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Review

Deep Learning for Channel Estimation in Physical Layer Wireless Communications: Fundamental, Methods, and Challenges

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Abstract: With the rapid development of wireless communication technology, intelligent communication has become one of the mainstream research directions after the fifth generation (5G). In particular, deep learning has emerged as a significant artificial intelligence technology widely applied in the physical layer of wireless communication for achieving intelligent receiving processing. Channel estimation, a crucial component of physical layer communication, is essential for further information recovery. As a motivation, this paper aims to review the relevant research on applying deep learning methods in channel estimation. Firstly, this paper briefly introduces the conventional channel estimation methods and then analyzes their respective merits and drawbacks. Subsequently, this paper introduces several common types of neural networks and describes the application of deep learning in channel estimation according to data-driven and model-driven approaches, respectively. Then, this paper extends to emerging communication scenarios and discusses the existing research on channel estimation based on deep learning for reconfigurable intelligent surface (RIS)-aided communication systems. Finally, to meet the demands of next-generation wireless communication, challenges and future research trends in deep-learning-based channel estimation are discussed.

Keywords: channel estimation; deep learning; wireless communication; physical layer; intelligent communication; RIS

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1. Introduction

In recent decades, there has been a rapid advancement in wireless communication technology. As a mobile communication technology that enables the "Internet of Everything", fifth generation (5G) technology has high-speed, large-connectivity, and low-latency properties. Its primary application scenarios include massive machine-type communications (mMTC), enhanced mobile broadband (eMBB), and ultra-reliable and low-latency communications (uRLLC) [1]. According to forecasts from the International Data Corporation (IDC), by 2025, an astonishing 152,200 Internet of Things (IoT) devices will be deployed every minute. Additionally, the data volume generated by global IoT devices is projected to reach 73.1 ZB. The exponential growth of wireless device access presents significant challenges to 5G, as its performance increasingly needs to improve to meet the explosive increase in mobile data traffic and the diversified service demands. Given this, forward-looking research on sixth generation (6G) technology is actively underway. Compared to 5G, 6G is expected to achieve order-of-magnitude improvements in key metrics such as throughput, spectral efficiency, energy efficiency, transmission rate, and security [2,3].

In wireless communication systems, the channel is complex and dynamic. Signals may suffer from attenuation and distortion due to the multipath effect, Doppler effect, shadow fading, etc., thus affecting the performance of the communication systems. The accuracy of transmitted and received signals heavily relies on channel state information (CSI), and the goal of channel estimation is to estimate CSI at the receiver. Accurate channel estimation helps in compensating for the amplitude and phase of the received signal, facilitating the precise recovery of the original data when demodulated at the receiver. For these reasons, channel estimation is a key part of physical layer wireless communication. In light of this, enhancing its performance can significantly improve the quality of communication networks, help overcome the performance limitations of 5G, and pave the way for achieving the "Intelligent Interconnection of Everything" goal of 6G [4,5].

Conventional channel estimation methods are typically classified as pilot-based, blind, and semi-blind. Due to the simplicity of the principle behind the pilot-based channel estimation method, it can be implemented relatively quickly in practice. However, this method requires transmitting both data and pilot symbols, which leads to low spectrum utilization and reduced transmission efficiency. While the blind channel estimation method does not require pilots, it is computationally complex, sluggish to converge, and demands many statistical samples. The semi-blind channel estimation method represents a compromise approach that integrates the benefits of pilot-based and blind channel estimation methods. Nevertheless, it is worth noting that the implementation complexity of this method remains substantial.

It is evident that, with their significant limitations, conventional channel estimation methods are inadequate for addressing the growing complexity of future communication systems. Hence, there is a pressing need to develop a novel approach that exhibits enhanced precision, efficacy, and intelligence in estimating CSI. The ongoing advancement of artificial intelligence in recent years has sparked a fresh surge of technological innovation in human society. As a significant research avenue in artificial intelligence, deep learning has successfully addressed a range of previously challenging issues. It has exhibited excellent performance across numerous areas, including speech recognition, natural language processing, and computer vision [6]. In wireless communications, applying deep learning to the physical layer has become a hot research topic, and papers [7,8] summarize the possible research directions. In this paper, the focus is on exploring the application of deep learning to channel estimation.

The primary purpose of using deep learning for channel estimation is to enhance the receiver's performance, thereby optimizing the recovery process for impaired transmitted data. Compared to traditional methods, deep-learning-based methods have greater advantages in terms of estimation accuracy or computation overhead in complex channel environments. After thoroughly reviewing the relevant literature, we observe that deep-learning-based channel estimation methods can fall into two distinct classes: data-driven and model-driven.

The data-driven approach abandons the modular structure of wireless communication systems and replaces it with neural networks trained on massive data. In 2017, the authors of [9] started to utilize a data-driven deep learning approach for implicit channel estimation. In this procedure, the orthogonal frequency division multiplexing (OFDM) receiver is regarded as a "black box", and the channel estimation and signal detection modules are substituted by a deep neural network (DNN). The DNN is trained offline to obtain the best parameters and then deployed online to directly recover the transmitted data. For massive multiple-input–multiple-output (MIMO) systems, the data-driven approach proposed in [10] employs a multilayer perceptron (MLP). This method does not leverage channel statistics and can achieve considerable performance gains over traditional channel estimators in low signal-to-noise ratio (SNR) regions.

The model-driven approach is based on known physical layer prior knowledge, decreasing the need for data [11]. The ComNet developed in [12] is a typical example of model-driven schemes. Unlike the data-driven method in [9], ComNet retains the basic OFDM system framework. In ComNet's channel estimation module, a DNN learns the error between the least square (LS) estimation and the actual channel response, resulting in a more accurate channel estimation. In ComNet's signal detection module, the network with nonlinear activation functions introduces nonlinearity, making the module a nonlinear signal detector that can more effectively process and recognize nonlinear features and distortions within the signal. In the model-driven scheme proposed in [13] for millimeter-wave massive MIMO systems, neural networks are fused into an iterative signal reconstruction algorithm to estimate channels. This scheme improves the dilemma of difficult CSI acquisition in scenarios where antenna arrays are dense, and receivers are equipped with restricted radio frequency (RF) chains.

Numerous studies have shown that deep-learning-based methods can outperform traditional methods, and they hold the potential to perform well in future wireless communications. In recent years, some scholars [14–18] have reviewed the research on channel estimation based on deep learning. The main contributions of these reviews are summarized in Table 1. While these previous reviews offer valuable assistance on deep-learning-based channel estimation, their discussion is limited to traditional communication scenarios. However, it is crucial to recognize that the emergence of techniques such as the reconfigurable intelligent surface (RIS) [19] has spawned novel communication scenarios that present novel challenges and opportunities. Therefore, to better assist future research, it is also necessary to review state-of-the-art deep-learning-based methods for emerging scenarios, such as scenarios incorporating the RIS technique.

Table 1. Summary of recent review papers on deep-learning-based channel estimation.

Article	Year	Main Contribution
[14]	2019	It groups the challenges (such as feedback overhead) in massive MIMO channel modeling and estimation according to four technical details, followed by a discussion of each group's relevant deep-learning-based solutions.
[15]	2020	It outlines how to use deep learning to enhance the performance of massive MIMO channel estimation while reducing training overhead, followed by introducing some data-driven methods.
[16]	2022	It reviews various deep learning models used for channel estimation. Subsequently, it introduces the channel estimation methods that use deep learning in different systems.
[17]	2022	It overviews recent channel estimation methods using deep learning in doubly-dispersive channels and conducts experimental comparisons and simulation analyses under various frame sizes, modulation orders, and mobility scenarios.
[18]	2022	It provides a comprehensive summary of artificial intelligence-assisted channel estimation methods in multicarrier systems, which include machine learning and neural networks.
This review	2023	This paper discusses data-driven channel estimation methods based on different fundamental neural networks. It also introduces model-driven methods, which are categorized according to various benchmark algorithms. Additionally, this paper overviews recent studies on deep-learning-based channel estimation in RIS-aided communication systems.

RIS, also referred to as intelligent reflection surface (IRS), is a promising 6G communication technique. It can achieve multiple purposes, including capacity expansion, coverage expansion, interference suppression, high beamforming gain, and improving the wireless propagation environment [20]. Nevertheless, RIS is an approximately passive device that cannot actively transmit and receive signals or further process them. This limitation, coupled with the introduction of cascaded channels with high dimensionality, presents a challenge in channel estimation. As a result, conventional channel estimation methods are computationally expensive and inaccurate for practical RIS-aided communication systems. In this context, deep learning is particularly apt for addressing channel estimation challenges in RIS-aided communication systems, owing to its ability to effectively solve nonlinear mapping problems. Specifically, this approach achieves its goal by learning an approximate mapping function from the training data to the CSI of a single or cascaded channel.

Given the ongoing advancements in wireless communication technologies and the vital role played by deep learning in solving channel estimation problems, we provide a review of deep-learning-based channel estimation. The main contributions of this paper are as follows:

- Before discussing deep-learning-based channel estimation methods, conventional methods are introduced and classified as pilot-based, blind, and semi-blind, followed by an analysis of the advantages and disadvantages of each category.
- Dividing deep-learning-based channel estimation methods into data-driven and model-driven approaches, then reviewing their recent studies based on neural network types and benchmark algorithm types, respectively.
- We extend the discussion on applying deep learning to channel estimation to RIS-aided communication systems, which are emerging scenarios in next-generation wireless communications.

The remainder of this paper is structured as follows: Section 2 introduces the three main classes of conventional channel estimation methods and analyzes their advantages and disadvantages; Section 3 presents several commonly used neural networks and reviews recent research on deep-learning-based channel estimation; Section 4 discusses the application of deep learning in channel estimation for RIS-aided communication systems; Section 5 describes the challenges and future research trends of deep-learning-based channel estimation; and finally, Section 6 summarizes the entire paper. Figure 1 illustrates the organization of this paper.

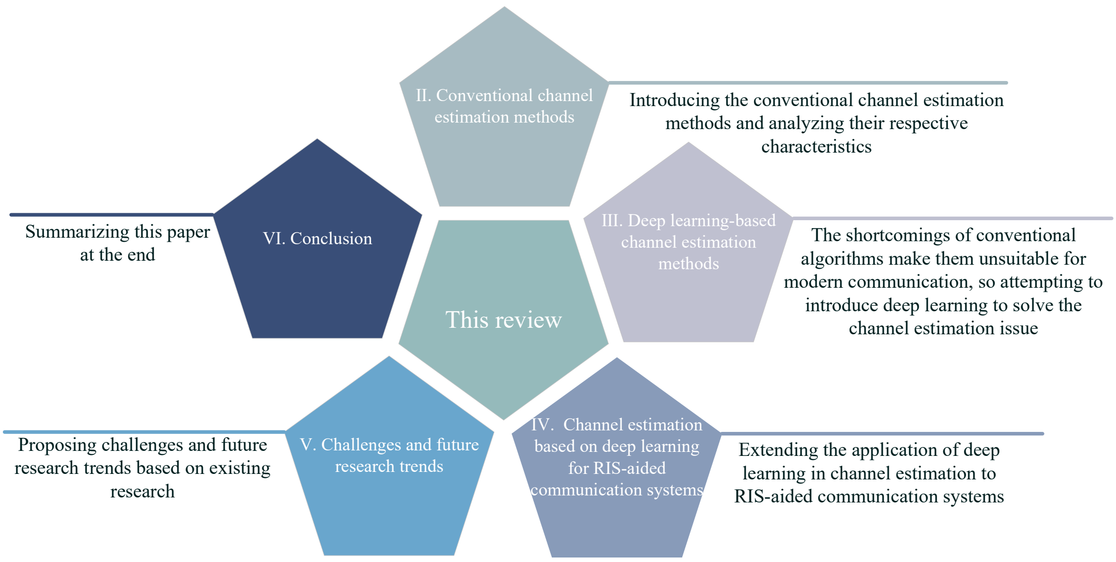


Figure 1. Organization of this paper.

2. Conventional Channel Estimation Methods

Irrespective of the specific channel model employed in any wireless communication system, a shared challenge arises: how to provide accurate and rapid channel estimation to facilitate precise signal demodulation, equalization, decoding, and other baseband processing tasks [21]. As delineated in Section 1, the conventional channel estimation methods already developed for wireless communications mainly include pilot-based, blind, and semi-blind methods. Figure 2 shows the classification of different conventional channel estimation methods.

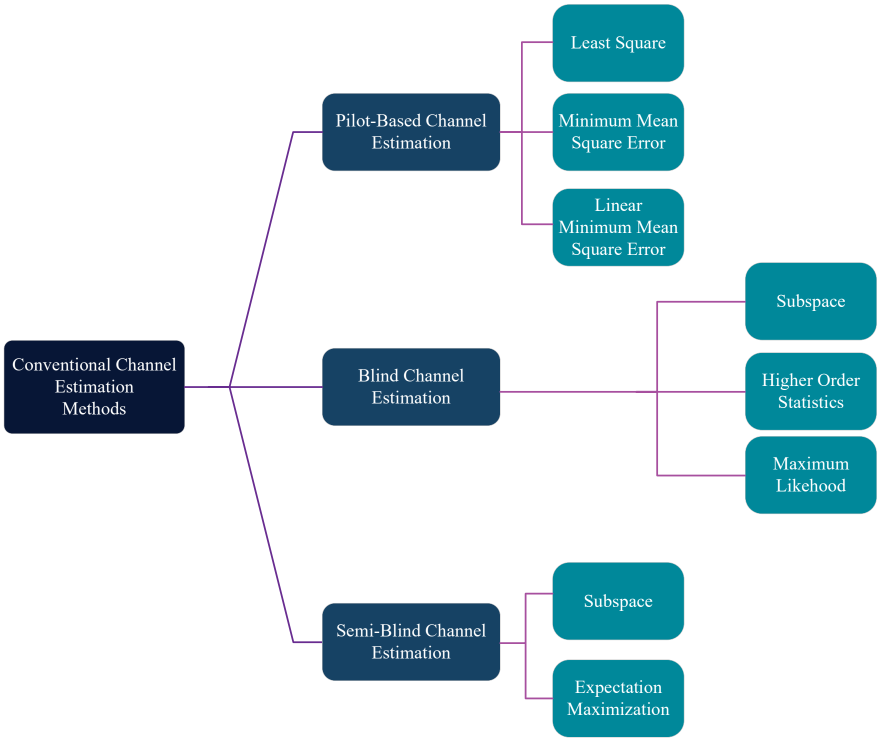


Figure 2. Classification of conventional channel estimation methods.

