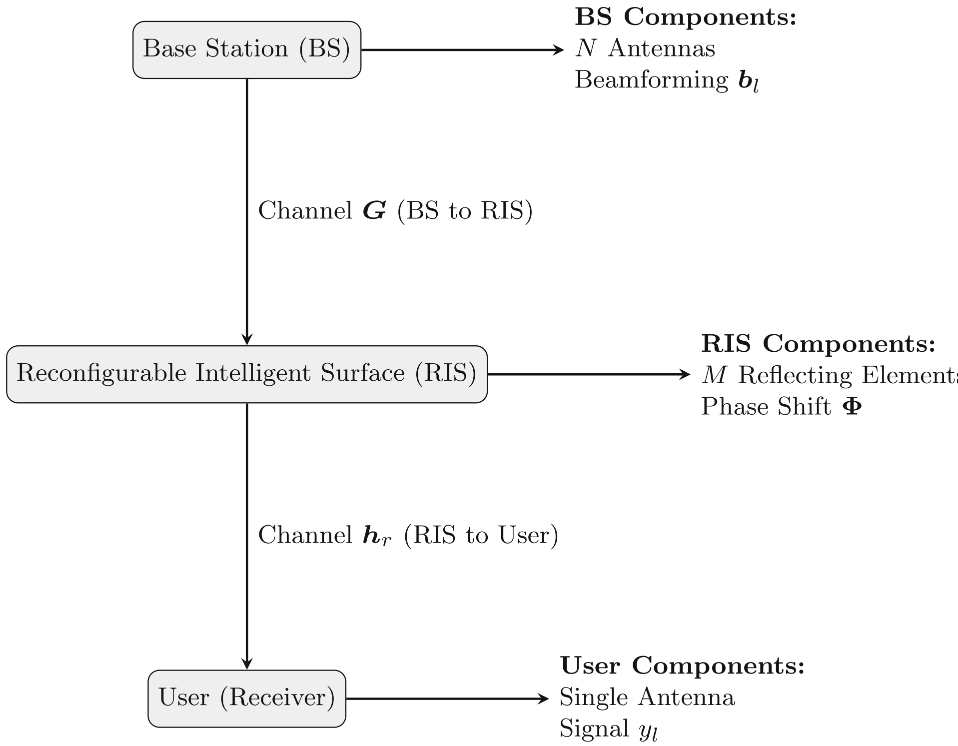

Fig. 1 The block diagram of the RIS-assisted mmWave system model

$$\boldsymbol{H}_k = \boldsymbol{U}_M \check{\boldsymbol{H}}_k \boldsymbol{U}_N^H. \tag{4}$$

Substituting Eqs (4) into (3), we obtain:

$$\boldsymbol{Y}_k = \boldsymbol{U}_M \check{\boldsymbol{H}}_k \boldsymbol{U}_N^H \boldsymbol{\Phi} + \boldsymbol{W}_k. \tag{5}$$

To further simplify, we define $\tilde{\boldsymbol{Y}}_k = \boldsymbol{U}_M^H \boldsymbol{Y}_k \boldsymbol{U}_N$ and $\tilde{\boldsymbol{\Phi}} = \boldsymbol{U}_N^H \boldsymbol{\Phi}$. The transformed signal model is:

$$\tilde{\boldsymbol{Y}}_k = \check{\boldsymbol{H}}_k \tilde{\boldsymbol{\Phi}} + \tilde{\boldsymbol{W}}_k, \tag{6}$$

where $\tilde{\boldsymbol{W}}_k = \boldsymbol{U}_M^H \boldsymbol{W}_k \boldsymbol{U}_N$ is the transformed noise matrix.

4.2 Proposed hybrid estimation method

The proposed hybrid channel estimation method consists of two main stages: a deep learning-based prediction stage and a compressive sensing-based refinement stage.

4.2.1 Deep learning-based prediction

In the first stage, a deep learning model, specifically a convolutional neural network (CNN), is employed to predict an initial estimate of the angular cascaded channel matrix $\check{\boldsymbol{H}}_k$. The CNN is trained using a large dataset of channel realizations, where the input features are derived from the transformed received signal $\tilde{\boldsymbol{Y}}_k$ and the output labels are the corresponding angular channel matrices $\check{\boldsymbol{H}}_k$.

The CNN acquires the ability to associate input features with output labels by minimizing a mean squared error (MSE) loss function, which is defined as:

$$\mathcal{L} = \frac{1}{N_{\text{train}}} \sum_{i=1}^{N_{\text{train}}} \left\| \check{\boldsymbol{H}}_k^{(i)} - \hat{\check{\boldsymbol{H}}}_k^{(i)} \right\|_F^2, \tag{7}$$

where N_{train} denotes the number of training samples, $\check{\boldsymbol{H}}_k^{(i)}$ represents the true angular channel matrix, and $\hat{\check{\boldsymbol{H}}}_k^{(i)}$ represents the CNN-predicted channel matrix.

