Intelligent Reflecting Surface (IRS) assisted mmWave Wireless Communication Systems: A Survey

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Abstract—Intelligent Reflecting Surface (IRS) is a promising technology for enhancing the coverage of millimeter wave (mmWave) based future wireless communication systems. Severe path loss and high directivity make mmWave transmission vulnerable to blockage. To overcome these issues, Intelligent Reflecting Surface (IRS) is introduced as a revolutionizing technology to provide better communication with the help of a virtual line-of-sight (LOS) link to bypass obstacles between transceivers through intelligent reflections. Significant performance improvement is achieved by smartly reconfiguring the wireless propagation environment using low-cost passive reflecting elements integrated on a planar surface. In this paper, we provide a survey of the IRS technology, its applications in mmWave wireless communication scenario, advantages over existing technologies, key design challenges, hardware architecture and the practical constraints while deployment. Furthermore, we highlight the relevant directions in future work.

Index Terms—IRS assisted mmWave systems, mmWave wireless communication, IRS hardware architecture, IRS reflection optimization, IRS channel estimation, passive beamforming, IRS deployment

1. INTRODUCTION

Future beyond-5G wireless communication systems aim at ultra-high data rate, very high reliability, increased energy efficiency, better coverage and low latency. However, these requirements are not completely achieved with the existing key technologies such as massive Multiple-Input Multiple-Output (MIMO), millimeter wave (mmWave) communication and Ultra-Dense Networks (UDN) [1]. Nevertheless, the increased hardware complexity and cost as well as boosted energy consumption are yet significant issues that remain unsolved. Future cellular networks have the potential to offer very high data rate of the order of gigabits-per-second by utilizing the large bandwidth available at mmWave frequencies [2], [3].

For the past several years, there has been increasing importance in developing unique communication models in which the inevitable random characteristics of the environment are utilized to simplify the transceiver design and improve the Quality of Service (QoS). One such example is spatial modulation [4]-[7]. Spatial modulation maps information bits onto transmit antenna indices by exploiting different fading realizations of Multiple-Input Multiple-Output (MIMO) antennas. An extension to this is spatial scattering modulation [8] and beam index modulation [9] in which the indices of the scatterers available in the environment are employed to convey information. In addition, research works are also done to develop media-based modulation (MBM) in which reconfigurable antennas [10], [11] are used to encode the data over multiple distinguishable radiation patterns [12]. Recently, with the development of Intelligent Reflecting Surfaces (IRS) [13]-[15], and the emergence of the smart radio environment concept, we might be able to control the wireless channel itself.

In a wireless communication scenario, the idea of controlling the ambient environment to provide more promising propagation aspects will create a paradigm shift in system design. Reflection and scattering in the environment are generally modelled in a stochastic fashion in any communication system. But, instead of considering them as uncontrollable phenomena, they are treated as system parameters. Optimizing these parameters helps to overcome many challenges of wireless communication systems. In general, the number of spatial streams and the modulation order limit the practically achievable rate over a wireless link. The modulation order is adjusted based on the signal strength observed at the receiver, resulting from the channel gain. In order to reduce the error rate and avoid re-transmissions, a user present at the cell edge may be forced to use lower order modulation, resulting in lower achievable rates. At the same time, based on the number of available eigenmodes of the channel, the number of spatial streams is adapted. The channel gain of a direct link may have a comparatively high channel gain. Still, it will experience a spatially-sparse low-rank channel, resulting in a limited number of spatial streams and consequently a less achievable rate. These situations may occur in any wireless environment, but future communication systems such as millimeter wave systems (30 GHz - 300 GHz) are expected to be significantly affected. Intelligent reflecting surfaces can help modify the channel realization in these scenarios and remarkably enhance the system's overall performance.

A vast spectrum band is available at the millimeter-wave range (30-300 GHz), but particularly for outdoor cellular communications, these frequencies experience performance degradation. The combination of millimeter-wave bands with high gain directional antenna arrays [16]
have pointed to significant potential, and this has led to enormous interest in millimeter wave wireless communications. Millimeter-wave communication experiences a lot of challenges. Compared to the sub 6 GHz frequencies, mmWave spectrum is more hostile. Scattering and first-order reflections become much more prevailing. The shadowing effect will severely impair average received power. Several adaptive beam steering techniques are developed to improve the fidelity of mmWave links. Still, communications at these frequencies are very much challenging. Spatial sparsity is yet another challenge experienced by mmWave channels. This is because of the lesser number of propagation paths that exist between the transmitter and the receiver. Sparse nature of mmWave channels may be utilized for channel estimation and precoding, particularly for hybrid architectures [17]. At the same time, it limits the number of spatial data streams through the channel, thereby limiting its spatial multiplexing capability.

Intelligent Reflecting Surfaces (IRS) can be utilized to overcome the above-mentioned challenges. If the average received power is significantly less, IRS can operate as a centralized beamformer to increase the channel gains. It also helps to build a propagation path around obstacles to rebuild an outage link. IRS can emulate a robust scattering environment to improve the channel condition number and spatial multiplexing capacity. One fundamental technology to implement IRS is by using dynamic reflect arrays [18]. The elements of reflect arrays are omnidirectional antennas whose termination is controlled to backscatter and phase shift the incident waveform. An extended version of this is by using a dynamically tunable meta surface [19]. A two-dimensional planar form of metamaterials will hold excellent EM wave manipulation abilities. In addition to the scattering abilities, the IRS elements can provide phase-shift to the incident signals and also act as a strange mirror. It can control the reflection angles and can manipulate the polarization. Since IRS elements have more wave manipulation abilities, their optimization grows to be more complex.

In this article, we provide a comprehensive survey on Intelligent Reflecting Surfaces for mmWave wireless communication scenarios. Initially, we discuss Intelligent Reflecting Surfaces and their prospects for future wireless networks. We then discuss the channel model and optimization of various IRS parameters to improve system performance. We also discuss channel estimation and passive beamforming techniques. Finally, we highlight the potential opportunities and challenges.

The rest of this article is organized as follows. In Section II, we introduce the basic principles and concept behind intelligent reflecting surfaces, hardware architecture and channel model. In Section III, we discuss various IRS channel estimation techniques. In Section IV, we explain the different signal processing methods for channel estimation. In Section V, we present the optimization techniques for active-passive beamforming and precoder design in IRS systems. The IRS deployment aspects are discussed in Section VI. Finally, we identify some future research directions and challenges in Section VII and conclude the article in Section VIII.