2.1. Pilot-Based Channel Estimation Method

In wireless communications, the pilot-based method is the most used channel estimation method, with its process illustrated in Figure 3. The central idea of this method is inserting known pilots into the transmitted signal according to specific rules. After that, the corresponding received signal is extracted at pilot positions at the receiver. Following this, the CSI at pilot positions is computed by combining them with the known transmitted pilots. Finally, various interpolation algorithms are employed to estimate the CSI at non-pilot positions (data positions) [22–25]. Among them, the LS algorithm [26,27], the minimum mean square error (MMSE) algorithm [28,29], and the linear MMSE (LMMSE) algorithm [30,31] are the most classical pilot-based channel estimation methods. While we will introduce these pilot-based estimation methods using the OFDM system as an example, it is essential to note that these methods are not limited to OFDM systems.

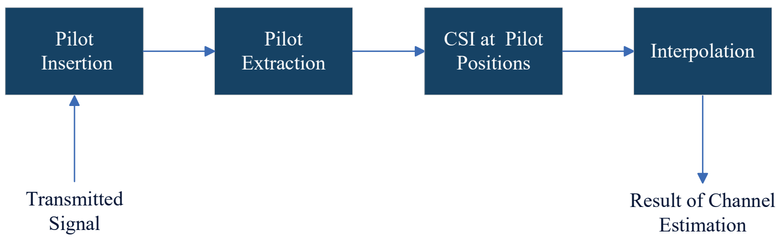


Figure 3. Flowchart of pilot-based channel estimation.

2.1.1. Pilot Arrangements

According to the different ways of pilot insertion, the pilot arrangements can be roughly categorized into block-type, comb-type, and lattice-type.

- Block-Type Pilot Arrangement

Figure 4 shows the block-type pilot arrangement. This pilot arrangement periodically transmits pilot symbols (i.e., OFDM symbols with pilots inserted) along the frequency axis. For each pilot symbol, pilots are inserted into all subcarriers (as pilot subcarriers). Then, these pilots are used to interpolate in the time domain and estimate the channel along the time axis. To track the characteristics of the time-selective channel, the period of the pilot symbols must be equal to the channel coherence time. Let S_t denote the period of the pilot symbols, and since the channel coherence time is in inverse proportion to the Doppler frequency deviation $f_{Doppler}$, S_t must be satisfied:

$$S_t \leq \frac{1}{f_{Doppler}} \tag{1}$$

Since the pilots are periodically inserted into all subcarriers of the pilot symbols, the block-type pilot arrangement is more suitable for frequency-selective channels compared to time-selective channels.

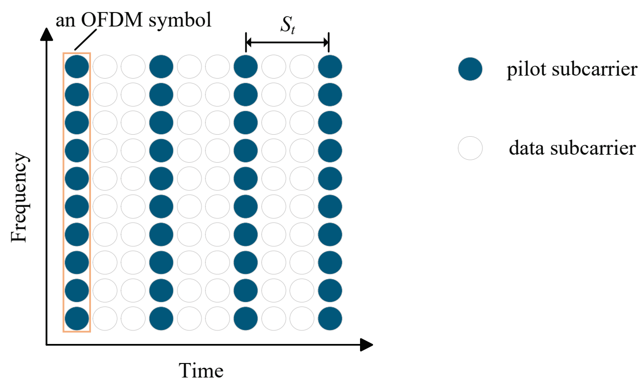


Figure 4. Block-type pilot arrangement.

- Comb-Type Pilot Arrangement

Figure 5 shows the comb-type pilot arrangement. The pilots are regularly inserted into the subcarriers within each OFDM symbol, utilized to interpolate in the frequency domain and estimate the channel along the frequency axis. To accurately track the frequency-selective channel's properties, the pilots' period on the frequency axis must be consistent with the coherent broadband. The period of the pilots on the frequency axis is denoted by S_f. Since the coherence bandwidth depends on the reciprocal of the maximum delay extension σ_{max}, S_f must be satisfied:

$$S_f \leq \frac{1}{\sigma_{max}} \tag{2}$$

Unlike the block-type pilot arrangement, the comb-type pilot arrangement is more suitable for time-selective channels compared to frequency-selective channels.

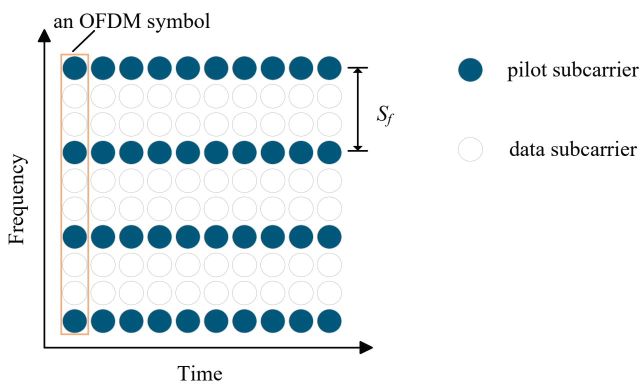


Figure 5. Comb-type pilot arrangement.

- Lattice-Type Pilot Arrangement

Figure 6 shows the lattice-type pilot arrangement. The pilots are inserted at a specified period and concurrently into both the time and frequency domains. With the regular distribution along the time and frequency axes, they facilitate the interpolation of channel estimation in the two domains. The insertion of the pilots must satisfy Equations (1) and (2) to trace the channel's time-selective and frequency-selective characteristics. This pilot arrangement is a compromise between the block-type and comb-type pilot arrangements. It has a superior performance against time-selective fading compared to the block-type pilot arrangement and performance against frequency-selective fading compared to the comb-type pilot arrangement.

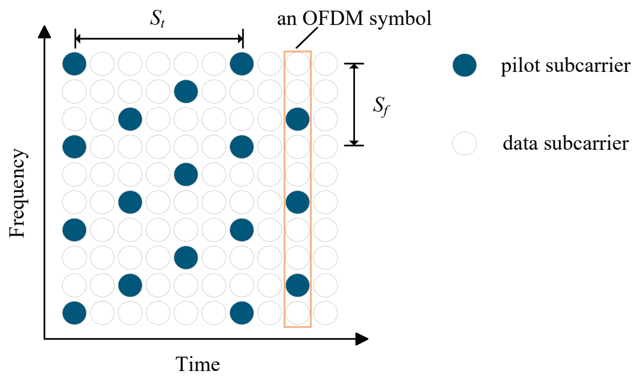


Figure 6. Lattice-type pilot arrangement.

2.1.2. LS Channel Estimation

The criterion of the LS algorithm is to minimize the weighted error between the estimated value and the true one. Considering a simple OFDM system, let N_p denote the number of pilots inserted, $\mathbf{y} = [y(0), y(1), \ldots, y(N_p - 1)]^{\mathrm{T}}$ denote the frequency domain received signal at the pilot position, and $\mathbf{X} = \mathrm{diag}\{\mathbf{x}\} = \mathrm{diag}\{[x(0), x(1), \ldots, x(N_p - 1)]\}$ denote the corresponding transmitted signal at the pilot position. Furthermore, assume $\mathbf{w} = [w(0), w(1), \ldots, w(N_p - 1)]^{\mathrm{T}}$ represents the noise, and the cost function of the LS estimation result $\hat{\mathbf{h}}_{\mathrm{LS}}$ can be mathematically represented as:

$$J\left(\hat{\mathbf{h}}_{\mathrm{LS}}\right) = \left\|\mathbf{y} - \mathbf{X}\hat{\mathbf{h}}_{\mathrm{LS}}\right\|^2 \tag{3}$$

The LS algorithm aims to estimate the channel by minimizing the cost function, and this is achieved by setting the partial derivative to zero, as follows:

$$\frac{\partial\left(J\left(\hat{\mathbf{h}}_{\mathrm{LS}}\right)\right)}{\partial\hat{\mathbf{h}}_{\mathrm{LS}}} = \frac{\partial\left(\left(\mathbf{y} - \mathbf{X}\hat{\mathbf{h}}_{\mathrm{LS}}\right)^{\mathrm{H}}\left(\mathbf{y} - \mathbf{X}\hat{\mathbf{h}}_{\mathrm{LS}}\right)\right)}{\partial\hat{\mathbf{h}}_{\mathrm{LS}}} = 0 \tag{4}$$

thus, $\mathbf{X}^{\mathrm{H}}\mathbf{X}\hat{\mathbf{h}}_{\mathrm{LS}} = \mathbf{X}^{\mathrm{H}}\mathbf{y}$ can be obtained to derive the LS estimation of pilot subcarriers:

$$\hat{\mathbf{h}}_{\mathrm{LS}} = \left(\mathbf{X}^{\mathrm{H}}\mathbf{X}\right)^{-1}\mathbf{X}^{\mathrm{H}}\mathbf{y} = \mathbf{X}^{-1}\mathbf{y} = \left[\frac{y(0)}{x(0)}, \frac{y(1)}{x(1)}, \ldots, \frac{y(N_p - 1)}{x(N_p - 1)}\right]^{\mathrm{T}} \tag{5}$$

The LS algorithm is widely adopted because of its low computational requirement and simple implementation. Nevertheless, due to the omission of channel and noise factors in the computation process, the estimation performance is vulnerable to inter-carrier interference and noise, thereby limiting the algorithm's precision.

2.1.3. MMSE Channel Estimation

The purpose of the MMSE algorithm is to minimize the mean square error between the actual value and the estimated value, and the cost function of the MMSE estimation result $\hat{\mathbf{h}}_{\text{MMSE}}$ can be represented as:

$$J\left(\hat{\mathbf{h}}_{\text{MMSE}}\right) = \mathrm{E}\left\{\left(\mathbf{h} - \hat{\mathbf{h}}_{\text{MMSE}}\right)\left(\mathbf{h} - \hat{\mathbf{h}}_{\text{MMSE}}\right)^{\mathrm{H}}\right\} \tag{6}$$

in a similar vein, setting the partial derivative of $J\left(\hat{\mathbf{h}}_{\text{MMSE}}\right)$ to zero, it can be concluded:

$$\hat{\mathbf{h}}_{\text{MMSE}} = \mathbf{R}_{hy}\mathbf{R}_{yy}^{-1}\mathbf{y} \tag{7}$$

where $\mathbf{R}_{hy}$ represents the cross-correlation matrix between the actual channel response $\mathbf{h}$ and the received signal $\mathbf{y}$, and $\mathbf{R}_{yy}$ is the autocorrelation matrix of $\mathbf{y}$. $\mathbf{R}_{hy}$ can be further expressed as:

$$\mathbf{R}_{hy} = \mathrm{E}\left\{\mathbf{h}\mathbf{y}^{\mathrm{H}}\right\} = \mathrm{E}\left\{\mathbf{h}(\mathbf{X}\mathbf{h} + \mathbf{w})^{\mathrm{H}}\right\} = \mathbf{R}_{hh}\mathbf{X}^{\mathrm{H}} \tag{8}$$

also, $\mathbf{R}_{yy}$ can be further expressed as:

$$\mathbf{R}_{yy} = \mathrm{E}\left\{\mathbf{y}\mathbf{y}^{\mathrm{H}}\right\} = \mathrm{E}\left\{(\mathbf{X}\mathbf{h} + \mathbf{w})(\mathbf{X}\mathbf{h} + \mathbf{w})^{\mathrm{H}}\right\} = \mathbf{X}\mathbf{R}_{hh}\mathbf{X}^{\mathrm{H}} + \sigma^2\mathbf{I} \tag{9}$$

where $\mathbf{R}_{hh}$ is the autocorrelation matrix of the actual channel response and σ^2 is the noise variance. Therefore, it can be concluded:

$$\hat{\mathbf{h}}_{\text{MMSE}} = \mathbf{R}_{hh}\left(\mathbf{R}_{hh} + \sigma^2\left(\mathbf{X}\mathbf{X}^{\mathrm{H}}\right)^{-1}\right)^{-1}\hat{\mathbf{h}}_{\text{LS}} \tag{10}$$

Since the MMSE algorithm considers the noise impact and introduces the priori information R_{hh} and σ^2, its channel estimation accuracy is high. Under the same MSE accuracy condition, at least 10 dB of SNR gain can be obtained compared to the LS algorithm. However, the practical implementation of the MMSE algorithm is constrained due to challenges in acquiring prior knowledge and second-order statistical features in communication systems. Moreover, the need for multiple matrix inversions significantly amplifies the algorithm's complexity.

2.1.4. LMMSE Channel Estimation

As expressed in Equation (10), the inverse of the matrix needs to be recalculated when the pilot signal $\mathbf{X}$ changes, making the computation more difficult. The LMMSE algorithm is a simplified version of the MMSE algorithm by replacing $\left(\mathbf{X}\mathbf{X}^{\mathrm{H}}\right)^{-1}$ with its expectation $\mathrm{E}\left\{\left(\mathbf{X}\mathbf{X}^{\mathrm{H}}\right)^{-1}\right\}$. Furthermore, the SNR is defined as $SNR = \mathrm{E}\left\{|x|^2\right\}/\sigma^2$, so that there is:

$$\hat{\mathbf{h}}_{\text{LMMSE}} = \mathbf{R}_{hh}\left(\mathbf{R}_{hh} + \frac{\beta}{SNR}\mathbf{I}\right)^{-1}\hat{\mathbf{h}}_{\text{LS}} \tag{11}$$

where $\beta = \mathrm{E}\left\{|x|^2\right\}\mathrm{E}\left\{1/|x|^2\right\}$ is the modulation type parameter. For instance, $\beta = 1$ corresponds to QPSK modulation, and $\beta = 17/9$ corresponds to 16QAM modulation. If both $\mathbf{R}_{hh}$ and SNR are known, only one matrix inverse operation is performed, effectively reducing computational complexity.

2.2. Blind Channel Estimation Method

Unlike the pilot-based channel estimation, the blind channel estimation does not require any pilots. The core concept of this method is to interpret the CSI. This is achieved by leveraging the inherent statistical characteristics of both received and transmitted signals while adaptively tracking the dynamic changes of channels [32]. In general, blind channel estimation may be performed using the subspace algorithm, the higher-order statistics (HOS) algorithm, and the maximum likelihood (ML) algorithm.