Algorithm 1 highlights the procedure for using a model developed using deep learning, particularly a convolutional neural network (CNN), to carry out initial channel estimate in a reconfigurable intelligent surface (RIS)-aided millimeter-wave (mmWave) system. The methodology intends to employ the data-driven capability of deep learning to estimate the angular cascaded channel matrix, serving as the basis for further enhancement using compressive sensing methods. This method has two main phases: the training phase and the prediction phase.

4.2.1.1 Training phase

In the training phase, the CNN model $\mathcal{M}$ is trained on a dataset including pairs of transformed received signal matrices $\{\tilde{\boldsymbol{Y}}_k^{(i)}\}$ and their associated true angular channel matrices $\{\check{\boldsymbol{H}}_k^{(i)}\}$. The objective is to learn the relationship between the input signal matrices and the output channel matrices. The procedures associated with this phase are as follows:

- **Initialization:** The CNN model $\mathcal{M}$ gets started with random weights. The learning rate η and the number of epochs E have defined as hyperparameters.

- **Forward Pass:** For each training sample, the CNN model yields an initial estimation of the angular cascaded channel matrix, represented as $\hat{\check{\boldsymbol{H}}}_k^{(i)}$.
- **Loss Computation:** The mean squared error (MSE) loss between the true channel matrix $\check{\boldsymbol{H}}_k^{(i)}$ and the predicted channel matrix $\hat{\check{\boldsymbol{H}}}_k^{(i)}$ is computed as:

$$\mathcal{L} = \frac{1}{N_{\text{train}}} \sum_{i=1}^{N_{\text{train}}} \left\| \check{\boldsymbol{H}}_k^{(i)} - \hat{\check{\boldsymbol{H}}}_k^{(i)} \right\|_F^2. \tag{8}$$

- **Backward Pass:** Gradients of the loss function $\mathcal{L}$ with respect to the model parameters are computed using backpropagation.
- **Parameter Update:** The model parameters are updated using gradient descent to minimize the loss function, following the update rule:

$$\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} - \eta \nabla_{\boldsymbol{\theta}} \mathcal{L}, \tag{9}$$

  where $\boldsymbol{\theta}$ represents the parameters of the CNN model.
- **Epoch Completion:** Steps 2–5 are repeated for all training samples in each epoch. The training continues for E epochs or until the loss function converges to a minimum value.

4.2.1.2 Prediction phase After the training phase, the CNN model $\mathcal{M}$ is utilized to predict the initial channel estimates for each user. The steps involved in this phase are as follows:

- **Input Transformation:** For each user k, the received signal matrix $\boldsymbol{Y}_k$ is transformed into the angular domain using the unitary matrices $\boldsymbol{U}_M$ and $\boldsymbol{U}_N$, resulting in $\tilde{\boldsymbol{Y}}_k = \boldsymbol{U}_M^H \boldsymbol{Y}_k \boldsymbol{U}_N$.
- **Channel Estimation:** The transformed received signal matrix $\tilde{\boldsymbol{Y}}_k$ is input to the trained CNN model $\mathcal{M}$ to predict the initial channel estimate $\hat{\check{\boldsymbol{H}}}_k$.
- **Output:** The initial channel estimates $\{\hat{\check{\boldsymbol{H}}}_k\}$ for all users are obtained and used as inputs for further refinement in the compressive sensing-based refinement phase.

Algorithm 1 effectively utilizes deep learning to provide a strong initial estimate of the channel matrix, leveraging the model's ability to learn complex patterns in data and adapt to varying channel conditions. This initial estimate serves as a valuable starting point for the subsequent compressive sensing-based refinement process.

CNNs are utilized due to their ability to automatically learn spatial and temporal features from the input data, significantly reducing the need for manual feature extraction. They can effectively capture the underlying patterns in channel matrices, making them particularly suitable for high-dimensional and complex data scenarios like mmWave systems. Unlike traditional methods, CNNs are robust to noise and variations in channel conditions, enabling more accurate and adaptive channel estimation.

When comparing the complexity of CNNs with algorithms like Orthogonal Matching Pursuit (OMP), CNN-based methods generally have higher computational requirements during the training phase due to the need for backpropagation and gradient descent optimization over multiple epochs. However, during the prediction phase, CNNs offer significant advantages in terms of speed and efficiency, as the inference process involves a fixed number of operations independent of the problem size. In contrast, OMP has a lower initial computational overhead but scales poorly with increasing problem dimensions, as its iterative nature requires sequential updates and matrix computations, leading to higher complexity for large-scale systems.