II. INTELLIGENT REFLECTING SURFACES (IRS)

IRS is a recently developing unique hardware technology that is used to increase signal coverage, lessen energy consumption and reduce implementation costs [20], [21]. IRS consists of many small, passive and low-cost reflecting elements. They only reflect the incident signal with an adjustable phase shift and doesn't require a dedicated energy source for further processing and retransmission. Because of these advantages, IRS has now been included in recent wireless communication systems [22]-[24]. Fig. 1 shows the basic principle of IRS for signal coverage extension. IRS is a two-dimensional planar surface of electromagnetic material called metasurface. They have a specially designed physical structure. In a software-defined manner, we can control the reflection in each scattering element. In particular, the phase shift and amplitude of the RF signals incident upon the scattering elements are changed independently. By doing joint phase control of all scattering elements, we shall create a desirable multi-path effect. The reflected RF signals are either added coherently to improve the received signal power or combined destructively to reduce interference. IRS can be deployed by coating on walls of buildings or as dedicated stand-alone units depending on the nature of the environment. IRS can turn the radio environment into an intelligent space to support wireless communications.

![Fig. 1. Basic principle of IRS](Image 310x224 to 534x386)

IRS is used to improve the received signal power by beamforming and modifying the channel rank and the condition number to achieve spatial multiplexing. In short, IRS is a passive reflective surface that can be reconfigured dynamically to manipulate incident electromagnetic waves. An IRS does not emit any power of its own and is meant to manipulate incident waves only. The concept of IRS is similar to backscatter technology, and the reflections are purely passive. Thus, IRS is emerging as a promising technology to attain an intelligent and reconfigurable wireless propagation environment beyond 5G and 6G wireless communication systems.
With the help of the IRS, we can create a virtual line-of-sight (LoS) link to bypass obstacles between transceivers. This is done by intelligent reflections and by adding additional signal paths in the intended direction. The channel rank condition is thus improved, and the channel distribution is also modified. i.e., a Rayleigh-fast fading channel is transformed to a Rician-slow fading channel. This increases the reliability and mitigates the co-channel and inter-cell interference. In some cases, low-cost printed dipoles are used as reflecting elements, and they only passively reflect the incident radio signals. One of the advantages is that no transmit radiofrequency (RF) chains are required, resulting in a much-reduced hardware and energy cost compared to the conventional active antenna array systems and the active surface models [25].

IRS poses several advantages over conventional active relays, which suffer from low spectral efficiency in the case of half-duplex (HD) mode and require advanced technologies for self-interference cancellation in the case of full-duplex (FD) mode. IRS, which operates in the FD mode, is free of self-interference and antenna noise amplifications. IRS is commonly lightweight and can be easily fixed on or detached from environment surroundings for installation or replacement. The main advantage is that IRS provides adaptability and compatibility with existing wireless communication systems. Hence IRS is best suited for deployment in wireless communication scenarios to improve spectral efficiency and energy efficiency without additional cost overhead.

A. IRS Hardware Architecture

IRS is realized using metasurfaces [26]. The metasurfaces are made of synthetic materials with special electromagnetic properties. It is a two-dimensional reconfigurable sheet of metamaterials. In the embryonic stages, they were employed in optical applications to replace custom-built lenses. The metasurface consists of many closely spaced resonating fabrications called meta-atoms [26]. The dimensions of meta-atoms and the spacing between adjacent meta-atoms are very much smaller than the wavelength of transmission. The controlling of incident waves thus gains much higher degrees of freedom. The metasurface can provide quasi-continuous amplitude/phase profiles [27] on the incident wave by carefully designing the meta-atoms, thereby controlling the scattered electric field.

IRS reflections are obtained in practical scenarios by leveraging the digitally programmable and reconfigurable metasurfaces [28]. By properly designing the shape, dimensions, orientation, and arrangement, each element’s reflection amplitude or phase shift is realized. Real-time tuning of IRS is done if the channel is time-varying due to the mobility of surrounding objects, transmitter, receiver, or both. Hence dynamically adjustable reflection coefficients are an important requirement during the manufacturing of IRS.

One typical architecture of IRS is illustrated in fig. 2. The architecture consists of three layers and an IRS controller. The first layer contains a large number of metallic patches imprinted on a dielectric substrate. These metallic patches are tunable or reconfigurable and can manipulate incident signals. A copper plate is used as the second layer, which helps to reduce the signal energy leakage during reflection. The third layer is a control circuit board that triggers the reflecting elements by tuning their reflection amplitudes and phase shifts. A field-programmable gate array (FPGA) implemented IRS smart controller is used to control the reflections. The IRS controller also communicates with base stations and user devices through wired or wireless backhaul links. In some practical scenarios, dedicated sensors can also be kept interlaced with the reflecting elements in the first layer to sense the channel and surrounding signals.

Three different methods are available in literature to control the reflections, thereby reconfiguring the IRS elements. The first approach is by mechanical actuation using mechanical rotation and translation, and the second method uses materials like liquid crystals and graphene. The third approach is with electronic devices like positive-intrinsic-negative (PIN) diodes, field-effect transistors (FETs), and micro-electromechanical system (MEMS) switches [29]. The third approach is widely employed in most practical scenarios because of the lesser response time, faster switching, small reflection losses, low energy consumption, and reduced hardware cost. A typical reflecting element using a PIN diode is shown in Fig. 3. Through the direct-current (DC) feeding line, the various biasing voltages are fed to the PIN diode. The PIN diode can be switched between “ON” or “OFF” states by applying proper bias, thereby introducing the phase shift to the incident wave.