2.2.1. Subspace-Based Blind Channel Estimation

The subspace-based blind channel estimation does not require any known training sequence, making it useful for systems where the training sequence cannot be sent or takes up a significant amount of bandwidth. The core concept of this algorithm is to use the statistical characteristics of the signal to separate the signal and noise subspaces and then estimate the channel parameters [33]. In [34], Kang et al. proposed a generalized subspace algorithm via a minimized cost function, which focuses on integrating the kernel matrix set from signals that share the target channel through a weighted sum of projection errors. Experiments demonstrate that the proposed algorithm has exceptional performance, which can be further enhanced by employing a particular weight set for the cost function and adding more kernel matrices. Most subspace-based blind algorithms primarily estimate channel coefficients by utilizing the orthogonality of the correlation matrix of the signal and the noise subspaces of the received signal. However, in practice, the correlation matrix is unknown and necessitates time-averaging estimation using multiple received samples. For this reason, Tu et al. [35] proposed a scheme that leverages the frequency correlation between neighboring subcarriers in MIMO-OFDM systems to minimize the time averaging.

2.2.2. HOS-Based Blind Channel Estimation

The utilization of HOS information on the signal can yield additional insights into both the signal and noise details, which has the potential to enhance the channel estimation accuracy. The HOS-based blind channel estimation mainly estimates the CSI through the HOS characteristics of received signals. Acar et al. [36], faced with channels with constant scaling phases and identical alignments, proposed to compute channel estimation values in a recursive scheme using the parallel factor (PARAFAC) decomposition and the HOS tensor of the system output. The proposed method eliminates pre-whitening and has a lower estimation error than conventional methods. In [37], Choqueuse et al. investigated a blind estimation algorithm for space-time block coding (STBC) systems based on HOS. Leveraging the statistical independence of sources before space–time encoding, this algorithm estimates the channel matrix by minimizing a kurtosis-based cost function following zero-forcing (ZF) equalization. In simulations, the proposed algorithm exhibits superior generalization ability over other methods, and it applies to the whole linear STBC class.

2.2.3. ML-Based Blind Channel Estimation

Some researchers have employed the ML algorithm to perform blind channel estimation as well. The ML-based blind algorithm constructs a likelihood function to measure the similarity between the predicted and actual received signals under the given channel parameters. By optimizing this likelihood function, one can obtain the best channel estimation result. In [38], Cirpan et al. investigated the deterministic ML (DML) and stochastic ML (SML) iterative methods for jointly estimating Doppler frequency shift and channel parameters. These methods offer maximum likelihood solutions and thus perform better than most HOS-based and blind adaptive methods, particularly if only a short data record is available. In [39], Necker et al. developed the first fast converging, fully blind channel estimation algorithm based on the ML principle. This algorithm recovers the absolute phase of the channel transfer function without reference symbols. Compared to the pilot-based method, there is a higher spectrum utilization and a lower mean square error (MSE) and bit error rate (BER).

The blind channel estimation method can effectively utilize spectrum resources and adaptively track the changes in CSI, without requiring extra pilots. Nevertheless, the blind method is not without its limitations. These include the method's high computing cost, relatively slow convergence speed, extra observation data, and the presence of phase ambiguity [33,35]. Thus, these challenges pose difficulties for the practical use of such a method.

2.3. Semi-Blind Channel Estimation Method

The semi-blind channel estimation method combines the computational simplicity of the pilot-based method with the increased spectrum utilization of the blind method. It utilizes a few pilots and integrates the received signal statistics from the blind channel estimation method, intending to reduce computational complexity and ensure accurate channel estimation. Among them, researchers commonly use the subspace and expectation maximization (EM) algorithms for semi-blind channel estimation.

2.3.1. Subspace-Based Semi-Blind Channel Estimation

Similar to the subspace-based blind algorithm, the semi-blind subspace-based algorithm also leverages the statistical characteristics of the signal. It aims to find the channel parameters that best match the signal or noise subspace to achieve channel estimation. In the scheme presented by Wu et al. [40], the received signals are initially projected into the subspace with minimal interference. Following this, a low-complexity modified power method is employed to recursively establish the subspace base. Finally, an initial estimation of the projected channel is performed using a small number of pilots. Through experiments, the scheme demonstrates its ability to effectively reduce the impact of pilot contamination. In [41], Kawasaki et al. utilized out-of-band emission to suppress redundancy in their subspace-based scheme. Subsequently, they employed the LS estimation on pilot subcarriers to solve the scalar ambiguity. Through experiments, their scheme can perform channel estimation for the remaining subcarriers with a high accuracy equal to that of the pilot subcarriers.

2.3.2. EM-Based Semi-Blind Channel Estimation

As an iterative optimization algorithm, the EM algorithm [42] works to estimate parameters in probabilistic models with hidden variables. In semi-blind channel estimation, this algorithm is executed in the expectation step (E-step) and the maximization step (M-step). In the E-step, the algorithm fixes the current channel parameters and calculates the expectation of the correlation between the training sequence and the received signal. In the subsequent M-step, the algorithm updates the parameters to maximize the probability of consistency between predicted and actual data. Then, iterate these two steps until the parameters converge and achieve the channel estimation. In [43], Obradovic et al. proposed an EM-based temporal semi-blind method for MIMO-OFDM time-varying channels. Their method solves the problem of inadequate pilot sequence arrangement in standard pilot-aided channel estimation, which hinders the direct application of interpolation approaches. Furthermore, the method can handle systems that do not satisfy the sampling theorem. Specifically, in cases where the sampling theorem is not met, the method can aptly initialize the EM algorithm by performing local Wiener interpolation on the frequency axis. In [44], Nayebi et al. proposed two EM-based semi-blind algorithms (one introduces prior information while the other does not) for time division duplexing (TDD) massive MIMO systems. Experimentally, it is demonstrated that the EM algorithm, with the introduction of prior information, can perform better under low SNR conditions.

The semi-blind channel estimation adds a few pilots, building on the foundation of the blind channel estimation. Compared to blind channel estimation, it can achieve faster convergence, lower computational complexity, and address phase ambiguity. In addition, it boasts a higher bandwidth utilization than the pilot-based method. However, the semi-blind channel estimation still requires substantial computation, making it relatively difficult to realize.

Based on the introduction to conventional channel estimation methods, Table 2 summarizes their advantages and disadvantages.

Table 2. Summary of advantages and disadvantages of conventional channel estimation methods.

Methods	Advantages	Disadvantages
Pilot-based channel estimation	Low computational complexity Easy to implement Pilot can improve estimation performance	Waste of spectrum resources Low transmission efficiency
Blind channel estimation	Efficient use of spectrum resources Able to adaptively track the dynamic changes of the channel	High computational complexity Slow convergence speed Presence of phase ambiguity Long observation time
Semi-blind channel estimation	Relatively high bandwidth efficiency Able to solve phase ambiguity Relatively fast convergence speed	Relatively large amount of calculation Relatively difficult to implement

From Table 2, we can conclude that conventional channel estimation methods have limitations that will restrict their application in increasingly complex future communication systems. Therefore, researchers in related fields have set out to figure out how to improve the performance of channel estimation while simultaneously reducing its computational complexity. Deep learning has made a big splash in physical layer wireless communications in recent years, opening up a new horizon for scholars. Numerous studies have introduced deep learning as a novel approach to channel estimation and have obtained outstanding results. Section 3 highlights the application of deep learning in channel estimation.

3. Deep-Learning-Based Channel Estimation Methods

Deep learning is transforming the paradigms and methods of physical layer communications, with application areas including channel estimation, resource allocation, and signal detection [45,46]. Conventional channel estimation methods work well in systems with a clear and linear representation of the input–output relationship. However, when the wireless environment becomes more complicated, the input–output relationship exhibits nonlinear characteristics, potentially reducing the effectiveness of conventional techniques. Deep learning aims to enable machines to learn to deal with complex and highly nonlinear relationships between input datasets and desired outputs without human intervention [47]. As stated in Section 1, the existing research on deep-learning-based channel estimation can be broadly classified into two main categories: data-driven and model-driven approaches. Therefore, this section will describe deep-learning-based channel estimation according to these two approaches and introduce their representative studies.

3.1. Overview of Neural Networks

As a branch of artificial intelligence technology, deep learning uses neural networks as models, so it is necessary to briefly introduce neural networks before introducing deep-learning-based channel estimation methods. Neural networks, which mimic the neuronal network of the human brain, consist of input, hidden, and output layers with numerous interconnected neurons through the weights in each layer. By adjusting these weights through learning, neural networks can process input information and produce output. According to the application of deep learning in various fields, the structure of the basic network is different, primarily including the deep neural network (DNN), convolutional neural network (CNN), recurrent neural network (RNN), generative adversarial network (GAN), etc. Most deep learning models can be combined or optimized based on these four networks. Next, we will introduce these common neural networks.

3.1.1. DNN

A basic structure of DNN is shown in Figure 7, which consists of one input layer, L hidden layers, and one output layer, with several neurons in each layer and full connectivity between layers. A DNN can be considered a neural network that contains numerous hidden layers, and the purpose of adding multiple hidden layers is to enhance the learning and mapping capabilities of the network. Additionally, to introduce the nonlinearity, activation functions like the sigmoid, rectified linear unit (ReLU), or hyperbolic tangent (Tanh) are applied after the outputs of each layer.

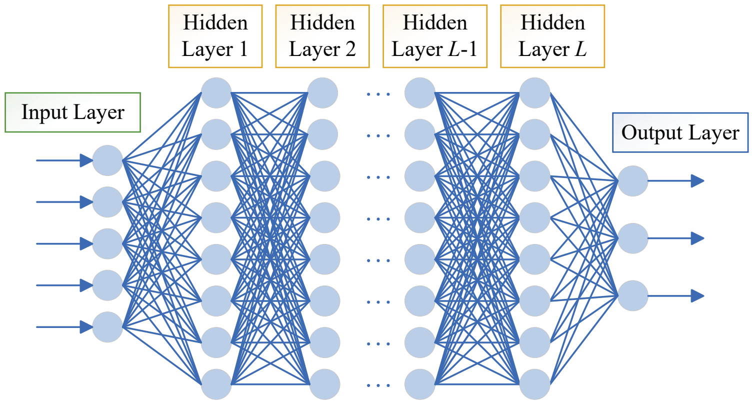


Figure 7. Basic structure of DNN.

3.1.2. CNN

CNN is among the most representative model structures for deep learning, with the earliest proposition dating back to the publication of the seminal literature [48]. Figure 8 shows a basic CNN structure comprising an input layer, multiple convolutional and pooling layers, a fully connected layer, and an output layer. The input layer's primary function is to preprocess the data. After this, the convolutional layer extracts features from the processed data, and its output is then mapped nonlinearly via the activation function. Following this, the pooling layer is introduced to decrease computation and prevent overfitting. The convolutional and pooling layers are alternately stacked, and after a series of operations, the output is obtained through the fully connected and output layers. In the convolutional layer, the convolutional kernel is locally connected to its input feature map. For each position in the output feature map, the value is obtained by the weighted sum of the local inputs and connection weights, plus the bias. As this process is equivalent to the convolutional operation, the network is termed a convolutional neural network.

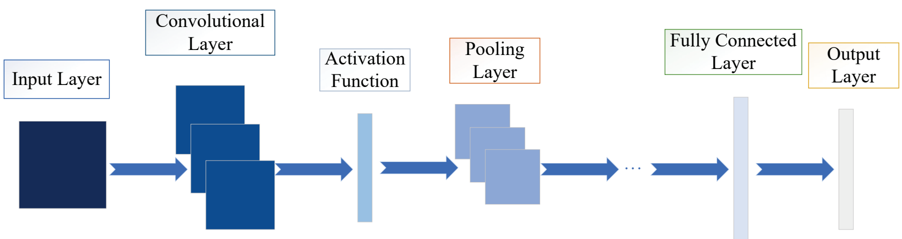


Figure 8. Basic structure of CNN.

3.1.3. RNN

Figure 9 shows a basic RNN structure. In contrast to the previously discussed DNN and CNN, RNN is uniquely designed to handle sequential data. It can remember information from past moments and utilize it for the current output calculation. In this case, the nodes among the hidden layers are interconnected. Moreover, the hidden layer's input depends on both the input layer's value and the hidden layer's output from the previous moment.

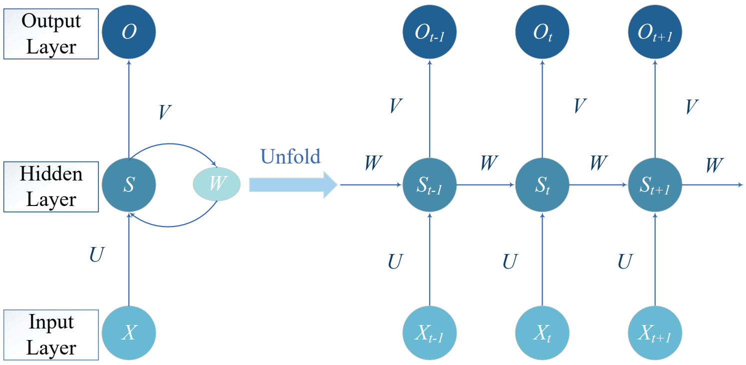


Figure 9. Basic structure of RNN.

During the training process, RNNs may suffer from long-term dependency, leading to gradient vanishing or gradient explosion. Therefore, the literature [49] conducted further research and proposed a special RNN called the long short-term memory (LSTM) network to effectively resolve this issue.

3.1.4. GAN

Figure 10 represents the general GAN structure, which consists of a generator and a discriminator. The generator receives a latent vector (usually random noise) as input and generates samples analogous to the training data. On the other hand, the discriminator receives samples (which can be real or generated by the generator) as input and predicts their veracity. Notably, the generator and the discriminator train against each other in a competitive and collaborative dynamic. Specifically, the generator's objective is to trick the discriminator by bringing the generated samples closer and closer to the real samples to the point where they cannot be distinguished accurately. Concurrently, the discriminator is tasked with accurately classifying the samples as possible, thereby heightening the distinction between the real and generated samples. During the iterative adversarial training process, the generator and the discriminator keep adjusting their parameters until they reach an equilibrium point. That is to say, the generator can generate realistic samples, while the discriminator cannot distinguish between real and generated samples.

