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№ 15995

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August 18, 2025

Pilots Overhead in Reconfigurable Intelligent Surface-Assisted Wireless Communication Channel Estimation - A Review of the Art

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Abstract. Reconfigurable Intelligent Surface (RIS) technology is the main candidate for 5G-beyond. However, the increased number of passive components within the structure increases the number of links to be estimated. As a result, existing RIS-assisted channel estimation schemes are more error-prone than traditional communications, thus confounding a very large pilot load. Many approaches have been used to overcome this obstacle. This paper reviews different options studied ranging from RIS configuration optimization, channel feature exploitation, deep learning to blind estimation types with the assistance of adaptive mMIMO smart antennas.

Keywords: Reconfigurable intelligent surface, Pilots overhead, Channel estimation.

1 Introduction

After the 5G wireless network became standardized, it was clear that no single enabling technology could meet all future requirements [1]. Researchers then began to explore other alternatives, gradually moving away from the comfort zone of 5G-focused solutions. At this point, the reconfigurable intelligent surface (RIS) remains the undisputed counterweight to the needs of future applications. It is a passive device capable of controlling and modifying the propagation of electromagnetic waves. It can dynamically adjust the direction, phase, and amplitude of signals to improve coverage and reduce interference.

However, Pilots overhead is a major obstacle in RIS-assisted systems. Each RIS element must be configured and estimated individually, which results in an increase in the time and resources required for channel estimation. This reduces spectral and energy efficiency, limiting the overall system performance, especially in large-scale environments. Much work has been addressed to overcome this annoyance with a wide range of approaches, some more attractive than others, this end among many others.

2 Contributions

Specifically, many art reviews have been published to provide detailed advances on reconfigurable smart surface-assisted wireless communications. Wu et al. [2] provided an overview of wireless communication systems incorporating RIS, examining the operating principles, hardware architecture, and potential applications. Zheng et al. [3] focused on new research directions and innovative architectural designs associated with RIS. The works of Pan et al. [4] and Jian et al. [5] explored channel estimation approaches and propagation models specific to RIS-assisted systems. Liang et al. [6] analyzed RIS-based wireless communications, differentiating the roles that smart surfaces can play as information transmitters or reflectors. Noh et al. [7] and Chen et al. [8] investigated the properties of RIS in high frequency bands. Swindlehurst et al. [9] synthesized RIS system models by structuring their analysis around structured and unstructured configurations, while integrating the contributions of machine learning algorithms into their study.

Despite the progress, challenges remain, such as generalizing approaches to diverse environments or reducing computational complexity. Driver overhead is one cause. This focused review helps evaluate solutions that could make RIS systems more practical and efficient by centralizing current knowledge. Many approaches have been proposed to mitigate the overhead, including the use of sparse channel estimation techniques, machine learning algorithms, or tensor-based methods. The goal is to synthesize these works, compare their advantages and limitations, and guide researchers toward the most promising solutions.

We plan the rest of the paper in these steps: First, we highlight the advantages and limitations of conventional algorithms and then develop techniques based on optimization and deep learning before tackling the so-called blind and semi-blind approaches. The last step will be dedicated to identifying gaps and proposing directions.

3 Pilots Overhead In Reconfigurable Intelligent Surface Assisted Systems

Popular beamforming methods for RIS typically involve full channel state information (CSI). However, the computational cost of channel acquisition increases exponentially with the number of surface elements that are typically passive and therefore have no signal processing capability.

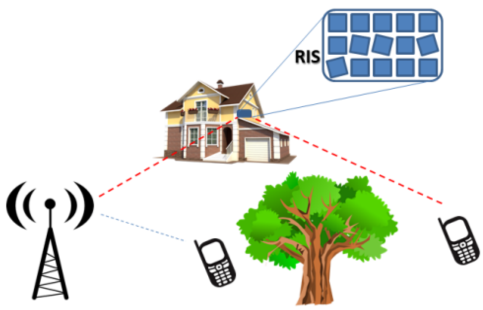

Fig. 1. Model of wireless communication system assisted by reconfigurable intelligent surface

3.1 Conventional Algorithms For Estimation Of RIS-assisted Systems

In the generic channel estimation method, the transmitter transmits the pilot sequence and the receiver receives the signal sequence after reflection by the RIS to recover the channel matrix in the constructed channel model. LS/MMSE estimation [10]-[14] is a classical method to find solutions of these models, which has been widely used in pilot-based RIS-assisted systems. These models are simple and lead to straightforward algorithms, but the required training overhead is very large and may make these approaches impractical. The estimator of the minimal linear average quadratic error (LMMSE) has also been studied in the context of reconfigurable intelligent surfaces (RIS) for the estimation of relative channels. However, its implementation remains complex, because it is based on a precise knowledge of the covariance of the relative canals. This constraint is aggravated by the nature of the distributions of these channels, often characterized by heavy tails, making their statistical modeling and their estimate particularly difficult.