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The PIN diode's switching frequency is a few microseconds (μs) [30], which is very much smaller than the practically experienced coherence time in mobile communication scenarios that is on the order of a few milliseconds. Reflection amplitude of the elements is also controlled in addition to the phase shifts, which provides a reduced hardware cost since the implementation cost of amplitude control is generally less than phase control (also called phase beamforming). Multiple methods are proposed in literature to control the reflection amplitude, and one of the methods is by adjusting the load impedance in each reflecting element [31]. In this method, the energy of the incident signal is dissipated as heat by varying the resistance of each reflecting element, thereby achieving the desired reflection amplitude, which is in the range [0, 1]. However, to obtain the optimized reflection design, we must control both amplitude and phase shifts independently. The reflection coefficient $R$ of the element is defined given by (1), where $\beta \in [0, 1]$, $\theta \in [0, 2\pi]$ and $|R| \leq 1$.

$$ R = \beta e^{j\theta} \quad (1) $$

The phase shifts and reflection amplitudes mentioned in (1) can ideally have continuous range of values as shown below:

$$ R_\theta = \{\theta : \theta \in [0, 2\pi]\} \quad (2) $$

$$ R_\beta = \{\beta : \beta \in [0, 1]\} \quad (3) $$

But practically, continuous range of amplitude and phase values leads to many challenges. Hence two fundamental reflection models in practical IRS aided communication systems are as follows:

Discrete Reflection Model: Practical implementation of high-resolution reflecting elements requires complex hardware design, which in turn increases the cost. As the number of phase shift levels increases, the number of PIN diodes required for implementation also increases. This turns out to be challenging since the size and number of pins at the IRS controller are limited. Hence, it is desirable to implement only discrete and finite amplitude and phase shift levels, requiring fewer control bits per element. A two-level amplitude and phase control is explained in [22]. In general, if the number of bits required for controlling the phase shifts, $N_\theta$, the number of discrete amplitude levels equals $N_\beta = 2^{d_\beta}$. Similarly, if $d_\theta$ is the number of bits required for controlling the phase shifts, then the number of discrete phase shifts will be $N_\theta = 2^{d_\theta}$.

The discrete sets of phase shifts and reflection amplitudes is now expressed as:

$$ \tilde{R}_\theta = \{\theta_1, \theta_2, \ldots, \theta_N_\theta\} \quad (4) $$

$$ \tilde{R}_\beta = \{\beta_1, \beta_2, \ldots, \beta_N_\beta\} \quad (5) $$

In some cases, either discrete phase shift control or discrete amplitude control alone are implemented to reduce hardware complexity and cost. In general, phase beamforming is more expensive compared to amplitude control.

Coupled Reflection Model: Due to the challenges involved while implementing independent control, a coupled reflection model was proposed in [32]. Each reflecting element is modeled as a resonant circuit with specific resistance, inductance and capacitance. In this model, the amplitude and phase are non-linearly coupled, and hence both are dependent. If the phase shift is zero, the reflection amplitude reaches its minimum value, and this is because of the in-phase nature of the element currents and reflective currents. Correspondingly, the energy dissipation will be maximum, resulting in a lesser value of reflection amplitude [33]. Reflection coefficients are optimally coupled to maximize the signal-to-noise ratio (SNR) at the receiver.

The functioning of the IRS controller and reflecting elements will consume power in practical scenarios. Hence, even though the theoretical models of IRS seem to be passive, practical IRS will consume energy. The PIN diodes associated with the reflecting elements also drain power when it is switched ON. But compared to the array of high power-consuming active antennas used in mmWave massive MIMO systems, these passive IRS reflectors will consume very little power.

B. IRS-enhanced Signal and Channel Model

In this section, we discuss the channel model in IRS-assisted mmWave wireless communication systems. The implementation method (reflectarrays or metasurfaces) determines the modelling technique to be adopted. Consider an IRS consisting of $N$ passive reflecting elements on a two-dimensional plane. For ease of discussion, we initially assume a narrowband system with a single antenna at both the transmitter and the receiver. Wideband multiple antenna systems will be discussed later in this paper.

Let $x_b(t)$ denote the complex baseband transmitted signal and $a_k e^{-j\phi_k}$ be the baseband channel coefficient between transmitter and the $k^{th}$ reflecting element, where $k \in \{1, 2, \ldots, N\}$. The received passband signal $\hat{y}_k(t)$ at the $k^{th}$ element is given as follows:

$$ \hat{y}_k(t) = \text{Re} \{a_k e^{-j\phi_k} x_b(t) e^{j2\pi f_c t}\} \quad (6) $$

Let $\beta_k$ denote the reflection amplitude in the $k$th element and $t_k$ be the time delay introduced to the incident signal, then the reflected signal from the IRS element, $y_k(t)$ is given as:

$$ y_k(t) = \beta_k \hat{y}_k(t - t_k) \quad (7) $$

$$ = \text{Re} \{\beta_k a_k e^{-j\phi_k} x_b(t - t_k) e^{j2\pi f_c (t - t_k)}\} \quad (8) $$

Considering the narrowband assumption, this can be approximated as:

$$ y_k(t) \approx \text{Re} \{[\beta_k e^{-j\phi_k} a_k e^{-j\phi_k} x_b(t)] e^{j2\pi f_c t}\} \quad (9) $$
where $\theta_k$ is the phase shift introduced by the $k^{th}$ reflecting element. Thus,
\[ y_k(t) = \text{Re} \left( \beta_k e^{-j\theta_k} x_k^H(t) e^{j2\pi f_ct} \right) \quad (10) \]
where $x_k^H(t) = \alpha_k e^{-j\theta_k} x_k(t)$ is the equivalent baseband signal of $y_k(t)$. Eq. (10) can be re-written as
\[ y_k(t) = \text{Re} \left( \alpha_k^e e^{-j\theta_k^e} x_k(t) e^{j2\pi f_ct} \right) \quad (11) \]
where $x_k^e(t) = \beta_k e^{-j\theta_k^e} x_k^H(t)$ is the baseband equivalent of $y_k(t)$. From the $k^{th}$ reflecting element to the user device, the IRS reflected signal will experience a similar narrowband flat fading and the baseband channel coefficient is given by $\alpha_k e^{-j\theta_k^e}$. The received passband signal at the user device via the IRS, $y_k^u(t)$ is thus given as:
\[ y_k^u(t) = \text{Re} \left( \alpha_k^e e^{-j\theta_k^e} x_k(t) e^{j2\pi f_ct} \right) \quad (12) \]
The channel coefficients in the cascaded channel model in Eq. (12) can be written as $f_k^u = \alpha_k^e e^{-j\theta_k^e}$ and $g_k = \alpha_k e^{-j\theta_k^e}$, where $f_k^u$ corresponds to the channel coefficients between transmitter and $k^{th}$ reflecting element and $g_k$ represents the element-user device link. Eq. (12) can thus be re-written as
\[ y_k^u(t) = \text{Re} \left[ \left( f_k^u \beta_k e^{j\theta_k} g_k x_k(t) \right) e^{j2\pi f_ct} \right] \quad (13) \]
where, $y_k(t)$ is the baseband signal model from Eq. (13). The resultant baseband signal from all the $N$ reflecting elements (neglecting coupling effects) can thus be expressed as:
\[ y(t) = \left( \sum_{k=1}^{N} f_k^u \beta_k e^{j\theta_k} g_k x_k(t) \right) x_k(t) \quad (15) \]
\[ = f^H Q g x_k(t) \quad (16) \]
where $f^H = [f_1^u, f_2^u, \ldots, f_N^u]^T$, $g = [g_1, g_2, \ldots, g_N]^T$ and $Q = \text{diag}(\beta_1 e^{j\theta_1}, \beta_2 e^{j\theta_2}, \ldots, \beta_N e^{j\theta_N})$. $Q$ is called reflection matrix and is a complex diagonal matrix of size $N \times N$. Reflection matrix is diagonal since the elementwise reflections are independent and there is no coupling between IRS elements [34]. These channel coefficients depend on the pathloss, large-scale shadowing and small-scale fading effects. If there exists a direct channel between transmitter and the receiver, the received signal $y$ based on the reflection model in Eq. (16) can be written as
\[ y = (f^H Q g + h^u) \sqrt{P_t} x + n \quad (17) \]
where, $P_t$ is the transmitted power at the base station and $n$ denotes the additive white Gaussian noise (AWGN). Extending the above channel model to the MIMO case with $N_t$ transmit antennas, $N_r$ receive antennas and assuming a narrowband flat-fading environment, the received signal is expressed as
\[ y = (F^H Q G + H_d)x + n \quad (18) \]
where, $F \in \mathbb{C}^{N_r \times N}$, $G \in \mathbb{C}^{N_t \times N_r}$ and $H_d \in \mathbb{C}^{N_t \times N_r}$. Considering large-scale propagation gain $\sqrt{PG_d}$ and $\sqrt{PG_{IRS}}$ corresponding to $H_d$ and $H_{IRS}$ respectively, we have
\[ y = \left( \sqrt{PG_d} H_d + \sqrt{PG_{IRS}} H_{IRS} \right) x + n \quad (19) \]
where, $H_d$ represents the direct channel between transmitter and the receiver and $H_{IRS}$ represents the controlled channel through IRS. Thus, the effective channel $H$ can be written as:
\[ H = \left( \sqrt{G_d} H_d + \sqrt{G_{IRS}} H_{IRS} \right) \quad (20) \]