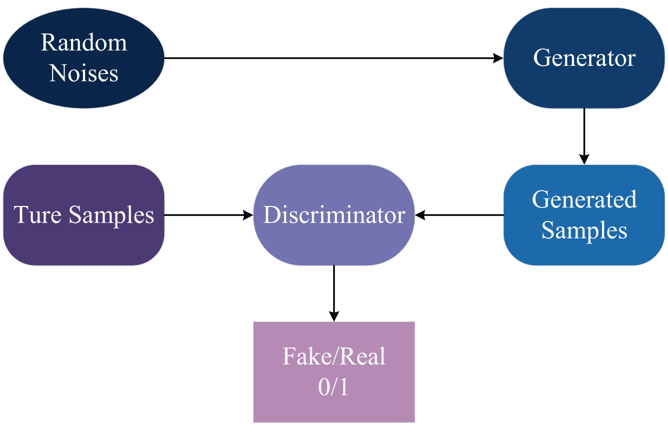


Figure 10. Basic structure of GAN.

Sometimes, GAN is "too free", and thus, we cannot control the generator to generate the required data. For this reason, researchers have proposed a variant of GAN, conditional GAN (CGAN) [50], where conditions are introduced into the modeling of both the generator and the discriminator to guide the data generation process.

3.2. Toy Example of Deep Learning Application in Channel Estimation

Before reviewing the research on deep-learning-based channel estimation, we provide a toy example to illustrate the application of deep learning in channel estimation. The example aims to demonstrate the ability of deep learning to enhance channel estimation performance.

This simulation is set in a vehicular communication scenario within an OFDM system that conforms to the IEEE 802.11p standard. In this environment, the channel exhibits time-varying characteristics, and there is a strong correlation between adjacent OFDM symbols. The classic LS algorithm, performed based on two preambles in an OFDM frame, struggles to track rapid changes in the channel, resulting in poor performance. In contrast, the constructed data pilot (CDP) algorithm constructs virtual pilots from data subcarriers and uses the correlation between adjacent OFDM symbols. It treats the data subcarriers of the previous symbol as a preamble to conduct the current symbol's channel estimation. This algorithm somewhat improves the channel estimation performance but reduces reliability due to error propagation from one symbol to the next.

The flowchart of our example is shown in Figure 11. In our example, we aim to employ a DNN to capture more channel time–frequency features, thereby reducing the error between the CDP estimation results and the actual channel response and improving the channel estimation accuracy. This DNN comprises three hidden layers, each with 20 neurons, and an output layer, and it takes the coarse estimation result from the CDP algorithm as its input.

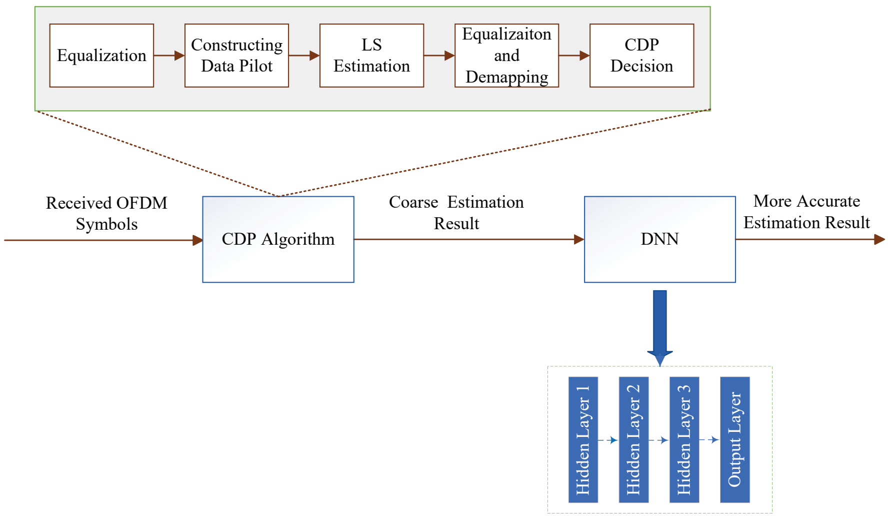
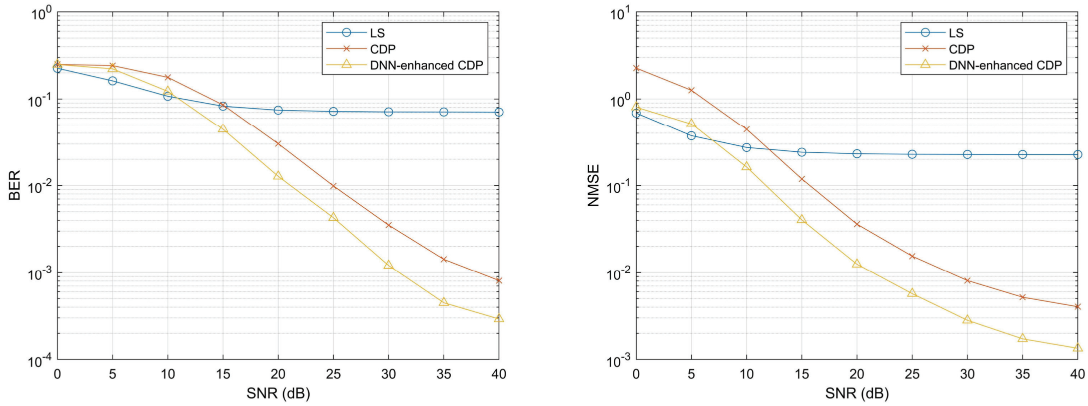


Figure 11. Flowchart of the toy example.

In the experiments, we used the VTV Urban Canyon (VTV-UC) channel model with a velocity setting of 48 km/h and a Doppler shift of 500 Hz. To obtain a robust DNN model, we trained it at a high SNR of 40 dB. Then, we tested it in a SNR range of 0–40 dB and compared its performance with the LS algorithm and the original CDP algorithm. Figure 12a,b display the performance comparison in terms of BER and NMSE, respectively. These results indicate that the DNN-enhanced CDP approach significantly improves the channel estimation accuracy in most scenarios. Even though the performance is not the best in a few low-SNR conditions, it still outperforms the other two traditional algorithms in general, showing the potential of deep learning in channel estimation applications.



(**a**) (**b**)

Figure 12. Performance comparison with the LS algorithm and the original CDP algorithm; (**a**) BER performance comparison; and (**b**) NMSE performance comparison.

3.3. Data-Driven Deep-Learning-Based Channel Estimation Methods

Figure 13 illustrates the structure of a simple channel estimator based on data-driven deep learning. The core idea of the data-driven approach is to consider neural networks as "black boxes", replacing the original traditional communication system structure with them and perpetually updating their parameters through training with massive amounts of data. Next, we will summarize the data-driven deep learning channel estimation methods by categorizing them according to different kinds of neural networks.

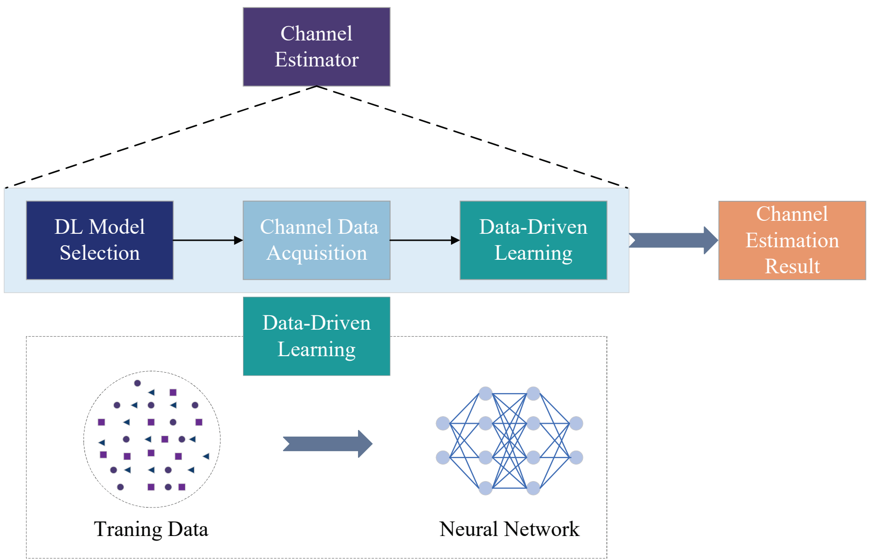


Figure 13. Structure of a data-driven deep-learning-based channel estimator.

3.3.1. Application of DNN in Data-Driven Channel Estimation

DNN is a fundamental network for deep learning with a simple model, and as such, it was first applied in channel estimation. It allows end-to-end learning, i.e., from the original input to the target output. Figure 14 shows a DNN-based channel estimator proposed in [9], serving as one of the typical examples. In this model, the authors estimated the CSI end-to-end by recovering the transmitted data from the received data, including the pilot and data blocks. Moreover, DNN is highly adaptable and flexible, and its structure and hyperparameters can be modified to accommodate various application scenarios.

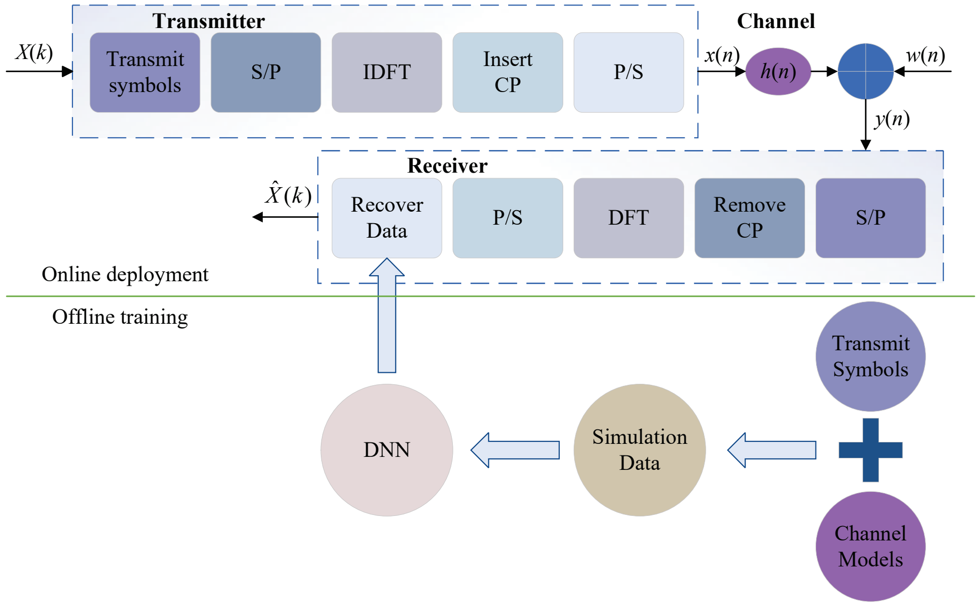


Figure 14. DNN-based end-to-end channel estimator [9].

In 2020, Ma et al. [51] investigated a DNN-based method that combines channel estimation and pilot design. The proposed DNN model is composed of a dimensionality reduction subnetwork and a reconstruction subnetwork. In the first subnetwork, the fully connected layer is designed to compress the high-dimensional channel vector into low-dimensional received measurements, and this compression process treats the weights in the layer as pilot signals. In the second subnetwork, several cascaded convolutional layers and a fully connected layer are designed to recover the high-dimensional channel. Through experimental comparison, this method exhibits a superior NMSE performance to the simultaneous orthogonal matching pursuit (SOMP) algorithm. Furthermore, when the DNN trained with multi-carrier samples is tested on single-carrier samples, and it still performs well, demonstrating its excellent generalization ability.

The interpolation approach is closely connected with the performance of the pilot-based method. In [52], Ge et al. proposed to utilize DNN to replace the interpolation process of the conventional pilot-based method. Firstly, the position index and the channel estimation result of pilot subcarriers are used as training data to train the DNN model. Then, the position index of data subcarriers is used as the input to the DNN, and the channel estimation of data subcarriers is finally obtained. This method does not require prior statistics or matrix inverse operations like the MMSE algorithm and thus has a lower complexity. Moreover, the proposed method exhibited superior estimation accuracy in experiments compared to the LS algorithm, which requires interpolation. Finally, the author tested the model trained with eight multipath paths in conditions with 4, 8, and 12 multipath paths. The BER performance remains almost unchanged, showing the excellent generalization ability of the proposed model.

In 2021, Zheng et al. [53] developed an online DNN-based channel estimation method under limited pilot conditions. This method can dynamically learn and compute in real time, inferring and updating the DNN weights from the pilot symbols received online without knowing the real channel matrix to adapt to the actual communication environment. The proposed DNN-based method exhibits the strongest robustness in experiments. Furthermore, its estimation accuracy approaches the group orthogonal matching pursuit (GOMP) algorithm and the burst LASSO algorithm while surpassing the MMSE algorithm. Significantly, it surpasses all these methods by orders of magnitude in terms of computational speed. Additionally, the proposed DNN model, trained at an SNR of 30 dB, consistently surpasses the MMSE algorithm in terms of NMSE performance when tested at lower SNR levels. Specifically, the experiments conducted on the 3GPP SCM TR 25.996

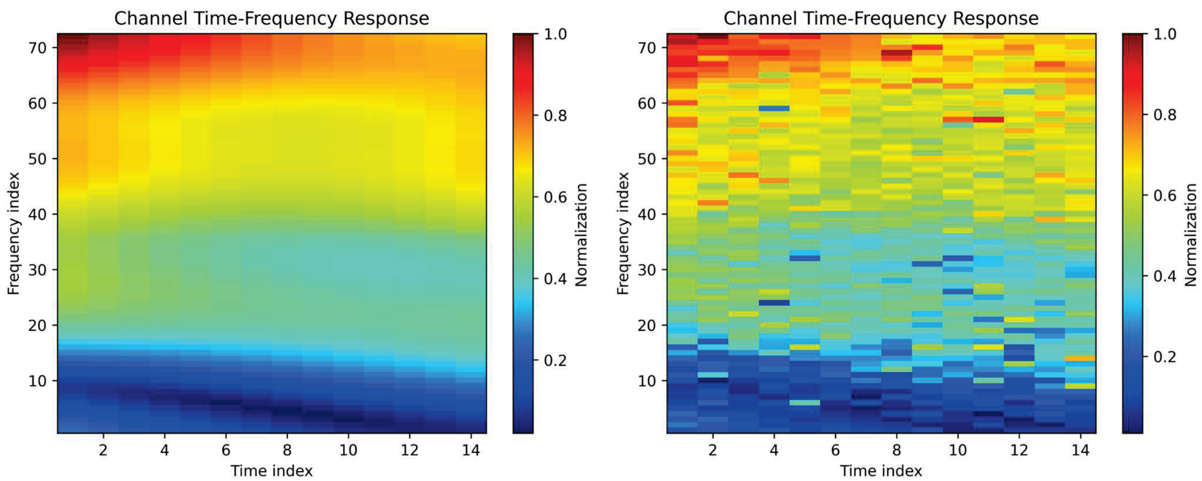
and the DeepMIMO channel models can both yield this result, demonstrating the model's strong generalization on lower SNR.