Algorithm 1 Deep learning-based prediction for channel estimation

Require: Training dataset $\{\tilde{\boldsymbol{Y}}_k^{(i)}, \check{\boldsymbol{H}}_k^{(i)}\}_{i=1}^{N_{\text{train}}}$, learning rate η, number of epochs E
Ensure: Trained CNN model $\mathcal{M}$, initial channel estimates $\{\hat{\check{\boldsymbol{H}}}_k\}$
Initialize CNN model $\mathcal{M}$ with random weights
for epoch $= 1$ to E **do**
  for each training sample $i = 1$ to N_{train} **do**
    Forward pass: Predict $\hat{\check{\boldsymbol{H}}}_k^{(i)} = \mathcal{M}(\tilde{\boldsymbol{Y}}_k^{(i)})$
    Compute loss: $\mathcal{L} = \frac{1}{N_{\text{train}}} \sum_{i=1}^{N_{\text{train}}} \left\| \check{\boldsymbol{H}}_k^{(i)} - \hat{\check{\boldsymbol{H}}}_k^{(i)} \right\|_F^2$
    Backward pass: Compute gradients of loss $\mathcal{L}$ with respect to model parameters
    Update model parameters using gradient descent: $\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} - \eta \nabla_{\boldsymbol{\theta}} \mathcal{L}$
  end for
end for
Return trained CNN model $\mathcal{M}$
Prediction Phase:
for each user k **do**
  Input $\tilde{\boldsymbol{Y}}_k$ to the trained CNN model: $\hat{\check{\boldsymbol{H}}}_k = \mathcal{M}(\tilde{\boldsymbol{Y}}_k)$
end for
Return initial channel estimates $\{\hat{\check{\boldsymbol{H}}}_k\}$ for all users

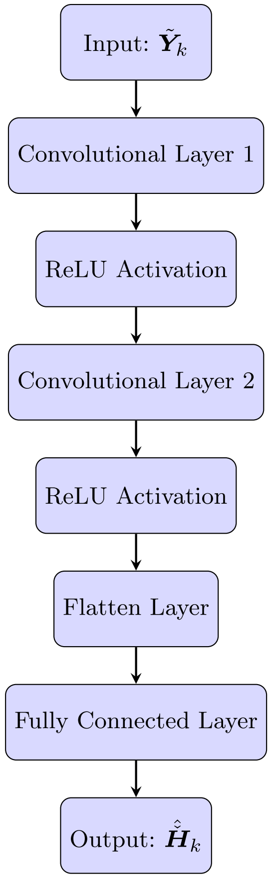

Fig. 2 Block diagram of the proposed CNN-based channel estimation technique. Each layer's function is highlighted, illustrating the progression from input to output

A block diagram of the proposed CNN-based channel estimation technique has been included has been depicted in Fig. 2, clearly annotating each layer and its function. This diagram provides a visual summary of the deep learning model's structure, emphasizing its role in channel estimation.

4.2.2 Compressive sensing-based refinement

The initial estimate $\hat{\hat{\boldsymbol{H}}}_k$ obtained from the CNN is refined using a compressive sensing technique. At this point, we use the sparsity of the mmWave channels in the angular domain to enhance the precision of channel estimate. The simplified estimation problem may be stated as a sparse recovery problem:

$$\hat{\hat{\boldsymbol{H}}}_k = \arg\min_{\boldsymbol{X}} \left\| \tilde{\boldsymbol{Y}}_k - \boldsymbol{X}\tilde{\boldsymbol{\Phi}} \right\|_F^2 + \lambda \|\boldsymbol{X}\|_1, \tag{10}$$

where λ represents a regularization parameter that manages the sparsity of the solution. This optimization problem can be solved using the Orthogonal Matching Pursuit (OMP) method.

5 Compressive sensing-based refinement for channel estimation

Algorithm 2 highlights the procedure for enhancing the channel estimation produced by deep learning predictions using a compressive sensing (CS) methodology. The improvement based on compressive sensing utilizes the sparsity of the angular cascaded channel matrix to enhance the precision of channel estimation in a reconfigurable intelligent surface (RIS)-assisted millimeter-wave (mmWave) system.

The technique enhances the initial estimates by repeatedly adjusting the channel matrix to align more accurately with the observed received signals, so guaranteeing that the final estimate takes advantage on the sparse features of the mmWave channels.

5.1 Initialization

During this phase, for each user k, the initial channel estimate $\hat{\hat{\boldsymbol{H}}}_k$, determined from the deep learning-based prediction, serves as the basis. The mixing matrix $\tilde{\boldsymbol{\Phi}}$ is converted into the angular domain to align with the domain of the channel estimation. The residual matrix $\boldsymbol{R}$ is set up as the difference between the converted received signal matrix $\tilde{\boldsymbol{Y}}_k$ and the result of the initial estimate $\hat{\hat{\boldsymbol{H}}}_k$ and the converted mixing matrix $\tilde{\boldsymbol{\Phi}}$.

5.2 Iterative refinement

The key component of the compressive sensing method is an iterative loop that maintains until a stopping requirement is satisfied (e.g., convergence of the residual or the maximum number of iterations). The procedures entailed in each iteration are as follows:

- **Compute Correlation Vector:** The correlation vector $\boldsymbol{c}$ is determined as the correlation between the columns of the mixing matrix $\tilde{\boldsymbol{\Phi}}$ and the residual matrix $\boldsymbol{R}$.
- **Identify Maximum Correlation:** The index j of the maximum absolute value in the correlation vector $\boldsymbol{c}$ is identified. This index corresponds to the component of the channel that will be updated in this iteration.
- **Update Support Set:** The support set $\mathcal{S}$, which keeps track of the indices of non-zero elements in the sparse channel matrix, is updated by adding the newly identified index j.
- **Solve Least-Squares Problem:** A least-squares optimization problem is solved over the current support set $\mathcal{S}$ to update the refined channel estimate $\boldsymbol{X}_{\mathcal{S}}$. This step ensures that the channel estimate is the best fit for the observed data, given the current support.

