Ước lượng kênh cho hệ thống thông tin không dây hỗ trợ bởi bề mặt phản xạ thông minh: Phương pháp, thuật toán và thách thức thực tiễn

TÓM TẮT

Công nghệ bề mặt phản xạ thông minh (Intelligent Reflecting Surface - IRS) đã nổi lên như một yếu tố then chốt cho các hệ thống truyền thông không dây thế hệ thứ sáu (6G) trong tương lai, nhờ khả năng cải thiện vùng phủ sóng, hiệu suất phổ và độ tin cậy truyền dẫn thông qua việc tái cấu hình môi trường lan truyền vô tuyến. Bằng cách điều khiển thích ứng pha và/hoặc biên độ của một số lượng lớn các phần tử phản xạ thụ động chi phí thấp, IRS mang lại một giải pháp linh hoạt và tiết kiệm năng lượng nhằm đáp ứng các chỉ số hiệu suất khắt khe. Tuy nhiên, những lợi ích này phụ thuộc chặt chẽ vào việc thu thập thông tin trạng thái kênh (CSI) chính xác, vốn gặp nhiều thách thức do bản chất thụ động của các phần tử IRS và chi phí huấn luyện lớn. Bài báo này cung cấp kết quả nghiên cứu theo hệ thống về các kỹ thuật xử lý tín hiệu tiên tiến cho ước lượng kênh trong các hệ thống truyền thông không dây có hỗ trợ IRS. Hai kiến trúc IRS hoàn toàn thụ động và bán thụ động đều được xem xét dưới nhiều cấu hình hệ thống khác nhau. Các phương pháp hiện có được phân loại theo mô hình kênh, chiến lược ước lượng và kịch bản triển khai. Ngoài ra, bài báo phân tích ảnh hưởng của các khiếm khuyết phần cứng, bao gồm điều khiển pha rời rạc, ADC độ phân giải thấp và các suy hao RF, đồng thời nêu bật các thách thức còn tồn tại đối với triển khai IRS trong hệ thống 6G.

Từ khóa: *Bề mặt phản xạ thông minh (IRS), Thông tin trạng thái kênh (CSI), Ước lượng kênh (CE), Truyền thông không dây 6G.*

Channel estimation for intelligent reflecting surface-aided wireless communication systems: Methods, algorithms and practical challenges

ABSTRACT

Intelligent reflecting surface (IRS) technology has emerged as a key enabler for future sixth-generation (6G) wireless communication systems, owing to its capability to enhance coverage, spectral efficiency, and transmission reliability by reconfiguring the wireless propagation environment. By adaptively controlling the phase and/or amplitude of a large number of low-cost passive reflecting elements, IRS provides a flexible and energy-efficient solution to meet increasingly stringent performance requirements. However, realizing these benefits critically relies on the availability of accurate channel state information (CSI), which is particularly challenging due to the inherently passive nature of IRS elements and the resulting high training overhead. This paper presents a systematic investigation of advanced signal processing techniques for channel estimation in IRS-aided wireless communication systems. Both fully passive and semi-passive IRS architectures are examined under diverse system configurations. Existing approaches are classified according to channel models, estimation strategies, and deployment scenarios. Furthermore, the impact of practical hardware impairments, including discrete phase control, low-resolution analog-to-digital converters (ADCs), and radio-frequency (RF) impairments, is analyzed, and key open challenges for the practical deployment of IRS in 6G systems are highlighted.

Keyword: *Intelligent Reflecting Surface (IRS), Channel State Information (CSI), Channel Estimation (CE), 6G wireless communications.*

1. INTRODUCTION

Fifth-generation (5G) wireless communication systems have been rapidly deployed worldwide, supporting a wide range of services, including :[1-3] enhanced mobile broadband (eMBB), which provides data rates of up to 1 Gbps for mobile users; ultra-reliable and low-latency communications (URLLC), enabling end-to-end latencies on the order of milliseconds with reliability levels no lower than 99.999%; and massive machine-type communications (mMTC), which allow the simultaneous connection of up to 10^6 devices per km2 in Internet-of-Things (IoT) networks. However, driven by the explosive growth in the number of mobile subscribers and wireless devices, as well as the rapid emergence of new wireless applications-such as augmented reality (AR), mixed reality (MR), virtual reality (VR), wireless industrial automation, the tactile Internet, and beyond 5G is no longer sufficient to meet the ever-increasing demands for system capacity, spectral efficiency, and massive connectivity in the IoT era. Moreover, practical 5G deployments still face several inherent limitations, including high energy consumption, costly hardware implementations, and severe propagation losses, even when advanced enabling technologies such as massive multiple-input multiple-output (MIMO) and millimeter-wave (mmWave) communications are employed. These challenges have motivated intensive research efforts toward sixth-generation (6G) wireless systems, which aim to support unprecedented performance targets, including data rates exceeding 1 Tbps, energy efficiency improvements by a factor of 10-100 compared with 5G to enable green communications, ultra-high system reliability beyond 99.99999%, support for ultra-high-mobility scenarios with speeds up to 1000 km/h, and connection densities approaching 10^7 devices per km2 to accommodate future IoT and immersive AR/MR/VR applications.[4-9]

The emergence of intelligent reflecting surfaces (IRSs) has been recognized as a disruptive paradigm capable of fundamentally transforming intelligent wireless communication systems by effectively reshaping the wireless propagation environment at a relatively low cost.[10-12] Specifically, an IRS is a digitally controllable metasurface composed of a large number of nearly passive reflecting elements with extremely low power consumption, which can manipulate the phase shifts and/or amplitudes of the incident signals in a programmable manner to achieve desired propagation characteristics. IRSs exhibit significant potential in several key aspects:

i) Coverage enhancement and data rate improvement**:** By creating virtual line-of-sight (LoS) links, IRSs can substantially extend coverage in unfavorable propagation environments. In this way, signal blockage and coverage holes between transmitters and receivers can be effectively mitigated;

ii) Channel power and rank enhancement: By introducing additional controllable signal paths, IRSs can improve the channel power and matrix rank, thereby enhancing spatial multiplexing gains and spectral efficiency in broadband and multi-antenna communication systems;

iii) Reliability improvement: IRSs can transform fast-fading Rayleigh channels into more stable Rician fading channels, significantly improving link reliability;

iv) Interference management: Through intelligent reflection control, IRSs can facilitate interference suppression and coordination, including co-channel and inter-cell interference mitigation, leading to improved quality of service (QoS) for users;

v) Cost-effective densification: IRSs enable higher connection densities in a cost- and energy-efficient manner, without the need for dense deployment of power-hungry base stations (BSs) or access points (APs).

As illustrated in Fig. 1, several potential deployment scenarios and application contexts of Intelligent Reflecting surface-aided Wireless Communications (IRS-aWC) can be envisioned for future wireless networks, including smart cities, smart offices, smart industrial environments, as well as communication infrastructures serving remote areas such as mountainous regions, forests, and deserts. In these scenarios, IRSs can be flexibly installed on building facades, streetlight poles, billboards, and even mounted on or integrated into high-mobility platforms, such as vehicles and high-speed transportation systems, thereby enabling programmable and energy-efficient reconfiguration of the wireless propagation environment.

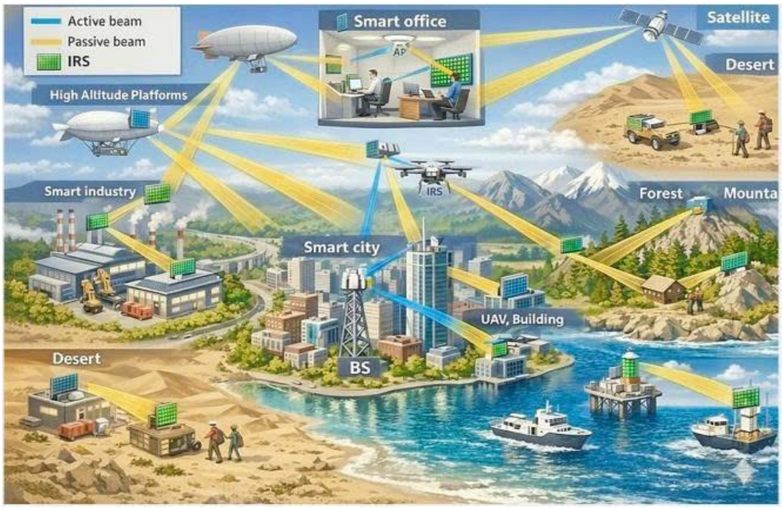

Figure. 1. Deployment model and representative applications of intelligent.

In summary, IRS represents a disruptive enabling technology that can be applied to a wide range of scenarios to transform today's inefficient wireless propagation environments into intelligent and programmable ones, thereby providing enhanced support for massive device connectivity in the Internet of Everything (IoE). The remarkable advantages of IRSs have stimulated extensive research on their design and performance evaluation in various wireless communication systems, including OFDM-based systems,[13-15] multi-antenna systems, and NOMA-enabled networks.[16-17] In parallel, several survey and tutorial papers have systematically summarized existing results on IRS channel modeling and system design, as well as hardware implementation and practical deployment aspects of IRSs.[21-23] However, the majority of existing works typically assume the availability of perfect channel state information (CSI), an assumption that is highly unrealistic in practice, especially for passive IRSs whose reflecting elements are incapable of signal processing or transmission. Moreover, although some studies have addressed IRS hardware mplementations, practical hardware limitations-such as finite phase resolution, reflection noise, reflection loss, and mutual coupling among IRS elements are often not fully incorporated into channel estimation models and system-level designs.[21-23] Consequently, there is still a lack of in-depth and comprehensive investigations that jointly consider IRS channel estimation and the impact of realistic hardware constraints from a wireless communications perspective. This gap constitutes the primary motivation of the present paper.

Although IRSs exhibit great potential in enhancing the performance of wireless communication systems, their practical deployment still faces several critical challenges. The key issues include: i) channel estimation and acquisition of IRS-related channel state information (CSI); ii) reflection design under imperfect CSI; and iii) practical hardware limitations of IRSs.

In this paper, we focus on a detailed investigation of IRS channel estimation and the impact of practical IRS hardware on channel estimation performance, which are fundamental to the realistic deployment of IRS-aided wireless communication (IRS-aWC) systems. These two issues can be summarized as follows.

• Challenges in IRS channel estimation and CSI acquisition: For IRSs to effectively control the wireless propagation environment, accurate CSI acquisition is a fundamental requirement in IRS-aWC systems. However, this task is particularly challenging because IRS elements are typically passive and lack signal processing and transmission capabilities, making conventional pilot-based channel estimation inapplicable. Moreover, the large number of reflecting elements at the IRS significantly increases the number of channel coefficients to be estimated, leading to high training overhead and computational complexity.[11-12,19-20] In addition, the diversity of system configurations and communication scenarios, such as the number of users, the number of IRSs, narrowband versus wideband transmission, and user mobility, imposes heterogeneous requirements on CSI acquisition and estimation strategies. This diversity calls for efficient, scalable, and practically implementable IRS channel estimation methods.

• **Impact of practical IRS hardware impairments on channel estimation:** Most early studies on IRS-aWC systems assume ideal IRS reflection models in order to simplify system design and performance optimization. In practice, however, IRSs suffer from various hardware limitations and imperfections, including discrete phase and amplitude resolutions, phase-dependent reflection amplitudes, reflection losses, and mutual coupling among adjacent reflecting elements. These non-idealities fundamentally alter the reflection behavior of IRSs and, consequently, the structure of the effective channels to be estimated. Therefore, IRS channel estimation schemes must be designed based on realistic hardware models rather than idealized assumptions. Accurately capturing and modeling these hardware constraints is essential to fully exploit the performance gains promised by IRSs, but it also significantly complicates the system design and signal processing tasks. These challenges will be discussed in detail in Section 3 of this paper.

Unlike existing survey and overview papers on IRS channel estimation, which mainly focus on limited system models or rely heavily on idealized assumptions, this paper provides a comprehensive, systematic, and practice-oriented review of recent advances in Intelligent Reflecting Surface–aided Wireless Communications (IRS-aWC). Beyond a mere compilation of prior work, this paper offers in-depth analysis of the fundamental limitations of existing approaches and explicitly bridges the gap between theoretical developments and practical deployment considerations. The key novel contributions and distinguishing features of this paper are summarized as follows:

• Unified and structured framework for IRS channel estimation: We present a unified and structured framework for IRS channel estimation across a wide range of system configurations, including semi-passive and fully passive IRS architectures, single-IRS and multi-IRS systems, narrowband and wideband transmissions, as well as single-user and multiuser scenarios. These aspects are often treated in isolation or insufficiently covered in existing surveys.

• Joint perspective on signal processing, channel modeling, and hardware constraints: Moving beyond a purely algorithm-centric survey, this paper establishes clear connections between signal processing techniques, such as LS/LMMSE estimation, compressed sensing, matrix/tensor factorization, and deep learning and IRS channel models, hardware architectures, and training overhead in practical IRS-aWC systems.

• Comprehensive treatment of IRS hardware impairments: For the first time, this paper provides a systematic and comprehensive discussion on the impact of IRS hardware impairments and constraints, including discrete phase/amplitude control, phase-dependent reflection amplitudes, mutual coupling effects, low-resolution ADCs, and RF impairments, on the accuracy and robustness of IRS channel estimation. These critical aspects are often overlooked or overly simplified in existing survey works.

- Unified comparison between model-based and learning-based approaches: We offer a unified comparison between conventional model-based channel estimation methods and data-driven deep learning approaches, highlighting their respective advantages, limitations, and applicability under realistic IRS-aWC scenarios.

- Identification of open challenges and future research directions: The paper identifies key open challenges and outlines promising future research directions, including channel estimation for multi-IRS and wideband systems, hardware impairment aware estimation algorithms, and hybrid model driven and learning based frameworks. These directions are expected to play a pivotal role in enabling efficient and scalable IRS deployment in future 6G wireless systems.

Overall, this work aims to serve as a timely and insightful reference that not only surveys the state of the art but also guides future research toward practically viable IRS-aided wireless communication systems. The remainder of this paper is organized as follows. Section 2 provides a comprehensive survey of representative channel estimation results for intelligent reflecting surface-aided wireless communication (IRS-aWC) systems. Section 3 further discusses practical hardware limitations and impairments of IRSs, along with existing modeling approaches and their impacts on IRS channel estimation performance. Finally, concluding remarks are drawn in Section 4. For ease of reference, the definitions of the main acronyms used throughout this paper are summarized in Table 1.

Table 1. List of Acronyms and Abbreviations

Acronyms	Definition	Acronyms	Definition
5G	Fifth-generation communication system	LoS	Line-of-sight
6G	Sixth-generation communication system	LS	Least square
ADC	Analog-to-digital converter	MIMO	Multiple-input multiple-output
AO	Alternating optimization	MISO	Multiple-input single-output
AoA	Angle-of-arrival	(L)MMSE	(Linear) Minimum mean-squared-error
AoD	Angle-of-departure	mMTC	Massive machine-type communication
AP	Access point	mmWave	Millimeter-wave
BCD	Block coordinate descent	MRT	Maximum ratio transmission
BS	Base station	NOMA	Non-orthogonal multiple access
CFR	Channel frequency response	OFDM	Orthogonal frequency division multiplexing
CIR	Channel impulse responses	OMP	Orthogonal matching pursuit
CNN	Convolutional neural network	PHY	Physical layer
CRLB	Cramer-Rao lower bound ´	PU	Primary User
CSI	Channel state information	QoS	Quality-of-service

DFT	Discrete Fourier transform	RF	Radio-frequency
DNN	Deep neural network	RIS	Reconfigurable intelligent surface
eMBB	Enhanced mobile broadband	SCA	Successive convex approximation
FDD	Frequency-division duplexing	SDR	Semi-definite relaxation
GNN	Graph neural network	SINR	Signal-to-interference-plus-noise ratio
IoE	Internet-of-Everything	SISO	Single-input single-output
IoT	Internet-of-Things	SNR	Signal-to-noise ratio
IRS	Intelligent reflecting surface	SU	Secondary user
IRS-aWC	Intelligent reflecting surface- aided Wireless Communications	SVD	Singular value decomposition
ISAC	Integrated sensing and communication	TDD	Time-division duplexing
ITS	Intelligent transmitting surface	THz	Terahertz
ITU	International Telecommunication Union	URLLC	Ultra-reliable low-latency communication
KPI	Key performance indicator	WPT	Wireless power transfer
LISA	Large intelligent surface/antennas	V2X	Vehicle-to-Everything

2. CHANNEL ESTIMATION TECHNIQUES FOR IRS-AIDED WIRELESS COMMUNICATIONS

In this section, we conduct a systematic survey and classification of existing studies on channel estimation for IRS-aWC systems. The reviewed works are broadly categorized into three main groups. The first group focuses on signal processing–based channel estimation approaches, encompassing both classical and advanced techniques, such as least squares (LS), linear minimum mean square error (LMMSE), compressed sensing, matrix factorization, as well as machine learning and deep learning-based methods.

The second group classifies channel estimation methods according to the hardware architecture of the IRS, including fully passive and semi-passive IRS designs. Within this category, existing studies investigate the separate or joint estimation of the constituent channels, namely the base station-to-IRS channel, the IRS-to-user channel, and the corresponding cascaded channel. The third group categorizes channel estimation methods based on different IRS-aWC system configurations. These configurations include single and multi-User scenarios with a single IRS, as well as wideband and multi-User systems assisted by multiple IRSs. Following the presentation of each group, we provide a comprehensive evaluation and in-depth discussion, highlighting the advantages, limitations, and open challenges of the existing approaches, and thereby identifying promising directions for future research on IRS-assisted communication systems.