Methods to reduce training overhead, e.g. based on clustering of RIS elements or exploiting the common BS-RIS channel between users, have been proposed, but larger reductions are possible when channels are sparse if parametric or geometric channel models are used instead. These approaches seek to compensate for the difficulties linked to traditional statistical modeling while adapting to the complex nature of RIS systems.

3.2 Optimization And Adaptability Of RIS Systems

Optimization techniques are essential in RIS-assisted systems especially since the efficiency of channel estimation can be improved by implementing a reasonable transmission protocol. To estimate cascaded channels with reduced training overhead, Liu et al. [15] model the channel estimation in a RIS-assisted multi-user MIMO system as a matrix factorization problem based on a specific calibration. By exploiting the slowly varying properties of channel components and the sparse structure of hidden channels, they introduce a novel message-passing algorithm to solve the cascaded channel factorization. Building on this approach, Chen et al. [16] exploit the block sparsity of rows and columns to capture the correlation between users, thus enabling joint channel recovery for multiple users. This method significantly reduces the pilot overhead compared to conventional techniques such as least squares (LS) or multiple measurement vector (MMV) models.

To reduce the pilot overhead, the sparsity and correlation of mmWave multi-user have been exploited in [17] with an orthogonal matching search (OMP) based method to estimate the angles of departure (AoD) among users and in [18] where partial information of a single user can be estimated in the first time, and then the channel between BS and RIS is estimated at a large time scale. Furthermore, a RIS-assisted mmWave channel estimation method based on Re'nyi entropy function combined with compressive sensing methods has been proposed in [19]. Re'nyi entropy function is used as a sparse promotion regularizer with the aim of reducing the pilot overhead. Chung et al. [20] explored the estimation of angular information based on position data. A channel estimation approach based on atomic norm minimization (ANM) has also been proposed to effectively reduce the pilot overhead.

Moreover, many studies converge on the superiority of tensor-based signal processing, which fully exploit the multidimensional structure of transmitted and received signals as well as communication channels. For example, the work of [21] shows that received signals can be accurately modeled using parallel factor tensor (PARAFAC) models, integrating specific temporal structures for pilots and phase adjustments of RIS.

Methods called two-phase or three-phase ON/OFF have also been developed. The authors propose an N-phase channel estimation strategy, where the direct and reflected channels associated with a typical user are estimated in the first phase. In the following, the CSI associated with the other users is estimated. However, the implementation of ON/OFF switching is costly because each RIS element must be controlled separately in terms of amplitude. The authors of [22] proposed an always-ON RIS model that can be used with orthogonal reflection coefficients derived from the DFT matrix.

Separate channel estimation can be easily achieved by installing active elements with transceiver signal capability on the RIS. An architecture was proposed in [23]. A CS method was used to perform channel reconstruction for the sampled channels detected by a few elements and then a deep learning-based solution was developed, in which the RIS learns to interact with the incident signal based on the channels of the active elements, which represent the environment state and the locations of the transmitters and receivers. To reduce the significant pilot overhead, Schroeder et al. [24] proposed a two-stage channel estimation scheme based on ANM. The proposed channel estimation requires fewer active RIS elements and only one-way training, which provides better estimation performance.

On the other hand, novel methods for generating training sets of RIS reflection coefficients are introduced, showing significant performance advantages in terms of complexity, pilot overhead, and signaling requirements. The work in [25] explores solutions based on a pre-designed codebook for RIS reflection models, reducing the overhead, without relying on complex model assumptions. The studies in [26] propose a low-complexity framework for RIS-assisted (MIMO) channel estimation. The approach consists of partitioning the channel training phase and pre-designing the RIS reflection coefficients to estimate the effective overlapping channel. The results demonstrate the competitive advantage over traditional methods, especially in fast-changing channels with limited coherence time. The table below summarizes a little the approaches mentioned based on methods of optimizing system assisted by RIS.