- **Update Channel Estimate:** The refined channel estimate $\boldsymbol{X}$ is updated with the solution from the least-squares problem.
- **Update Residual Matrix:** The residual matrix $\boldsymbol{R}$ is recalculated based on the updated channel estimate. This updated residual reflects the difference between the observed data and the current estimate, guiding the next iteration.

5.3 Reconstruction

After the iterative refinement process converges or reaches the maximum number of iterations, the final step is to reconstruct the estimated channel matrix $\hat{\boldsymbol{H}}_k$ in the original domain. This is done by transforming the refined angular domain channel estimate $\boldsymbol{X}$ back using the unitary matrices $\boldsymbol{U}_M$ and $\boldsymbol{U}_N$.

The algorithm ensures that the final refined channel estimate fully exploits the sparsity of the mmWave channels, leading to more accurate and reliable channel estimation for RIS-assisted systems.

Algorithm 2 Compressive sensing-based refinement for channel estimation

Require: Initial channel estimates $\{\hat{\tilde{\boldsymbol{H}}}_k\}$ from CNN, transformed received signal matrices $\{\tilde{\boldsymbol{Y}}_k\}$, transformed mixing matrices $\{\tilde{\boldsymbol{\Phi}}\}$, regularization parameter λ
Ensure: Refined channel estimates $\{\hat{\boldsymbol{H}}_k\}$

for each user k **do**
  Initialize refined channel estimate $\boldsymbol{X} = \hat{\tilde{\boldsymbol{H}}}_k$
  Transform mixing matrix: $\tilde{\boldsymbol{\Phi}} = \boldsymbol{U}_N^H \boldsymbol{\Phi}$
  Define residual matrix $\boldsymbol{R} = \tilde{\boldsymbol{Y}}_k - \boldsymbol{X}\tilde{\boldsymbol{\Phi}}$
  while stopping criterion not met **do**
    Compute correlation vector $\boldsymbol{c} = \tilde{\boldsymbol{\Phi}}^H \boldsymbol{R}$
    Find index of maximum correlation: $j = \arg\max |\boldsymbol{c}|$
    Update support set: $\mathcal{S} \leftarrow \mathcal{S} \cup \{j\}$
    Solve least-squares problem on current support: $\boldsymbol{X}_{\mathcal{S}} = \arg\min_{\boldsymbol{X}_{\mathcal{S}}} \left\| \tilde{\boldsymbol{Y}}_k - \boldsymbol{X}_{\mathcal{S}} \tilde{\boldsymbol{\Phi}}_{\mathcal{S}} \right\|_F^2$
    Update refined channel estimate: $\boldsymbol{X} \leftarrow \boldsymbol{X}_{\mathcal{S}}$
    Update residual matrix: $\boldsymbol{R} \leftarrow \tilde{\boldsymbol{Y}}_k - \boldsymbol{X}\tilde{\boldsymbol{\Phi}}$
  end while
  Reconstruct the estimated channel: $\hat{\boldsymbol{H}}_k = \boldsymbol{U}_M \boldsymbol{X} \boldsymbol{U}_N^H$
end for
Return refined channel estimates $\{\hat{\boldsymbol{H}}_k\}$ **for all users**

6 Proposed hybrid channel estimation algorithm

Algorithm 3 highlights the proposed hybrid channel estimation technique that integrates deep learning-driven prediction with compressive sensing-based refinement. This hybrid technique aims to use the advantages of both approaches to get accurate and effective channel estimates in reconfigurable intelligent surface (RIS)-assisted millimeter-wave (mmWave) systems.

The hybrid approach consists of two main phases: the deep learning-based prediction phase and the compressive sensing-based refining phase. The proposed method increases estimation accuracy and decreases pilot overhead by first using a convolutional neural network (CNN) to predict channel estimations, followed by refinement via compressive sensing methods.

6.1 Deep learning-based prediction phase

In the first phase of the Proposed Hybrid Channel Estimation Algorithm, a Convolutional Neural Network (CNN) model is used to predict first estimations of the angular cascaded channel matrices from the converted received signal matrices. This method utilizes the capacity of CNNs to identify complicated spatial patterns, establishing a robust basis for further enhancement. The procedures in this phase are listed as follows:

- **Model Initialization and Training:** The CNN model $\mathcal{M}$ is started with arbitrary weights and trained with a dataset of transformed received signal matrices, $\{\tilde{\boldsymbol{Y}}_k^{(i)}\}$, alongside their corresponding angular channel matrices, $\{\check{\boldsymbol{H}}_k^{(i)}\}$. The training method entails reducing the mean squared error (MSE) loss between the anticipated and real channel matrices, enabling the model to acquire the mapping from input signals to the angular domain representation of the channels.
- **Initial Channel Estimation:** Subsequent to training, the CNN model is used to predict the first channel estimations for each user. The transformed received signal matrices, $\{\tilde{\boldsymbol{Y}}_k\}$, are input into the trained model $\mathcal{M}$, which produces the first estimations of the angular cascaded channel matrices, $\hat{\check{\boldsymbol{H}}}_k$. These estimates provide the basis for subsequent refining, encompassing the most important attributes of the channels based on acquired spatial patterns.