2.1 Classification of IRS architectures and signal model for IRS-aWC systems

To facilitate the investigation of channel estimation methods, we first specify the types of IRS architectures considered in this paper. In practice, depending on whether sensing and signal processing units are integrated into the IRS elements, IRSs can be broadly classified into two categories: semi-passive IRSs and fully passive IRSs.[18] A semi-passive IRS architecture is equipped not only with passive reflecting elements but also with a small number of active sensing components capable of signal reception and basic processing. In contrast, a fully passive IRS consists solely of passive reflecting elements without any sensing or signal processing capability, and thus can only reflect the impinging signals.

Accordingly, existing approaches for estimating IRS-related channels can be divided into two main classes, namely separate channel estimation for semi-passive IRS architectures and cascaded channel estimation for fully passive IRS architectures, as illustrated in Fig. 2.

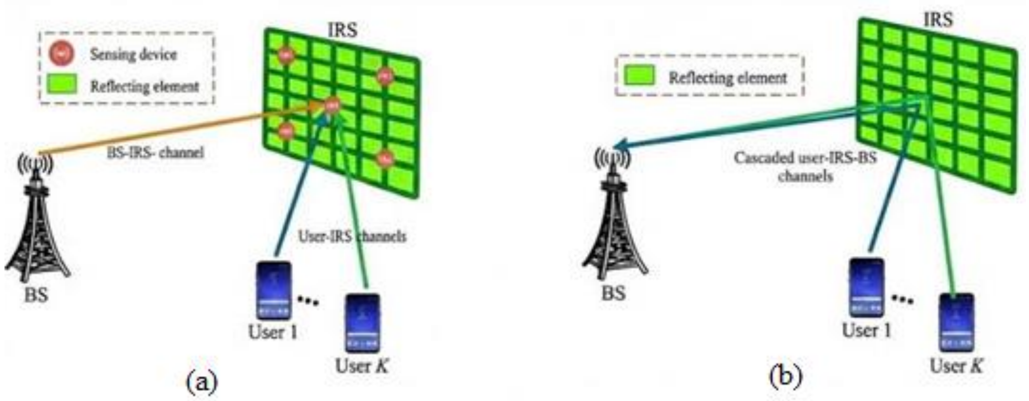

Figure 2. Illustration of separate channel estimation for semi-passive IRSs (a) and cascaded channel estimation (uplink) for fully passive IRSs (b).

Next, we present the signal model, which mainly describes a narrowband IRS-aWC system. The considered system consists of the following components:

- A base station (BS) equipped with M_B antennas;
- An IRS operating in one of two possible architectures: i) a semi-passive IRS comprising N passive reflecting elements and N_S sensing elements ($N_S \ll N$) as illustrated in Fig. 2(a); and ii) a fully passive IRS consisting of N passive reflecting elements only, as shown in Fig. 2(b);
- K co-channel Users, each equipped with M_U antennas.

Let:

+ $\boldsymbol{H}^{IRS-BS} \in \mathbb{C}^{M_N \times N}$ là ma trận kênh giữa trạm gốc BS và IRS (BS-IRS),

+ $\boldsymbol{G}_k^{Us-IRS} \in \mathbb{C}^{N \times M_U}$ là ma trận kênh giữa người dùng k (User k) và IRS (User k-IRS),

+ $\boldsymbol{D}_k \in \mathbb{C}^{M_B \times M_U}$ là ma trận kênh trực tiếp giữa người dùng k và trạm gốc BS (User$k$-BS),

+ $\boldsymbol{\theta} = [\theta_1, \theta_2, ..., \theta_N]^T \in \mathbb{C}^{N \times 1}$ là vector của luồng tín hiệu phản xạ IRS.

It should be noted that, in the absence of IRS reflection, the IRS phase shifts satisfy $\boldsymbol{\theta} = 0$. This scenario corresponds to channel estimation in conventional wireless systems without IRS assistance, where the base station can estimate the direct channels, i.e. $\{\boldsymbol{D}\}_{k=1}^{K}$, typically by employing sequential or orthogonal pilot signaling transmitted by different users. In this work, we mainly focus on the estimation of IRS related channels, namely the BS-to-IRS channel $\boldsymbol{H}^{BS-IRS}$ and the IRS-to-User channel $\{\boldsymbol{G}_k\}^{Us-IRS}$.

2.2 Signal processing frameworks for IRS-aided channel estimation

In the existing literature, regardless of the considered communication system model or architecture, signal processing–based channel estimation plays a crucial role in optimizing system parameters and overall performance. For different IRS channel models, substantial research efforts have been devoted to the design of efficient IRS channel estimation methods based on various signal processing techniques, including LS/LMMSE estimation, compressed sensing, matrix factorization, and deep learning.

2.2.1 IRS channel estimation using conventional signal processing methods

Two conventional channel estimation methods that are widely adopted in the literature are the least squares (LS) and linear minimum mean square error (LMMSE) estimators. Owing to their relatively simple algorithmic structures and low implementation complexity, these methods are often preferred in practical systems. In the context of channel estimation for IRS-aided wireless communication (IRS-aWC) systems, LS/LMMSE-based approaches typically require the number of observations (or measurements) to be no smaller than the number of unknown channel parameters in order to avoid estimation ambiguity and ensure identifiability.

For analytical convenience, we consider a fully passive IRS channel model, as illustrated in Fig. 2(b). Specifically, we focus on uplink channel training, where the users transmit pilot signals and the base station (BS) collects the received observations. The pilot signals are transmitted over a training interval of length t. Accordingly, the received signal vector at the BS can be expressed as

$$\boldsymbol{y}_B^{(t)} = \sum_{k=1}^{K} \sqrt{P_U} \boldsymbol{H}^{BS-IRS} \boldsymbol{\Theta}^{(t)} \boldsymbol{G}_k^{Us-IRS} \boldsymbol{x}_k^{(t)} + \boldsymbol{n}_B^{(t)} \tag{1}$$

where $\boldsymbol{x}_k^{(t)} \in \mathbb{C}^{M_U \times 1}$ denotes the pilot signal transmitted by the k-th User, $\boldsymbol{\Theta}^{(t)} = diag(\theta^{(t)})$ represents the diagonal IRS reflection matrix during the training interval of length t, and $\boldsymbol{n}_B^{(t)} \in \mathbb{C}^{M_B \times 1}$ denotes the additive white Gaussian noise (AWGN) vector at the BS.

By exploiting the properties of the Khatri–Rao product, we have

$$vec\left(\boldsymbol{H}^{BS-IRS} \boldsymbol{\Theta}^{(t)} \boldsymbol{G}_k^{User-IRS}\right) = \boldsymbol{G}_k \boldsymbol{\theta}^{(t)},\ k = 1,2...,K \tag{2}$$

$$\boldsymbol{G}_k = \left[\left(\boldsymbol{G}_k^{User-IRS}\right)^T \odot \boldsymbol{H}^{BS-IRS}\right] \in \mathbb{C}^{M_B M_U \times N}$$

where,

represents the cascaded channel matrix associated with the k-th User, vec(·) denotes the vectorization operation, and ⊙ denotes the Khatri–Rao product. By expanding the Kronecker product, the received signal vector at the BS in (1) can be compactly rewritten as

$$\boldsymbol{y}_B^{(t)} = \sum_{k=1}^{K} \sqrt{P_U} \left[\left(\boldsymbol{x}_k^{(t)}\right)^T \otimes \boldsymbol{I}_{M_B}\right] G_k \boldsymbol{\theta}^{(t)} + \boldsymbol{n}_B^{(t)}, \tag{3}$$

where, ⊗ denotes the Kronecker product.

For simplicity, without loss of generality, we consider a signal model with a single user and a single fully passive IRS. Accordingly, the baseband received signal in (3) with $K = 1$ can be expressed as

$$\boldsymbol{y}_B^{(t)} = \sqrt{P_U}\left[\left(\boldsymbol{x}^{(t)}\right)^T \otimes \boldsymbol{I}_{M_B}\right] \boldsymbol{G} \boldsymbol{\theta}^{(t)} + \boldsymbol{n}_B^{(t)} \tag{4}$$

$$= \sqrt{P_U}\left[\left(\boldsymbol{x}^{(t)}\right)^T \otimes \boldsymbol{I}_{M_B}\right]\left(\sum_{n}^{N} \hat{\boldsymbol{g}}_n \boldsymbol{\theta}_n^{(t)}\right) + \boldsymbol{n}_B^{(t)} \tag{5}$$

where, $\boldsymbol{G} \triangleq [\hat{\boldsymbol{g}}_1, \hat{\boldsymbol{g}}_2, ..., \hat{\boldsymbol{g}}_N]$.

By leveraging the properties of the Kronecker product, (4) can be equivalently expressed as

$$\boldsymbol{y}_B^{(t)} = \sqrt{P_u}\left[\left(\boldsymbol{\theta}^{(t)} \otimes \boldsymbol{x}^{(t)}\right) \otimes \boldsymbol{I}_{M_B}\right] \hat{\boldsymbol{g}} + \boldsymbol{n}_B^{(t)}, \tag{6}$$

where $\hat{\boldsymbol{g}} \triangleq vec\left(\hat{\boldsymbol{G}}\right)$ denotes the cascaded channel vector.

In (6), the term

$$\left(\boldsymbol{\theta}^{(t)} \otimes \boldsymbol{x}^{(t)}\right) \otimes \boldsymbol{I}_{M_B} \triangleq \boldsymbol{F}^{(t)} \in \mathbb{C}^{M_B T \times M_B M_u N}$$

serves as the observation matrix associated with the estimation of $\hat{\boldsymbol{g}}$.

Assume that Σ_t denotes the number of pilot symbols within a channel training period. By stacking the received signal vectors $\left\{\boldsymbol{y}_B^{(t)}\right\}_{t=1}^{\Sigma_t}$ into $\boldsymbol{y}_B$, we obtain

$$\underbrace{\begin{bmatrix} \boldsymbol{y}_B^{(1)} \\ \vdots \\ \boldsymbol{y}_B^{(\Sigma_t)} \end{bmatrix}}_{\boldsymbol{y}_B} = \sqrt{P_u} \underbrace{\begin{bmatrix} \boldsymbol{F}^{(1)} \\ \vdots \\ \boldsymbol{F}^{(\Sigma_t)} \end{bmatrix}}_{\boldsymbol{F}} \hat{\boldsymbol{g}} + \underbrace{\begin{bmatrix} \boldsymbol{n}_B^{(1)} \\ \vdots \\ \boldsymbol{n}_B^{(\Sigma_t)} \end{bmatrix}}_{\boldsymbol{n}_B}, \tag{7}$$

Where, $\boldsymbol{F}^{(t)} \in \mathbb{C}^{M_B T \times M_B M_u N}$ denotes the overall observation matrix, which depends on the IRS training reflection patterns $\left\{\boldsymbol{\theta}^{(t)}\right\}_{t=1}^{\Sigma_t}$ and the transmitted pilot sequence $\left\{\boldsymbol{x}^{(t)}\right\}_{t=1}^{\Sigma_t}$. It is worth noting that, in order to estimate the matrix $\hat{\boldsymbol{g}}, \boldsymbol{F}$ must have full column rank, which requires $\Sigma_t \geq M_U N$. Assuming that $\boldsymbol{F}$ is full column rank, two conventional approaches can be employed to estimate $\hat{\boldsymbol{g}}$.

- **LS Channel Estimation**

For the LS channel estimation algorithm, the estimator is given by,[25]

$$\tilde{\boldsymbol{g}}_{LS} = \arg\min_{\hat{\boldsymbol{g}}} \left\|\boldsymbol{y}_B - \sqrt{P_u} \boldsymbol{F} \hat{\boldsymbol{g}}\right\|^2, \tag{8}$$

In closed form, the LS estimate is given by

$$\tilde{\boldsymbol{g}}_{LS} = \frac{1}{\sqrt{P_u}} \boldsymbol{F}^{\dagger} \boldsymbol{y}_B = \hat{\boldsymbol{g}} + \frac{1}{\sqrt{P_u}} \boldsymbol{F}^{\dagger} \boldsymbol{n}_B, \tag{9}$$

where $\boldsymbol{F}^{\dagger} = \left(\boldsymbol{F}^H \boldsymbol{F}\right)^{-1} \boldsymbol{F}^H$.

- **LMMSE Channel Estimation:**

Unlike the LS estimator, the LMMSE estimator exploits the second-order statistical information of both the channel and the noise in order to minimize the mean square error (MSE). By leveraging the channel and noise covariance matrices, the LMMSE approach achieves improved estimation accuracy, particularly in low-SNR regimes. Specifically, the LMMSE-based channel estimator is formulated as follows:[25]

$$\boldsymbol{W}_{LM} = \arg\min_{\boldsymbol{W}} \Im\left\{\left\|\boldsymbol{W}\boldsymbol{y}_B - \tilde{\boldsymbol{g}}\right\|^2\right\}, \quad (10)$$

with, $\tilde{\boldsymbol{g}}_{LM} = \boldsymbol{W}_{LM}\boldsymbol{y}_B$, the closed-form LMMSE estimator is given by

$$\tilde{\boldsymbol{g}}_{LM} = \sqrt{P_u}\boldsymbol{R}_{\hat{\boldsymbol{g}}}\boldsymbol{F}^H\left(P_u\boldsymbol{F}\boldsymbol{R}_{\hat{\boldsymbol{g}}}\boldsymbol{F}^H + \sigma_B^2\boldsymbol{I}_{M_BT}\right)^{-1}\boldsymbol{y}_B, \quad (11)$$

where, we have used $\Im\{\hat{\boldsymbol{g}}\} = 0$, $\boldsymbol{R}_{\hat{\boldsymbol{g}}} \triangleq \Im\left\{\hat{\boldsymbol{g}}\hat{\boldsymbol{g}}^H\right\}$ which represents the spatial correlation matrix of $\hat{\boldsymbol{g}}$, σ_B^2 denotes the noise variance at the base station (BS).

It should be emphasized that, to ensure the feasibility of the aforementioned LS and LMMSE estimators and to reduce channel estimation errors, the IRS training reflection patterns $\left\{\boldsymbol{\theta}^{(t)}\right\}_{t=1}^{\Sigma_t}$ and the transmitted pilot sequences $\left\{\boldsymbol{x}^{(t)}\right\}_{t=1}^{\Sigma_t}$ at the transmitter must be carefully designed to construct a well-conditioned observation matrix $\boldsymbol{F}$. In the following, we provide an overview and critical assessment of existing works on LS/LMMSE-based IRS channel estimation under various channel models.

In,[13,24,25] the authors propose the use of an on-off training reflection pattern at the IRS to perform separate channel estimation based on the least squares (LS) method. Specifically, the direct User-BS channel is first estimated using a conventional LS algorithm by turning off all IRS reflecting elements. Subsequently, the cascaded UserIRS-BS channel is estimated sequentially over time by activating one IRS element at a time, while keeping all remaining elements in the off state. Although this approach features a simple structure and is easy to implement, it suffers from several notable limitations. In particular, the effective power of the on-off training reflection patterns is severely attenuated, and the estimation process is further impaired by interference from the direct channel. These factors significantly degrade the accuracy of channel estimation. To overcome the aforementioned drawbacks, several studies have proposed the use of fully activated IRS training reflection patterns, where all reflecting elements are simultaneously turned on throughout the channel training phase. This approach is further developed and rigorously analyzed in,[14,25] demonstrating that the LS estimation accuracy can be substantially improved by fully exploiting the aperture gain of the IRS. However, the estimation performance of these methods remains highly dependent on the training sequence length and the transmit power. Consequently, the works in[15,26] focus on the joint optimization of the IRS training reflection patterns and the pilot sequences at the transmitter. Analytical and simulation results demonstrate that these approaches are capable of achieving optimal estimation performance under the LS or LMMSE criteria. In addition, in,[13-14] adjacent IRS elements with inter-element spacing smaller than one wavelength are grouped into sub-surfaces to reduce the estimation complexity and the number of parameters to be estimated, while still preserving the desired reflection characteristics of the overall IRS. Fig. 3 illustrates the grouping of IRS elements into sub-surfaces.

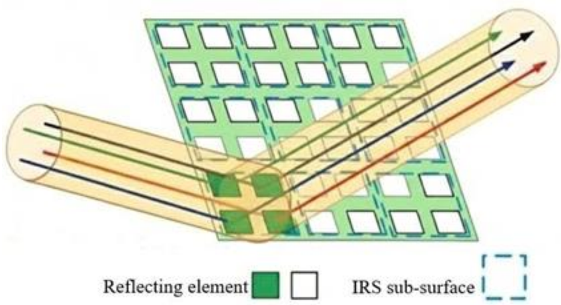

Figure 3. Illustration of IRS element grouping into sub-surfaces.

Assume that the IRS consists of N reflecting elements that are partitioned into $\bar{N}$ sub-surfaces, where each sub-surface contains a ratio $B = N/\bar{N}$ of adjacent elements sharing a common reflection coefficient, as illustrated in Fig. 3. Accordingly, the IRS reflection vector can be redefined as $\boldsymbol{\theta} = \bar{\boldsymbol{\theta}} \otimes \boldsymbol{1}_{M\times 1}$, and the cascaded channel in (4) can be reformulated as

$$\hat{\boldsymbol{G}}\boldsymbol{\theta} = \hat{\boldsymbol{G}}\left(\bar{\boldsymbol{\theta}} \otimes \boldsymbol{1}_{B\times 1}\right) = \left[\bar{\boldsymbol{g}}_1, \bar{\boldsymbol{g}}_2, \ldots, \bar{\boldsymbol{g}}_{\bar{N}}\right]\bar{\boldsymbol{\theta}} = \bar{\boldsymbol{G}}\bar{\boldsymbol{\theta}}, \quad (12)$$

where $\bar{\boldsymbol{\theta}} \in \mathbb{C}^{\bar{N}\times 1}$ denotes the grouped IRS reflection vector, $\bar{\boldsymbol{G}} \in \mathbb{C}^{M_BM_U\times\bar{N}}$ represents the effective cascaded channel after element grouping, and $\bar{g}_{\bar{n}} = \sum_{b=1}^{B}\hat{g}_{b+(\bar{n}-1)B}$ characterizes the equivalent aggregate channel of the sub-surface $\bar{n}$, with $\bar{n} = 1, 2, \ldots, \bar{N}$.