A major challenge in IRS channel modelling is accommodating the effect of large-scale propagation path loss. The channel modelling of reflectarrays is different from metasurface-based IRS. For reflectarrays, the elements are half-wavelength sized antennas, while for meta-surface, the element dimensions are much larger than the wavelength. If the object's physical size is much larger than the wavelength, then they tend to reflect the incident wave. Scattering will happen if the object dimension is comparable to the wavelength [35]. Assume that each IRS element is much larger in dimension than the wavelength. Using the parametric spatial model explained in [36], the channel through IRS can be expressed as:
\[ H_{IRS} = \sum_{i=1}^{L} a_i^d a_i^{IRS} a_g(\theta_i^T, \phi_i^T) a_r^T(\theta_i^r, \phi_i^r) \quad (21) \]
where $a_i^d$ and $a_i^{IRS}$ represents the path gain corresponding to $i^{th}$ direct path and $i^{th}$ IRS-assisted path. $a_g$ and $a_r$ denotes the array response vector at the receiver and transmitter respectively with azimuth angle $\theta$ and elevation angle $\phi$. The amplitude/phase parameter $a_i^{IRS}$ is controllable by IRS. Moreover, a meta-surface-based IRS can control the angles of arrival $\theta_i^T$ and $\phi_i^T$. Clustered spatial models explained in [37] can also be used for better accuracy. Here, $a_i^{IRS}$ is deterministic and depends on the IRS configuration while $a_i^d$ is stochastic in nature and is used to model the fading caused due to scattering. In reflectarray-based IRS, the element functions as a widely separated scatterer. Diffusion scattering happens for the incident wavefront, and thus, the power loss will be very high. Conversely, for metasurface-based IRS, each element performs as a reflector and functions based on a controllable reflection angle. Since there is no further wavefront spreading on the metasurface element, the reflection angle doesn't follow Snell's law, and the reflection is irregular and is referred to as anomalous reflection [38].

For metasurface based IRS, the path loss through a single reflecting element is inversely proportional to the total distance between the transmitter and the receiver $d_{ti} + d_{ir}$, where $d_{ti}$ is the distance between the transmitter and the IRS element and $d_{ir}$ is the distance between the IRS element and the receiver [35], [39]. This model is usually referred as sum-distance pathloss model.

\[ \text{Pathloss}_{\text{reflected}} \propto (d_{ti} + d_{ir})^{-n} \quad (22) \]

Here, $n$ denotes the path loss exponent (typically 2 for free space). For reflectarray-based IRS, the path loss is proportional to the product of the distances $d_{ti}$ and $d_{ir}$.

\[ \text{Pathloss}_{\text{scattered}} \propto (d_{ti} \times d_{ir})^{-n} \quad (23) \]
This model is referred as product-distance pathloss model. For further reading of the pathloss models, refer [40] and [41]. It is worth notable that, for Eq. (22) to be valid, the physical size of the IRS must be large compared to $d_{tx}$ and $d_{rx}$ so that the transmitter and the receiver are within the near-field of the IRS. The near-field of IRS extends up to $(2L^2/\lambda)m$ from its own position, where $L$ is the physical dimension of IRS and $\lambda$ is the wavelength. For example, an IRS with a physical dimension $2m \times 2m$, employing radio signals of frequency $30$ GHz, will have a near-field up to $800m$. If the transceivers here are located within $800m$, the path loss model can be very well approximated by Eq. (22).

III. IRS CHANNEL ESTIMATION

To improve the spectral and energy efficiency in IRS-assisted mmWave wireless communication systems, various joint active-passive beamforming methods are suggested in literature [23], [34], [42]-[46]. Active and passive beamforming are done at the base station and IRS units, respectively. A typical assumption in these reference works is the perfect knowledge of channel state estimation (CSI). But in practice, the channel has to be estimated, which is a challenging task due to the passive nature of IRS elements. Channel estimation in IRS-assisted wireless communication is challenging, primarily due to the lack of active RF components for signal processing. The IRS elements can only perform passive reflections of the incident signal. Another challenge is the large number of elements resulting from many reflective elements, leading to increased system overhead.

There are two prominent techniques for estimating the IRS channel. The first one is passive/fully-passive IRS channel estimation, in which only passive reflecting elements are involved in the estimation of the channel. The second method is semi-passive IRS channel estimation, where a few low-power sensors are interlaced with IRS reflecting elements. A low-cost, low-resolution analog to digital converter (ADC) is used to process the signals received at the sensors. A more detailed explanation regarding the two configurations is provided in the subsequent sub-sections.