In the realm of ocean exploration, underwater acoustic (UWA) communication is pivotal. In 2022, Zhang et al. [54] investigated a DNN-based scheme for underwater acoustic channel estimation in OFDM systems. The DNN utilizes transmitted pilots and received symbols in this scheme to reconstruct the UWA channel. Encouragingly, the scheme shows outstanding signal detection performance on the estimated channel. Simulation results demonstrate its efficacy, reducing the BER by over 40% in comparison to the LS algorithm. Furthermore, as the pilot number grows, the BER performance approaches that of the MMSE algorithm.

To improve the estimation performance in impulse noise environments, Li et al. [55] developed a method based on the denoising autoencoder-DNN (DAE-DNN). The proposed method consists of three steps: first, utilizing DAE for preprocessing, namely learning the impaired data and restoring clean received signals under conditions where impulse noise is present; second, employing the preprocessed data from DAE to train the DNN offline; and finally, the DNN estimates the CSI online. Experimental results demonstrate that this method has strong robustness under impulse noise conditions, outperforming the MMSE algorithm, the orthogonal matching pursuit (OMP) algorithm, and the LS algorithm in terms of MSE and BER.

3.3.2. Application of CNN in Data-Driven Channel Estimation

CNN is advantageous for channel estimation since it can reduce the computation of feature parameters and automatically select the appropriate training weights. In addition, CNN's excellent feature extraction capability contributes to its excellent image processing performance. Hence, the channel estimation problem can be transformed into an image processing problem in the application, enabling it to learn from the training data and obtain accurate CSI. Figure 15 shows examples of transforming the channel time–frequency response into a 2D image under the Vehicular-A (VehA) channel model [56]. Specifically, Figure 15a,b represent the channel time–frequency response images under the perfect channel model without noise and the noisy channel model with an SNR of 22 dB, respectively.



(a) **(b)**

Figure 15. Two-dimensional image examples of the channel time–frequency response: (**a**) under the VehA perfect channel model (without noise); and (**b**) under the VehA noisy channel model (SNR = 22 dB).

In 2019, the ChannelNet proposed by Soltani et al. [57] with regard to the channel time–frequency response as a low-resolution 2D image and the values are only known at pilot positions. The ChannelNet consists of a super-resolution CNN (SRCNN) and a denoising CNN (DnCNN), which are cascaded into a two-step channel estimator. In the first step, the low-resolution image is enhanced into a high-resolution image by the SRCNN. In the second step, the DnCNN removes the noise effect to obtain a higher-quality image (i.e., an accurately estimated channel). Through experimental verification, the ChannelNet's MSE performance is superior to the ALMMSE algorithm (an approximation to linear MMSE) but inferior to the MMSE algorithm in low SNR. However, the performance of ChannelNet trained at the SNR of 22 dB shows a decreasing trend when the SNR exceeds 23 dB, which indicates that its generalization ability on real noise is not good enough. Notably, this literature is a pioneer in using image processing methods for channel estimation, providing a novel idea for many subsequent studies. Inspired by this, Li et al. [58] investigated a deep residual channel estimation network (ReEsNet) based on residual learning, which can work in a wide range of scenarios and significantly reduce the complexity while improving estimation accuracy.

The numerous convolutional layers in the denoising structure (DnCNN) of ChannelNet [57] lead to a large amount of computation and a long execution time, which greatly consumes memory. For this reason, Pradhan et al. [59] made improvements and proposed the channel estimation network (CENet). Compared with ChannelNet, CENet also uses SRCNN for image resolution enhancement, with the difference that a convolutional blind denoising network (CBDNet) is used as the denoising structure instead of DnCNN. The CBDNet reduces the overall number of convolutional layers, thereby reducing the complexity of the proposed CNN model. Through experimental comparison, the CENet is superior to the ChannelNet but inferior to the ideal MMSE algorithm in terms of MSE. Furthermore, the author tested the CENet trained with 48 pilots under conditions of different numbers of pilots. The results showed that CENet maintains high performance even with fewer pilots, unlike other methods, which exhibited a significant decrease in performance under the same conditions.

Most research utilizing deep learning for channel estimation focuses on constructing complex neural networks, which leads to increased storage and computational requirements. Li et al. [60] addressed this phenomenon by combining the CNN and Transformer and proposing a lightweight channel estimation Transformer (LCET). This scheme treats the channel response matrix as a 2D image, with the channel features extracted using a lightweight feature extraction CNN (LFEC) and then transmitted to a lightweight-adjusted Transformer (LAT) for channel estimation. Through experimental comparison, the estimation accuracy of the LCET surpasses the LS algorithm and some neural networks, closely approximating the performance of LMMSE algorithms in multi-pilot scenarios.

In general, the transceiver of millimeter wave (mmWave) massive MIMO systems employs a hybrid precoding structure, and thus, the acquisition of CSI in the low SNR regime poses difficulties. To overcome this challenge, Zhao et al. [61] proposed ResNet-UNet, a network that combines the residual network (ResNet) and the U-shaped network (U-Net) for channel estimation. In particular, the proposed ResU-net consists of a denoiser and an estimator. Firstly, the received noisy pilot signal is converted into an image and processed by the denoiser. Then, the obtained clean pilot signal image is fed to the estimator to obtain the estimation result. Through experimental verification, the Res-UNet surpasses the conventional algorithms and the deep CNN in estimation accuracy and is robust to noisy environments.

In 2023, Rahman et al. [62] proposed a deep residual convolutional blind denoising network (ResCBDNet) for massive MIMO visible light communication systems to estimate more realistic and accurate CSI. The proposed ResCBDNet comprises two subnetworks: the noise estimation network and the non-blind denoising network, and it transforms the sparse channel matrix into a 2D image. Initially, the scheme employs a noise estimation network to enhance the generalization ability of the true noise. It then interactively reduces the effect of noise in the channel matrix through the adjustment of the noise level mapping. Subsequently, the noiseless estimated channel is recovered using the non-blind denoising network. Experiments demonstrate that the ResCBDnet surpasses some existing deep-learning-based methods in terms of normalized MSE (NMSE) and peak SNR (PSNR). Moreover, with its exceptional noise generalization capability, ResCBDNet demonstrates the superior MSE performance to other methods when SNR = 20 dB.

3.3.3. Application of RNN in Data-Driven Channel Estimation

RNN is not as widely used as other neural networks in channel estimation. However, some researchers have recently delved into RNN-based methods to improve the channel estimation accuracy. Given the time-dependent properties of RNN, it can be used for time-varying channels to improve time-series information processing. Moreover, it is especially well suited for channel estimation in high-speed mobile settings.

For high-speed mobile environments, channel estimation becomes problematic due to the impact of multipath and Doppler effects, and conventional methods perform poorly due to the limited number of available pilots. Consequently, Gizzini et al. [63] proposed a frame-by-frame (FBF) channel estimation method based on bi-directional RNN (Bi-RNN) for doubly-selective channels. The goal is to perform end-to-end 2D interpolation after estimating the channel of pilot symbols, thereby obtaining the channel estimation of data symbols. Simulation results demonstrate that the proposed Bi-RNN is robust and adaptive, and the estimation accuracy is superior to some existing deep learning schemes. Although the estimation accuracy is marginally lower than the conventional 2D-LMMSE algorithm, the complexity is reduced by nearly 10^6 times, making it a viable alternative.

In 2021, Essai Ali et al. [64] estimated CSI using a variant of LSTM, namely a bi-directional LSTM (Bi-LSTM) neural network. The proposed network model relies on pilot assistance, does not require prior knowledge of channel statistical information, and employs online training with offline deployment. Under the conditions of limited pilots and uncertain channel prior statistics, this model is robust and has a superior symbol error rate (SER) performance over the LSTM and the conventional algorithms (LS and MMSE). The proposed Bi-LSTM can analyze massive data and establish relationships between features, thus having excellent generalization capabilities and applicability to new datasets.

The gated recurrent unit (GRU) is a lightweight variant with potential developed from LSTM. In 2022, Essai Ali et al. [65] designed an end-to-end channel estimation method based on GRU to recover the transmitted signal from the received signal, thereby estimating the CSI. Through experimental verification, the GRU-based method surpasses the conventional estimation algorithms (LS and MMSE), DNN, and ReEsNet in terms of SER. In 2023, Helmy et al. [66] combined LSTM and GRU to develop an LSTM-GRU estimator, which is designed for channel estimation from the received signal. It consists of three parts: the LSTM, the GRU, and the smoothing module. In this framework, the LSTM serves as a minimum absolute filter that denoises the pre-processed received signals, and the GRU module compensates for the information loss in the LSTM module as a compensator. Finally, the model's output is smoothed using batch normalization and convolutional layers. Through experimental comparison, the proposed LSTM-GRU estimator has a superior NMSE performance over the CNN and CGAN estimators. Additionally, the LSTM-GRU trained with a pilot length of 8 is tested in scenarios of varying pilot lengths. The estimation performance of this model does not degrade significantly in the short pilot length range, indicating its outstanding generalization ability.

3.3.4. Application of GAN in Data-Driven Channel Estimation

In channel estimation, GAN has the ability to serve by generating additional data to augment the required training dataset, which is particularly valuable in scenarios without sufficient information about the actual CSI. Moreover, GAN can adaptively improve its performance during training, thereby achieving more accurate estimation results through the adversarial process between the generator and the discriminator.

Motivated by ReEsNet in [58], Zhao et al. [67] developed a super-resolution GAN (SRGAN) for channel estimation in 2021. However, the estimation results of ReEsNet have lost high-frequency details and failed to match the desired fidelity at higher resolutions. In the SRGAN scheme, the channel generated by the generator is closer to the actual channel distribution. Meanwhile, the discriminator recovers more details, significantly enhancing the estimation accuracy. Through experimental comparison, the SRGAN's MSE performance surpasses both the LS algorithm and the ReEsNet, and it approaches the MMSE algorithm in high SNR.

For massive MIMO systems, Dong et al. [68] investigated a CGAN channel estimator in the same year. The proposed CGAN learns how to map from quantized observations to the actual channel and learns a suitable adaptive loss function for network training, resulting in a highly robust model and a more realistic estimated channel. Even when the model is tested on a different channel (i.e., a millimeter wave channel), its performance remains almost unchanged, demonstrating its exceptional generalization capability. In 2023, Zhang et al. [69] also employed CGAN, but their focus was obtaining accurate CSI for MIMO-OFDM systems in high-speed railway scenarios. Their scheme is executed in two steps and regards the pilot signal as a 2D image. In the denoising step that employs the U-Net framework, the received noisy pilot image is denoised using the Noise2Noise (N2N) algorithm. In the estimation step, the CGAN completes the channel estimation by learning the features of the denoised pilot image. Through experimental verification, the N2N-CGAN has high estimation accuracy in high-speed mobile scenarios, exhibits strong robustness in noisy environments, and has low computational complexity.

In the pilot-based channel estimation scheme, the estimation efficacy highly depends on the pilot insertion pattern. To improve the estimation accuracy while reducing the pilot overhead, Kang et al. [70] proposed a network model called CAGAN as a channel estimation scheme for joint pilot design. The CAGAN comprises a CGAN and a concrete autoencoder (concrete AE). First, the concrete AE is used to search for the most informative location in the time–frequency grid and insert pilots here, thereby optimizing the pilot design. Next, the optimized pilots are fed into the CGAN for channel estimation. Experimental results show that the CGAN can exhibit outstanding estimation performance with a limited number of pilots. In order to verify the generalization ability of noise, the CAGANs trained with an SNR of 15 dB and trained at different SNRs are compared in a 0–30 dB SNR range. The result demonstrates that, when the SNR is above 9 dB, the performance of these two models is comparable.

Table 3 summarizes the reviewed data-driven deep-learning-based channel estimation methods and their performance. This type of method exhibits high performance when dealing with high-dimensional, complex data, and it can also show self-learning capabilities in capturing channel characteristics. However, these methods also have glaring disadvantages. They are highly reliant upon an extensive quantity of training data; if the training data are insufficient or not well regularized, this could lead to overfitting, resulting in a decline in generalization ability on new data. In addition, because the neural network structure is often regarded as a "black box", its internal working mechanism and decision-making process are difficult to understand and explain, leading to the poor interpretability of the data-driven approach.

Table 3. Data-driven deep-learning-based channel estimation methods and their performance.