As a result, it is sufficient to estimate only the equivalent aggregate channel of each sub-surface, which reduces the training overhead by a factor of B. It is worth noting that by adjusting the size of each sub-surface, i.e., tuning the grouping factor B to reduce the training cost, the element grouping strategy enables a flexible tradeoff between training overhead (or design complexity) and passive beamforming performance, without relying on any specific channel model assumptions. Beyond the design of IRS training reflection patterns and transmit pilot sequences, various channel training protocols have been proposed to further enhance LS/LMMSE-based channel estimation performance, particularly in multi-user or multi-IRS scenarios, where efficient training coordination is required to limit resource consumption. For instance, the IRS channel estimation methods developed for single-user systems have been extended to narrowband and wideband multi-User systems in.[27] The core idea of these approaches is to exploit the cascaded channel of a representative user as a reference channel state information (CSI). Based on this reference, the cascaded channels of the remaining users can be expressed in lower-dimensional forms, enabling efficient LS estimation at the BS with substantially reduced training overhead. Moreover, in,[28] the authors propose an LS-based cascaded channel estimation method for two BS-IRS-BS links to identify the common IRS-BS channel, by utilizing pilot signals transmitted from the BS and reflected back through the IRS. Building upon this approach,[29] introduces the use of two anchor nodes deployed near the IRS to assist in estimating the common IRS-BS channel by exploiting dedicated training and feedback signals from these anchor nodes. The CSI of the common IRS-BS channel obtained via LS estimation is then leveraged to estimate the dynamic IRS-User channels. The results in,[28-29] demonstrate that accurate estimation of the common channel can be achieved with low real-time training overhead, making these approaches well suited for systems requiring frequent channel updates. In addition to single-IRS scenarios, LS-based channel estimation methods for dual-IRS systems have been investigated in,[30-32] where various training protocols are proposed to achieve low practical deployment costs. For highly mobile IRS-aided wireless communication (IRS-aWC) systems, LS and LMMSE estimators remain particularly attractive due to their low computational complexity. Specifically, the hierarchical training reflection scheme proposed in[33] employs LS estimation to sequentially acquire the CSI of the cascaded channel, showing that the training latency can be significantly reduced depending on the quality of the passive reflected signal. Furthermore, in,[34] the authors study highly mobile IRS-aWC systems for intelligent transportation applications and propose low-complexity LS-based channel estimation methods capable of effectively tracking rapid channel variations. In,[35] by exploiting the quasi-static nature of the BS-IRS channel $\boldsymbol{H}^{BS\text{-}IRS}$ and modeling the time-varying User-IRS channel $\boldsymbol{G}^{User\text{-}IRS}$ using a first-order autoregressive model, a Kalman filter is applied to track the temporal evolution of the cascaded User-IRS channel $\boldsymbol{G}^{User\text{-}IRS}$ under high mobility. In addition,[83] proposes the parallel use of two Kalman filters to simultaneously track the time-varying direct channel and the IRS-assisted cascaded channel. In,[36] the quasi-static BS-IRS channel $\boldsymbol{H}^{BS\text{-}IRS}$ is first estimated using a hierarchical search algorithm, after which an extended Kalman filter (EKF) is employed to efficiently estimate and track the dynamic User-IRS channel $G^{User\text{-}IRS}$ in highly mobile environments.

2.2.2 Compressed sensing-based signal processing techniques for sparse IRS channel estimation

Signal processing methods based on compressed sensing (CS) are particularly well suited for channel estimation scenarios in which the wireless channel exhibits pronounced sparsity, as commonly observed in millimeter-wave (mmWave) systems and massive MIMO deployments. In such systems, due to severe path loss and a limited number of effective propagation paths, the channel typically contains only a small number of dominant components in the angular or delay domains, which makes CS-based techniques highly attractive. In this context, channel estimators can exploit either the phase or amplitude characteristics of the received signals to accurately identify the time of arrival (ToA) or other geometry-related parameters of the propagation paths. By leveraging these sparse representations, CS-based approaches are capable of significantly reducing the required training overhead while maintaining high estimation accuracy. Nevertheless, it is important to note that the sparsity assumption does not always hold in practice. The degree of channel sparsity can vary substantially depending on the propagation environment, system configuration, and the geometry of the antenna arrays. In certain scenarios, such as densely scattering environments or array structures that do not induce a clearly sparse representation, the direct application of CS-based methods may provide limited performance gains or even degrade estimation accuracy. Therefore, the selection and design of CS-based channel estimators must be carefully tailored to the underlying channel characteristics and the specific deployment conditions of the IRS-aided system.

For sparse channels (e.g., mmWave MIMO channels), the sparse channel matrix also referred to as the angular-domain channel matrix, $\boldsymbol{H}_S \in \mathbb{C}^{M_B \times M_U}$, where M_B and M_U denote the numbers of antennas at the receiver and transmitter, respectively, contains the coefficients representing the physical path gains. The sparse channel matrix $\boldsymbol{H}_S$ can be expressed as

$$\boldsymbol{H}_S = \begin{bmatrix} h_{1,1} & h_{1,2} & \cdots & h_{1,M_U} \\ h_{2,1} & h_{2,2} & \cdots & h_{2,M_U} \\ \vdots & \vdots & \cdots & \vdots \\ h_{M_B,1} & h_{G_R,2} & \cdots & h_{M_B,M_U} \end{bmatrix}, \quad (13)$$

where each element $h_{i,j}$ represents the channel gain corresponding to a propagation path from a specific angle of departure (AoD) to a specific angle of arrival (AoA). Specifically, for practical propagation scenarios:[37]

- The entries $h_{i,j}$ are complex-valued and represent the path gain associated with the (i,j)-th propagation component;
- If no physical propagation path exists between the corresponding AoD-AoA pair, then $h_{i,j} = 0$.

For sparse channels, the number of effective physical propagation paths is significantly smaller than the product $M_B \times M_U$. As a result, the angular-domain channel matrix $\boldsymbol{H}_S$ exhibits a high degree of sparsity, where the number of nonzero elements $h_{i,j}$ is equal to the number of actual propagation paths, while the remaining entries are zero or negligible. Consequently, identifying the locations and values of the nonzero elements in $\boldsymbol{H}_S$ constitutes a sparse channel estimation problem. This problem can be efficiently addressed using compressed sensing (CS) algorithms, which explicitly exploit the inherent sparsity of the channel structure to substantially reduce the training overhead and computational complexity compared with conventional channel estimation methods.

For IRS-aWC systems operating at high frequencies, such as the mmWave and THz bands, severe distance-dependent path loss and frequent blockages significantly limit the number of effective propagation paths between the IRS and the base station (IRS-BS channel) as well as between the IRS and Users (IRS-User channel). Consequently, the IRS-associated cascaded channels, formed by the combination of the IRS-User channel and the IRS-BS channel at mmWave and THz frequencies, typically exhibit pronounced sparsity and low-rank characteristics in the spatial or angular domains. These structural properties can be effectively exploited in channel estimation to substantially reduce the required training overhead while maintaining high estimation accuracy.

Specifically, let $\boldsymbol{\Pi}_B \in \mathbb{C}^{M_B \times L_B}$, $\boldsymbol{\Pi}_R \in \mathbb{C}^{N \times L_R}$ and $\boldsymbol{\Pi}_U \in \mathbb{C}^{M_U \times L_U}$ denote the dictionary matrices whose columns consist of array response (steering) vectors sampled over the possible angle-of-arrival (AoA) regions at the base station (BS) and the User, respectively, while L_B, L_R and L_U denotes the dictionary matrix corresponding to the IRS. These dictionaries are constructed by discretizing the angular domains associated with the BS, IRS, and user arrays. Based on the geometric channel model, the IRS-BS channel $\boldsymbol{H}^{\text{IRS-BS}}$ and the User-IRS channel $\boldsymbol{G}^{\text{User-IRS}}$ can be expressed as,[38,39]

$$vec\left(\boldsymbol{G}^{User-IRS}\right) = \left(\boldsymbol{\Pi}_R^* \otimes \boldsymbol{\Pi}_B\right)\boldsymbol{\rho}_G \quad (14)$$

$$vec\left(\boldsymbol{H}_k^{IRS-BS}\right) = \left(\boldsymbol{\Pi}_U^* \otimes \boldsymbol{\Pi}_R\right)\boldsymbol{\rho}_k \quad (15)$$

where, $\boldsymbol{\rho}_G \in \mathbb{C}^{L_B L_R \times 1}$ and $\boldsymbol{\rho}_k \in \mathbb{C}^{L_R L_U \times 1}$ are sparse vectors with sparsity levels d_G and d_H, respectively. The parameters d_G and d_k denote the numbers of dominant spatial propagation paths in the User-IRS channel $\boldsymbol{G}^{User\text{-}IRS}$ and the IRS-BS channel $\boldsymbol{H}_k^{IRS-BS}$, respectively. It is worth noting that $d_G \ll L_B L_R$ and $d_k \ll L_R L_U$, which highlights the strong angular-domain sparsity of the IRS-assisted channels.

By substituting (14) and (15) into (2), the resulting cascaded channel exhibits pronounced sparsity in the corresponding representation domain. Consequently, constructing an appropriate signal representation model that matches the inherent sparsity level of the channel is a key requirement for effectively exploiting the intrinsic structure of the channel estimation problem. In this context, compressed sensing (CS) algorithms have emerged as a highly promising tool for sparse IRS channel estimation, owing to their ability to efficiently leverage the sparsity of wireless propagation channels to substantially reduce both training overhead and computational complexity. By reformulating the channel estimation task within the CS framework, the dominant channel parameters can be accurately recovered even when the number of training observations is severely limited. In the following, we provide an overview of representative recent studies on CS-based channel estimation, with a particular focus on sparse IRS channel models and the corresponding signal recovery techniques.

For IRS-aided wireless communication (IRS-aWC) systems operating in scenarios where the propagation channels exhibit pronounced sparsity, the cascaded channel estimation problem can be equivalently reformulated as a sparse signal recovery problem, as demonstrated in.[38-40] Solving this problem using compressed sensing (CS) techniques has been shown to achieve superior estimation accuracy while significantly reducing training overhead, as reported in.[41-45] In particular, studies in,[46,47] reveal that, due to the sparse nature of the $\boldsymbol{H}^{IRS\text{-}BS}$ channel, the cascaded channel matrices corresponding to all Users in the system tend to share a common block-wise sparsity structure across both row and column dimensions. Motivated by this observation, a variety of CS based channel estimation methods have been developed to jointly recover the cascaded channel state information (CSI) of multiple users with low training cost, making them especially attractive for large-scale multiuser IRS-aWC systems. For THz-band MIMO systems, the channel sparsity level has been observed to increase significantly, often nearly doubling compared to lower-frequency bands, across both the angular and delay domains. This property has been effectively exploited in,[48] opening up a promising research direction for wideband CS-based channel estimation with substantially reduced training requirements. Moreover, fundamental performance limits of sparse channel estimation have been investigated through the Cramér-Rao lower bound (CRLB) in,[49,50] providing important theoretical benchmarks for evaluating and comparing CS-based estimators in IRS-aWC systems. By exploiting the inherent sparsity of IRS-aided channels, a wide range of CS algorithms have been developed to efficiently address the IRS channel estimation problem. Among them, Orthogonal Matching Pursuit (OMP) stands out as a low-complexity algorithm that iteratively selects the most relevant projections matching the received measurements. OMP has been widely adopted in,[38,40-41] for estimating cascaded channels in the beamspace or angular domain. In addition, approximate message passing (AMP)-based algorithms have been proposed in,[45,52-54] where the cascaded channel estimation problem is formulated using probabilistic graphical models and solved via iterative inference, enabling the exploitation of statistical channel structures to further enhance estimation performance. Beyond these approaches, several advanced CS techniques have also been applied to IRS channel estimation, including Adaptive Grid Matching Pursuit (AGMP),[39] Atomic Norm Minimization (AnM),[41] Iterative Reweighted Methods (IRM),[42] Iterative Atomic-Pruning Subspace Pursuit (IAPSP),[43] manifold optimization-based methods,[44] and Sparse Bayesian Learning (SBL).[55] In a recent contribution, to address the high control overhead and computational complexity associated with OMP and SBL based estimation algorithms, the authors in,[56] proposed an online channel estimation scheme based on the Variable Step-Size Zero-Attracting Least Mean Square (VSS-ZALMS) algorithm for IRS-assisted hybrid mmWave MIMO systems. In that work, analytical expressions were derived for the admissible ranges of the adaptive step size and the regularization parameter, leading to simultaneous improvements in estimation accuracy and convergence speed.

Despite the superior estimation performance demonstrated by compressed sensing-based methods, these approaches typically incur high computational complexity, particularly in large-scale systems or multiuser scenarios. Consequently, achieving an effective trade-off between computational cost and estimation performance for CS-based algorithms in IRS-aided wireless communication systems remains an open research problem, calling for further theoretical analysis and algorithmic innovation.

2.2.3 Matrix Factorization/Decomposition-based channel estimation methods

For fully passive IRSs, the cascaded User-IRS-BS channel is estimated at the base station (BS) or at the user side as the product of the User-IRS channel $\boldsymbol{G}^{User\text{-}IRS}$ and the IRS-BS channel $\boldsymbol{H}^{IRS\text{-}BS}$, in the presence of noise. As a result, the channel estimation problem in such systems can be formulated as a bilinear channel estimation problem. Compared with the conventional linear channel estimation problem encountered in IRS-free wireless systems, this bilinear estimation problem is considerably more challenging, mainly due to the high dimensionality of the cascaded channel and the multiplicative coupling between its constituent channel components. To address these challenges, several approaches have been proposed to decompose the high dimensional cascaded channel into multiple lower imensional subchannels, thereby enabling channel estimation with reduced training overhead and more manageable computational complexity. However, a fundamental challenge of matrix factorization and matrix decomposition based approaches lies in the scaling ambiguity between the constituent channel components. Specifically, decomposing the cascaded channel into the IRS-BS channel $\boldsymbol{H}^{IRS\text{-}BS}$ and the User-IRS channel $\boldsymbol{G}^{User\text{-}IRS}$ is generally identifiable only up to an unknown scalar factor, which makes the accurate recovery of each individual channel component difficult. Therefore, to fully resolve this issue, additional constraints must be incorporated into the estimation framework, such as power normalization, statistical prior information, sparsity constraints, or array geometric information, to eliminate the scaling ambiguity and enhance the accuracy of channel estimation.

To further clarify this issue, consider an invertible diagonal matrix $\boldsymbol{\Lambda} \in \mathbb{C}^{N\times N}$. It always holds that

$$\begin{aligned}\boldsymbol{H}^{IRS-BS}\boldsymbol{\Theta}\boldsymbol{G}_k^{User-IRS} &= \boldsymbol{H}^{IRS-BS}\boldsymbol{\Lambda}\boldsymbol{\Theta}\boldsymbol{\Lambda}^{-1}\boldsymbol{G}_k^{User-IRS} \\ &= \boldsymbol{H}'^{IRS-BS}\boldsymbol{\Theta}\boldsymbol{G}_k'^{User-IRS},\end{aligned} \tag{16}$$

where $\boldsymbol{H}'^{IRS-BS} = \boldsymbol{H}^{IRS-BS}\boldsymbol{\Lambda}$ and $\boldsymbol{G}_k'^{User-IRS} = \boldsymbol{\Lambda}^{-1}\boldsymbol{G}_k^{User-IRS}$ denote the corresponding constituent channel matrices, respectively. This relationship shows that the product of the two channel matrices remains invariant under the transformation induced by the invertible diagonal matrix $\boldsymbol{\Lambda}$.

Based on the received signal model in (1), it is not possible to uniquely solve the channel estimation problem for the individual constituent channels $\boldsymbol{H}^{IRS\text{-}BS}$ and $\boldsymbol{G}^{User\text{-}IRS}$ independently, due to the inherent scaling ambiguity in bilinear channel estimation problems. In other words, multiple pairs of constituent channel solutions may result in the same observed cascaded channel at the receiver. Nevertheless, it is worth noting that, in many passive beamforming design scenarios at the IRS, completely resolving this scaling ambiguity is not always necessary. In practice, as long as the overall cascaded channel is accurately estimated, IRS phase shift design strategies can still achieve optimal or near-optimal performance, even when the individual constituent channels are identifiable only up to an unknown scalar factor. In the remainder of this subsection, we review representative studies on IRS channel estimation based on matrix factorization theory and matrix decomposition techniques, with a focus on how scaling ambiguity is addressed and the associated trade offs among estimation accuracy, training overhead, and computational complexity. In,[57] the authors proposed two cascaded channel estimation methods based on parallel factor tensor modeling of the received signals. Essentially, these approaches extend the modeling of the three-dimensional (3D) MIMO cascaded channel into two corresponding two-dimensional (2D) MIMO channels associated with $\boldsymbol{G}^{User\text{-}IRS}$ and $\boldsymbol{H}^{IRS-BS}$, thereby enabling effective separation and estimation of the constituent channels in IRS-aWC systems. By exploiting the tensor structure of the training signals, these methods significantly reduce training overhead while maintaining high estimation accuracy. Moreover, by interchanging the roles of the multi-antenna base station and the Users, the main methods and results based on parallel factor tensor modeling can be readily extended to the downlink scenario, where all users perform parallel estimation of their respective cascaded BS-related channels, as reported in.[58] This approach highlights the flexibility of tensor-based models in accommodating both uplink and downlink transmission scenarios in IRS-assisted systems. In addition, in,[59] IRS-assisted MIMO channels are modeled as keyhole MIMO channels. Based on this model, a cascaded channel estimation method relying on singular value decomposition (SVD) was proposed, in which the cascaded channel matrix is decomposed into a sum of rank-one matrices, each corresponding to the contribution of an individual IRS element. This approach effectively exploits the inherent low-rank structure of the cascaded channel, thereby simplifying the channel estimation problem. Beyond low-rank channel models, the works in,[52-54,60] investigated IRS channel estimation under the assumption that the cascaded MIMO channel is sparse, and accordingly developed sparse matrix analysis and recovery techniques. These methods jointly exploit the sparsity and the cascaded structure of the channel to enhance estimation performance, particularly in mmWave and THz systems, where the number of effective propagation paths is inherently limited.