A. Semi-passive IRS Channel Estimation

In semi-passive IRS channel estimation, low-power sensors are mounted between the reflecting elements. These sensing devices can estimate user(s)-IRS and base station-IRS channels separately based on the pilots transmitted. A fewer number of sensors and low-resolution ADCs are used to reduce the overhead. Constructing a large-dimension accurate channel from fewer sensing devices is a critical challenge. Efficient signal processing methods are available in literature by exploiting channel characteristics like low-rank, sparsity, and spatial correlation [36], [47]-[49]. Semi-passive IRS estimation is best suited for Time-Division Duplexing (TDD) schemes but is inappropriate for Frequency-Division Duplexing (FDD) systems. In TDD systems, reverse channel from the IRS to base station and users can be estimated by exploiting the channel reciprocity characteristics. Moreover, Alternation Optimization (AO) and deep learning methods are also proposed for semi-passive channel estimation [50]-[51].

Semi-passive IRS channel estimation is illustrated in Fig. 4. It operates under two modes: sensing and reflection modes. The sensors are activated to receive the pilot signals in the sensing mode while the reflecting elements will be deactivated (turned OFF). In the reflection mode, the sensors are deactivated, while the reflecting elements are activated to reflect the incident signals. The user devices and/or the base station will send the pilot signals during the channel sensing time slot. The channel is thus estimated based on the received signal at the sensing elements. Once the estimation is done, the CSI is sent to the IRS controller and the base station to design the active and passive beamforming coefficients jointly. This information is exchanged via dedicated backhaul links between the IRS controller and the base station. IRS then enters the reflection mode in which beamforming is done based on the received coefficients.

Using semi-passive estimation in TDD systems, the downlink channel from the base station and uplink channel from the user device can be estimated using pilot signals. The reverse channel may be computed by exploiting the channel reciprocity property. The base station – IRS channel is denoted as $\tilde{F}$ and user – IRS channel is denoted as $\tilde{G}$, where $\tilde{F} \in \mathbb{C}^N_x \times N_r$ and $\tilde{G} \in \mathbb{C}^{N_s} \times N_r$. Even though the channels $\tilde{F}$ and $\tilde{G}$ are not same as $\mathcal{F}$ and $\mathcal{G}$ respectively, they are highly correlated. Hence, we use several signal processing methods like data interpolation, compressed sensing and machine learning to recover high-dimension channels $\mathcal{F}$ and $\mathcal{G}$ from the low-dimension channels $\tilde{F}$ and $\tilde{G}$ respectively [50]-[51].

The advantages of using semi-passive IRS estimation are the moderate hardware implementation cost and the reduced power consumption, mainly because of the lesser number of sensing elements used. One of the main limitations of semi-passive IRS channel estimation is the limited estimation accuracy due to the fewer sensing
elements, and the lesser resolution of the ADCs used. It is worth noting that the channel coherence time of the user-IRS link is less than the coherence time of the base station-IRS channel. This is due to users’ mobility and more scattering components. Hence, user-IRS channel estimation is more challenging than base station-IRS link.

**B. Fully-passive IRS Channel Estimation**

In fully-passive IRS, no sensing devices are interlaced with IRS reflecting elements. Hence, it is impossible to get the individual channels between base station-IRS and user-IRS separately. But instead, a cascaded channel between base station-IRS-user is estimated for uplink and downlink communication. A fully-passive scheme is illustrated in Fig. 5. The fully-passive estimation can be used in FDD systems by providing feedback regarding the cascaded channel state information. In TDD systems, the cascaded channel is estimated in one direction (uplink/downlink), and by exploiting the channel reciprocity property, the CSI in the other direction can also be computed. Thus, a fully-passive scheme is best suited for both TDD and FDD systems. Since no active sensing devices are required in this method, the hardware complexity and energy consumption are much less than the semi-passive scheme. But, the dimension of the cascaded channel is large, and hence the training overhead required is much higher.

The total number of channel coefficients in the cascaded channel is $K \times N \times N_r \times N_r$. This is much higher compared to the semi-passive method in which the total number of coefficients is equal to $K \times (N \cdot N_r + N \cdot N_r)$. The users transmit orthogonal pilot signals to the base station. The base station receives both the direct channel coefficients and cascaded channel coefficients. The base station can estimate the cascaded channel coefficients since the IRS reflects the incident signals based on a predefined pattern. Once the channel is estimated, the optimum reflection coefficients are determined at the base station, and the same is transmitted to the IRS controller via the backhaul link. The challenging task is the collaborative design of pilot signals and reflection coefficients with minimum training overhead. In TDD systems, the estimated channel coefficients for the uplink are used for downlink transmission or vice-versa. In FDD systems, the channel estimated at the base station or the user device is sent as feedback to the other end for reflection optimization.

If the number of reflective elements is very large and all the reflection elements are ON, then the power consumption and the training overhead become very high. Since the IRS channels exhibit good spatial correlation, IRS elements are grouped to a sub-surface to improve efficiency [52]-[53]. The channel corresponding to each sub-surface is estimated in IRS element grouping, significantly reducing the pilot overhead. An intra-symbol reflection technique for improving the training efficiency of cascaded channel estimation is proposed in [54]. In a MIMO system, as the number of users and the number of transmitting and receiving antennas increases, the overall training overhead increases, and channel properties like low-rank, high spatial correlation, and sparsity are utilized to reduce the training overhead [55]-[59]. In addition to this, several deep learning-based algorithms for channel estimation are also developed [60]-[63].

The estimation in the case of broadband frequency selective channels is complex due to multi-path delay spread resulting in more coefficients of the cascaded channel. For OFDM based systems, the design of reflection coefficients for individual subcarriers is challenging. But in such systems, the number of reflected paths is much less than the number of sub-carriers, thereby utilizing the channel redundancy for estimation purposes [64].

**IV. SIGNAL PROCESSING METHODS FOR IRS CHANNEL ESTIMATION**

Various signal processing methods are employed for the efficient and accurate estimation of IRS channels. Least-Square (LS)/Minimum Mean Square Error (MMSE), matrix factorization, compressed sensing and deep learning are the various methods available in literature.