6.2 Compressive sensing-based refinement phase

The second step emphasizes the enhancement of the first channel estimations acquired from the CNN by a compressive sensing (CS) methodology. This phase leverages the sparsity of mmWave channels to improve estimate accuracy. The procedures involved are:

- **Initialization:** For each user k, the initial channel estimate $\hat{\check{\boldsymbol{H}}}_k$ functions as the baseline. The mixing matrix $\tilde{\boldsymbol{\Phi}}$ is modified to correspond with the channel estimate domain, while the residual matrix $\boldsymbol{R}$ is initialized as the difference between the converted received signal and the original estimate. The residual matrix denotes the portion of the signal that remains unexplained and will be minimized throughout the refining process.
- **Iterative Refinement:** An iterative method is used to enhance the channel estimate by addressing a sequence of least-squares problems centered on the support set of non-zero elements, which represents the critical components of the channel. In each iteration, the algorithm refines the channel estimate and residual matrix, progressively enhancing accuracy by focusing on the channel's sparse representation. This procedure continues until convergence is achieved, signified by a negligible change in the residual or a certain number of rounds.
- **Reconstruction:** Once the refinement converges, the refined channel estimate is transformed back to the original domain using unitary matrices. This step ensures the final refined channel estimate, $\hat{\boldsymbol{H}}_k$, accurately represents the true channel state in the spatial domain, ready for further processing or practical application.

6.3 Algorithm description

The complete proposed hybrid channel estimation algorithm is presented in Algorithm 3. The algorithm combines the initial estimation capabilities of deep learning with the sparsity-exploiting power of compressive sensing to provide an accurate and efficient solution for channel estimation in RIS-assisted mmWave systems.

Algorithm 3 Proposed hybrid channel estimation algorithm

Require: Training dataset $\{\tilde{\boldsymbol{Y}}_k^{(i)}, \check{\boldsymbol{H}}_k^{(i)}\}_{i=1}^{N_{\text{train}}}$, received signal matrices $\{\boldsymbol{Y}_k\}$, mixing matrices $\{\boldsymbol{\Phi}\}$, learning rate η, number of epochs E, regularization parameter λ
Ensure: Estimated channel matrices $\{\hat{\boldsymbol{H}}_k\}$ for all users
Step 1: Deep Learning-Based Prediction
Initialize CNN model $\mathcal{M}$ with random weights
for epoch $= 1$ to E **do**
  for each training sample $i = 1$ to N_{train} **do**
    Forward pass: Predict $\hat{\check{\boldsymbol{H}}}_k^{(i)} = \mathcal{M}(\tilde{\boldsymbol{Y}}_k^{(i)})$
    Compute loss: $\mathcal{L} = \frac{1}{N_{\text{train}}} \sum_{i=1}^{N_{\text{train}}} \left\| \check{\boldsymbol{H}}_k^{(i)} - \hat{\check{\boldsymbol{H}}}_k^{(i)} \right\|_F^2$
    Backward pass: Compute gradients of loss $\mathcal{L}$ w.r.t. model parameters
    Update model parameters: $\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} - \eta \nabla_{\boldsymbol{\theta}} \mathcal{L}$
  end for
end for
Obtain trained CNN model $\mathcal{M}$
for each user k **do**
  Transform received signal: $\tilde{\boldsymbol{Y}}_k = \boldsymbol{U}_M^H \boldsymbol{Y}_k \boldsymbol{U}_N$
  Input $\tilde{\boldsymbol{Y}}_k$ to the CNN model: $\hat{\check{\boldsymbol{H}}}_k = \mathcal{M}(\tilde{\boldsymbol{Y}}_k)$
end for
Step 2: Compressive Sensing-Based Refinement
for each user k **do**
  Initialize refined channel estimate $\boldsymbol{X} = \hat{\check{\boldsymbol{H}}}_k$
  Transform mixing matrix: $\tilde{\boldsymbol{\Phi}} = \boldsymbol{U}_N^H \boldsymbol{\Phi}$
  Define residual matrix $\boldsymbol{R} = \tilde{\boldsymbol{Y}}_k - \boldsymbol{X}\tilde{\boldsymbol{\Phi}}$
  while stopping criterion not met **do**
    Compute correlation vector $\boldsymbol{c} = \tilde{\boldsymbol{\Phi}}^H \boldsymbol{R}$
    Find index of maximum correlation: $j = \arg\max |\boldsymbol{c}|$
    Update support set: $\mathcal{S} \leftarrow \mathcal{S} \cup \{j\}$
    Solve least-squares problem on current support: $\boldsymbol{X}_{\mathcal{S}} = \arg\min_{\boldsymbol{X}_{\mathcal{S}}} \left\| \tilde{\boldsymbol{Y}}_k - \boldsymbol{X}_{\mathcal{S}} \tilde{\boldsymbol{\Phi}}_{\mathcal{S}} \right\|_F^2$
    Update refined channel estimate: $\boldsymbol{X} \leftarrow \boldsymbol{X}_{\mathcal{S}}$
    Update residual matrix: $\boldsymbol{R} \leftarrow \tilde{\boldsymbol{Y}}_k - \boldsymbol{X}\tilde{\boldsymbol{\Phi}}$
  end while
  Reconstruct the estimated channel: $\hat{\boldsymbol{H}}_k = \boldsymbol{U}_M \boldsymbol{X} \boldsymbol{U}_N^H$
end for
Return refined channel estimates $\{\hat{\boldsymbol{H}}_k\}$ **for all users**