Although tensor decomposition and singular value decomposition (SVD), based channel estimation methods have demonstrated significant effectiveness in exploiting the multi-dimensional and low rank structures of IRS-assisted cascaded channels, they still suffer from several inherent limitations. First, tensor-based methods, such as parafac and Tucker decomposition, typically require a sufficiently large number of training samples to satisfy identifiability conditions and guarantee solution uniqueness, which may substantially increase training overhead in large scale systems or highly mobile environments. In addition, the computational complexity of tensor decomposition and SVD algorithms generally grows rapidly with the tensor order and system dimensions, especially when the number of IRS elements and BS antennas becomes large, posing serious challenges for real-time implementation. Moreover, under strong noise or model mismatch conditions, the performance of these methods may degrade significantly, as they rely heavily on assumptions regarding low-rank structure or linear tensor models. Furthermore, scaling and permutation ambiguities may still persist, particularly in general tensor models, unless additional constraints or prior information are incorporated into the estimation framework. From a broader perspective, existing IRS channel estimation approaches can be broadly categorized into three main classes: (i) tensor/SVD based methods, (ii) compressed sensing (CS)-based methods, and (iii) alternating least squares based methods (ALS/BALS), each exhibiting distinct advantages and limitations. Tensor and SVD-based approaches are particularly well suited for systems with pronounced multi-dimensional structures and low rank channels, as they enable the joint exploitation of multiple domains (e.g., spatial, temporal, and frequency) and can achieve high estimation accuracy. However, their superior performance often comes at the cost of high computational complexity and stringent training requirements, which limit their applicability in large scale or high-mobility systems. In contrast, CS based methods capitalize on the sparsity of wireless channels and are especially effective in mmWave, THz, and massive MIMO systems. These approaches can significantly reduce training overhead and achieve reliable estimation performance even with limited observations. Nevertheless, CS algorithms are typically sensitive to sparsity assumptions and array geometry, and often entail high computational complexity or require careful parameter tuning. Meanwhile, ALS/BALS-based methods serve as an intermediate solution, offering relatively simple structures, ease of implementation, and lower computational complexity. Such methods are suitable for systems of moderate size and scenarios requiring fast channel updates. However, their performance is often constrained by slow convergence, sensitivity to initialization, and limited estimation accuracy in complex propagation environments or under severe noise conditions.

In summary, there is no single IRS channel estimation method that is universally optimal across all scenarios. The choice of an appropriate estimation technique must be carefully determined based on channel characteristics (e.g., sparsity or low-rank structure), system scale, mobility level, and the trade-off between estimation performance and computational complexity. Recent research trends increasingly favor hybrid estimation frameworks that combine the strengths of tensor-based methods, compressed sensing, and ALS type algorithms to achieve high estimation accuracy with practical implementation costs. Despite the substantial progress made in channel estimation for IRS-aWC systems, this problem remains fundamentally challenging due to its bilinear nature, large-scale dimensions, and the increasingly stringent requirements of next-generation wireless networks. Several promising research directions and key open challenges can be identified:

(i) Performance–complexity trade-off: One of the most critical challenges is balancing estimation accuracy against computational and training overhead. Advanced techniques such as tensor decomposition and compressed sensing often achieve superior performance but at the expense of high computational complexity, which hinders real-time deployment. Consequently, the development of low complexity approximate, adaptive, or online algorithms that can maintain near optimal performance represents an important research direction.

(ii) Hybrid estimation frameworks: Current research increasingly focuses on hybrid approaches that integrate complementary estimation paradigms, such as combining compressed sensing with tensor decomposition to jointly exploit sparsity and low-rank structures; incorporating CS or Bayesian constraints into ALS/BALS to improve convergence and mitigate scaling ambiguity; or fusing model-based estimation with machine learning techniques to enhance robustness and adaptability in practical environments. While these hybrid frameworks are promising in terms of performance and training efficiency, their convergence behavior and stability properties require further theoretical investigation.

(iii) Channel estimation in high-mobility and non-stationary environments: In high-mobility scenarios (e.g., V2X communications, UAV-assisted networks, and intelligent transportation systems), IRS-assisted channels vary rapidly over time, rendering quasi-static channel assumptions ineffective. This motivates the development of time adaptive estimation techniques, such as Kalman filtering, particle filtering, and online learning algorithms. At the same time, accurately modeling the non-stationary behavior of cascaded IRS channels remains an open and challenging problem.

2.2.3 Deep learning-based IRS channel estimation

Deep learning (DL) has emerged as a powerful mathematical tool for solving high-dimensional nonlinear mapping problems and has therefore attracted significant attention in channel estimation for IRS-aWC systems. In this context, deep learning techniques can be employed to estimate IRS-related channels by learning an implicit mapping from input training data to output channel state information (CSI), including both individual CSI components and cascaded CSI.

Specifically, suppose that the transmitted pilot symbols $\left\{\boldsymbol{x}_k^{(t)}\right\}_{t=1}^{\Sigma_t}$, the IRS-reflected training signals $\left\{\boldsymbol{\theta}^{(t)}\right\}_{t=1}^{T}$, , and the corresponding desired channel impulse responses (CIRs) $\left\{\hat{\boldsymbol{G}}_k\right\}_{k=1}^{K}$, are used as the training dataset for a deep learning model. The CSI estimation problem can then be formulated as a supervised learning task, in which the deep learning model is trained to accurately reconstruct the CSI from the observed received signals. In general, applying deep learning to CSI estimation requires the construction and storage of a fingerprint database, which captures the mapping between observed signal patterns and the corresponding channel states under diverse propagation environments. Based on this paradigm, the following subsection reviews and analyzes representative studies that exploit deep learning techniques for IRS channel estimation, and discusses the advantages, limitations, and future potential of this data-driven approach.

In,[61,62] a deep neural network (DNN) and a convolutional neural network (CNN) were respectively exploited to estimate the cascaded channels in IRS-aided wireless communication systems, with the primary objective of reducing real-time training overhead. The reported results demonstrate that deep learning models are capable of effectively learning the nonlinear mapping between the received signals and the CSI, thereby achieving significantly improved estimation accuracy compared to conventional model-based approaches. Subsequently, in,[63,64] two CNN-based cascaded channel estimation methods were proposed, where the estimation process was formulated as a denoising problem. These approaches were shown to approximate the optimal minimum mean square error (MMSE) solution and to outperform traditional linear channel estimators across a wide range of operating scenarios. Moreover, in,[65] the cascaded channel estimation problem was, for the first time, formulated as a sparse signal recovery problem for IRS-assisted MIMO systems operating in the THz band. Based on this formulation, an efficient deep learning-based estimation scheme was developed, in which the neural network learns to directly map the received signals to the channel vectors by exploiting the path gain information of the cascaded channel. Simulation results indicate that the proposed method can accurately reconstruct the CSI even under low signal-to-noise ratio (SNR) conditions. Beyond single-User scenarios,[66] employed CNNs to simultaneously estimate both the direct and cascaded channels in multi-user IRS-assisted systems, demonstrating the scalability of deep learning-based approaches in more complex network environments. Furthermore, in,[67] CNNs were applied to estimate the channel frequency response (CFR) of both direct and cascaded links in an IRS-assisted MISO-OFDM system. In this work, an offline training database was constructed to enable the CNN to learn the statistical characteristics of the channel, thereby enhancing estimation performance during practical deployment. In ,[68] the cascaded channel estimation problem in multi-user IRS-assisted systems was, for the first time, investigated from a denoising perspective. Based on this formulation, a residual deep learning framework built upon CNNs was proposed, in which the network is trained to refine the channel coefficients from noisy pilot observations. The results demonstrate that the proposed method can substantially improve estimation accuracy compared with conventional estimators, particularly in low signal-to-noise ratio (SNR) regimes. By exploiting the inherent angular-domain sparsity of mmWave channels, the authors in[69] developed an individual channel estimation method based on a deep denoising neural network. This approach effectively leverages the intrinsic sparse structure of mmWave channels, thereby reducing the required number of training samples while maintaining high estimation performance. Beyond conventional CNN and DNN-based models, a variety of other deep learning paradigms have also been applied to channel estimation in IRS-aided wireless communication systems, including federated learning, supervised learning, and reinforcement learning, as reported in.[70-72] These approaches enable flexible adaptation to diverse system requirements, such as user data privacy preservation, reduction of CSI feedback overhead, and optimization of IRS control strategies. Moreover, depending on the system architecture and design objectives, these learning-based methods can be employed to estimate either individual CSI components or cascaded CSI.

A comprehensive review of existing studies indicates that deep learning (DL) has emerged as a highly promising tool for channel estimation in IRS-aWC systems, particularly in scenarios where conventional model-based approaches face inherent limitations. Owing to its strong capability to learn complex nonlinear mappings from observed data to channel state information (CSI), DL-based methods are able to achieve superior estimation performance, even under low signal to noise ratio (SNR) conditions, highly scattering environments, or channel structures that are difficult to model accurately using analytical frameworks. One notable advantage of DL-based approaches lies in their ability to reduce real-time training overhead, as the majority of computational complexity can be shifted to an offline training phase. Furthermore, DL techniques can simultaneously exploit multiple channel characteristics, such as sparsity, spatial temporal correlation, and multi-dimensional structural features, without relying on stringent mathematical modeling assumptions. This endows DL-based channel estimation with enhanced flexibility and scalability, making it particularly attractive for large-scale or multi-user IRS-assisted systems. Nevertheless, DL-based methods also suffer from several fundamental limitations. First, their performance is highly dependent on the quality and diversity of training data, which may lead to degraded generalization capability when real-world channel conditions deviate significantly from those represented in the training dataset. Second, most DL models lack physical interpretability, thereby complicating theoretical analysis, reliability assessment, and performance guarantees. In addition, the storage, maintenance, and updating of large-scale fingerprint databases pose non-negligible challenges, especially in dynamic or large-scale deployment scenarios.

Looking ahead, the role of deep learning in IRS channel estimation is expected to further expand toward a tighter integration with model-based signal processing techniques. Promising research directions include model-driven deep learning, hybrid DL-CS-tensor frameworks, as well as online learning, federated learning, and reinforcement learning paradigms, which aim to enhance adaptability, data privacy, and deployment efficiency. Rather than fully replacing conventional channel estimation methods, deep learning is more appropriately viewed as a strategic complementary component that helps bridge the gap between theoretical channel models and practical deployment conditions. By embedding domain knowledge and physical constraints into learning architectures, DL-based approaches can achieve improved robustness, interpretability, and generalization, thereby enabling reliable and scalable channel estimation for next-generation IRS-aided wireless communication systems.

2.2.4 Summary of signal processing methods for IRS channel estimation

As summarized in Table 2, representative studies on channel estimation for IRS-aWC can be systematically classified according to their underlying signal processing frameworks and the corresponding channel/signal modeling assumptions. Such a classification not only clarifies the applicable scenarios of different approaches, but also highlights the fundamental trade-offs among estimation accuracy, computational complexity, and practical deployability.

First, least squares (LS) and linear minimum mean square error (LMMSE) methods are among the most widely adopted techniques in IRS-aWC, owing to their low computational complexity, transparent algorithmic structure, and flexible implementation across a broad range of scenarios, including narrowband/wideband systems, SISO/SIMO/MISO/MIMO configurations, as well as single-user and multi-user settings. These methods are particularly suitable for over-determined linear signal models and wireless environments with moderate channel dynamics. However, in scenarios involving large scale IRS deployments, multiple IRSs, or high mobility, the performance of LS/LMMSE estimators is often limited, as they fail to exploit the intrinsic structural properties of cascaded IRS channels. In contrast, compressed sensing (CS)-based approaches are specifically designed to address under-determined linear estimation problems, where the number of training observations is insufficient relative to the number of unknown channel parameters. By leveraging channel sparsity or low-rank characteristics, CS-based methods are especially effective in mmWave and THz systems, where propagation channels typically consist of only a few dominant paths. Nevertheless, the performance of CS techniques is highly dependent on the validity of sparsity assumptions and array geometry, and often comes at the cost of high computational complexity and sensitivity to model mismatch. Matrix and tensor factorization/decomposition methods represent an intermediate class of approaches that exploit low-rank structures, keyhole MIMO characteristics, or multi-dimensional correlations of the cascaded IRS channel. These methods can alleviate scaling ambiguities and improve channel identifiability in large-scale MIMO or multi-user systems. However, they generally require a large number of training samples, incur significant computational overhead, and may exhibit reduced robustness in low-SNR environments or when the assumed channel model deviates from practical conditions. Finally, deep learning (DL)-based approaches extend IRS channel estimation to nonlinear signal models, where conventional linear assumptions are no longer adequate. By learning direct nonlinear mappings from observed pilot signals to channel state information (CSI), DL-based methods can be applied to a wide variety of scenarios, including narrowband/wideband systems, single-user and multi-user settings, and highly complex channel structures. Despite their promising performance, these methods typically require large-scale training datasets, entail high offline training costs, and still lack rigorous theoretical performance guarantees and generalization analysis.

Table 2. Comparison of representative channel estimation methods for IRS-aWC systems.

Signal Processing Method	**Underlying Channel / Signal Model**	**Typical Application Scenarios**	**Advantages**	**Limitations**
Least Squares (LS) / Minimum Mean-Squared Error (LMMSE)	•General channel models (flat fading and frequency-selective fading) •Over-determined linear signal model	•Narrowband and broadband systems •SISO/SIMO/MISO/MIMO •Single-user and multi-user scenarios •Moderately dynamic environments	•Low computational complexity •Simple implementation •Well-understood theoretical properties	• Limited performance in under-determined settings • Inefficient for large-scale IRS • Does not exploit sparsity or low-rank structures
Compressed Sensing (CS)	•Sparse or low-rank channel model •Under-determined linear signal model	•mmWave and THz communications • Massive MIMO •Sparse angular-delay domain channels	•Significant training overhead reduction •High estimation accuracy for sparse channels	• Sensitive to sparsity assumptions • High computational complexity • Performance degradation under model mismatch
Matrix / Tensor Factorization	•Low-rank or structured channel model •Keyhole MIMO or cascaded channel model	• MIMO and multi-user IRS systems • Multi-dimensional training signals	•Exploits low-rank and multi-dimensional structures •Reduced scaling ambiguity under certain conditions	•High computational cost •Requires sufficient training samples •Potential identifiability and convergence issues
Deep	• Nonlinear	• Narrowband and	• Learns nonlinear	• Requires large

Learning (DL)	signal model • Data-driven channel representation	broadband systems • Single-user and multi-user scenarios • Complex or poorly modeled channels	channel mappings • Reduced real-time estimation cost • Flexible and scalable	training datasets • Limited interpretability • Generalization and robustness concerns

Based on the above analysis, it can be concluded that the performance and practical applicability of signal processing based methods for IRS-aWC channel estimation are highly dependent on the degree of compatibility between the employed methodology and the underlying channel and signal models. In particular, this dependency is governed by: (i) the channel characteristics (sparse versus dense, low-rank versus full-rank); (ii) the signal model (linear versus nonlinear); (iii) the level of problem determinacy (over-determined versus under-determined); and (iv) the system scale and practical deployment requirements.

Consequently, a promising future research direction lies in the development of adaptive and hybrid channel estimation frameworks that can dynamically switch or jointly exploit LS/LMMSE, compressed sensing, matrix/tensor factorization, and deep learning techniques, depending on channel conditions and available system resources. Such flexible frameworks are expected to play a pivotal role in enhancing IRS channel estimation performance**,** while simultaneously ensuring practical feasibility and scalability for deployment in next generation wireless communication systems.

2.3 Channel estimation for semi passive and fully passive IRS architectures

In this section, we investigate the channel estimation problem in IRS-aWC systems from the perspective of IRS hardware configurations, focusing on two representative architectures: semi-passive IRS and fully passive IRS. We first analyze the architectural characteristics and signal acquisition mechanisms of each IRS type, thereby clarifying the fundamental differences in channel observability and estimation feasibility. Subsequently, the key factors that critically affect channel estimation performance are highlighted, including training overhead, channel observability, and signal processing complexity. Finally, we systematically summarize and compare the representative signal processing techniques developed for each IRS configuration, and identify the corresponding channel models and transmission scenarios for which these methods are most suitable.

2.3.1 Individual channel estimation with semi-passive IRS

A semi-passive IRS, also referred to as a Hybrid Reconfigurable Intelligent Surface, represents an intermediate architecture between a fully passive IRS and a fully active transceiver. In this configuration, the IRS is equipped with N_S dedicated low-power RF sensing elements capable of receiving signals, where typically $N_S \ll N$, with N denoting the total number of IRS reflecting elements. Thanks to the presence of these sensing elements, the individual channels from the base station (BS) or the User to the IRS can be directly estimated at the IRS, based on pilot signals transmitted by the BS or the User. This capability enables the decoupled estimation of the constituent channels, namely the BS-IRS and User-IRS links, rather than relying solely on the cascaded channel observation. The channel estimation mechanism for semi-passive IRS architectures is illustrated in Fig. 2(a).