**A. Least Square/Minimum Mean Square Error**

LS/MMSE is a conventional low-complex method used in pilot-based IRS channel estimation. The dimension of the observation vector is higher than the unknown parameter vector. For LS estimation, an ON/OFF based training reflection pattern is implemented in [53],[65] and [66]. Initially, all the IRS elements are turned OFF, and the channel is estimated using the conventional LS method. The cascaded channel is estimated in the next phase by following a sequential ON-OFF pattern of IRS elements. Since this method’s power loss and interference are high, accuracy decreases substantially. A fully-ON IRS configuration eliminates the accuracy problem. To further improve the performance, joint design of pilot sequence and training reflection pattern is presented in [54], [64] and [67].

Several methods are available in literature to improve the training efficiency of LS/MMSE estimation. One such
method, particularly for multi-user systems, is explained in [68]. In this method, channel state information of one of the users is kept as reference, and all other users use lower-dimensional scaled versions of this reference CSI to perform the LS/MMSE estimation with reduced overhead. An anchor-based channel estimation scheme is proposed in [69]. In this method, two anchor nodes are deployed close to the IRS and training, and feedback from these two nodes are utilized for LS estimation. In addition to this, LS-based double IRS channel estimation methods with reduced training overhead were proposed in [70]-[73]. A channel estimation method with discrete phase shifts and progressive refinement is explained in [74]. A low complex LS-based channel estimation for a highly mobile communication environment was proposed in [75] and [76]. In [77], a Kalman filter-based time-varying channel estimation is explained. Parallel estimation of direct and cascaded channels using two Kalman filters was proposed in [78]. A hierarchical beam searching and extended Kalman filter-based algorithm for channel estimation and tracking are also developed in [79].

B. Matrix Factorization

In IRS systems, the cascaded channel is considered as a bilinear model in which the channel dimension is much higher than the conventional wireless communication systems. We can reduce the increased complexity involved in these high-dimension channels by decomposing the channel into lower-dimensional sub-channels. Singular value decomposition (SVD) based cascaded channel estimation is proposed in [80], in which the high-rank matrix is decomposed into a sequence of matrices of rank one. Several sparse matrix factorization methods are presented in [81]-[83]. Moreover, a parallel factor tensor modelling based method is proposed in [84].

C. Compressed Sensing

The mmWave channel in IRS-aided communication systems is sparse because of the limited number of scattering paths. The sparsity and low-rank properties are thus utilized to reduce the pilot overhead in such systems. Hence, compressed sensing is a significant signal processing tool for cascaded channel estimation in IRS systems. In [57], a compressed-sensing-based channel estimation scheme was proposed with reduced training overhead. The Cramer–Rao Lower Bound (CRLB) of the estimation error is explained in [85]. One of the most fundamental iterative greedy algorithms for sparse channel estimation is Orthogonal Matching Pursuit (OMP), applied in [57] and [86], which is a low complex method. Other compressed sensing algorithms are Sparse Bayesian learning (SBL) [87], adaptive grid matching pursuit [88], atomic norm minimization [89], and iterative reweighted method [90]. The performance of various compressed sensing algorithms can be increased at the cost of higher computational complexity.

D. Deep Learning

Deep Learning (DL) is a powerful technique for feature extraction from input data, and it provides a model-free mapping based on learnable parameters. The performance of learning model prediction is effective even with wireless channel imperfections. DL learns from the pattern of features, resulting in lower computational complexity than model-based optimization in the long run. IRS channel estimation with deep learning consists of a mapping from received signals and CSI of direct and cascaded paths. A supervised learning approach is explained in [61], in which channel estimation is done with a twin convolutional neural network (CNN). In this method, the IRS elements are switched ON and OFF sequentially and obtain the transmitted pilot sequence at the receiver, then used to get the LS estimate of both cascaded and direct links. Mapping of channel estimate to true data is then done. The system, as mentioned above, requires high computational capabilities due to the large datasets used. Hence, a federated learning (FL) based approach is presented in [91]. The learning model is trained at the base station in the FL approach. Instead of sending the data, only the model updates are transmitted, which greatly reduces the overhead. Moreover, rather than a large data set, each user computes model updates based on their local dataset. Only a single CNN is employed here instead of twin CNN to estimate both direct and cascaded paths.

Increased training overhead is the main limitation of SL and FL-based approaches. To overcome this, estimation with deep denoising neural networks (DDNNs) is presented in [49]. It uses a hybrid architecture with both active and passive elements. Active IRS elements are employed for uplink pilot training, and passive IRS elements are used for passive reflections. Here also sparse recovery algorithms like OMP are employed for channel reconstruction. DDNN used here helps to improve the accuracy of channel estimates. In this method, both compressed sensing (CS) and deep learning (DL) are employed, resulting in an improved performance than using these methods individually.

In [92], a synthetic deep neural network (DNN) with reduced training overhead is employed for channel estimation. Sparse cascaded channel estimation in the IRS-terahertz MIMO system based on deep learning was proposed in [93]. Channel estimation in IRS-assisted MISO-OFDM systems is presented in [94], in which a suitable database is used to train the CNN offline. Besides CNN, DNN and FL, deep reinforcement learning is proposed in [51], exploiting a typical agent-environment interaction in a Markov Decision Process (MDP). The agent takes action by observing the current state, and in return, the agent gets reward and proceeds to a new state. The main aim of reinforcement learning (RL) is to maximize the long-term rewards [94].
V. BEAMFORMING OPTIMIZATION

This section analyzes the optimization of passive reflections in IRS elements for multiple objectives, including rate maximization, power minimization, spectral optimization, etc. Consider a wireless communication scenario consisting of a single IRS with N-elements. For simplicity, initially consider a single transmitter and receiver antenna system. The received signal can be modeled as given in Eq. (18). The signal to noise ratio at the receiver can be written as:

$$ SNR_r = P_t | f^H Q g + h_d^H |^2 / \sigma^2 $$  (24)

The capacity of the above channel is defined by:

$$ C = B \log \left( 1 + SNR_r \right) $$  (25)

The system’s objective is to maximize this capacity by optimizing the passive reflections at IRS. Eq. (24) can be re-written as:

$$ SNR_r = | \sum_{k=1}^N f_k^H \beta_k e^{j \theta_k} g_k + h_d^H | P_t |^2 / \sigma^2 $$  (26)

The optimization problem can thus be formulated as:

$$ \max_{\theta, \beta} | \sum_{k=1}^N f_k^H \beta_k e^{j \theta_k} g_k + h_d^H | P_t |^2 $$  (27)

where $\theta \in [0, 2\pi)$ and $\beta \in [0, 1]$. Assuming that there is a random but same value of phase shift to BS-IRS link and reflected path, and there exists no direct path between the transmitter and the receiver, the optimization problem mentioned in Eq. (27) can be modified as:

$$ \max_{\theta, \beta} | \beta_k \sum_{k=1}^N f_k | g_k | P_t |^2 $$  (28)

From (28), it is obvious that the optimum value of reflection amplitude $\beta_k$, i.e., $\beta_k = 1$ for all $k$.