The proposed hybrid channel estimation technique adeptly integrates the advantages of deep learning with compressive sensing, offering an adaptive and efficient resolution for channel estimation in RIS-assisted mmWave systems. The first CNN-based prediction provides a solid foundation for channel estimation, but the CS-based refinement guarantees that the final estimate maximally utilizes the channel's sparsity, leading to enhanced accuracy and decreased pilot overhead.

7 Results and comparative analysis

This section presents the simulation results used to evaluate the performance of the proposed hybrid channel estimation technique. We evaluate the proposed technique in relation to two alternative channel estimation techniques: the conventional compressive sensing (CS) method using the Orthogonal Matching Pursuit (OMP) algorithm [31] and the Oracle Least Squares (LS) scheme, which assumes complete knowledge of the supports for all sparse channels, is used as a benchmark for comparison.

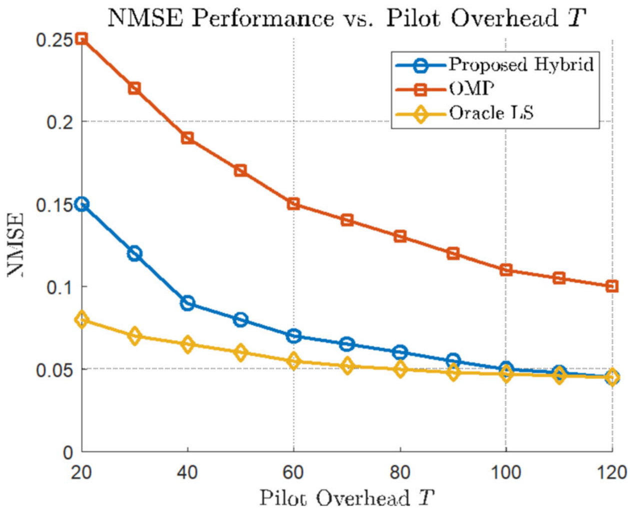

Fig. 3 NMSE performance vs. the pilot overhead T

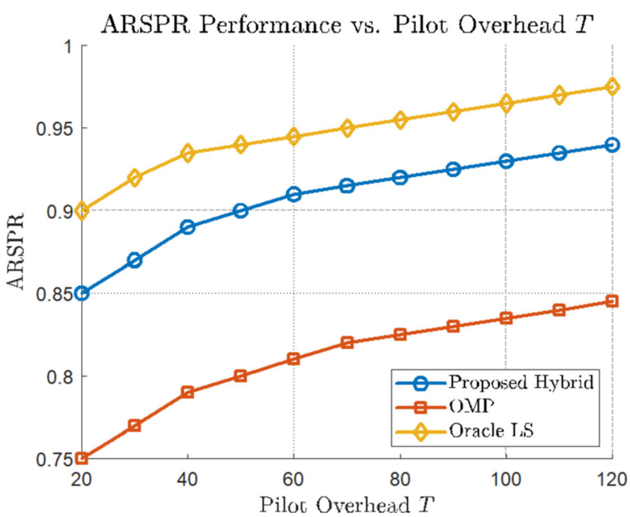

Fig. 4 ARSPR performance vs. the pilot overhead T

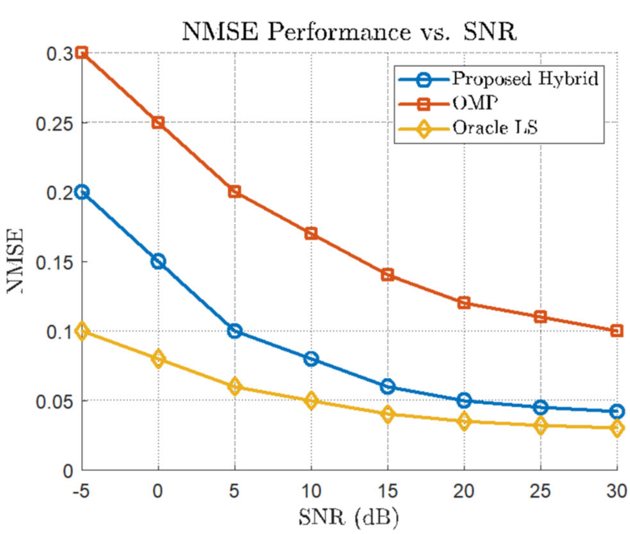

Fig. 5 NMSE performance vs. the SNR

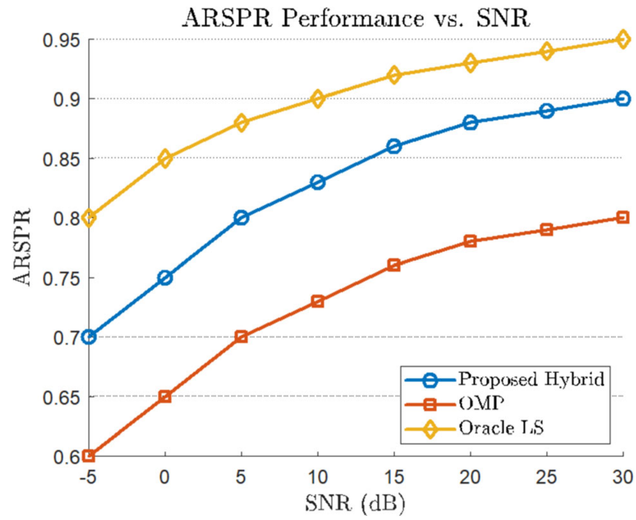

Fig. 6 ARSPR performance vs. the SNR

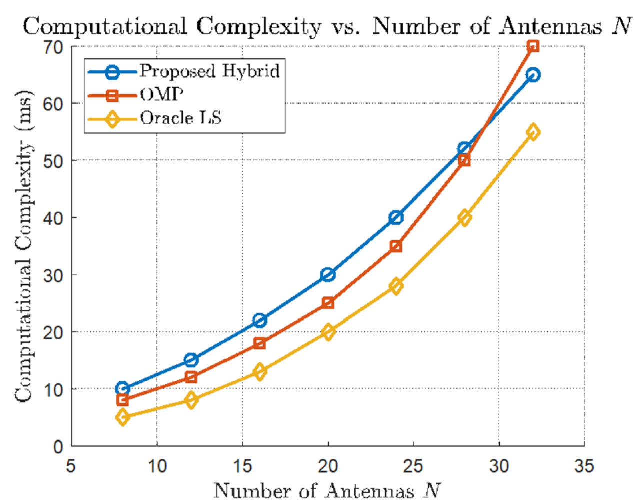

Fig. 7 Computational complexity vs. number of antennas N

Table 1 Average runtime comparison of different methods

Method	Average runtime (ms)
Proposed Hybrid Method	160
OMP-Based Method	120
Oracle LS Estimator	80

7.1 Simulation setup

This section considers a system with a base station (BS) that has $N = 16$ antennas arranged in a uniform linear array (ULA) and a reconfigurable intelligent surface (RIS) with $M = 8 \times 8$ elements. The RIS reflection coefficients are chosen from values in the range $\left[-\frac{1}{\sqrt{M}}, \frac{1}{\sqrt{M}}\right]$ [35]. To capture both line-of-sight (LOS) and non-line-of-sight (NLOS) effects, a Rician channel model is assumed, with a Rician factor of 13.2 dB [39]. Angles of arrival (AoAs) and departure (AoDs) are uniformly distributed in $\left[-\frac{\pi}{2}, \frac{\pi}{2}\right]$.

