Intelligent Reflective Surface Deployment in 6G: A Comprehensive Survey

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***Abstract*—Intelligent reflecting surfaces (IRSs) are considered a promising technology that can smartly reconfigure the wireless environment to enhance the performance of future wireless networks. However, the deployment of IRSs still faces challenges due to highly dynamic and mobile unmanned aerial vehicle (UAV) enabled wireless environments to achieve higher capacity. This paper sheds light on the different deployment strategies for IRSs in future terrestrial and non-terrestrial networks. Specifically, in this paper, we introduce key theoretical concepts underlying the IRS paradigm and discuss the design aspects related to the deployment of IRSs in 6G networks. We also explore optimization-based IRS deployment techniques to improve system performance in terrestrial and aerial IRSs. Furthermore, we survey model-free reinforcement learning (RL) techniques from the deployment aspect to address the challenges of achieving higher capacity in complex and mobile IRS-assisted UAV wireless systems. Finally, we highlight challenges and future research directions from the deployment aspect of IRSs for improving system performance for the future 6G network.**

***Index Terms*—Intelligent reflecting surface, unmanned aerial vehicle, Reinforcement learning, ultra-reliable and low-latency communications**

I. INTRODUCTION

Emerging wireless applications, such as augmented/mixed/virtual reality (AR/MR/VR) and Internet of Everything (IoE), require ultra-high data rates, ubiquitous/massive connectivity, extremely low latency, and high reliability [1]–[3]. In this context, beyond fifth-generation (B5G) and sixth-generation (6G) networks are expected to satisfy the stringent quality of service (QoS) requirements of the three emerging communication classes, i.e., ultra-reliable and low-latency communications (URLLC), massive machine-type communications (mMTC), and enhanced mobile broadband (eMBB) [4]. To this end, the key performance indicators (KPIs) of B5G and 6G networks are summarized as follows: [1], [3], [5]–[7].

1) **Bandwidth:** 6G networks will need to support frequencies of up to 100 GHz in the visible frequency, and terahertz (THz) bands and frequencies of up to 10 GHz can be reached in the millimeter-wave (mmWave) frequency bands.
2) **Peak data rate:** The peak data rate in 6G is expected to be $>$ 500 Mbps for uplink communications and $\geq$1 Gbps for downlink communications, which is more than ten times that of 5G. For outdoor and indoor scenarios $\geq$ 1 Terabit per second (Tbps) is expected, which is 100-1000 times more than in 5G.
3) **Mobility management:** The 6G is expected to support unmanned aerial vehicles (UAVs) and high-speed trains with a maximum speed of 1000 km per hour.
4) **Spectral efficiency:** The spectral efficiency of 6G is expected to be five times that of 5G.
5) **Energy efficiency:** For achieving a green communication network, the energy efficiency of 6G should be 10 to 100 times greater than 5G.
6) **Latency:** The 6G has a more stringent enhanced URLLC requirement to support $\leq$ 100 μs for applications such as AR/MR/VR.

To satisfy these requirements, optimization techniques have been proposed at the network operator and base station (BS) to improve the spectral efficiency, energy efficiency, coverage, and quality of wireless networks [8]. However, with the advent of complex and dynamic wireless networks, such as UAV, B5G, and 6G, the random wireless channels remains an uncontrollable factor [9]. Existing optimization techniques formulated for resource allocation in wireless communication fail to satisfy stringent performance requirements for futuristic wireless networks in such a random and uncontrollable propagation environment.

The concept of intelligent reflecting surfaces (IRSs) has been emerged as a promising paradigm to reconfigure the random radio/channel propagation environment to satisfy the targeted KPIs for B5G [7], [10], [11]. An IRS consists of a large number of passive reflecting elements that can dynamically tune the phase or amplitude of the incident signal to improve the performance of wireless systems [11], [12]. In particular, the reflected signals can be combined constructively to improve the strength of the received signal or destructively to mitigate interference [13]. By densely deploying IRSs in the wireless system and intelligently reconfiguring their reflections, the wireless channels between the transmitter and receiver can be dynamically reconfigured to achieve the desired distributions and gains. This enables the radio environment, to some extent, to be controlled, resulting in a quantum leap of improvement in reliability, capacity and addressing the issue of wireless channel interference and fading in future B5G networks [9].