Reference	Model	Input	Output	Compared with	Performance	Complexity
Ma et al. [51]	DNN	Original channel	Estimated channel	SOMP algorithm	Has better NMSE performance and can reduce pilot overhead	$O\left(2N_{BS}^2\rho\right)$
Ge et al. [52]	DNN	Data subcarrier position index	Channel estimation of data subcarriers	LS algorithm	Has better NMSE and BER performance	\
Zheng et al. [53]	DNN	Received signals and pilot symbols	Estimated channel	GOMP, MMSE, and burst LASSO algorithms	The NMSE performance is close to the GOMP and the burst LASSO algorithms while exceeding the MMSE algorithm	CPU time = 0.338 ms
Zhang et al. [54]	DNN	Received OFDM symbols and transmitted pilot symbols	Estimated channel	LS and MMSE algorithms	The BER performance is close to the MMSE algorithm, over 40% better than the LS algorithm	Parameters = 267.168 K, CPU time = 2.995 ms
Li et al. [55]	DAE-DNN	Noisy received signal	Estimated CSI	LS, OMP, MMSE algorithms, and DNN	Outperforms other methods in terms of BER and the MSE in impulse noise environments	\
Soltani et al. [57]	ChannelNet (SRCNN + DNCNN)	Estimated channel at pilot positions	Estimated whole channel	Ideal MMSE and ideal ALMMSE algorithms	At SNR below 20 dB, the MSE performance is superior to the ideal MMSE algorithm but inferior to the ideal ALMMSE algorithm	Floating-point operations per second (FLOPs) = 1533.583 M, parameters = 130.754 K, predict time = 4.422 ms
Li et al. [58]	ReEsNet	Estimated channel at pilot positions	Estimated whole channel	LS, MMSE algorithms, and ChannelNet	The MSE performance is superior to the LS algorithm and the ChannelNet, comparable to the LMMSE algorithm	FLOPs = 5.875 M, parameters = 23.554 K, predict time = 1.737 ms
Pradhan et al. [59]	CENet (SRCNN + CBDNet)	Estimated channel at pilot positions	Estimated whole channel	Ideal MMSE algorithm and ChannelNet	The MSE performance is superior to the ChannelNet but inferior to the ideal MMSE algorithm	\
Li et al. [60]	LCET (LFEC + LAT)	Estimated channel at pilot positions	Estimated whole channel	LS, LMMSE algorithms, ChannelNet, ReEsNet, and SRGAN	The MSE and the BER performance are superior to the LS algorithm and other deep learning networks and approach the LMMSE algorithm in multi-pilot scenarios	FLOPs = 19.316 M, parameters = 21.970 K, predict time = 5.439 ms
Zhao et al. [61]	ResNet-UNet	Noisy pilot sequences	Estimated channel	LS, MMSE algorithms, and deep CNN	Has the best NMSE performance and exhibits strong robustness in noisy environments	\
Rahman et al. [62]	ResCBDNet	Noisy channel matrix	Estimated channel	DnCNN and FFDNet	The NMSE and the PSNR performance are significantly superior to the DnCNN and the FFDnet	Parameters = 536 K, inference time = 0.119 s

Table 3. *Cont.*

Reference	Model	Input	Output	Compared with	Performance	Complexity
Gizzini et al. [63]	Bi-RNN	Estimated channel at pilot symbols	Estimated whole channel	2D-LMMSE algorithm, ChannelNet, and Bi-LSTM	The BER performance is superior to the ChannelNet and the Bi-LSTM and is slightly inferior to the 2D-LMMSE algorithm	$O(2QK_{in} + 4Q^2)$
Essai Ali et al. [64]	Bi-LSTM	Transmitted signal sequence	Prediction matrix of features extracted from the input sequence	LS, MMSE algorithms, and LSTM	With limited pilots, the SER performance is superior to all three	\
Essai Ali et al. [65]	GRU	Received signals	Transmitted signals	LS, MMSE algorithms, DNN, and ReEsNet	With limited pilots, the SER performance is superior to other methods	\
Helmy et al. [66]	LSTM-GRU	Received signals	Estimated channel	CNN and CGAN	Has the best NMSE performance	Computation time = 23.34 ms
Zhao et al. [67]	SRGAN	Estimated channel at pilot positions	Estimated whole channel	LS, LMMSE algorithms, and ReESNet	At low SNR, it provides the best MSE performance; while at high SNR, it is only slightly inferior to the LMMSE algorithm	FLOPs = 48.590 M, parameters = 24.102 K, predict time = 3.464 ms
Dong et al. [68]	CGAN	Received signals and pilot sequences	Estimated channel	U-Net and CNN	Has the best NMSE performance	Computation time = 25.88 ms
Zhang et al. [69]	N2N-CGAN	Noisy pilot sequences	Estimated channel	LS, MMSE algorithms, and CGAN	In terms of MSE, it is superior to the LS algorithm and CGAN and only slightly inferior to the MMSE algorithm at high SNR	$O(N^2)$
Kang et al. [70]	CAGAN (concrete AE + CGAN)	Noisy channel	Estimated channel	LS, MMSE algorithms, and ChannelNet	Outperforms the LS algorithm in terms of MSE and, under high SNR conditions, approaches the ideal MMSE algorithm, surpassing the ChannelNet	FLOPs = 548 K, parameters = 275 K

3.4. Model-Driven Deep-Learning-Based Channel Estimation Methods

The model-driven approach is built on known mathematical models, and its central idea is to combine deep learning with conventional algorithms to improve or expand existing methods. Moreover, it does not depend on extensive labeled data to select the right standard neural network, thus making deep learning more interpretable and predictable. Figure 16 illustrates the components of the model-driven approach. Currently, most research on model-driven channel estimation primarily unfolds on the basis of the LS algorithm and the algorithms in compressive sensing (CS) that include the OMP algorithm and the approximate message passing (AMP) algorithm. This section will discuss model-driven deep-learning-based channel estimation methods based on these three algorithms.

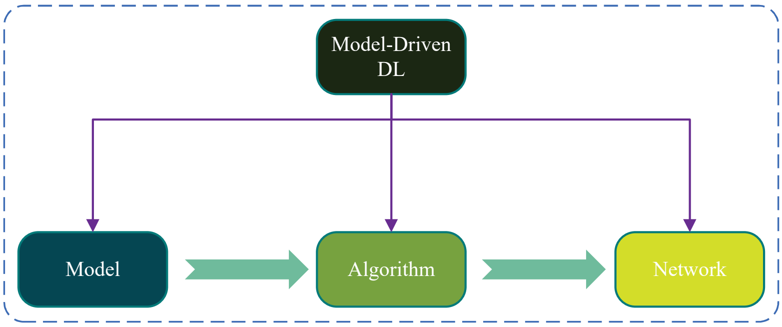


Figure 16. Components of the model-driven approach.

3.4.1. Model-Driven Channel Estimation Combining LS Algorithm

As previously mentioned, the conventional LS channel estimation algorithm is computationally simple but leads to poor performance since it ignores the impact of noise. The ComNet proposed by Gao et al. [12] solves the problem using deep learning networks, which provides a reference for subsequent research. As shown in Figure 17, the ComNet is constructed by cascading the channel estimation and the signal detection subnets. In the channel estimation subnet part, the authors utilized a DNN to refine the coarse estimation of the traditional LS algorithm. Specifically, the DNN takes the LS coarse estimation as input and learns from the discrepancies between this initial estimation and the actual channel. Then, the DNN adjusts its parameters through training to minimize the prediction error, resulting in a more accurate channel estimation.

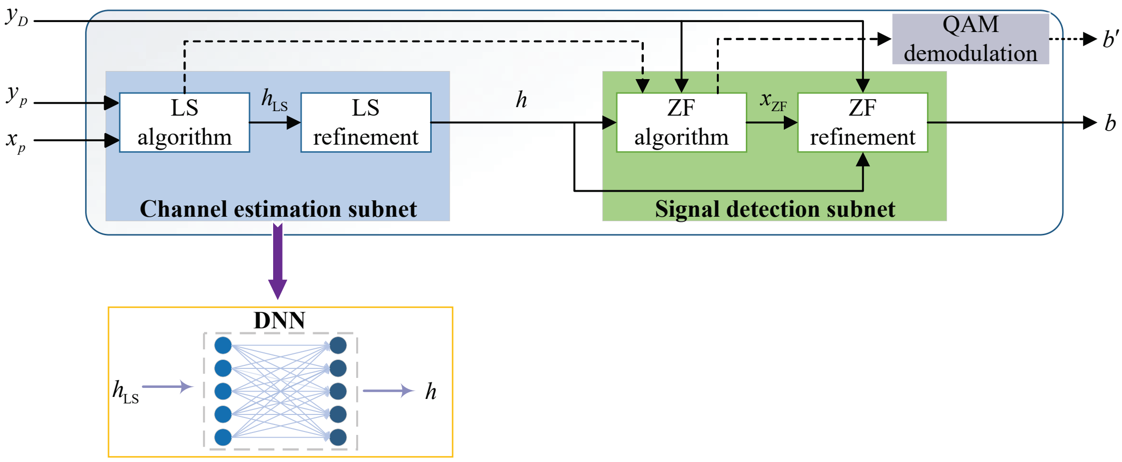


Figure 17. ComNet structure [12].

In 2021, Jiang et al. [71] introduced a dual CNN structure to improve the LS algorithm's estimation accuracy with lower complexity than the general CNN-based methods. The initial channel estimation obtained by the LS algorithm is used as the input for the dual CNN, which consists of a spatial-frequency CNN (SFCNN) and an angle-delay CNN

(ADCNN). In particular, the SFCNN effectively leverages the channel's sparsity to process white noise, while the ADCNN utilizes the channel correlation to reduce interference. These two CNNs are connected through a discrete Fourier transform (DFT) process. Owing to the dual CNN combining the advantages of SFCNN and ADCNN, it exhibits superior NMSE performance to the single-domain CNN in experiments.

In 2023, Haq et al. [72] innovatively implemented channel estimation on a System on Chip (SoC) based on deep learning. Specifically, the authors proposed a channel estimation method called DNN-augmented LS (LSDNN) for the preamble-based OFDM physical layer. This method employs a fully connected feedforward DNN to process the LS estimation results. Specifically, the DNN uses the initial LS estimation as input, learning from its errors to improve the initial estimation. It does this by minimizing the cost function, thereby refining the LS estimation of the previous preamble. Finally, the proposed LSDNN, the LS algorithm, and the LMMSE algorithm are mapped onto a Zynq multiprocessor SoC (ZMPSoC) platform for extensive experimental comparison. Experimental results verify that the LSDNN has a superior estimation accuracy over the LS and the LMMSE algorithms. However, there is still room for improvement in resource utilization and power consumption.

To overcome the challenge of SNR mismatch in multipath time-varying channels, Li et al. [73] introduced a cascaded network called NDR-Net for channel estimation. The NDR-Net consists of a cascade of a noise level estimation subnet (NLE), a DnCNN, and residual learning, and the channel matrix is regarded as an image in this scheme. Firstly, the LS algorithm estimates the coarse value of the channel matrix, which is then inputted into NLE to obtain the noise level estimation. Subsequently, the estimated noise level and the initial noisy channel matrix image are inputted into DnCNN for noise reduction, resulting in a pure noisy image. Finally, the noiseless channel matrix image is obtained by residual learning. Through experimental comparison, the NDR-Net has better estimation accuracy than conventional methods when the SNR is mismatched. In addition, it applies to different Doppler shifts.

3.4.2. Model-Driven Channel Estimation Combining OMP Algorithm

As a greedy algorithm, the OMP algorithm offers optimal solutions to sparse recovery problems. Leveraging the sparsity of channels, it facilitates channel estimation with minimized pilot overhead. However, due to the grid mismatch issue, the OMP algorithm may not provide satisfactory estimation results [74]. To achieve better channel estimation performance, combining the OMP algorithm with deep learning is a viable approach.

In 2022, Li et al. [75] designed a model-driven ResNet-based scheme for orthogonal time–frequency space (OTFS) systems. Considering the sparsity of the channel in the delay-Doppler domain, they first employed the OMP algorithm to obtain a coarse estimation. Then, this initial estimation was fed into the proposed ResNet for a more accurate result. During the training process, the ResNet learns from the error between the OMP rough estimation and the actual channel response. Then, this network continuously optimizes the parameters, resulting in a more realistic channel estimation result. Compared to the conventional OMP algorithm, the ResNet-based scheme has a superior NMSE performance. Furthermore, it applies to various scenarios and displays outstanding robustness to Doppler spread.

In [76], Tong et al. introduced a two-step OMP-based channel estimation algorithm. First, a composite convolution kernel function (CKF) is constructed based on the autocorrelation matrix, which then coarsely estimates the angles of arrival/departure (AoAs/AoDs) for multipath channels. Second, a squeeze-and-excitation ResNet (SE-ResNet) utilizing the Noise2Void (N2V) algorithm is proposed to refine the AoAs/AoDs estimation. Then, the channel amplitude is estimated using the LS algorithm. Finally, the channel matrix is accurately recovered based on all the results above. In the experiments, the proposed algorithm exhibits a superior NMSE performance over the simultaneous weighted OMP (SW-OMP) algorithm, the Newtonized OMP (NOMP) algorithm, and the channel estimation neural network (CENN), while having computational complexity.

To enhance the effectiveness of the conventional OMP algorithm in hybrid-field channel estimation, Nayir et al. [77] developed a novel scheme called OMP-CAE by incorporating the convolutional autoencoder (CAE) for massive MIMO channels. In this scheme, the OMP algorithm first provides a rough channel estimation. Since the channel parameters from the OMP rough estimation contain significant errors at low SNR, they are fed into the CAE network. Then, the CAE network uses its strong denoising ability to improve the accuracy of channel estimation. Through experimental verification, the OMP-CAE surpasses the MMSE algorithm and the conventional OMP algorithm in terms of NMSE and applies to different scenarios.

3.4.3. Model-Driven Channel Estimation Combining AMP Algorithm

The AMP algorithm is a significant iterative algorithm that excels at recovering sparse signals. It can achieve channel estimation in sparse channel environments with low computational complexity [78]. Nevertheless, the AMP algorithm's performance is highly dependent on certain preset parameters, and it presents a challenge to determine the optimal parameters, leading to its limited estimation performance. Therefore, some researchers have combined the AMP algorithm with deep learning. This approach allows the deep learning network to learn and optimize the iterative steps of the AMP algorithm, forming a novel and effective channel estimation method.

The learned AMP (LAMP) algorithm is a variant of the AMP algorithm that unfolds and maps the AMP algorithm's iterative steps directly into a DNN, thereby utilizing the DNN's ability to jointly optimize the coefficients of the linear transformations and the parameters of the nonlinear shrinkage function. However, the existing LAMP networks may not achieve the desired performance in beamspace channel estimation. In light of this, Wei et al. [79] investigated an enhanced scheme based on a prior-assisted Gaussian mixture LAMP (GM-LAMP). Specifically, the authors replaced the soft threshold shrinkage function in the original LAMP network with a Gaussian mixture shrinkage function, which is able to reflect more of the beamspace channel's prior information. Compared to the OMP, the AMP, and the LAMP algorithms, the GM-LAMP algorithm has a superior NMSE performance with less pilot overhead.