Table 1. Summary of approaches to optimization of RIS systems

References	Approaches discussed	Results
[15]	Problem in the form of matrix factorization	Reducing Overhead by Message Passing
[16]	Capturing correlation between users	Reduced overhead compared to LS or multiple measurement vector (MMV) models
[17]	Orthogonal Matching Pursuit (OMP)	Reduced pilots overhead by leveraging mmWave multi-user rarity and correlation
[18]	Partial information from a single user then generalized on a large scale	Saving pilot signals, remarkable performance
[19]	Re'nyi entropy function / CS	Sparse promotion regulation, Reduced pilots overload
[20]	Atomic Norm Minimization (ANM)	Effective reduction of driver overload
[21]	PARAFAC integrating specific temporal structures	Accurate signal modeling, RIS phase adjustments

References	Approaches discussed	Results
[22]	Always ON with coefficients taken from the DFT matrix	Outline of the disadvantages of the ON/OFF method in particular the driver overload
[23]	Active Element Integration - CS / Deep learning	RIS interaction with incident signal, performance improvement
[24]	ANM with fewer active elements	Better estimation performance
[25]	Pre-designed codebook for RIS thinking models	Significant performance in terms of complexity, pilots overhead and signaling requirements
[26]	Pre-designed reflection coefficient according to the learning phase	Effective reduction of pilots overload

Other optimization approaches in the existing literature include successive convex approximation [27], [28], the minorization-maximization algorithm [29], and the alternating direction method of multipliers [30] (ADMM).

3.3 Reducing Computational Overhead Using Machine Learning

In the literature, the learning capability of neural networks has been used to estimate the full channel from the partial pilot channel information, it can also be combined with image processing techniques to imagine the RIS channel information as two images. They are presented by different network architectures: CNN, Graph Attention Network (GANet), DNN, Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM) and more.

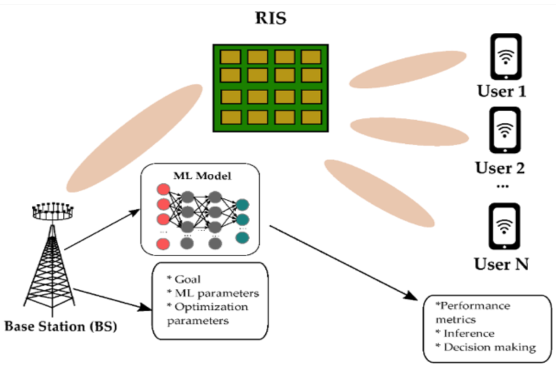

Fig. 2. Neural network-assisted RIS system estimation model

In [31], the authors introduced an offline-trained deep neural network (DNN)-based model to capture the implicit relationship between the measured receiver (Rx) coordinates and the optimal configuration of reconfigurable intelligent surfaces (RIS). To overcome the limitations of labeled data collection in supervised approaches, the authors of [32] adopted an unsupervised learning method. They proposed an innovative RIS beamforming neural network (RISBFNN) architecture, which is capable of predicting the optimal phase shift configuration with a loss function defined by the inverse of the transmission rate. The authors of [33] propose a learning scheme called learning phase shift neural network (LPSNet), to efficiently find the solution to the spectral efficiency maximization problem in RIS-assisted MIMO systems.

Combined refinement of neural networks with classical tuning to maximize overall performance can be found in the literature. For the purpose of optimal estimation, Ginige et al. [34] implement an untrained deep neural network (DNN) based on deep image network (DIP) to denoise the effective channel of the system obtained from conventional least squares (LS) estimation and acquire a more accurate estimation using orthogonal frequency division multiplexing (OFDM) while favoring reduced pilot usage. Kundu et al. [35] considered the initial conventional LS channel matrix as a noisy image and proposed a CNN-based image denoising network (DnCNN) to clean this image and produce improved RIS channel estimates. The work in [36] unfolds the AMP algorithm into a learnable network, where the shrinkage function in the AMP algorithm is replaced by the denoising convolutional neural network. Assuming that the arrival and departure angle bases fall exactly on the discrete grid during computation, Mao et al. [37] merged deep learning into the CS-OMP algorithm to achieve improved performance.