Under this framework, the system is particularly well suited to time-division duplexing (TDD) operation, since the inherent wireless channel reciprocity can be directly exploited to infer the channel state information (CSI) of the reverse links, i.e., from the IRS to the base station (BS) or from the IRS to the User. This mechanism enables a substantial reduction in both training overhead and CSI feedback signaling, while maintaining reliable channel estimation accuracy in static or quasi-static propagation environments. In contrast, under frequency-division duplexing (FDD) operation, the channel reciprocity assumption no longer holds. As a result, channel estimation methods based on semi passive IRS architectures cannot be directly applied, unless the sensing devices embedded in the IRS are capable of both receiving and transmitting pilot signals to support bidirectional channel estimation. However, such functionality would significantly increase the hardware cost and power consumption, thereby undermining the intrinsic energy efficiency advantages of IRSs. To strike a balance between channel estimation performance and implementation cost, a practical and widely considered approach is to equip the semi-passive IRS with only a small number of low cost sensing elements. In particular, these sensing units may employ low-resolution analog-to-digital converters (ADCs) to acquire pilot signals with minimal hardware complexity and energy consumption. Although the reduced ADC resolution inevitably degrades the quality of the observed signals, existing studies have demonstrated that, with appropriately designed channel estimation algorithms, the resulting performance loss can be effectively mitigated.

Considering the illustrative configuration shown in Fig. 2(a), let $\overline{\overline{\boldsymbol{H}}}^{BS-N_S} \in \mathbb{C}^{N_S \times M_B}$ and $\overline{\overline{\boldsymbol{G}}}^{User-N_S} \in \mathbb{C}^{N_S \times M_U}$ denote the channel matrices from the base station (BS) and the k-th User to the N_S sensing elements embedded in the IRS, respectively. Furthermore, let $\boldsymbol{X}_B \in \mathbb{C}^{M_B \times \Sigma_t}$ and $\boldsymbol{X}_k \in \mathbb{C}^{M_U \times \Sigma_t}$ denote the pilot signal matrices transmitted by the BS and the k-th User, respectively, where Σ_t represents the number of pilot symbols used within one channel sensing interval.

The received signal at the N_S sensing elements of the IRS can be modeled as

$$\boldsymbol{Y}_S = \mathbb{Q}\left(\sqrt{P_B}\,\overline{\overline{\boldsymbol{H}}}^{BS-N_S}\boldsymbol{X}_B + \sum_{k=1}^{K}\sqrt{P_U}\,\overline{\overline{\boldsymbol{G}}}^{User-N_S}\boldsymbol{X}_k + \boldsymbol{n}_S\right) \tag{17}$$

here, $\mathbb{Q}(.)$ denotes the quantization function, which depends on the resolution of the analog-to-digital converters (ADCs); B_P and P_U denote the transmit powers at the base station (BS) and the User, respectively; and $\boldsymbol{n}_S \in \mathbb{C}^{N_S \times \Sigma_t}$ represents the additive white Gaussian noise (AWGN) matrix at the sensing elements.

From (17), it can be observed that the received signal matrix at the IRS, $\boldsymbol{Y}_S$, depends jointly on the training signal matrix transmitted by the base station, $\boldsymbol{X}_B$, and the training signal matrix transmitted by User k, $\boldsymbol{X}_k$. Consequently, the core challenge of individual channel estimation at the IRS lies in ensuring accurate channel state information (CSI) for the links from the BS or the user to the IRS reflecting elements. In practice, the accuracy of such CSI is determined by the signal parameter measurements in (17), which depend directly on the number, spatial placement, and quality of the RF sensing elements integrated into the IRS. As a result, to obtain high-accuracy CSI for the BS-IRS or User-IRS links, it is necessary to design efficient signal processing techniques capable of interpolating or extrapolating channel information from the observation matrix $\boldsymbol{Y}_S$, particularly in scenarios where the number of sensors N_S is much smaller than the total number of reflecting elements N. Along this line of research, many existing works exploit the statistical properties and intrinsic structures of wireless channels-such as low rankness, sparsity, and spatial correlation which commonly arise in high-frequency communication systems operating in the mmWave band, [73] or the THz band.[74]

However, to achieve highly accurate and robust CSI estimation, future studies need to go beyond idealized channel models by explicitly accounting for practical non-idealities, including quantization errors induced by low-resolution ADCs, environmental noise, as well as hardware nonlinearities and impairments in RF circuits. Proper modeling and compensation of these measurement distortions play a pivotal role in narrowing the gap between theoretical analysis and practical deployment of semi-passive IRS architectures. For semi-passive IRSs, several representative approaches for individual channel estimation have been proposed in the existing literature. Specifically:

- When the sensing elements on the IRS are arranged in an L-shaped array, the work in,[75] proposed a low-complexity method for estimating the individual BS-IRS and User-IRS channels by jointly estimating the angle of arrival (AoA) and the corresponding path gains.
- When the sensing devices are randomly distributed over the IRS, a configuration commonly considered in narrowband systems, a variety of signal processing techniques have been developed to estimate the individual CSI from the BS or the user to the IRS. In particular, compressed sensing–based methods have been investigated in,[55,69,70,76] while deep learning–based approaches were studied in[70-71] to further enhance estimation accuracy under scenarios with a limited number of sensing elements.
- For broadband communication systems, the works in,[69,71] proposed channel estimation methods that improve training efficiency by exploiting the angular domain sparsity of mmWave MIMO channels, thereby significantly reducing the training overhead compared with conventional approaches.

Although encouraging preliminary results have been reported, more systematic and comprehensive investigations are still required, particularly with respect to: (i) the design of optimal pilot sequences at the base station (BS) and/or user terminals; (ii) the development of suitable sensing architectures and hardware for semi-passive IRSs; and (iii) the design of efficient signal processing and channel sensing algorithms capable of achieving high estimation accuracy with low hardware cost and short channel sensing durations. In practice, despite the potential of semi-passive IRSs to deliver superior system performance, their relatively complex architecture and higher deployment cost have hindered extensive investigation and commercialization. This, in turn, opens up a wide range of important research opportunities for future studies.

2.3.2 Cascaded channel estimation for fully passive IRSs

For fully passive IRS architectures, the reflecting elements are not equipped with any RF sensing or processing components; as a result, the IRS is incapable of receiving or processing signals. Consequently, the individual channels associated with the BS-IRS and User-IRS links cannot be estimated separately. Instead, channel estimation in this architecture can only be carried out in the form of cascaded channel estimation, i.e., estimating the composite channel that jointly accounts for signal propagation from the user to the IRS and from the IRS to the BS (User-IRS-BS). This estimation is typically performed at one end of the communication system, most commonly at the BS, where sufficient signal processing capability and computational resources are available. The underlying mechanism of cascaded channel estimation for fully passive IRSs is illustrated in Fig. 2(b).

Unlike the separate channel estimation problem in semi-passive IRS architectures, cascaded channel estimation can be applied in both time-division duplexing (TDD) and frequency-division duplexing (FDD) systems. Specifically, in TDD systems, the channel state information (CSI) can be estimated in one transmission direction and reused for both the uplink and downlink by exploiting the reciprocity of the wireless channel. In contrast, in FDD systems, channel reciprocity does not hold between the two transmission directions; hence, the CSI must be estimated and fed back separately for the uplink and downlink, which leads to increased signaling overhead and feedback latency. From a practical implementation perspective, cascaded channel estimation for fully passive IRSs is generally regarded as a more attractive approach than separate channel estimation, primarily due to the significantly lower hardware cost and energy consumption at the IRS, as no active sensing devices are required. However, this advantage comes at the expense of increased estimation complexity, since the cascaded channel is typically high-dimensional, bilinear in nature, and subject to inherent ambiguities in channel decomposition. As a result, more advanced signal processing techniques are required to achieve the desired channel estimation accuracy.

As illustrated in Fig. 2(b), this subsection considers the uplink channel training process, in which the user transmits pilot signals and the received signals are processed at the base station (BS). This approach is well suited to fully passive IRS architectures, where the IRS is incapable of sensing or processing signals; consequently, the entire channel estimation procedure is carried out at one end of the communication system, typically at the BS. For analytical convenience and to clearly highlight the characteristics of the cascaded channel estimation problem, we reuse the signal models established in (1), (2), and (3) in section 2.2.1, while keeping the underlying assumptions and notations consistent. Based on these models, the cascaded channel estimation methods for fully passive IRS-aided systems will be presented and analyzed in the subsequent sections.

From (2) and (3), it can be observed that the cascaded User-IRS-BS channel involves a substantially larger number of channel coefficients to be estimated than in the case of separately estimating the individual BS-IRS and User-IRS channels. This significant increase in the degrees of freedom of the cascaded channel results in much higher training overhead, in terms of both the required pilot sequence length and the signal processing complexity at the base station. Consequently, the design of efficient channel training and estimation strategies that can scale to large-size IRS deployments has become one of the central challenges in fully passive IRS-aided systems. In recent years, the cascaded channel estimation problem has attracted considerable attention from the research community, leading to a growing body of literature aimed at reducing training overhead and improving estimation accuracy under various system settings. Within the scope of this paper, our objective is not to exhaustively survey all existing results, but rather to discuss a number of representative and effective works. Through this focused discussion, we aim to elucidate the fundamental design principles and provide a structured overview that serves as a basis for the subsequent analysis and discussion.

First, the most straightforward and intuitive approach to cascaded channel estimation can be interpreted as a sequential estimation process, in which the channel components associated with individual IRS elements are estimated one by one based on the received signal observations at the receiver, which in the considered model is the base station (BS). To realize and further develop this approach, a number of studies have been reported in.[13-15,24-25] Specifically, cascaded channel estimation can be carried out by applying on/off training reflection patterns at the IRS, while pilot sequences are transmitted from the user side. To further improve training efficiency, the works in[34-36] proposed the use of specially structured reflection matrices, such as discrete Fourier transform (DFT) matrices, Hadamard matrices, or circulant matrices constructed from Zadoff-Chu sequences, to control the IRS training reflection patterns such that all reflecting elements remain in the "on" state. The results in these studies demonstrate that the accuracy of cascaded channel estimation can be significantly enhanced by exploiting the full aperture gain of the IRS, rather than relying on discrete on/off configurations. Moreover, in,[15,26] the authors investigated the joint design of IRS training reflection patterns and transmitter side pilot sequences in order to achieve full orthogonality among the reflected signals from the IRS. Owing to this orthogonality property, inter-component interference in the cascaded channel is effectively mitigated, thereby substantially improving the channel estimation accuracy at the BS. In addition to the aforementioned training-signal design based methods, a variety of other works have proposed the joint estimation of the direct channel and the cascaded channel at the receiver by leveraging widely used and advanced signal processing techniques, including least squares (LS), linear minimum mean-square error (LMMSE), compressed sensing, and deep learning, as discussed in detail in the preceding sections.

In summary, cascaded channel estimation methods $\left\{\hat{\boldsymbol{G}}_k\right\}_{k=1}^{K}$ in fully passive IRS systems fundamentally revolve around three core design components: (i) the pilot sequences transmitted from the transmitter side (the User); (ii) the training reflection patterns configured at the IRS; and (iii) the signal processing algorithms employed at the receiver, typically the base station (BS). This framework can be naturally extended to the estimation of the direct channel $\boldsymbol{D}_k$, with the overarching objective of achieving the highest possible estimation accuracy while incurring minimal training overhead. Such design principles are particularly well suited to practical large-scale IRS deployments, where scalability and training efficiency are of paramount importance.

2.3.3. Comparison and hybridization of channel estimation methods for semi-passive and fully passive IRS

As summarized in Table 3, both individual-channel estimation and cascaded channel estimation in IRS-aided wireless communication (IRS-aWC) systems exhibit their own advantages and limitations. In,[77] the authors conducted a quantitative comparison between these two approaches based on fundamental performance metrics, including estimation accuracy, hardware cost, and energy consumption. Their results indicate that cascaded channel estimation can achieve higher estimation accuracy while maintaining lower hardware cost and energy consumption than individual-channel estimation in many practical scenarios. Nevertheless, it should be emphasized that the accuracy of the channel state information (CSI), as well as the associated performance–cost trade-offs of these two approaches, strongly depends on multiple factors, such as the adopted signal processing techniques, channel models, training sequence design, and hardware constraints. Therefore, a more systematic and comprehensive comparison of these issues remains necessary and constitutes an important direction for future research.

In the existing literature, individual channel estimation and cascaded-channel estimation are typically investigated separately, under different assumptions and optimization objectives. However, combining or hybridizing these two approaches to exploit their respective advantages and thereby achieve superior overall channel estimation performance has recently emerged as a promising research direction. It is worth noting that, in IRS-aWC systems, the BS-IRS channel matrix $\boldsymbol{H}^{BS\text{-}IRS}$ is usually of large dimension, due to the large number of antennas equipped at the base station (BS), but remains quasi-static, since the locations of the BS and the IRS are generally fixed. In contrast, the User-IRS channels are much more dynamic owing to user mobility, yet their channel matrices are of significantly smaller dimensions, as the number of antennas at each user device is typically limited.[28-29]

Based on these characteristics, a reasonable strategy is to first estimate the quasi-static BS-IRS channel using individual-channel estimation methods, which can be efficiently performed by the sensing devices integrated into the IRS. Subsequently, the dynamic User-IRS channels can be estimated or tracked in real time at the base station (BS) through cascaded channel estimation, by exploiting the previously obtained BS-IRS channel information. This approach naturally leads to a hybrid or combined channel estimation framework, as illustrated in Fig. 4, which enables a substantial reduction in real-time training overhead while extending the applicability to both TDD and FDD systems.

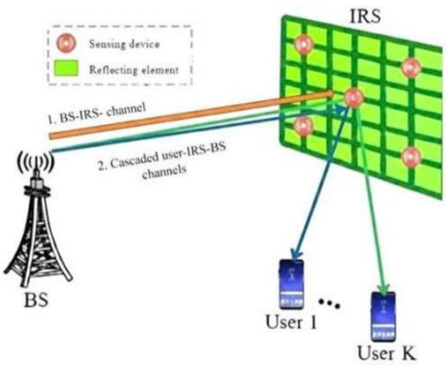

Figure. 4. Hybrid or combined framework integrating individual-channel estimation and cascaded channel estimation.

Table 3. Comparison between channel estimation for semi-passive IRS and fully passive IRS.

Criterion	Semi-passive IRS	Fully passive IRS
Hardware configuration	Equipped with a small number of RF sensors/ADCs ($N_S << N$)	No RF sensors, fully passive
Signal acquisition capability at IRS	Yes, via embedded sensing elements	No
Type of channel that can be estimated	Individual channels: BS-IRS and User-IRS	Only cascaded channel: User-IRS-BS
Location of CSI estimation	At the IRS (and/or at the BS)	At the BS
Supported duplexing mode	Mainly TDD (exploiting channel reciprocity); limited support for FDD	Supports both TDD and FDD
Training overhead	Low to moderate	High, increases significantly with the number of IRS elements
Channel estimation complexity	Moderate (linear or near-linear estimation problems)	High (large-scale bilinear estimation problem)
Typical signal processing methods	LS/LMMSE, AoA-based methods, CS, DL	LS/LMMSE, CS, tensor decomposition, DL
CSI estimation accuracy	Higher (due to direct observation of individual channels)	Lower, highly dependent on training design
Energy consumption at the IRS	Higher (due to sensors and ADCs)	Very low
Scalability	Limited for very large IRS sizes	Good, suitable for large-scale IRS deployments
Practical deployment feasibility	Moderate (higher hardware cost)	High (simple architecture, low cost)
Suitable application scenarios	Scenarios requiring accurate CSI and quasi-static environments	Large-scale deployments with strict energy-efficiency requirements

One of the earliest representative works along the line of hybrid channel estimation was reported in,[78] where the authors investigated a hybrid IRS architecture comprising both passive reflecting elements and embedded sensing devices. Based on this architecture, two independent subproblems were formulated to estimate the User-IRS channel and the BS-IRS channel, respectively. By exploiting the inherent sparsity of the wireless channel, the training signals were modeled as a multidimensional tensor and decomposed via Canonical Polyadic Decomposition (CPD). Dedicated algebraic algorithms were then developed to solve the resulting tensor decomposition problem and to recover the multipath channel parameters. Simulation results demonstrated that the proposed approach achieves superior channel estimation performance with relatively low computational complexity, even when only a limited number of sensing elements on the IRS are active. More recently, in,[79] the authors investigated an Integrated Sensing and Communication (ISAC) system supported by a self-sensing IRS. Unlike a fully passive IRS, a self-sensing IRS is capable of significantly reducing path loss in sensing-related links. The authors proposed a two-phase transmission scheme, in which coarse and refined sensing and channel estimation results are obtained in the first phase (using scanning-based IRS reflection coefficients) and the second phase (using optimized IRS reflection coefficients), respectively. For each phase, an angle-domain turbo variational Bayesian inference (AS-TVBI) algorithm was developed by integrating variational Bayesian inference (VBI), message passing, and expectation-maximization (EM) techniques. This algorithm effectively exploits the partial overlapping structured sparsity and two-dimensional (2D) block sparsity inherent in sensing and communication (SAC) channels, thereby substantially improving the overall estimation performance. Based on the initial estimation results, a Cramér–Rao bound (CRB) minimization problem was formulated to optimize the IRS reflection coefficients, and a low-complexity manifold-based optimization algorithm was proposed to solve this problem efficiently.

Although initial results have demonstrated the significant potential of hybrid channel estimation approaches, the design and practical realization of such architectures in an efficient, flexible, and cost-effective manner remain open research problems. Addressing these challenges requires more in-depth investigations, particularly for large-scale IRS deployments, highly dynamic environments, and scenarios involving integrated sensing and communication (ISAC) requirements.