A. Joint Active and Passive Beamforming Optimization

Consider a single user MISO system downlink case where joint active-passive beamforming optimization is required. The signal-to-noise ratio/rate maximization problem here can be formulated as:

$$ \max_{u, \theta} | f^H Q g + h_d^H u |^2 $$  (29)

where $u$ is the transmit beamforming vector at the base station such that $\| u \|^2 \leq P_t$. The active transmit beamforming at the base station has to be designed jointly with the IRS phase shifts to maximize the combined gain. Since the objective function is non-concave with respect to $u$ and $\theta$, the optimization problem mentioned in Eq. (29) is non-convex. Sub-optimal solution of Eq. (29) can be obtained by keeping $u$ as a fixed vector. With fixed value of $\theta$, the optimum solution to transmit beamforming vector $u$ is obtained as a maximum ratio transmitter (MRT) design. The expression for optimal solution is:

$$ u_{MRT} = \sqrt{P_t} \frac{f^H Q g + h_d^H}{\| f^H Q g + h_d^H \|} $$  (30)

To ensure locally optimal solution, the above approach is done iteratively until convergence.

B. Reflection Optimization in IRS-MIMO Systems

In IRS-aided MIMO systems, the capacity is improved by parallel transmissions of multiple data streams, which is the fundamental concept behind spatial multiplexing. In such MIMO systems with IRS, the covariance matrix of the base station has to be taken care of while optimizing the IRS reflections. The overall channel in IRS-MIMO systems can be expressed as $H_m = F^H Q G + H_d$. Let the transmit covariance matrix is denoted as $C$, then the capacity optimization problem can be written as:

$$ \max_{C} \log_2 \det \left[ \frac{1}{\sigma^2} H_m C H_m^H \right] $$  (31)

such that $\text{trace}(C) \leq P_t$

The optimization problem in Eq. (31) is non-convex. In [95], an effective algorithm based on AO is explained to solve this problem iteratively. In cases where the base station-user channel is of low rank, the AO-based algorithm explained in [95] impacts attaining a higher rank channel with increased spatial multiplexing gain, enhancing the channel capacity.

A matched filter-based system to improve the capacity in IRS-MIMO systems is explained in [96]. IRS-space shift keying and IRS spatial modulation methods for MIMO systems are proposed in [97], where greedy and ML detectors are employed to improve the bit error rate performance. Authors in [98] proposed a second-order cone programming (SOCP) based majorization-minimization (MM) optimization algorithm and joint optimization of reflection matrix and precoder matrix, thereby improving the system's spectral and energy efficiency.

Optimization of beamforming using greedy search algorithms with automatic interference cancellation is proposed in [99]. Furthermore, compared to MRC based beam formation, a low complex zero-forcing-based optimized beam formation is proposed to improve the sum-rate [100]. A deep learning-based reflection design is proposed to minimize the pilot overhead and increase energy efficiency [101]. Authors in [102] proposed an inexact-alternating-optimization method. In this method, optimization of both transmit and reflective beamforming subproblems are unraveled inexacty on an iterative basis based on the principle of successive convex approximation (SCA). Alternating stochastic gradient descent (SGD) algorithm and cosine similarity-based low complex phase shift adaptation algorithm for optimization are proposed in [102] and [103], respectively. A low complex adaptation for reconfigurable intelligent surface-based MIMO systems is presented in [104]. A reflection pattern modulation (RPM) technique is proposed in [105] to maximize the received signal power in which a section of elements out of the total IRS elements are activated to target the preferred destination. A recursive algorithm...
named Multi-Beam Multi-Hop Routing (MBMH) based on graph theory is proposed in [106] to control the inter-user interference in the presence of multi-IRS.

C. Precoding Matrix Optimization

Precoding matrix is a significant parameter that has to be optimized for better performance in IRS-aided wireless communication systems. Several works are available in literature for optimizing the precoder matrix. An optimization algorithm named optimal linear precoder (OLP) that helps to improve the ergodic capacity of a downlink MISO channel based on the project gradient ascent was proposed in [43]. In [107], a block coordinate descent (BCD) algorithm was proposed for optimization, and it provides a near closed-form solution. As an extension to this, for optimization of phase, MM and Complex Circle Manifold (CCM) algorithms are also incorporated along with the BCD algorithm for transmitter precoding matrix optimization [108].

Several research works are available in literature that focuses on the joint optimization of passive beamforming and precoder matrix [109]-[111]. This results in an improvement in the overall performance of the system. Joint optimization based on penalty dual decomposition (PDD) based algorithm and two-timescale (TTS) transmission protocol was proposed in [112]-[113]. Several methods, including maximizing the mutual information and approximating the optimal unconstrained fully digital precoder using OMP, were proposed by exploiting the channel sparsity [114]. By considering the hardware impairments, optimized beamforming and enhanced system security using the semidefinite program (SDP) technique and successive convex approximation (SCA) approach were proposed in [115].

D. Reflection Optimization in IRS-OFDM Systems:

Consider an IRS-OFDM system with a frequency-selective fading channel. For simplicity, initially consider a SISO system and let \( l_d, l_b, \) and \( l_u \) be the delayed taps in the direct channel, base station-IRS channel, and IRS-user channel, respectively. The equivalent time-domain channels for direct path, base station-IRS link, and IRS-user link be

\[
h_d^t = [h_{0d}^t, h_{1d}^t, h_{2d}^t, \ldots h_{ld-1}^t]^T \quad (32)
\]

\[
h_b^{bi} = [h_{0b}^{bi}, h_{1b}^{bi}, h_{2b}^{bi}, \ldots h_{lb-1}^{bi}]^T \quad (33)
\]

\[
h_u^{iu} = [h_{0u}^{iu}, h_{1u}^{iu}, h_{2u}^{iu}, \ldots h_{lu-1}^{iu}]^T \quad (34)
\]

The signal hitting on the IRS element can be written as

\[
y_{irs}(t) = Re\left\{\sum_{m=0}^{\ell_d-1} h_m^t \beta_m e^{j\theta_m} [\sum_{i=0}^{\ell_b-1} h_i^{bi} x(t - \frac{i}{B})] e^{j2\pi f_c t}\right\} \quad (35)
\]

where \( \frac{i}{B} \) corresponds to the time delay of \( l_b \) path.