Resource-based task allocation can also be optimal. To reduce the training overhead in time-varying dynamic channels, Xu et al. [38] proposed a two-part channel subsampling and neural network approach. The first part describes the RIS dynamic channel using neural ordinary differential equation (ODE) to improve the time series reconstruction performance of the recurrent neural network (RNN), and the last part uses ODE to modify the relationship between different data layers in the network and improve the time series estimation performance, which is better suited for time-varying channel estimation scenarios. Jin et al. [39] proposed an approach to reshape the channel matrix into a two-dimensional image, using a single-scale enhanced deep super-resolution (EDSR) neural network and a multi-scale deep super-resolution (MDSR) neural network to recover the channel using sparse channel properties. The approach can increase generalization capability and reduce hardware complexity.

In [40], Xu et al. designed an LSTM-based neural network framework for the decomposition process and channel prediction process by modifying the connection layer based on the nonlinear mapping relationship between input and output, thereby reducing the complexity. A trainable deep learning-based Proximal Gradient Descent Network (TPGD-Net) for mmWave channel estimation was presented in [41]. Simulation results on the Saleh-Valenzuela channel model and DeepMIMO dataset demonstrate its effectiveness compared with state-of-the-art mmWave channel estimators.

Another learning alternative, deep reinforcement learning (DRL), which uses online collected data to train the model, has gained momentum in various RIS-assisted wireless network scenarios. Usually, authors introduced a DRL approach to study the joint design of the transmission beamforming matrix at the BS and the RIS phase shift configuration for a significant improvement of MIMO or MISO channel estimation. The work in [42] exploits the advances in deep reinforcement learning (DRL) to determine the optimal RIS beamforming vector. Their solutions can approach the upper bound obtained with perfect channel state information (CSI). However, the introduction of active elements at the RIS incurs additional hardware costs and power consumption. In [43], the authors proposed a deep deterministic policy gradient (DDPG) based algorithm. In the applied model, the successive transmission beamforming and RIS phase shifting have been cooperatively optimized with less complexity. Using the work of [42] where the authors applied a deep RL algorithm to maximize the achievable communication throughput in the RIS wireless network, the proposed algorithm can avoid the data collection phase during the training period, which reduces the computation time and thus less pilot load. The table below summarizes the approaches discussed using deep learning methods to compensate for the overload of pilots in the systems assisted by RIS.

Table 2. Summary of approaches using deep learning against pilot overload in RIS systems

References	Approaches discussed	Results
[32]	RISBFNN	Prédiction de la configuration optimale des dépha-sages
[33]	Learning Phase Shift Neural Network (LPSNet)	Solution to the problem of maximizing spectral effi-ciency
[34]	DNN DIP LS	Good performance, reduced drivers
[35]	LS-DnCNN	Increased performance, reduced driver overhead
[38]	EDO-RNN-EDO	Optimizing Results in Time-Varying Channel Esti-mation Scenarios
[39]	EDSR+MDSR on a two-dimensional image	Generalization capability and reduction of hardware complexity
[40]	LSTM for channel decomposition and prediction	Reduction of calculation time
[41]	TPGD-Net	Increased efficiency over state-of-the-art mmWave channel estimators
[42]	DRL	Superior performance with active element constraints
[43]	DDPG	Cooperative optimization with less complexity

The approaches discussed above use either estimated channel information or measured pilots at the transmitter (Tx) or base station (BS) to predict the optimal beamforming matrix for the RIS. Alternatively, they can learn the optimal RIS configuration based only on the receiver (Rx) location coordinates, without explicitly considering the propagation environment between the Tx and Rx.

4 Blind Estimation Of RIS Systems, An Alternative Worth A Detour

Unlike most existing approaches on RIS-assisted systems, which first estimate channels and then optimize phase shifts, the focus of this approach is to explore the wireless environment by extracting statistical features directly from random samples of the received signal power. This new method simply requires a polynomial number of random samples to provide a quadratic increase in the signal-to-noise ratio in the number of reflecting elements without CSI.