The denoising AMP (DAMP) algorithm is also a variant stemming from the AMP algorithm, replacing the shrinkage function with a denoiser. Pu et al. [80] deeply unfolded the DAMP algorithm by replacing its original denoiser with a DnCNN. They developed the model-driven learned denoising AMP (LDAMP) algorithm for channel estimation with noisy channels in OTFS systems. Then, they predicted the theoretical NMSE performance of the LDAMP algorithm using the state evolution (SE) equation. Owing to the integration of the DAMP algorithm's superior performance and the nonlinear fitting capability of deep learning, the proposed algorithm exhibits effectiveness and high accuracy.

In 2022, Wang et al. [81] introduced an AMP-based multi-stage scheme with deep learning for quasi-sparse channel environments. This scheme treats the entire system as an end-to-end DNN, and each iterative process of the sensing matrix, noise introduction, and AMP algorithm is regarded as a DNN layer. Firstly, the AMP sensing matrix is trained to adapt to the quasi-sparse channel and learn the optimal sensing matrix. Secondly, the AMP algorithm's nonlinear shrinkage parameters and linear coefficients are optimized layer-by-layer. Finally, all trainable parameters are jointly optimized, thereby optimizing the entire system. Compared to the AMP, the LAMP, and the LDAMP algorithms, the proposed scheme has a superior NMSE performance while reducing pilot overhead.

Table 4 summarizes the reviewed model-driven deep-learning-based channel estimation methods and their performance. The model-driven approach utilizes some prior knowledge of communication systems, which can enhance its interpretability. Based on existing models in the physical layer, it decreases the quantity of parameters to be learned and the sample complexity of the learning model. However, the model-driven approach is less flexible, and the model could be negatively impacted if the prior knowledge is inaccurate in practical scenarios.

Table 4. Model-driven deep-learning-based channel estimation methods and their performance.

Reference	Deep Learning Model	Input	Output	Compared with	Performance	Complexity
Jiang et al. [71]	Dual CNN (SFCNN + ADCNN)	LS rough channel estimation result	Accurate channel estimation result	LMMSE, robust LMMSE (RLMMSE) algorithms, SFCNN, and ADCNN	The NMSE performance surpasses the RLMMSE algorithm, the SFCNN, and the ADCNN, while it is comparable to the LMMSE algorithm	FLOPs = 3.7 M, parameters = 1764
Haq et al. [72]	DNN	LS rough channel estimation result	Accurate channel estimation result	LS and MMSE algorithms	Has the best NMSE and BER performances on SoC, the resource utilization is lower than the MMSE algorithm but higher than the LS algorithm	Execution time = 0.0179 ms, SoC power = 2.849 W
Li et al. [73]	NDR-Net (NLE + DnCNN + residual learning)	LS rough channel estimation result	Accurate channel estimation result	LS, MMSE algorithms, and DnCNN	Has a better MSE performance when the SNR is mismatched, with nearly 5–7 dB of gain compared to the MMSE algorithm	Parameters = 1231 K, FLOPs = 67 K
Li et al. [75]	ResNet	OMP rough channel estimation result	Accurate channel estimation result	OMP algorithm	Significantly superior to the OMP algorithm in terms of NMSE, especially when the frame size is 128 × 16, and the NMSE is 0.00173, the gain is close to 6dB	\
Tong et al. [76]	SE-ResNet	Coarsely estimated AoAs/AoDs	Finely estimated AoAs/AoDs	SW-OMP, NOMP algorithms, and CENN	Has better NMSE performance even with low SNR and fewer training frames	$O((K_{\text{iter}}+1)\ MN_s\ G_rG_t \log(G_rG_t)\ +K_{\text{iter}}N_{\text{layer}}\ G_rG_tS_{\text{filter}}\ C_{\text{in}}C_{\text{out}}\ )$
Nayir et al. [77]	CAE	OMP rough channel estimation result	Accurate channel estimation result	OMP and MMSE algorithms	Performs best in terms of NMSE, even at low SNR	\
Wei et al. [79]	GM-LAMP	Measurement signal vector and beam selection matrix	Estimated channel	OMP, AMP and LAMP algorithms	Achieves better NMSE performance with lower pilot overhead	$O(TMN)$
Pu et al. [80]	LDAMP	Received signal vector and transmitted signal matrix	Estimated channel	OMP, AMP algorithms, and ResNet	Has the best NMSE performance, with the NMSE already less than 10^{-2} in the low SNR scenario with an SNR of 2dB	$O\left(L\left(MN+M^2N^2\right)\right)$
Wang et al. [81]	DNN	Original channel	Estimated channel	AMP, LAMP, and LDAMP algorithms	The NMSE performance outperforms the AMP and the LAMP algorithms; it outperforms the LDAMP algorithm when the SNR is above 8 dB	\

According to the discussion in this section, we can learn that most existing studies on channel estimation using deep learning mainly concentrate on the data-driven approach. However, both data-driven and model-driven approaches have the potential to achieve or even exceed conventional methods' performance in the appropriate application scenarios. Table 5 provides a detailed comparison of the advantages and disadvantages of these two approaches.

Nevertheless, the studies mentioned above are limited to traditional communication scenarios and do not address future communication scenarios. As one of the critical techniques for 6G networks, the research on RIS is in full swing. The introduction of RIS improves the performance of communication systems but also increases their complexity, making conventional techniques, including channel estimation, confront new challenges. With the accelerated advancement in deep learning, numerous researchers have adopted this technique to solve the aforementioned issue. The following section will introduce channel estimation methods based on deep learning for RIS-aided wireless communication systems.

Table 5. Comparison of the advantages and disadvantages of data-driven and model-driven approaches.

Characteristics		Data-Driven Approach	Model-Driven Approach
Advantages	Self-learning/automatic feature extraction	✓	
	High accuracy	✓ (With sufficient training data)	✓ (When the model is well designed)
	Utilization of prior knowledge		✓
	Interpretability		✓
Disadvantages	Large data requirements	✓	
	Risk of overfitting	✓	
	High computational complexity	✓	
	Inflexibility		✓

4. Channel Estimation Based on Deep Learning for RIS-Aided Communication Systems

RIS is one of the most promising techniques for 6G communications, consisting of numerous passive reflective metamaterial antenna elements that form a plane with low cost, low power consumption, easy deployment, etc. RIS can reconfigure the wireless propagation environment by intelligently adjusting the amplitude and phase to enhance wireless communications' spectrum and energy efficiency [82]. When combined with wireless communication systems, RIS can modify or improve existing communication concepts, thereby assisting in meeting the high standards of 6G communication. Figure 18 shows an example of RIS-aided communication systems. In this setup, the base station (BS) is outfitted with M antennas and serves K users, each with a single antenna, and the RIS is outfitted with a total of N passive reflective elements. Furthermore, the BS adjusts the parameters of the reflective elements through the RIS controller. The direct link between the BS and the users is blocked, making the BS unable to communicate properly with the users. With the deployment of RIS, an additional link between them is established.

Let $\mathbf{h}_{d,k} \in \mathbb{C}^{M\times 1}$ represent the direct channel between the kth user and the BS, $\mathbf{h}_{r,k} \in \mathbb{C}^{N\times 1}$ is the channel between the kth user and the RIS, and $\mathbf{G} \in \mathbb{C}^{M\times N}$ is the channel between the RIS and the BS. Then, the received signal at BS can be expressed as:

$$\mathbf{y} = \sum_{k=1}^{K} (\mathbf{h}_{d,k} + \mathbf{G}\mathrm{diag}(\theta)\mathbf{h}_{r,k}) u_k + \mathbf{v} \tag{12}$$

where $\theta = [\theta_1, \theta_2, \ldots, \theta_N]^{\mathrm{T}}$ denotes the reflection vector of the RIS, θ_n is the reflection coefficient of the nth reflection element, u_k is the symbol sent by the kth user, and $\mathbf{v} \in \mathbb{C}^{M\times 1}$ is the received noise. In particular, θ_n can be further denoted by $\theta_n = \beta_n e^{j\phi_n}$, with $\beta_n \in [0, 1]$

and $\phi_n \in [0, 2\pi]$ corresponding to the amplitude and phase of the nth reflection element, respectively. Since passive RIS elements cannot actively transmit and receive signals and perform additional signal processing, $\mathbf{h}_{r,k} \in \mathbb{C}^{N\times 1}$ and $\mathbf{G} \in \mathbb{C}^{M\times N}$ cannot be directly estimated. Therefore, it is necessary to estimate the channel between the kth user and the RIS and between the RIS and the BS as the cascaded channel $\mathbf{H}_k \triangleq \mathbf{G}\mathrm{diag}(\mathbf{h}_{r,k}) \in \mathbb{C}^{M\times N}$. In this instance, Equation (12) can be re-expressed as:

$$\mathbf{y} = \sum_{k=1}^{K} (\mathbf{h}_{d,k} + \mathbf{H}_k\theta)u_k + \mathbf{v} \tag{13}$$

It is noteworthy that, in a TDD system, the downlink CSI can be obtained from the uplink channel estimation because of the channel reciprocity [83].

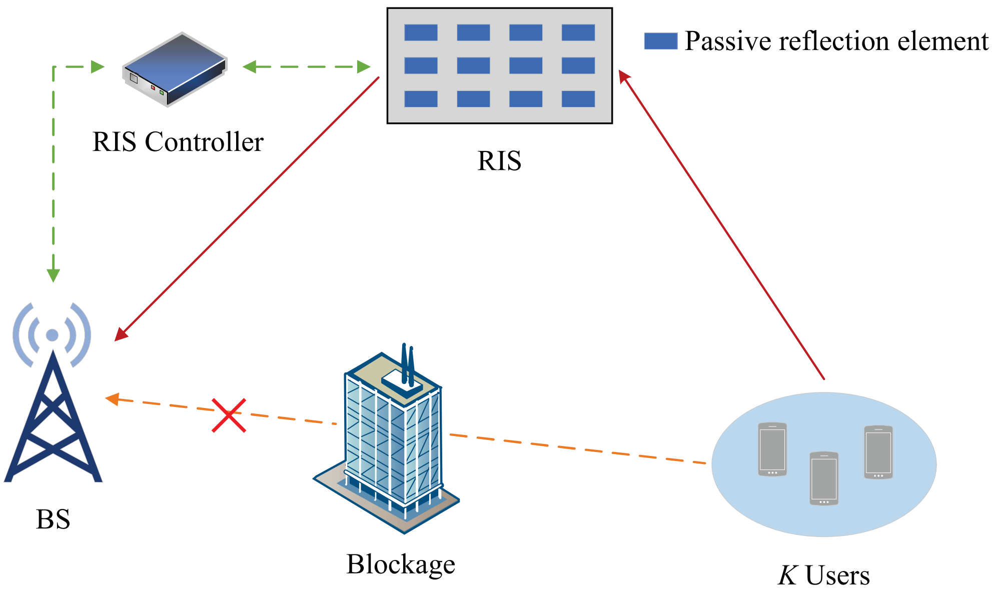


Figure 18. RIS-aided communication system.

Channel estimation in RIS-aided systems presents more challenges compared to traditional systems. During signal reflection, RIS functions as a passive device without the capability to receive or sample signals. Therefore, it can only carry out low-dimensional signal sampling at the transmitter and receiver to estimate the high-dimensional CSI. When the number of RIS reflective elements is substantial, the channel matrix that needs to be estimated becomes larger in dimension, increasing the overhead and computational complexity required for channel estimation. Suppose a few passive reflection elements of RIS are replaced with active elements (i.e., semi-passive RIS architecture). In that case, the sensing devices can estimate the CSI of the separate channels. Still, installing the active elements will diminish the benefit of RIS as a low-cost passive device. In response to the above challenges, numerous researchers have started to work on utilizing deep learning's strong ability to estimate RIS-aided channels. Massive MIMO, millimeter wave (mmWave), and multi-user (MU) systems are all popular areas of research in 5G and 6G communications. Therefore, this section will concentrate on channel estimation for RIS-aided communication systems based on deep learning related to them.

4.1. Application of Deep Learning in Channel Estimation for RIS-Aided Massive MIMO Systems

Massive MIMO systems use a lot of antenna elements to achieve a high level of spatial multiplexing and beamforming, which improves the throughput and spectral efficiency of wireless communications. These advantages make massive MIMO an integral part of 5G and subsequent technologies. However, it poses challenges such as low coverage, high power consumption, and high cost. To mitigate these issues, RIS has been introduced as a promising solution. Nonetheless, the employment of RIS makes channel estimation more difficult. Against this backdrop, the intervention of deep learning offers a novel approach to addressing the complex issue of channel estimation.

In 2022, Mao et al. [84] utilized the cascaded channel's quasi-sparse structure to transform the channel estimation for RIS-aided massive MIMO systems into a CS problem. Their scheme targeted the uplink, introducing a residual structure-based OMP (RS-OMP) architecture. This architecture is designed to address the impacts of noise and grid mismatch on the traditional OMP algorithm. Within this architecture, the ResNet uses a rectangular convolutional kernel, which makes it more capable of learning the row or column sparsity. Through experimental comparison, the proposed RS-OMP outperforms the DnCNN and the traditional OMP algorithm in terms of NMSE.

In [85], Xie et al. investigated an estimation method based on deep compressive sensing (DCS) for RIS-aided massive MIMO channels, with the aim of reducing the pilot overhead. Specifically, they developed a ResU-Net by combining U-Net with the DCS framework while introducing residual learning. The received low-dimensional pilot signals are first transformed into high-dimensional signals by matrix multiplication. Then, the ResU-Net with skip connections is utilized to compress the input data and recover the high-dimensional cascaded channel. Experiments are conducted using varying pilot lengths and quantization bits, and the results verify the ResU-Net's excellent generalization ability and robustness.

In 2023, Liu et al. [86] proposed a skip-connection attention (SC-attention) network for accurate CSI acquisition in double-RIS-aided massive MIMO systems. In this scheme, they modelled channel estimation as an image restoration-like denoising problem. Moreover, they used self-attention layers to improve the model capacity and receptive field size of the network, which allows for recovering the CSI matrix more accurately. Meanwhile, by employing the skip-connection architecture, the estimation accuracy can be enhanced by 16% while reducing the computational complexity. Through experimental comparison, the SC-attention network exhibits a superior NMSE performance over the CNN and the conventional algorithms (LS and MMSE).