7.1.1 Data preparation and network training

A convolutional neural network (CNN) is used to estimate the channel. Training and test data are derived from the *DeepMIMO* dataset [40], which offers diverse channel realizations at different user locations. Part of the data is allocated for training, while the rest is held out for testing, ensuring no overlap between the two sets.

7.1.2 Performance metrics

We evaluate the system using the normalized mean square error (NMSE) and the average reflection signal-to-pilot ratio (ARSPR). The NMSE is defined as

$$\mathrm{NMSE} = \frac{\mathbb{E}\left[\|\boldsymbol{H}_k - \hat{\boldsymbol{H}}_k\|_F^2\right]}{\|\boldsymbol{H}_k\|_F^2}, \tag{11}$$

where $\boldsymbol{H}_k$ is the true channel for user k and $\hat{\boldsymbol{H}}_k$ is its estimate. The ARSPR measures the ratio between the actual received signal power and the ideal power, given by

$$\mathrm{ARSPR} = \mathbb{E}\left[\frac{\|\mathbf{v}^{\mathrm{H}}\boldsymbol{H}\|_F^2}{\|(\mathbf{v}^{\star})^{\mathrm{H}}\boldsymbol{H}\|_F^2}\right], \tag{12}$$

where $\mathbf{v}$ and $\mathbf{v}^{\star}$ are beamforming vectors derived from the estimated and true channels, respectively [41].

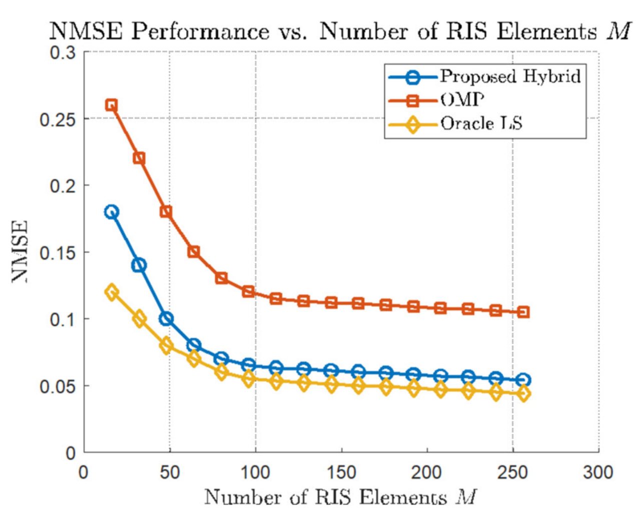

Fig. 8 NMSE performance vs. number of RIS elements M

7.2 Performance evaluation

Figure 3 shows the NMSE performance as a function of the pilot overhead, defined by the total number of time slots T dedicated to pilot transmission. As depicted, the proposed hybrid method achieves similar estimation accuracy with significantly reduced pilot overhead compared to the OMP-based method. This demonstrates the efficiency of our approach in reducing the training time while maintaining high estimation accuracy.