2.4. IRS channel estimation under different system configurations

In practical deployments of IRS-assisted wireless communication systems (IRS-aWC), the requirements on channel state information (CSI) are highly dependent on the specific system configuration. Key influencing factors include the number of users (single-user versus multi-user), the number and size of IRSs, the number of antennas at the base station (BS) and user devices, user mobility characteristics (low versus high mobility), as well as the nature of the propagation channel (narrowband versus wideband). Different system configurations impose distinct requirements in terms of CSI accuracy, training overhead, and signal processing complexity. As a result, no single channel estimation method can be universally optimal across all scenarios. Therefore, the selection and design of appropriate IRS channel estimation schemes tailored to specific system configurations play a critical role in achieving high training efficiency while maintaining reliable CSI accuracy, particularly in large-scale IRS deployments. In this subsection, we systematically classify and review representative IRS channel estimation methods according to different system configurations, thereby highlighting the fundamental design principles and configuration-dependent challenges. Specifically, we first consider narrowband IRS-aided systems with a single fully passive IRS and one or multiple users, which represent the most fundamental and widely studied scenarios in early works. We then extend the discussion to wideband systems, where frequency-selective fading significantly increases the number of channel coefficients to be estimated, necessitating more sophisticated training strategies and signal processing techniques. Finally, we address multi-IRS systems involving two or more IRSs, an emerging research direction in which the presence of inter-IRS channels substantially increases the complexity of channel modeling and estimation algorithms.

2.4.1 Single-User system with a single IRS

For a single-user system assisted by a single fully passive IRS, the effective channel observed at the receiver is formed by the superposition of the direct propagation link and the reflected components via the IRS, where each IRS element contributes an individual reflected path. Specifically, in the single-user case (i.e., $K = 1$), the user index kkk can be omitted in the mathematical expressions for notational simplicity. Accordingly, the cascaded User-IRS-BS channel can be explicitly expanded as

$$\hat{\boldsymbol{G}} \triangleq \left[\vec{h}_1, \vec{h}_2, \ldots, \vec{h}_N\right] \qquad (18)$$

From (5), it can be observed that achieving perfect channel state information (CSI) of the cascaded channel requires a training overhead that grows linearly with the number of reflecting elements N. When N is large, which is a defining characteristic of large-scale IRS-assisted systems, this results in substantial training latency and a pronounced degradation in spectral efficiency, especially in fast time-varying channel scenarios. Consequently, a central research question in single-user IRS-aided wireless communication systems is how to effectively reduce the training overhead while maintaining an acceptable level of CSI estimation accuracy. In the following, we review and discuss representative works that address this fundamental challenge. Depending on the antenna configuration of the downlink transmission, i.e., the link from the base station (BS) to the IRS and subsequently to the user, existing studies on IRS channel estimation for single-user (point-to-point) systems can be broadly classified into three main categories: single-input single-output (SISO), multiple-input single-output (MISO), and multiple-input multiple-output (MIMO).

First, several representative works in,[13-15,24-25] investigated IRS channel estimation under SISO and MISO configurations, where the channel state information (CSI) of either the direct link or the cascaded link is independently estimated at one or multiple antennas of the base station (BS), based on IRS training reflection patterns and pilot sequences transmitted from a single user antenna. However, these approaches are difficult to scale effectively to general MIMO configurations due to the intricate coupling among multiple transmit and receive antennas, which necessitates the simultaneous estimation of a large number of channel coefficients. To overcome this limitation, as discussed in previous sections, a substantial body of research has focused on cascaded channel estimation for single-user IRS-aided MIMO systems by exploiting the inherent sparsity and low-rank structures of the channel at mmWave and THz frequency bands, primarily through compressed sensing–based algorithms, as exemplified in.[38-45,49] These methods significantly reduce the training overhead while maintaining high CSI estimation accuracy. In parallel, deep learning–based signal processing techniques have emerged as a promising alternative, enabling the learning of nonlinear mappings from pilot observations or training data to CSI without explicit channel modeling. Specifically, deep learning approaches have been successfully applied to single-user IRS-aided systems with MISO configurations in,[61-64] and MIMO configurations in,[65] demonstrating superior performance compared with conventional linear estimators across a wide range of scenarios. In addition, several studies, including,[52,57,59] have leveraged matrix and tensor factorization/decomposition techniques to reduce the effective dimensionality of the cascaded MIMO channel matrix, thereby simplifying the channel estimation problem and lowering the computational complexity in single-user IRS-aided MIMO systems. Beyond the aforementioned mainstream approaches, IRS channel estimation has also been investigated under more specialized scenarios. For instance,[80] considered an IRS-assisted backscatter communication system and proposed a least-squares (LS)-based channel estimation method for the SISO configuration. Moreover, in highly mobile environments with large-scale IRS deployments, various protocols and channel tracking algorithms have been developed to dynamically track the CSI of both direct and cascaded channels over time, covering SISO,[34] MISO,[35] and MIMO configurations.[36,81,82]

In broadband communication systems, wireless channels are typically frequency-selective and time-varying with rich multipath propagation, rendering the channel model substantially more complex than in the narrowband case. In this context, channel modeling, computation, and estimation in IRS-aided wireless communication (IRS-aWC) systems become particularly challenging, due to the dramatic increase in the degrees of freedom of the cascaded channel as well as the need to track channel state information (CSI) across both time and frequency domains. Although several preliminary studies have been reported, existing IRS channel estimation methods for broadband systems remain limited, both in quantity and in methodological maturity. Consequently, the development of accurate and tractable channel models, together with efficient channel estimation algorithms that are scalable and adaptive to time–frequency–selective channel variations, remains an open and highly promising research direction that warrants further in-depth investigation.

2.4.2 Multi-User systems with a single IRS

Next, we consider the channel estimation problem in multi-User IRS-aided wireless communication (IRS-aWC) systems with a single IRS, where multiple Users are simultaneously served by a common IRS (or, equivalently, multiple IRSs are deployed in a distributed manner within the same service area). In this analysis, we continue to adopt the received signal model introduced in (3) as the basis for characterizing the channel estimation properties in the multi-User scenario. It is worth noting that, in the presence of multiple users, directly applying channel estimation methods originally designed for the single-user case is generally inefficient. This inefficiency arises from inter-User interference as well as the substantial increase in the number of channel parameters to be estimated. This issue has been clearly identified and analyzed in ,[25,83,84] which highlights the necessity of developing dedicated channel estimation strategies for multi-User IRS-aWC systems. Such strategies should be capable of exploiting the shared structure of the cascaded channels while effectively reducing the overall training overhead.

To further elucidate the characteristics of the channel estimation problem in the multi-user scenario with a single IRS, we revisit the received signal model presented in (3), which can be compactly rewritten as

$$\boldsymbol{y}_{B,k}^{(t)} = \sqrt{P_U}\left[\left(\boldsymbol{x}^{(t)}\right)^T \otimes \boldsymbol{I}_{M_B}\right]\hat{\boldsymbol{G}}_k \boldsymbol{\theta}^{(t)} + \boldsymbol{n}_B^{(t)}, \quad (19)$$

with k =1,…, K. Similar to the single-User case presented in (4), the composite channel state information (CSI) of each User can, in principle, be estimated individually based on each $\boldsymbol{y}_{B,k}^{(t)}$ in (19) without incurring co-channel interference (CCI). However, this approach leads to a training duration that increases linearly with the number of users, and thus becomes impractical when the number of users K is large. Therefore, to achieve training-efficient operation in multi-User IRS-aWC systems, the key challenge lies in the design of more efficient channel estimation and signal processing strategies, including: (i) multi-User pilot sequences at the transmit side, (ii) training reflection patterns at the IRS, and (iii) channel estimation algorithms specifically tailored to the multi-User scenario. These components must be jointly designed to minimize the overall training overhead while maintaining reliable CSI estimation accuracy in the presence of noise and inter-User interference. In the multi-User IRS-aWC system illustrated in Fig. 5, all Users share a common IRS–BS channel, denoted by $\boldsymbol{H}^{BS\text{-}IRS}$, whereas each user experiences an individual composite User-IRS-BS channel, denoted by $\left\{\hat{\boldsymbol{G}}_k\right\}_{k=1}^{K}$. This shared channel structure induces strong correlations among the composite channels of different Users, thereby enabling the exploitation of common structural properties, such as angular-domain sparsity or low-rank characteristics, to design more efficient multi-User channel estimation algorithms. In the following, we summarize and discuss representative recent studies on channel estimation for multi-user IRS-aWC systems, highlighting the main methodological approaches and the remaining open challenges.

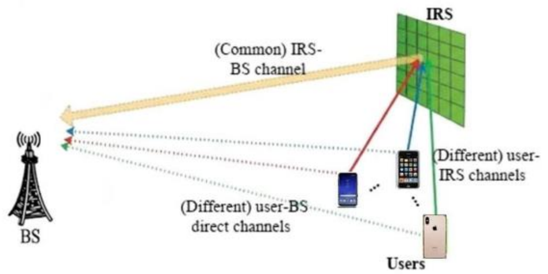

Figure 5. Uplink channel estimation in IRS-aided multi-User wireless communication systems.

Motivated by practical deployment considerations, the authors in,[27] proposed a representative User based channel estimation strategy. Specifically, the cascaded channel state information (CSI) of a representative User, for example, $\hat{\boldsymbol{G}}_1$ corresponding to the first User, is first estimated at the base station (BS). Exploiting the shared channel structure, the cascaded CSI of the remaining Users, denoted by $\left\{\hat{\boldsymbol{G}}\right\}_{k=2}^{K}$, can then be inferred with only marginal additional training overhead. Under this framework, the multi-User IRS-assisted system can be equivalently transformed into a multi-User IRS-aided MISO system, thereby significantly reducing the overall channel training cost. This approach effectively exploits the correlation among the cascaded channels of different users, particularly in wideband propagation environments. The channel estimation performance of the method in[27] was further improved in[85] by jointly estimating both the direct channels and the cascaded channels in a multi-user IRS-aided MISO system, which enhances CSI accuracy and improves the overall system performance. Moreover, in many practical scenarios, as discussed earlier, the IRS-BS channel is quasi-static or varies much more slowly over time compared to user-related channels. Leveraging this property, the authors in,[28,29] proposed to first estimate the quasi-static IRS-BS channel $\boldsymbol{H}^{BS\text{-}IRS}$, and subsequently utilize this information to estimate the dynamic IRS-User channels $\left\{\boldsymbol{G}_k\right\}_{k=1}^{K}$, in real time with low training overhead, making the approach particularly suitable for multi-User IRS-aided MISO systems.

For the problem of cascaded channel estimation in fully passive IRS-assisted systems, a wide range of approaches have been proposed for multi-User IRS-aided wireless communication (IRS-aWC) MISO systems by exploiting advanced signal processing techniques. Specifically, methods based on matrix/tensor factorization and decomposition have been investigated in;[57,58] compressed sensing based approaches that exploit the inherent sparsity of wireless channels have been proposed in;[53-55] meanwhile, deep learning-based techniques have been applied to directly learn the cascaded channel state information (CSI) from training data in.[66,68] channel estimation problem, the authors in[26,53] proposed to shift to downlink channel training, However, in multi-User scenarios, each User still needs to feed back either its direct CSI or especially in large-scale where the base station (BS) is required to jointly estimate the CSI of the direct channels in which each user It is worth noting that most of the aforementioned channel estimation methods are designed for uplink channel training, cascaded CSI to a central BS. Consequently, although downlink training can alleviate the processing burden at the BS, it incurs a significantly increased CSI feedback overhead, training reflection patterns. and/or cascaded channels from multiple users, resulting in high computational complexity and substantial training overhead. To simplify the joint uplink independently estimates its own CSI including the direct channel $\boldsymbol{D}_k$ and the cascaded channel $\{\hat{\boldsymbol{G}}\}_k$ based on pilot signals transmitted by the BS and reflected by the IRS using different systems with a large number of Users. On the other hand, for semi-passive IRS architectures, where dedicated sensing elements are integrated directly into the IRS, several efficient channel estimation methods have been developed for multi-User IRS-aWC MISO systems. In particular, approaches based on Sparse Bayesian Learning (SBL)[55] and Canonical Polyadic Tensor Decomposition (CPD)[76] have been proposed for both flat-fading and frequency-selective fading channels. In these methods, the IRS-BS channel (shared channel) and the User-IRS channels (User-specific channels) are estimated in parallel directly at the sensing elements embedded in the IRS, thereby significantly reducing the training overhead, system latency, and computational burden at the BS.

2.4.3 Channel estimation for systems with two or more IRSs

Most existing studies on IRS channel estimation have primarily focused on IRS-aWC systems assisted by a single IRS, or on scenarios involving multiple IRSs but considering only a single effective reflection path, as illustrated in Fig. 6(a).

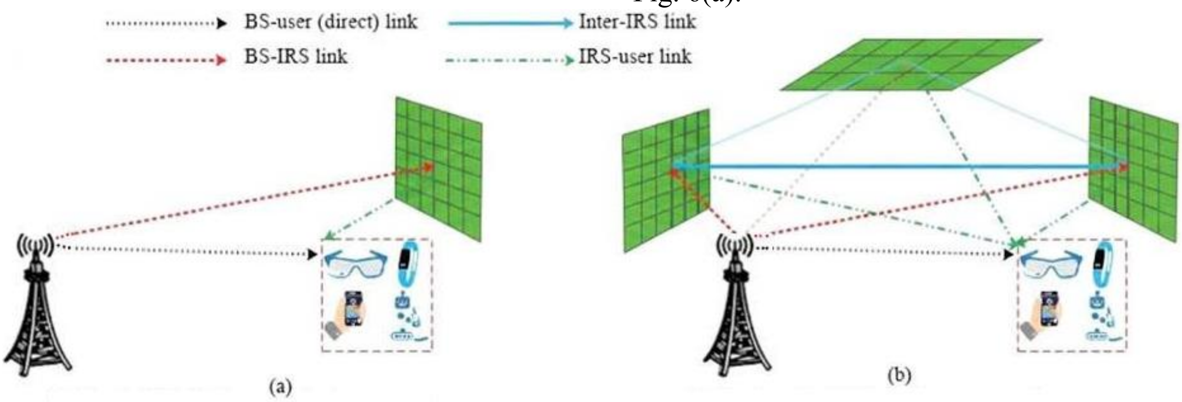

Figure 6. IRS-aWC system with different IRS deployments:
a) Single-IRS aided communicatin system, b) Multi-IRS aided communicatin system.

In these models, inter-IRS reflected signals are typically neglected in order to simplify channel modeling and reduce the computational complexity of the channel estimation problem. Recently, however, the considerable potential of forming cooperative passive signal flows among multiple IRSs has attracted growing research interest**.** In particular, the works in,[30,86-88] have demonstrated that deploying two or more coordinated IRSs can achieve significantly higher passive beamforming gains than systems assisted by a single IRS. These gains arise from enhanced energy focusing, extended coverage, and improved effective channel quality enabled by multi-hop reflection paths. Nevertheless, while cooperative multi-IRS architectures offer clear performance advantages, they simultaneously introduce new and more severe challenges for channel estimation. Specifically, the emergence of inter-IRS link channels, together with the substantial increase in the number of channel parameters to be estimated, renders the channel model considerably more complex than that of single-IRS systems. Consequently, the development of appropriate channel models and scalable, efficient channel estimation algorithms tailored for multi-IRS systems remains an important open research direction, warranting further in-depth investigation in future work.

To further clarify the above discussion, we consider a communication system assisted by two

IRSs, as illustrated in.[86] Specifically, in addition to the original IRS (denoted as IRS1) deployed in proximity to the user devices, a second IRS (IRS2) is placed near the base station (BS) to further enhance the controllability of passive signal propagation. In this configuration, besides the channel matrices already present in single-IRS systems, including the IRS1-BS channel $\boldsymbol{H}^{BS\text{-}IRS1}$ and the User-IRS1 channel $\boldsymbol{G}_k^{User-IRS1}$, additional channels arise due to the introduction of IRS2. In particular, $\tilde{\boldsymbol{H}}^{BS-IRS}$ and $\tilde{\boldsymbol{G}}_k^{User-IRS}$ denote the channels from IRS2 to the BS and from user kkk to IRS2, respectively. Moreover, in a two-IRS system, there exists an inter-IRS link channel, denoted by $\boldsymbol{S}$, which captures the signal interaction and mutual reflection between IRS1 and IRS2. Consequently, the effective channel between User k and the BS is no longer a simple superposition of a single reflected path and the direct link, but rather a composite of multiple components, including

$$\begin{aligned}\boldsymbol{E}_k = \tilde{\boldsymbol{H}}^{BS-IRS}\tilde{\boldsymbol{\Theta}}\boldsymbol{S}\boldsymbol{\Theta}\boldsymbol{G}_k^{User-IRS} + \\ + \tilde{\boldsymbol{H}}^{BS-IRS}\tilde{\boldsymbol{\Theta}}\tilde{\boldsymbol{G}}_k^{User-IRS} + \\ + \boldsymbol{H}^{BS-IRS}\boldsymbol{\Theta}\boldsymbol{G}_k^{User-IRS} + \boldsymbol{D}_k,\end{aligned} \tag{20}$$

where $\boldsymbol{\Theta} = diag(\boldsymbol{\theta})$ and $\tilde{\boldsymbol{\Theta}} = diag(\tilde{\boldsymbol{\theta}})$ denote the reflection coefficient matrices of IRS1 and IRS2, respectively;

$$\tilde{\boldsymbol{H}}^{BS-IRS}\tilde{\boldsymbol{\Theta}}\boldsymbol{S}\boldsymbol{\Theta}\boldsymbol{G}_k^{User-IRS}$$

represents the double-reflection signal component, while

$$(\tilde{\boldsymbol{H}}^{BS-IRS}\tilde{\boldsymbol{\Theta}}\tilde{\boldsymbol{G}}_k^{User-IRS} + \boldsymbol{H}^{BS-IRS}\boldsymbol{\Theta}\boldsymbol{G}_k^{User-IRS})$$

denotes the component; and $\boldsymbol{D}_k$ corresponds to the direct channel from user kkk to the base station (BS).