4.2. Application of Deep Learning in Channel Estimation for RIS-Aided mmWave Systems

Many researchers have pushed for the application of mmWave to enhance wireless system performance, which can generate narrow, highly energy-concentrated information-carrying beams. As one of the critical 6G techniques, mmWave offers higher transmission rates and greater connection capacity for wireless communications due to its ultra-high-frequency bandwidth. However, mmWave communication encounters challenges in coverage and signal quality. In addressing these issues, the emergence of RIS offers a promising solution: through the precise control of signals and improvement of their transmission properties, more excellent coverage can be achieved; additionally, by suppressing multipath fading and interference, the signal quality can be significantly enhanced [87]. Nevertheless, introducing RIS makes the higher-dimensional CSI need to be estimated. As an efficient tool, deep learning holds promise for successfully coping with this high-dimensional complexity.

For RIS-aided channels, increasing users and reflective elements elevate the training overhead, making accurate CSI acquisition difficult. To deal with this issue, Shtaiwi et al. [88] proposed a two-stage channel estimation scheme for entirely passive RIS-aided mmWave systems. In the initial stage, a pilot-based method for uplink is designed, where only randomly selected user terminals send known pilot sequences to the BS through the RIS, reducing the active user count during the training period. In the subsequent stage, a CNN-based spatial–temporal–spectral architecture (STS-CNN) is proposed to recover the CSI of inactive user terminals in the first stage. Through experimental comparison, this scheme outperforms the benchmark in terms of MSE. However, more research is needed on the CNN-based estimation method, as its complexity can be further reduced.

For semi-passive RIS-aided mmWave systems with a few distributed active sensing devices, Jin et al. [89] leveraged the sparsity of RIS-aided channels and used the image super-resolution method for channel estimation. In particular, their scheme used the multi-scale deep super-resolution (MDSR) and the enhanced deep super-resolution (EDSR) networks. First, the EDSR combines global feature fusion and residual blocks to obtain CSI for single-scale sparse channels, simplifying the RIS hardware. Next, the MDSR is employed to guarantee that the scale of active elements is adjustable to flexibly adapt to multi-scale, low-sparse, and low-resolution channel scenarios. Experiments demonstrate the scheme's effectiveness, and the estimation performance improves as the sensing device density and network size increase.

In 2023, Feng et al. [90] similarly transformed the channel estimation into an image super-resolution problem. Specifically, they developed a cascade channel estimation scheme for RIS-aided mmWave single-input–multi-output (SIMO) systems based on global attention ResNet (GARN). The RIS unit cells are first grouped in this scheme to reduce the pilot overhead. Then, the initial channel estimation is obtained using the LS algorithm, serving as the input to GARN. Since the GARN adopts the global attention mechanism, it can extract multi-channel features and enhance information fusion, improving the accuracy of channel estimation matrices. Experimental comparisons with multiple benchmark methods demonstrate the proposed scheme's excellent estimation performance and generalization ability.

In the same year, Abdallah et al. [91] developed two deep-learning-based schemes for RIS-aided mmWave MIMO systems, i.e., data-driven frequency-flat cascaded channel estimation (DD-FF-CE) and data-driven frequency-selective cascaded channel estimation (DD-FS-CE). For the DD-FF-CE, the authors turned channel estimation into a CS problem by leveraging the angular cascaded channel's double-structured sparsity and solving it using deep learning. In particular, they used two DnCNNs to find the row and column supports and then the LS algorithm to estimate the angular cascade channel. In contrast to the DD-FF-CE, the DD-FS-CE also utilizes the support information from each subcarrier to cope with frequency selectivity. In the experiments, these two schemes exhibit excellent NMSE performance and low computational complexity while having less pilot overhead.

4.3. Application of Deep Learning in Channel Estimation for RIS-Aided MU Systems

MU communication systems serve a vital role in modern wireless communications, which improve the spectrum efficiency by enabling multiple users to share the same spectrum resource simultaneously. By adjusting its surface units, RIS can modulate the reflective properties of signals to optimize channel conditions, thereby enhancing the system performance. However, accurately estimating the channels in RIS-aided MU systems presents a new challenge. Utilizing the powerful learning capability of deep learning to address this issue is a hot trend in current research.

In 2021, Ginige et al. [92] innovatively proposed a DNN based on the deep image prior (DIP) in channel estimation for RIS-aided MU SIMO-OFDM systems. This network is untrained and can optimize its parameters in real time. In this scheme, the LS algorithm first estimates the effective channel, which is then denoised using the untrained DNN. After denoising, the channel utilizes the information from the DFT-based reflection pattern matrix to obtain the CSI of the direct and cascade channels. In simulations, the untrained DNN exhibits a superior NMSE performance over the conventional methods (LS and MMSE), while it has low complexity because no pre-training is required. Moreover, it can maintain high accuracy in the case of hardware impairments and adjust flexibly to various scenarios and channel settings.

In 2022, Liu et al. [93] modelled channel estimation for RIS-aided MU communication (MUC) systems as a noise reduction problem and developed a flexible deep residual learning (DReL)-based channel estimation framework. They derived an MMSE estimator based on a deep residual network (DRN) using Bayesian theory under the MMSE criterion within this framework. In addition, they introduced a CNN-based DRN (CDRN) designed to recover the noisy channel matrix. The network features a CNN denoising module with an element-by-element subtraction structure. This design enables it to simultaneously extract the spatial properties of the noisy channel matrix and the additive characteristics of the noise. Experimental results demonstrate that this framework does not require additional sensing devices in the RIS. Furthermore, its NMSE performance closely approximates the optimal MMSE estimator, which requires deriving from the cascade channel's prior probability density function.

In RIS-aided MU MIMO-OFDM systems, the cascaded channel has high dimensionality and complex statistical properties. These factors make it challenging to achieve the ideal MMSE algorithm with the best performance. In [94], Shen et al. applied the concept of image super-resolution and developed an SRDnNet, which combines the properties of SRCNN and DnCNN to obtain accurate CSI. The central idea of SRDnNet is to regard the estimated channel of pilot positions as a low-resolution image. It uses the enhanced SRCNN to extract input features, learns the appropriate interpolation method, and generates a coarsely estimated channel matrix. After that, the DnCNN performs denoising to recover the channel coefficients from the noisy channel matrix. Compared to the ChannelNet [57], the SRDnNet can receive rawer inputs and requires just one division operation between the received and transmitted pilots, leading to decreased computational and time consumption. Without prior information on the direct and cascaded channels, the SRDnNet outperforms the conventional LS, MMSE algorithms, and the ChannelNet, with NMSE gains exceeding 10 dB.

In 2023, Li et al. [95] proposed a DCSaNet based on dilated convolution and self-attention to enhance the channel estimation accuracy of RIS-aided MUC systems. This network uses dilated convolutional blocks to enlarge the receptive field and optimize feature extraction. Additionally, it employs self-attention blocks to enable the system to concentrate on critical channel features. To meet the requirements of the real-world deployment of RIS, the authors further designed the lightweight DCSaNet-l network, which reduces the parameters by a significant amount (nearly 83.7%) but performs almost as well as DCSaNet. The simulation results demonstrate that these networks substantially improve the NMSE performance and the training speed across various channel dimensions and SNR levels.

This section focuses on deep-learning-based channel estimation methods for RIS-aided communication systems. These methods cover massive MIMO, mmWave, and MU systems and are summarized in Table 6. With deep learning, we can more accurately estimate complex RIS channels. However, there may still be challenges in this area of research. First, most existing studies on RIS focus on passive RIS. The passive reflection elements of RIS introduce high-dimensional channel parameters, which increase the input dimensions of the deep learning models. As a result, the complexity and training difficulty of the models rise. Second, the deployment location of RIS and the surrounding environment impact its reflective properties. Hence, the model must have a strong generalization capability, ensuring its performance in various scenarios is as effective as the one it was trained for. Given these, how to combine RIS technology with deep learning technology more effectively is an important topic worth studying in the future.

Table 6. Research on channel estimation based on deep learning for RIS-aided communication systems.

Reference	System	RIS Architecture	Deep Learning Model	Input	Output	Complexity
Mao et al. [84]	RIS-aided massive MIMO	Entirely passive	ResNet	OMP rough channel estimation result	Accurate channel estimation result	$O(KMNT_t + \sum_{l=1}^{D} MNS_l C_{l-1}C_l)$
Xie et al. [85]	RIS-aided massive MIMO	Entirely passive	ResU-Net	Received pilot signal	Estimated channel	CPU time = 95.7 ms, GPU time = 4.27 ms
Liu et al. [86]	Double-RIS-aided massive MIMO	Entirely passive	SC-attention network	LS rough channel estimation result	Accurate channel estimation result	\
Shtaiwi et al. [88]	RIS-aided mmWave MIMO	Entirely passive	STS-CNN	Partial CSI	Entire CSI	\
Jin et al. [89]	RIS-aided mmWave massive MIMO	Semi-passive	EDSR + MDSR	Partial CSI	Entire CSI	EDSR: average running time = 7.8 ms MDSR: average running time = 7.5 ms
Feng et al. [90]	RIS-aided mmWave SIMO	Entirely passive	GARN (ResNet + global attention)	Grouped LS channel estimation matrix	Reconstructed complete channel matrix	Parameters = 2.061 M, FLOPs = 1.807 G
Abdallah et al. [91]	RIS-aided mmWave MIMO	Entirely passive	DnCNN	Received pilot signal	Residual noise	$O(UN_{BS}Q + UL_G N_{RIS}Q + UL_G(2QL_u^2 + L_u^3))$
Ginige et al. [92]	RIS-aided MU SIMO-OFDM	Entirely passive	DNN	LS rough channel estimation result	Accurate channel estimation result	\
Liu et al. [93]	RIS-aided MUC	Entirely passive	CDRN (CNN + DRN)	Noisy channel matrix	Denoised channel matrix	computation time = 2.66 ms
Shen et al. [94]	RIS-aided MU MIMO-OFDM	Entirely passive	SRDnNet (SRCNN + DnCNN)	Estimated channel at pilot positions	Estimated whole channel	Predict time = 1.61×10^{-2} s
Li et al. [95]	RIS-aided MUC	Entirely passive	DCSaNet (dilated convolution + self-attention)	LS rough channel estimation result	Accurate channel estimation result	Execution time = 5.2×10^{-4} s, training time = 246 s

5. Challenges and Future Research Trends

Deep learning techniques have demonstrated the capability to effectively process large amounts of data and enhance the channel estimation performance. However, it is essential to acknowledge that several challenges in this field remain unresolved. According to the current advancements in wireless communications, the prospective research trends for deep-learning-based channel estimation are outlined below.

5.1. Theoretical Exploration

In deep-learning-based channel estimation, strict mathematical proof is essential to define its performance limits. However, this approach is not backed by a solid mathematical foundation. Moreover, mathematical and physical theories explaining deep learning are still exploratory, making it unclear why certain network structures could achieve a good channel estimation performance [96]. Additionally, without advanced optimization theory, finding the optimal policy and loss function during training is challenging. Hence, overcoming the theoretical challenge is urgently needed and research-worthy.

5.2. Enhancing Estimation with Limited Data

The estimation accuracy of deep-learning-based methods highly depends on the quantity and quality of training and testing data. However, obtaining channel data can be challenging in some special communication scenarios. With limited or no data available, the performance of these methods often suffers. Therefore, it is necessary to combine multiple approaches in channel estimation algorithms. In this case, integrating transfer learning [97] or meta-learning [98] with deep learning could be an effective strategy to enhance the channel estimation accuracy.

5.3. Attention Mechanism in Noise Processing

In prior research, noise processing in channel estimation often relies on image super-resolution algorithms or denoising neural networks. However, these approaches may destroy the actual channel information [99]. The attention mechanism [100] is a significant deep learning technique different from traditional neural networks, which treat all input data equally important. It assigns varying weights to different parts of the data, focusing more precisely on the most critical information. Therefore, adding the attention mechanism to channel estimation could be a valuable direction for future research. By doing so, the deep learning model would focus more on the effective information in the received signal and reduce noise impact by adjusting feature weights, thereby achieving more accurate channel estimation.

5.4. Adaptation to Dynamic Environments

A fixed channel estimation model may no longer maintain high accuracy in dynamic wireless communication environments. If the model is retrained to adapt, it will consume significant time and computational resources. This approach fails to meet the real-time and low-cost requirements. Therefore, research on adaptive model design can be strengthened in future work. Such a design would enable the model to adjust its parameters and structure autonomously, adapting to complex and changing environments for stable and high-performance channel estimation.

5.5. Channel Estimation for Other 6G Communication Scenarios

Beyond the RIS-aided communication systems we have mentioned, there are numerous emerging scenarios for next-generation wireless communications. These scenarios include those that employ terahertz (THz) communication technology [101] and visible light communication (VLC) technology [102]. Among them, THz communications can bring massive spectrum resources that meet the requirements of 6G. Additionally, VLC adopts an ultra-high bandwidth for high-speed data transmission, offering a wide range of applications in 6G. Given these, extending deep-learning-based channel estimation research to these two communication scenarios is necessary and an important future research direction.

5.6. Lightweight Networks for Channel Estimation

From extensive previous research, it is evident that large-size deep learning models can learn more complex data features due to more parameters and a deeper network structure. These factors enable them to achieve higher channel estimation performance. However, the performance improvement is often accompanied by higher computational complexity and resource consumption, which may be a significant limitation in resource-constrained practical applications. In light of this challenge, lightweight networks offer promising prospects for channel estimation. These networks are characterized by optimized structures and a reduced parameter count. Specifically, the design of these networks aims to balance the high estimation performance with reduced complexity and resource demands.

6. Conclusions

As wireless communication technology advances rapidly, the outline of 5G becomes increasingly clear. Meanwhile, with the advent of 6G on the horizon, integrating deep learning with traditional communication techniques has emerged as a focal point in academia. In this paper, we reviewed recent research on deep-learning-based channel estimation and classified it into data-driven and model-driven approaches. Meanwhile, we further summarized the application of deep learning in channel estimation for RIS-aided communication systems, one of the future novel communication scenarios. Numerous studies have showcased that deep-learning-based methods have the potential to match or surpass conventional methods. However, most of the technical implementations are still in their infancy, and their applications still face many challenges; thus, we also provided an outlook on possible future research trends. We expect that this paper can assist researchers interested in applying deep learning to channel estimation.

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