Figure 4 illustrates the ARSPR performance of the different algorithms as a function of T, with the signal-to-noise ratio (SNR) fixed at 12 dB. The results indicate that, in practical scenarios where $T > 60$, the proposed method achieves ARSPR performance comparable to that of the Oracle LS estimator. This further highlights the robustness of our method under varying conditions.

Figures 5 and 6 present the NMSE and ARSPR performances, respectively, as functions of the SNR with T set to 120. From Fig. 5, it is evident that the proposed hybrid method significantly improves system performance by achieving the lowest NMSE compared to the OMP-based method. Figure 6 shows that in real-world conditions, such as when SNR > 0, our method provides ARSPR performance close to that of the Oracle LS estimator.

7.3 Impact of number of antennas on computational complexity

To further evaluate the practicality of the proposed channel estimation methods, we examine their computational complexity as a function of the number of antennas at the base station (BS). Figure 7 illustrates the computational complexity, measured in terms of processing time, for the Proposed Hybrid Channel Estimation Algorithm, the OMP-based method, and the Oracle LS estimator.

As shown in Fig. 7, the computational complexity increases with the number of antennas for all methods. The Proposed Hybrid method, which combines deep learning and compressive sensing, exhibits higher complexity compared to the OMP-based method due to the additional steps involved in the deep learning prediction phase. The Oracle LS estimator, benefiting from ideal channel knowledge, demonstrates the lowest complexity. These results highlight the trade-off between accuracy and computational cost, where the Proposed Hybrid method, despite its higher complexity, provides superior estimation accuracy as seen in previous figures.

The runtime results, presented in Table 1, provide further insights into the practical feasibility of each method. The Proposed Hybrid method has a slightly higher average runtime (160 ms) compared to the OMP-based method

(120 ms), owing to the additional deep learning prediction stage. However, the Hybrid method demonstrates a significant improvement in accuracy compared to standalone methods, as shown in previous figures. The Oracle Least Squares (LS) estimator demonstrates the lowest complexity and runtime (80 ms), as it relies on ideal channel knowledge.

7.4 Effect of RIS element count on estimation accuracy

Another critical factor influencing channel estimation performance is the number of elements in the reconfigurable intelligent surface (RIS). Figure 8 depicts the normalized mean square error (NMSE) as a function of the number of RIS elements for the three estimation methods.

As seen in Fig. 8, increasing the number of RIS elements leads to improved NMSE performance across all methods. The Oracle LS estimator maintains the best performance due to its ideal assumptions. The Proposed Hybrid method, while slightly less accurate than the Oracle LS, consistently outperforms the OMP-based method, particularly as the RIS size increases. This indicates that the Proposed Hybrid method is well-suited for scenarios where the RIS configuration is large, leveraging the additional degrees of freedom provided by more RIS elements to enhance channel estimation accuracy.

The further results, shown in Figs. 7 and 8, demonstrate the benefits of the Proposed Hybrid Channel Estimation Algorithm. Although the technique results in higher computational costs, it demonstrates significant improvements in estimation accuracy.

8 Discussion

The simulation results shown in Figs. 3 to 8 provide a thorough assessment of the Proposed Hybrid Channel Estimation Algorithm related to the conventional OMP-based technique and the Oracle LS estimator.

As observed in Figs. 3, 5, and 8, the Proposed Hybrid Channel Estimation Algorithm consistently outperforms the OMP-based method in terms of NMSE across various pilot overheads, SNR levels, and RIS configurations. The hybrid approach, which integrates deep learning-based prediction with compressive sensing method, leverages the strengths of both methods to achieve superior estimation accuracy. The examination of computational complexity in Fig. 7 clarifies the trade-offs involved in using the Proposed Hybrid method. Although it entails more computing expenses than the OMP-based approach, the enhanced accuracy in channel estimation justifies this added complexity, particularly in situations requiring high levels of accuracy. In Figs. 7 and 8, The Proposed Hybrid method demonstrates robust performance as the number of antennas and RIS elements increases, maintaining lower NMSE and higher ARSPR compared to the OMP-based method.

9 Conclusion

An adaptable approach for channel estimate in RIS-assisted mmWave systems is proposed, which achieves an appropriate balance between complexity and accuracy. The proposed hybrid channel estimation technique adeptly integrates the advantages of deep learning with compressive sensing, offering an adaptive and efficient resolution for channel estimation in RIS-assisted mmWave systems. It outperforms conventional techniques like OMP and approaches Oracle LS estimator performance.

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Declarations

Conflict of interest The authors declare no competing interests.

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