According to (20) and as illustrated in Fig. 6(b), IRS-assisted propagation paths with different reflection orders including single- and double-reflection components are superimposed and intricately coupled, which leads to a substantial increase in the number of channel coefficients to be estimated. Consequently, channel estimation techniques originally developed for systems with a single IRS are, in general, not directly applicable to systems with two or more IRSs, either from a channel modeling perspective or in terms of algorithmic complexity. Therefore, the development of new channel estimation frameworks capable of exploiting the distinctive structural properties of multi-IRS channels and scaling efficiently with multiple reflection orders has become an urgent and critical requirement. In the following, we review and discuss the most recent research advances on channel estimation for wireless communication systems assisted by two or more IRSs, highlighting the current methodological approaches as well as the open challenges that remain.

In,[87] the authors investigated a single-User SISO system assisted by two semi-passive IRSs, where the individual channels between each IRS and the base station (BS) or the user are directly estimated via sensing devices integrated into the IRSs. In this model, the inter-IRS channel is assumed to be line-of-sight (LoS) and primarily determined by geometric relationships, which significantly simplifies the channel estimation problem. For the case of two fully passive IRSs, the problem of cascaded channel estimation through dual IRSs was studied in[30] for a single-User SISO system. Specifically, by assuming that the direct link is blocked and that a single dominant reflected path exists, the authors in[30] [proposed two efficient channel estimation schemes to recover the double-reflection channels through the two IRSs, under the condition that both the common IRS–BS channel and the inter-IRS channel are LoS-dominated. To achieve a practically low training overhead in multi-antenna systems, the authors in,[31] proposed an effective channel estimation method based on on–off reflection training patterns at the IRSs, which enables the acquisition of the cascaded channel state information (CSI) for both single-reflection and double-reflection links in a two-IRS-assisted multi-User MISO IRS-aWC system. This approach demonstrates the potential to significantly reduce training overhead while maintaining acceptable channel estimation performance.

Furthermore, to overcome the limitations associated with error propagation and reflected power loss caused by the on-off reflection control employed in,[31] the authors in,[32] developed an improved effective channel estimation scheme, in which the IRS elements remain continuously active (always on reflection) throughout the training phase. This strategy enables the simultaneous estimation of the cascaded CSI for both single and double-reflection paths, thereby fully exploiting the reflective power gain of the IRSs and leading to a substantial improvement in channel estimation accuracy for two IRS-assisted multi-User MISO IRS-aWC systems**.** Notably, both dual-IRS channel estimation schemes proposed in,[31-32] can achieve a training overhead comparable to that of single IRS systems. This result is made possible by exploiting the intrinsic relationships between single- and double-reflection channels, as well as the shared structural properties of the cascaded channels across multiple users, which effectively reduces the number of degrees of freedom to be estimated. However, for systems assisted by more than two cooperating IRSs, comprehensive studies on the accurate and efficient estimation of cascaded channels involving two or higher-order reflections are still largely lacking. The primary reason lies in the exponential growth in the number of channel coefficients as the number of IRSs increases, which renders both channel modeling **and** estimator design particularly challenging. Consequently, the development of scalable channel estimation frameworks for large-scale multi-IRS systems, capable of achieving However, for systems assisted by more than two cooperating IRSs, comprehensive studies on the accurate and efficient estimation of cascaded channels involving two or higher-order reflections are still largely lacking. The primary reason lies in the exponential growth in the number of channel coefficients as the number of IRSs increases, which renders both channel modeling and estimator design particularly challenging. Consequently, the development of scalable channel estimation frameworks for large-scale multi-IRS systems, capable of achieving acceptable training overhead and computational complexity, remains a critical open research direction that warrants substantial attention in future studies., remains a critical open research direction that warrants substantial attention in future studies.

2.4.4 Channel estimation for wideband IRS-aided systems with a single IRS

In practical deployments, a highly important and practically relevant issue is channel estimation for wideband multicarrier IRS-aWC systems, in which the propagation channels typically exhibit frequency-selective fading. Compared with narrowband systems, channel estimation in the wideband scenario becomes significantly more challenging due to the substantial increase in the channel degrees of freedom, as well as the need to track channel state information (CSI) across both the time and frequency domains. Specifically, in narrowband systems, the cascaded User-IRS-BS channel on each transmission link can be represented as a simple matrix product of the User-IRS and IRS-BS channels, as shown in (2). In contrast, in wideband systems, the effective cascaded channel is no longer characterized by a straightforward matrix multiplication, but rather by the convolution of the User-IRS and IRS-BS channels across multiple multipath components. This convolutional structure gives rise to inter-delay-path interference, which further complicates both channel modeling and channel estimation for IRS-assisted systems. As a result, channel estimation methods developed for narrowband systems cannot be directly applied to wideband scenarios. Instead, they must be extended or redesigned to exploit the intrinsic structural properties of frequency-selective channels, such as delay-angle sparsity**,** inter-subcarrier correlation**,** or low-rank structures in appropriate transform domains. These issues will be discussed in greater detail in the subsequent subsection.

Specifically, let L_G and L_H denote the numbers of delay taps of the time-domain channel impulse responses (CIRs) corresponding to the User-IRS and IRS-BS links, respectively. In this setting, to clearly elucidate the fundamental nature of the channel estimation problem in wideband IRS-assisted systems, we consider a simple yet representative scenario, namely a single-User single-base-station-single-IRS system with a SISO configuration, i.e., $K = M_B = M_U = 1$. Restricting the model to the SISO case does not compromise the generality of the subsequent analysis; rather, it enables a more transparent exposition of the convolutional relationship between the User-IRS and IRS-BS channels in the time domain, as well as the resulting increase in the number of channel coefficients to be estimated in wideband IRS-aWC systems. Based on this baseline model, the derived results can be systematically extended to MISO or MIMO configurations by incorporating the corresponding antenna dimensions.

Similarly, $\boldsymbol{g}_n \in \mathbb{C}^{L_H\times 1}$ and $\boldsymbol{h}_n \in \mathbb{C}^{L_H\times 1}$ denote the time-domain channel impulse responses (CIRs) from the n-th IRS element to the User and to the base station (BS), respectively. Consequently, the effective cascaded channel from the user to the BS via each IRS element nnn can be expressed as the convolution of the User-IRS channel, the IRS reflection coefficient, and the IRS-BS channel, which can be written as

$$\boldsymbol{h}_n * \boldsymbol{\theta}_n * \boldsymbol{g}_n = \boldsymbol{\theta}_n \boldsymbol{h}_n * \boldsymbol{g}_n = \boldsymbol{\theta}_n \boldsymbol{q}_n,\ n = 1, \ldots, N \qquad (21)$$

where $\boldsymbol{q}_n \triangleq \boldsymbol{h}_n * \boldsymbol{g}_n \in \mathbb{C}^{(L_H+L_G-1)\times 1}$ denotes the cascaded User-IRS-BS channel associated with the n-th IRS element (without accounting for the IRS phase-shift effect), and $(*)$ denotes the convolution operator.

Due to multipath propagation in wideband systems, the number of channel coefficients to be estimated for the cascaded User-IRS-BS channels $\{\boldsymbol{q}_n\}_{n=1}^{N}$ increases significantly compared to the narrowband case. Specifically, each IRS-assisted reflected link is characterized by a time-domain channel impulse response (CIR) with multiple delay taps, which leads to a substantial increase in the degrees of freedom of the effective cascaded channel. This, in turn, results in higher training overhead and increased computational complexity for channel estimation algorithms. Moreover, in wideband multicarrier systems employing orthogonal frequency-division multiplexing (OFDM), it is important to note that the reflection coefficients of passive IRS elements are typically frequency-flat over the entire operating bandwidth. As a consequence, the IRS reflection coefficients affect the channel frequency response (CFR) identically across all OFDM subcarriers. This property eliminates the inherent frequency-domain flexibility of OFDM and significantly limits the ability to design frequency-selective IRS reflection patterns or subcarrier-dependent channel training strategies. As a result, channel estimation methods developed for narrowband IRS-aWC systems, which generally rely on the assumptions of frequency flat fading and a limited number of channel parameters, cannot be directly applied to wideband systems with frequency-selective fading. This observation highlights an urgent need for more efficient wideband IRS channel estimation solutions that are capable of exploiting the underlying time-frequency correlation structures of the cascaded channels, while simultaneously controlling the training overhead and computational complexity. Based on these considerations, the following subsection provides a systematic review and discussion of existing research results on IRS channel estimation for wideband systems, and further highlights the remaining open challenges and promising research directions in the context of next-generation wireless communications.

First, in two pioneering works,[13-14] the authors investigated the channel estimation problem for single-user IRS-aided OFDM wireless communication systems. In these studies, comb-type pilot designs were proposed in conjunction with IRS training reflection patterns operating in on–off and always-on modes. Such designs enable the separation of the contributions of IRS-assisted reflected paths in the frequency domain, thereby facilitating the estimation of the cascaded channels under frequency-selective fading conditions. However, due to the large number of OFDM subcarriers and the increase in OFDM symbol duration with bandwidth, these methods still suffer from considerable training latency. To address this limitation, the work in,[15] proposed two more efficient training pattern structures, in which both the OFDM pilot signaling at the transmitter and the IRS training reflection patterns were jointly redesigned. This joint design significantly shortens the training duration while maintaining high channel estimation accuracy. These results clearly demonstrate that the joint optimization across the time–frequency domain of OFDM signals and the spatial domain of the IRS plays a crucial role in wideband IRS channel estimation. Extending the analysis to the multi-user scenario, the authors in,[15] further proposed an efficient channel estimation method for multi-User IRS-aided OFDM systems by multiplexing the pilots of different users in the frequency domain over disjoint subsets of OFDM subcarriers. This strategy enables more efficient utilization of frequency resources and substantially reduces the overall training overhead compared to conventional User-by-User sequential training schemes. In addition, by exploiting the angular delay sparsity inherent in wideband channels, which is a typical characteristic of mmWave systems, the Orthogonal Matching Pursuit (OMP) algorithm was applied in,[51] to an IRS-aided MISO-OFDM system to jointly estimate the wideband direct channels and cascaded channels for multiple users. In this model, the BS-IRS channel is assumed to be dominated by a line-of-sight (LoS) component, which significantly reduces the dimensionality of the estimation problem and enhances the effectiveness of compressed sensing-based algorithms, as discussed in previous sections.

In,[48] the authors proposed a two-stage wideband channel estimation framework for IRS-aided massive MIMO systems operating in the THz band. Specifically, the first stage performs coarse channel estimation in the downlink to extract the fundamental structural information of the channel, while the second stage conducts refined channel estimation in the uplink for the multi-User scenario. This two-stage design effectively balances estimation accuracy and training overhead in the presence of severe path loss and highly directional propagation characteristics inherent to THz channels. In IRS-aided OFDM systems, deep learning-based channel estimation methods have also attracted increasing attention in recent years. In particular,[67] exploited convolutional neural networks (CNNs) to learn nonlinear mappings from the received pilot signals to the direct channel state information (CSI) or the cascaded CSI for both MISO and MIMO configurations. Meanwhile, to reduce the communication overhead associated with training data exchange and to preserve user privacy, the authors in,[72] proposed the application of federated learning to the channel estimation problem in IRS-aided OFDM systems. In this framework, local models are trained in a distributed manner at edge nodes, and only learned model parameters are shared, rather than raw data. For semi-passive IRS architectures, where signals can be directly acquired by sensors integrated into the IRS, dedicated channel estimation methods have been proposed for single-user SISO-OFDM systems in.[70] These methods combine deep learning and compressed sensing to effectively exploit the inherent sparsity of mmWave channels. Furthermore, by employing deep denoising neural networks and leveraging angular-domain sparsity, the work in,[76] developed an efficient decoupled channel estimation approach for IRS-aided MIMO-OFDM systems, demonstrating the significant potential of deep learning techniques in wideband and multi-antenna scenarios.

In Table 4, we summarize the most recent research works on IRS channel estimation across different system configurations.

Table 4. Channel estimation methods for IRS-aWC systems under different system configurations

IRS Configuration	**Bandwidth**	**Users**	**Antenna Setup (DL)**	**Representative Channel Estimation Methods and Key Features**
Single IRS	Narrowband	Single-User	SISO	Progressive cascaded channel estimation under discrete phase-shift models;[33,39] cascaded channel estimation for IRS-assisted backscatter communications;[80] compressed sensing (CS)-based estimation exploiting channel sparsity with CRB analysis;[50] channel estimation for high-mobility scenarios with vehicle-mounted IRS;[34] separate channel estimation using a single RF chain at IRS.[40]
			MISO	Cascaded channel estimation using on/off IRS training reflection patterns;[24] full-on reflection training exploiting entire IRS aperture;[25] CS-based methods leveraging mmWave channel sparsity;[40] deep learning (DL)-based cascaded channel estimation;[49,62-64] Kalman filter–based tracking for high-mobility channels .[3581]
			MIMO	CS-based cascaded channel estimation exploiting low-rank and sparse structures of mmWave channels;[38-39,41-45,49] matrix factorization/decomposition-based methods,[52,57,59] DL-based cascaded channel estimation for THz channels;[65] channel estimation for high-mobility IRS-aided systems.[36,82]
		Multi-User	MISO	Successive User-by-User cascaded channel estimation;[84] exploitation of common IRS–BS channel and additional channel sparsity;[27,46-47] uplink IRS–BS channel estimation (offline) followed by online IRS–user channel estimation;[28-29] LMMSE-based downlink estimation;[26] matrix factorization and tensor-based methods;[53-54,57-58,60] DL-based multi-user channel estimation using CNNs.[66,68]
	Broadband (OFDM)	Single-User	SISO	Cascaded channel estimation with ON/OFF IRS reflection patterns and element grouping strategies;[13] DFT-based and circulant training reflection patterns;[14] fast (sampling-wise) full-ON training strategies;[15] DL/CS-based separate channel estimation for mmWave

IRS Configuration	Bandwidth	Users	Antenna Setup (DL)	Representative Channel Estimation Methods and Key Features
				channels.[70]
			MISO	Cascaded channel estimation using single CNN architectures to reduce training complexity.[67]
			MIMO	Deep denoising neural network-based cascaded channel estimation for mmWave channels;[69] joint estimation of direct and IRS-assisted channels in OFDM systems.[14]
		Multi-User	MISO	OMP-based cascaded channel estimation exploiting common sparsity across users and subcarriers;[51] separate channel estimation using canonical polyadic decomposition (CPD).[76]
	Narrowband		MIMO	DL-based cascaded channel estimation with federated learning;[72] CS-based methods exploiting dual sparsity in THz MIMO channels.[48]
Single IRS		Single-User	SISO	Double-IRS cascaded channel estimation under Rician fading with inter-IRS channels;[30] exploitation of channel relationships between single- and double-reflection links.[31]
			MISO	Double-IRS channel estimation exploiting common BS–IRS channels and inter-IRS links.[32]
		Multi-User	MISO	Double-IRS channel estimation leveraging common BS-IRS and inter-IRS channels as well as channel correlations among Users.[31-32]

As summarized in Table 4, research on IRS channel estimation has evolved along four major and progressively challenging dimensions: from single-IRS to multi-IRS architectures, from narrowband to broadband transmission, and from model-based to learning-based approaches. Early studies primarily focused on single-IRS narrowband systems, in which the cascaded channel can be effectively estimated using structured training reflection patterns and classical signal processing techniques, such as LS/LMMSE, compressed sensing, and matrix or tensor factorization. In these scenarios, the dominant challenges stem from the large number of IRS elements and the resulting training overhead, which are commonly alleviated by exploiting channel sparsity, angular-domain structure, or low-rank properties. More recently, research attention has shifted toward multi-IRS systems, where multiple passive surfaces cooperate to enhance passive beamforming gains and coverage. While multi-IRS deployments enable higher-order reflection diversity and increased array gains, they also significantly complicate channel estimation due to the emergence of inter-IRS channels and multi-hop cascaded links. Existing works mainly rely on exploiting common BS–IRS channels, geometric line-of-sight (LoS) dominance, or intrinsic relationships between single- and double-reflection links to keep the training overhead manageable. Nevertheless, scalable and generalizable channel estimation solutions for systems involving more than two cooperating IRSs remain largely unexplored. Another important research direction concerns the extension from narrowband to broadband (OFDM-based) IRS-aided systems, where frequency-selective fading and multipath propagation substantially increase the number of channel parameters to be estimated. In such systems, the convolutional structure of cascaded channels in the time domain, together with the frequency-flat nature of IRS reflection coefficients across subcarriers, introduces additional challenges. To address these issues, recent works leverage structured pilot designs, common sparsity across subcarriers, and joint delay–angle domain representations to reduce training latency and computational complexity.

Finally, learning-based channel estimation has emerged as a promising paradigm, particularly for large-scale MIMO, mmWave/THz communications, and highly dynamic environments where accurate analytical channel models are difficult to obtain. By learning nonlinear mappings directly from pilot observations to CSI, data-driven approaches offer improved robustness to model mismatch and hardware impairments, albeit at the cost of increased data requirements and training complexity. Deep learning techniques, including convolutional neural networks (CNNs), denoising neural networks, and federated learning, are capable of approximating complex nonlinear mappings between pilot observations and channel state information (CSI) without relying on explicit analytical channel models. While learning-based approaches have demonstrated superior estimation accuracy and enhanced robustness in challenging propagation environments, their effectiveness critically depends on the availability and diversity of training data, generalization capability across deployment scenarios, and the associated training and communication overheads. These factors remain key obstacles to large-scale and real-time practical deployment. Overall, the evolution of IRS channel estimation-from single-IRS to multi-IRS architectures, from narrowband to broadband transmission, and from model-driven to data-driven methodologies reflects a clear trend toward increasingly realistic yet significantly more complex IRS-aided wireless systems. In this context, the development of scalable, low-overhead, and robust channel estimation frameworks that effectively integrate model-based physical insights with the adaptability of learning-based techniques constitutes a critical and promising research direction for future IRS-assisted wireless communications.