The reflected signal from the IRS element is

\[
y_{ref}(t) = Re\left\{\beta_k e^{j\theta_k} [\sum_{i=0}^{\ell_u-1} h_i^{iu} x(t - \frac{i}{B})] e^{j2\pi f_c t}\right\} \quad (36)
\]

The received signal at the user is

\[
y_r(t) = Re\left\{\sum_{m=0}^{\ell_d-1} h_m^t \beta_m e^{j\theta_m} [\sum_{i=0}^{\ell_b-1} h_i^{bi} x(t - \frac{i}{B})] e^{j2\pi f_c t}\right\} \quad (37)
\]

Joint optimization of reflection matrix \( Q \) and transmit power allocation over the \( M \) subcarriers is required to maximize the achievable rate in IRS-OFDM systems, where \( Q = [\beta_0 e^{j\theta_0}, \beta_1 e^{j\theta_1}, \ldots, \beta_N e^{j\theta_N}]^T \).

This optimization problem is complex, and hence an efficient SCA-based algorithm was proposed in [53] in which the first-order Taylor expansion is utilized for approximation. The algorithm ensured convergence to a fixed point and needs merely polynomial complexity. A CIR-maximization algorithm was proposed in [52] that offers much lower complexity and performance close to SCA-based algorithm. To create a frequency-selective reflection design, different IRS reflection coefficients can be designed for different OFDM sub-carriers, which helps to increase the rate. The absence of frequency-selective passive reflection is the main limitation in IRS-OFDM systems. In IRS MIMO-OFDM systems, joint optimization of reflection with multiple transmit covariance matrices at different sub-carriers must be done. An efficient AO-based algorithm proposed in [95] helps improve the rate in MIMO-OFDM systems.

VI. IRS DEPLOYMENT

Deployment of IRS is a key factor behind controlling the wireless environment in 5G or beyond communication systems. The various deployment strategies available in literature are cooperative IRS, centralized and distributed deployment, machine learning-based deployment, and stochastic geometry-based deployment. Standalone and cooperative deployment strategies are discussed in [70] and [116]. Compared to the standalone case, cooperative deployment has higher received signal strength, cooperative beamforming gain, and spatial multiplexing gain. But path loss increases due to the higher number of reflections in cooperative deployment.

Authors in [117] employed multiple IRS deployment that cooperatively assists the communication between multiple base stations and single-antenna cell edge users to increase the weighted sum rate of cell edge users. IRS deployment in the indoor environment is discussed in [20], [118]-[120], in which the capability of IRS for minimizing the path loss and fading effects are explained. Distributed and centralized strategies are two important deployment categories in IRS-aided MIMO communication systems [121]. Authors in [121] claim that the centralized technique surpasses distributed deployment in multi-user MIMO systems. But the analysis in [122] demonstrates that by exploiting the available CSI, the distributed strategy outperforms the conventional centralized deployment in terms of achievable rate.

Methods for signal strength enhancement of cell edge users with reduced inter-cell interference in IRS scenarios are explained in [123]-[124]. Region optimization for
identifying the best location is critical and significant in IRS deployment. It enhances the power gain of all the users in non-orthogonal multiple access (NOMA) and Orthogonal Multiple Access (OMA) systems [125]. An asymmetric deployment approach is recommended in NOMA systems than OMA systems, where a symmetric scheme is preferred. A thorough investigation regarding blind spots in an area and their mitigation are explained in [126]. In this work, the blockage density is obtained by computing the probabilities of the line of sight and non-line of sight paths. One of the interesting facts presented in this paper is that by efficiently deploying IRS at key locations, we shall obtain more than 80% decrease in the deployment density at low blockage areas and more than 80% decrease at high blockage areas. A decaying double deep Q-network (D3QN) based algorithm that provides increased energy efficiency in MISO-NOMA systems is discussed in [127]. Many research works are available regarding the study of IRS deployment over unmanned aerial vehicles (UAV). IRS over UAV helps increase signal coverage and enhance anti-jamming performance.

VII. FUTURE RESEARCH DIRECTIONS AND CHALLENGES

Most of the research works in IRS are related to capacity, energy efficiency, coverage extension, inter-cell interference, physical layer security, etc. This section focuses on future research directions and the challenges experienced during the IRS system design and deployment. The influence of mobility and movement trajectory in IRS systems is an important research area. Joint optimization of active-passive beamforming is another hot research topic in this field. The introduction of various machine learning algorithms like reinforcement learning and deep learning are to be exploited for optimization. Another area of research is regarding the deployment of IRS. Another demanding research topic is modeling fading channel and efficient channel estimation techniques in IRS-aided communication scenarios. Several methods are being investigated for optimizing the overhead in training while estimating the IRS channel.

Hardware impairment is another key factor that affects the performance of IRS systems. Efficient physical layer design for improved system performance in the presence of hardware impairment is another area to be focused on. Various modulation techniques and the performance of correlated IRS channels are also interesting research topics. Mobility management between base station IRS units and users is challenging, and powerful management schemes are under the development stage. Power optimization in mmWave IRS systems is a hot topic of discussion as the penetration of mmWave in the human body is high compared to lower frequencies, which gives rise to new hazards. Researchers are exploiting the influence of IRS not just in massive MIMO and mmWave systems but also in terahertz systems and green communication systems. Physical layer security is another vast area of research in IRS systems, and most importantly, the validation of mathematical models with real-world scenarios needs to be proved.

VIII. CONCLUSION

This paper presents a comprehensive survey of the new IRS technology in SISO, SIMO, MISO, and MIMO wireless communication scenarios and the latest research trends. We have discussed the design aspects, focusing more on beamforming and reflection optimization for better performance of IRS systems. We have also presented a survey of hardware architecture, channel model, and various channel estimation techniques. We have elaborated on signal processing techniques for channel estimation, precoder optimization, and deployment. Based on the study, one can conclude that IRS technology unlocks a new generation of research in designing and configuring wireless communication scenarios. Hence, IRS-MIMO systems will be the most suitable candidate for future-generation (B5G/6G) wireless communications systems.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Nandan S. prepared the manuscript, M. Abdul Rahiman verified and approved the final version.

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