The authors of [44] proposed a novel strategy called blind beamforming that coordinates multiple RISs by means of statistics without knowing the CSI, exploring only a small part of the entire phase shift solution space to extract the key statistical quantity for beamforming. In [45], a DNN-assisted spatial modulation concept, called DeepSM, was proposed. The authors designed a pair of DNN structures to replace the data-driven channel estimator and detector. The conventional DNN relied on pilot symbols to estimate the channel and then performed data detection in a data-driven manner. In contrast, DeepSM operated in a more realistic time-varying channel, which updated the CSI in each time slot before detecting the data. Therefore, it can perform well even in a highly dynamic communication environment. Aware of the subtle problem of blind beamforming algorithms RFOCUS [46] and CSM (Conditional Sample Mean) [47], Lai et al. [48] suggest a blind adaptive beamforming algorithm by clustering that works regardless of the strength of the direct channel and is scalable to multiple users.

Mainly these studies focus on exploiting statistical correlations within observed data. They neglect the data generation process and the underlying causal relationships between the environment and RIS configurations. The estimation problem studied in [49] is formulated as a dataset between multiple RISs, as learning agents, in heterogeneous environments. By modeling two neural networks and using Invariant Risk Minimization (IRM) [50] combined with Federated Learning Games (FL) [51], they solved the RIS configuration problem by learning invariant causal representations across multiple environments and then predicting the phases.

However, in these approaches the received user power faces some mystery. This mystery can be solved by using partial training i.e. data and pilot signal assisted approach rather than a totally blind approach. The literature [52] has proposed a conventional full-depth CNN framework, via the use of data and pilot symbols constructed in a very specific manner. In order to recover the bits in the time domain OFDM signal without relying on any discrete Fourier transform, the authors designed a CNN network named DeepRx with multiple sublayers, which is capable of solving the channel change adaptation problem in a highly dynamic environment. Alwakeel et al. [53] proposed a semi-blind approach which improves the achievable throughput by reducing the channel estimation overhead. Since the data symbols are generally not orthogonal, they propose to estimate the direct channels (User-BS) using a conventional pilot transmission technique. Then by exploiting the characteristics of the direct and reflected signals via quasi-orthogonal channels (sufficiently long data symbols from different users), they managed to improve the spectral efficiency by 80% compared to systems based only on pilots. A two-stage semi-blind tensor-based Khatri-Rao factorization and Kronecker factorization (KAKF) receiver was proposed in [54] to jointly estimate the channel and transmission symbol matrices without the need of a dedicated pilot training stage. By exploiting the low-rank property of mmWave, a two-stage semi-blind fitting algorithm based on a generalized PARATUCK tensor model (derived from the combination of PARAFAC and Tucker tensor decompositions) of the RIS reflected signals was proposed in [55]. Simulation results demonstrate superior performance, in terms of normalized mean square error and symbol error rate, as well as lower computational complexity, compared to recently proposed parallel factor analysis-based receivers. The table below summarizes the approaches cited which use the data instead of the pilots or in part, in the systems assisted by RIS.

Table 3. Summary of so-called blind and semi-blind approaches

References	Approaches discussed	Results
[45]	DNN-assisted spatial modulation, called DeepSM	Regular channel update in a highly dynamic communication environment

References	Approaches discussed	Results
[48]	Blind Adaptive Beamforming Algorithm	Highly efficient and easily scalable to multiple users
[49]	IRM/FL Games	Optimal phase prediction, solving the RIS configuration problem
[52]	CNN named DeepRx	Fixed the problem of adaptation to channel change
[54]	Khatri-Rao factorization and Kronecker factorization (KAKF)	Cooperative optimization with less complexity
[55]	PARATUCK tensor model	Higher performance, lower symbol error rate, and lower computational complexity

5 Conclusion

Deep learning methods that use parameters to tune the pilot overload problem can outperform conventional methods under good convergence. In most studies, the ability to tune a large number of network parameters is stronger in models built using some prior knowledge of the communication channel. However, the pilot-assisted approach involves devoting part of the spectral resources to transmitting known pilot information, rather than real data, which compromises the efficiency of data transmission and spectral utilization.

Despite these advantages, blind estimation has challenges, including slower convergence of algorithms and increased sensitivity to noise or imperfection of assumptions. Several studies have shown that a phase predictor trained with geometric properties of environments performs better than a representation learner followed by a predictor. As the complexity of the problem increases, the advantage of deep learning becomes more obvious, and the conventional solution integrating a deep learning solution has broad development prospects. There is no doubt that recent advances in machine learning (deep learning, tensor-based algorithms) will contribute to improving the performance of these approaches.

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