3. IMPACT OF PRACTICAL IRS HARDWARE IMPAIRMENTS ON CHANNEL ESTIMATION

Early studies on intelligent reflecting surface (IRS)-assisted wireless communications typically assume idealized IRS hardware models and transceiver chains in order to simplify the channel estimation problem. However, in practical deployment scenarios, IRS hardware architectures are subject to various non-idealities and physical constraints, such as finite phase resolution, amplitude attenuation, hardware noise, and nonlinearities in the control circuitry. These impairments can lead to noticeable performance degradation in IRS-aWC systems if they are not properly accounted for. Recognizing the gap between idealized models and practical implementations, recent research efforts have increasingly focused on developing IRS channel estimation methods and passive beamforming designs that explicitly incorporate hardware imperfections. By accounting for realistic IRS hardware constraints, these approaches aim to improve the robustness, reliability, and practical applicability of IRS-aWC systems, especially in large-scale deployments and dynamic wireless environments.

3.1 Impact of discrete phase and amplitude control on IRS channel estimation

Ideal IRS reflection models, in which each reflecting element can continuously control both phase shift and amplitude, have proven useful in theoretical studies for optimizing passive beamforming and characterizing the fundamental performance limits of IRS-assisted systems. However, in practical deployments, realizing high-resolution phase shifters or amplitude controllers is highly challenging due to the high hardware cost, increased power consumption, and the complexity of circuit design and control. As a result, a more practical approach is to design IRS hardware architectures with a finite number of control bits per reflecting element, so as to achieve a reasonable trade-off between system performance and implementation cost. In this context, IRS models with discrete phase control (e.g., two-level phase shifts of 0 or π) and/or discrete amplitude control (e.g., reflecting versus absorbing states) have attracted considerable research interest. Although the number of available control levels is limited, such IRS architectures can still provide substantial performance gains when appropriately designed and exploited. In the following, we summarize and analyze representative studies addressing IRS channel estimation and passive beamforming design under discrete hardware constraints, highlighting the proposed signal processing techniques as well as the associated performance–complexity trade-offs.

Suppose that the numbers of quantization bits for controlling the reflection amplitude and phase are $N_\beta = 2^{d_\beta}$ and $N_\theta = 2^{d_\theta}$, respectively. Accordingly, the sets of discrete reflection amplitude and phase values at each IRS element can be expressed as in (21) and (22), respectively,

$$\bar{R}_\beta = \left\{\beta_1, \beta_2 ..., \bar{\beta}_{N_\beta}\right\}, \qquad (21),$$

$$\bar{R}_\theta = \{\theta_1, \theta_2 ..., \bar{\theta}_{N_\theta}\} \quad (22)$$

Compared with ideal reflection models featuring continuous valued amplitude and phase control, the estimation of quantized reflection parameters in (21) and (22) becomes considerably more challenging. This is because the corresponding channel estimation problem is no longer a continuous linear estimation task, but instead turns into a discrete estimation problem, in which the IRS reflection parameters are constrained to a finite set of quantization levels. Such discrete constraints significantly increase the algorithmic complexity of channel estimation and may also lead to noticeable performance degradation if conventional signal processing methods are not properly adapted to account for practical hardware limitations.

In,[33,39] the problem of cascaded channel estimation in IRS-aWC systems was investigated under discrete phase-shift constraints at the IRS. Specifically, the authors constructed nearly orthogonal training reflection matrices based on DFT and Hadamard matrices, combined with appropriate quantization strategies to mitigate the channel estimation errors induced by limited phase resolution. The results demonstrate that, although discrete phase constraints inevitably degrade performance compared with ideal continuous-phase models, properly designed training reflection matrices can still achieve acceptable channel estimation accuracy. This line of work was further extended in,[91] where a block coordinate descent (BCD) based optimization framework was proposed to iteratively refine individual elements of the training reflection matrix, initialized from a DFT-Hadamard structure. This approach enables further reduction of estimation error while maintaining practical feasibility for IRS architectures with finite phase resolution. In addition to discrete phase control, two-level (on-off) amplitude control models have also been investigated for IRS channel estimation in .[13,24] In these works, IRS elements operate only in two states reflection or absorption which significantly simplifies hardware implementation and training signal design. However, since only a subset of IRS elements is activated during each training interval, the effective reflected power is substantially reduced compared with always-on IRS schemes, resulting in a clear trade-off between channel estimation accuracy and overall reflection efficiency.

3.2 Impact of phase-amplitude coupling on IRS channel estimation

Most existing studies on intelligent reflecting surfaces (IRSs) commonly assume that the reflection amplitude and phase shift of each IRS element can be controlled independently, which significantly simplifies channel modeling, pilot signal design, and passive beamforming optimization. However, recent experimental studies reported in,[92-93] have demonstrated that this assumption does not hold for practical IRS hardware architectures. In real implementations, the reflection amplitude of each IRS element is inherently dependent on the applied phase shift, due to the physical characteristics of the underlying tunable components and control circuits.

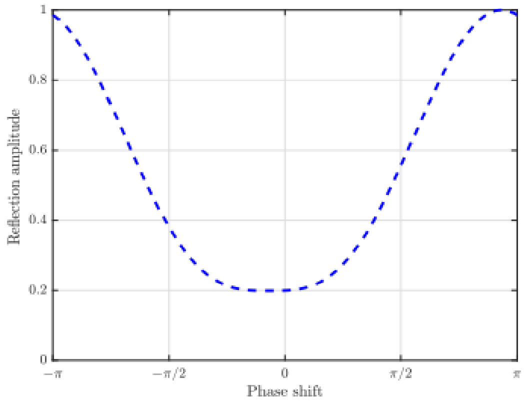

Figure 7. Reflection amplitude versus phase shift for the practical IRS reflecting element.[92]

Specifically, as illustrated in Fig. 7 of the reflection amplitude typically attains its minimum value when the phase shift is zero, and then increases monotonically, asymptotically approaching its maximum value of one as the phase shift approaches −π or π. This phase amplitude dependence fundamentally breaks the ideal linear reflection model, rendering the cascaded User-IRS-BS channel a nonlinear function of the IRS control parameters. Consequently, channel estimation methods developed under the assumption of independent phase and amplitude control are no longer applicable, or can only achieve limited performance in practical scenarios. The presence of a strong nonlinear coupling between the reflection phase and amplitude significantly complicates the IRS channel estimation problem, as the feasible control parameter space becomes highly constrained and nonconvex. To address this challenge, the authors in,[91] proposed customized IRS training reflection patterns, in which the reflection coefficients are directly optimized under the phase-amplitude coupling constraint using a block coordinate descent (BCD) method. Simulation results demonstrate that this approach achieves substantially improved channel estimation performance compared to conventional training designs that assume independent phase and amplitude control.

Although BCD based optimization methods have demonstrated a certain level of effectiveness, they typically rely on accurate hardware modeling, incur high computational complexity, and suffer from limited convergence scalability in large-scale IRS configurations. These limitations have motivated a promising research direction that leverages deep learning techniques to directly handle the inherent nonlinearities and complex hardware constraints, such as phase quantization, discrete amplitude control, and phase-amplitude coupling. By learning the mapping from received training signals to the CSI or to optimal reflection parameters without requiring explicit channel or hardware modeling, deep learning-based approaches are expected to provide enhanced robustness against hardware impairments, while simultaneously reducing the design complexity and implementation burden of practical IRS-WC systems.

3.3. Impact of mutual coupling among reflecting elements on IRS channel estimation

When the spacing between adjacent IRS reflecting elements is smaller than the signal wavelength, the phenomenon of mutual coupling becomes inevitable. In this case, the effective impedance of each reflecting element is no longer independent but is influenced by the impedances of its neighboring elements, resulting in complex coupled reflection coefficients across the IRS array.[94-95] This behavior stands in sharp contrast to ideal IRS hardware models, which typically assume independent reflection control for each element, and consequently renders the IRS channel estimation problem significantly more challenging. For IRS-assisted systems affected by mutual coupling, a fundamental challenge in channel estimation lies in accurately identifying the channel components associated with individual reflecting elements, given that their electromagnetic responses are no longer independent. In the existing literature, IRS channel estimation under mutual coupling effects has not yet been systematically investigated, particularly for large-scale IRS deployments. A practical and tractable approach is to group adjacent IRS elements among which mutual coupling is typically strong into multiple sub-surfaces.[13-14] Under this architecture, the mutual coupling within each sub-surface is absorbed into an equivalent composite reflection model, while the coupling between different sub-surfaces is assumed to be weak or negligible. As a result, the channel estimation problem is shifted from the element level to the sub-surface level, substantially reducing model complexity, mitigating the adverse effects of mutual coupling, and lowering training overhead, while still maintaining acceptable channel estimation performance.

However, for the sub-surface grouping strategy to be truly effective, further in-depth investigations are required to gain a comprehensive understanding of the underlying mutual coupling mechanisms among reflecting elements, as well as to determine optimal grouping strategies that account for the IRS geometry, inter-element spacing, and electromagnetic characteristics. The key objective is to mitigate or suppress the detrimental effects of mutual coupling while preserving high channel estimation accuracy and passive beamforming performance. This remains an open and challenging problem, particularly for large-scale and wideband IRS systems, calling for more accurate modeling approaches and robust, scalable channel estimation techniques in future research.

3.4 Impact of low-resolution ADCs and RF impairments on IRS channel estimation performance

Similar to conventional wireless communication systems without IRS, various hardware impairments persist in IRS-aWC systems, including distortions originating from the transmitter, the receiver, and the IRS itself. These impairments can lead to unstable system performance and a significant degradation in channel estimation accuracy. Common sources of hardware impairments include IRS phase noise,[96-98] transmitter/receiver RF impairments,[99-104] quantization errors caused by low-resolution analog-to-digital converters (ADCs),[105,106-109] power amplifier nonlinearities,[110] as well as other non-ideal hardware effects. In particular, IRS phase noise, which arises from discrete phase control and/or intrinsic imperfections of the hardware circuitry, has been modeled in the literature mainly from two perspectives. First, phase noise can be treated as independent and identically distributed random noise, uniformly distributed across IRS reflecting elements.[96] Second, more sophisticated models assume Gaussian-distributed phase noise, where the noise power increases with the distance from the center of the IRS, taking into account calibration effects and hardware non-uniformities among reflecting elements.[97] These models more accurately capture the non-ideal characteristics of large-scale IRS deployments in practical systems.

The aggregated effects of RF impairments at the transmitter and receiver, including oscillator phase noise, I/Q imbalance, automatic gain control (AGC) noise, and amplifier nonlinearities, are commonly characterized using the extended error vector magnitude (EVM) model.[113,114] In this framework, hardware impairments are modeled as zero-mean Gaussian noise whose variance is proportional to the power of the undistorted transmitted or received signal.[111] The EVM-based model provides a unified approach to evaluating the impact of multiple hardware impairment sources on system performance and channel state information (CSI) estimation accuracy.[115-116] Given that hardware impairments are inevitable in practical systems, IRS channel estimation methods that explicitly account for hardware degradations have attracted significant research interest in recent years. Representative works have focused on the development of robust channel estimation algorithms, adaptive training strategies, and hardware impairment compensation techniques at the transmitter, receiver, and IRS, as presented and discussed in.[96,98-110,112] These studies play a crucial role in enhancing the feasibility and performance of IRS-aWC systems in practical deployment scenarios. In,[99-100] the authors proposed cascaded channel estimation schemes based on the linear minimum mean square error (LMMSE) criterion for IRS-aWC systems under hardware impairments. Specifically, signal distortions at the transmitter and receiver are modeled as Gaussian random variables, while phase deviations at the IRS are characterized using circular distributions. This modeling framework enables a comprehensive analysis of the combined effects of hardware impairments on channel estimation accuracy.

Moreover, in IRS-aWC architectures particularly at massive MIMO base stations (BSs) or semi-passive IRSs equipped with sensing capabilities the use of high-resolution analog-to-digital converters (ADCs) throughout the entire receive chain is impractical due to the rapidly increasing hardware cost, power consumption, and circuit complexity as the number of antennas or sensing elements grows. Consequently, low-resolution ADCs (typically 1-3 bits) are widely regarded as a practical and energy-efficient solution.[117,118] To address the challenges induced by coarse quantization, several recent works have modeled low-resolution ADCs using the Bussgang decomposition,[119] whereby the quantized signal is approximated as a linearly attenuated version of the input signal plus an uncorrelated Gaussian noise term. Based on this model, channel estimation schemes that explicitly account for quantization noise have been developed and shown to significantly outperform approaches that ignore ADC effects. However, the accuracy of the Bussgang-based approximation degrades substantially in extreme low-resolution scenarios (e.g., 1-bit ADCs), thereby necessitating nonlinear estimation techniques or machine learning-based approaches. In,[106,107] the authors investigated IRS-assisted receivers employing low-resolution ADCs and proposed efficient cascaded channel estimation schemes that explicitly incorporate quantization errors during signal acquisition. The results demonstrate that, with appropriately designed algorithms, acceptable channel estimation performance can still be achieved even when using severely resolution-constrained hardware.

To better reflect practical deployment conditions, recent studies on channel estimation for IRS-aWC have increasingly taken into account various hardware impairments and constraints at the IRS as well as at the transmitter and receiver. These non-idealities not only invalidate the idealized channel models commonly assumed in early works, but also have a direct impact on the design of training signals, the structure of the IRS reflection matrix, and the performance of channel estimation algorithms. In practice, hardware-induced degradations may originate from multiple components of the system, including phase and/or amplitude quantization at the IRS, the intrinsic coupling between reflection amplitude and phase shift, mutual coupling effects among adjacent reflecting elements, as well as RF impairments at the transmitter and receiver.

When low-resolution ADCs and RF impairments coexist, their impact on IRS channel estimation is inherently non-additive and may mutually reinforce each other, leading to a compounded degradation in estimation performance. This interplay makes the design of practical IRS channel estimators particularly challenging. Promising research directions to address this issue include: (i) the joint design of pilot sequences, IRS training reflection patterns, and channel estimators that explicitly account for both low-resolution ADCs and RF impairments; (ii) the development of nonlinear estimators as well as deep learning–based and hybrid model-driven learning algorithms capable of directly learning hardware-induced distortions from training data; and (iii) the exploitation of inherent channel structures, such as sparsity, low-rank characteristics, and spatial correlation in IRS channels, to compensate for the loss of observation quality caused by non-ideal hardware.

Finally, to systematize existing research results and clarify the relationship between different sources of hardware impairments and their effects on IRS channel estimation, Table 5 provides a comprehensive classification of typical hardware non-idealities in IRS-aided wireless communication systems along with their corresponding impacts on channel estimation performance.

Table 5. Typical hardware impairments in IRS-aWC systems and their impact on channel estimation.

Hardware impairment source	**Location**	**Main impact on IRS channel estimation**
Discrete phase control	IRS elements	Reduces the orthogonality of IRS training reflection matrices; increases cascaded CSI estimation error, especially with low phase resolution
On-off or discrete amplitude control	IRS elements	Degrades effective reflection power; reduces received SNR; slows down the convergence of channel estimators
Phase-dependent reflection amplitude	IRS elements	Violates the independent phase–amplitude control assumption; distorts the linear channel model, leading to systematic CSI estimation errors
Mutual coupling among IRS elements	Dense IRS deployments	Causes interdependence among reflection coefficients; prevents element-wise independent channel estimation; significantly increases training overhead
Low-resolution ADCs	BS or semi-passive IRS	Introduces non-Gaussian quantization noise; degrades LS/LMMSE estimators; leads to performance saturation at high SNR
RF impairments at transmitter/receiver	BS/User	Generates signal-dependent distortion noise; reduces CSI accuracy and increases estimation error variance
Oscillator phase noise	BS/User/IRS	Causes time-varying phase drift in CSI; degrades CSI reuse efficiency and breaks channel reciprocity
IRS calibration errors	IRS	Induces spatially non-uniform estimation errors; severely affects large-scale IRS deployments
Power amplifier nonlinearity	BS/User	Distorts pilot signals; introduces bias in CSI used for estimation and learning-based algorithms
AGC noise and synchronization errors	BS/User	Causes instability in pilot signal amplitudes; degrades CSI estimation performance in multi-user systems

Although initial progress has been made, the joint impact and mutual interactions among multiple types of hardware impairments, such as IRS phase noise, transmitter/receiver RF distortions, quantization errors, and power amplifier nonlinearities, have not yet been comprehensively modeled and analyzed in the existing literature on IRS channel estimation. As a result, the development of unified hardware impairment models, together with robust channel estimation techniques and model-mismatch-resilient algorithms, remains an important and open research direction for future IRS-aided wireless communication systems.

4. CONCLUSION AND FUTURE RESEARCH DIRECTIONS

This paper has presented a comprehensive and up-to-date survey of IRS-aWC systems, with a particular focus on the key practical challenges hindering their real-world deployment, namely IRS channel acquisition/estimation and hardware-related constraints and impairments. We first reviewed representative IRS channel models and systematically examined state-of-the-art channel estimation techniques under different IRS architectures and system configurations, including fully passive and semi-passive IRS designs, single and multi-User scenarios, narrowband and wideband transmissions, as well as systems with single and multiple cooperating IRSs. The main signal processing paradigms employed for IRS channel estimation-ranging from classical LS/LMMSE approaches to compressed sensing, matrix/tensor factorization, and learning-based methods were discussed and comparatively analyzed.

Furthermore, this survey explicitly addressed the impact of practical hardware constraints and impairments at both the IRS and wireless transceivers, such as discrete phase and amplitude quantization, phase-dependent reflection amplitudes, mutual coupling among IRS elements, RF impairments, phase noise, and low-resolution data converters. Their effects on channel estimation accuracy, training overhead, and overall system performance were critically discussed, highlighting the gap between idealized theoretical models and practical IRS implementations. By consolidating fragmented research results into a unified and structured framework, this survey aims to serve as a timely and valuable reference for researchers and practitioners working on IRS-aWC technologies. We hope that the insights, comparative discussions, and identified open research directions provided in this paper will facilitate the design of practical, scalable, and robust IRS channel estimation schemes, and ultimately accelerate the integration of IRS into future wireless systems beyond 5G and toward 6G.

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