Notably, for B5G environments, the time-varying and ran-

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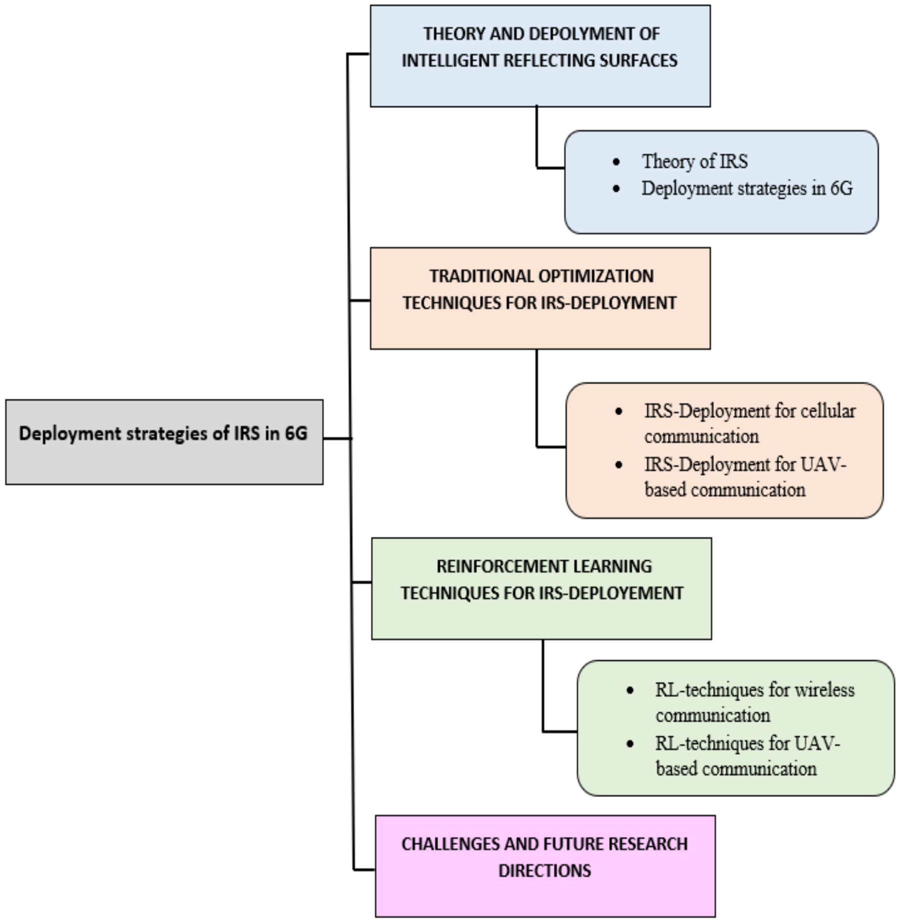

Fig. 1: Organization of the paper

dom wireless channel is a fundamental challenge facing the achievement of high capacity, and ultra-reliable communications [14]. Moreover, future networks are also expected to support aerial users in highly mobile and dynamic wireless environments [15]. In this context, IRS-assisted UAV communications have shown a significant performance improvement in capacity compared to the terrestrial network. IRSs deployment strategies for aerial communications have shown significant attention by improving the line-of-sight (LOS) channel conditions for increasing the capacity of the 6G network. Recent works investigate the importance of deployment strategies of IRS elements on the performance improvement in 6G network [15]–[18]. However, one of the key challenges is the autonomous deployment of IRS elements by identifying optimal locations, such as placing the IRS elements near the transmitter/receiver to increase the LOS link with the BS to increase the capacity in future wireless networks. This motivates to present a comprehensive literature review on the deployment strategies of IRSs for future terrestrial and non-terrestrial networks.

A. *Objective, Contribution and Organization*

Unlike recent works summarized in Table 1, this survey is the first that provides comprehensive literature for the placement strategies of IRSs in 6G-enabled terrestrial and non-terrestrial networks and presents promising future research directions. More specifically, our key contributions are summarized as follows. A systematic organization of the literature for the IRS deployment strategies for the wireless networks. We start from the fundamentals of IRS-assisted communication, covering the deployment aspects of IRSs in the 6G network. Then it provides a detailed analysis of optimization techniques formulated for placement of IRS-elements in terrestrial and non-terrestrial communication. Afterward, the paper surveys recent machine learning (ML) techniques, specifically model-free reinforcement learning (RL) used for IRS placement in a dynamic and complex wireless network. Finally, the paper suggests promising future research directions and open issues related to deployment strategies of IRSs in the 6G network.

II. Theory of IRS covering its architecture and fundamentals

An IRS is a two-dimensional (2D) planar meta-surface composed of digitally reconfigurable meta-atoms/reflecting elements with an electrical thickness in the range of sub-wavelength of the operating frequency of the signal of interest [22]. By properly designing the geometry shape (e.g., split ring or square), arrangement, size/dimension, and so on, the desired response of the signal (phase-shift and reflection amplitude) of

TABLE I: Comparison of existing survey in IRS-enabled 6G communication

Reference	Area of focus	Our contributions
[2]	Motivates the use of large integrated surface (LISs) for performance analysis and optimization frameworks in 6G networks	Compared to these existing surveys, our paper surveys the design aspects of IRS deployment strategies in 6G networks. The paper first discusses the theory of IRS communication with a perspective of IRS placement strategies in 6G network. Then, it provides a compreh-ensive comparative analysis of existing optimization and reinforcement learning techniques used for the dep-loyment of IRSs in UAV and terrestrial communication. Finally, some open research issues are highlighted on the deployment strategies of IRS in 6G network.
[9]	Outlines the design and applications aspects of IRSs in wireless systems.	
[19]	Explores deep learning (DL) architectures, especially for channel estimation, beam-forming and signal detection in IRS-assisted communication	
[20]	Focuses on channel estimation, capacity analysis, and reliability analysis of 6G networks	
[21]	Summarizes the applications, principles, and future research directions for 6G	

the meta-surface elements can be controlled accordingly. The typical architecture of IRS is based on three layers connected to an intelligent controller, as shown in Fig. 2. The first layer consists of a large number of reconfigurable metallic patches printed on a substrate to control the incident signal intelligently [18]. The second layer is based on a copper plate to minimize the energy leakages during the reflection phase. In the third layer, a control board is used to tune and excite the phase shifts and reflection amplitude in real-time. The intelligent controller based on a field-programmable gate array (FPGA) is attached to the third layer and is used to regulate the configuration and reflection intelligently. Moreover, the smart controller also acts as a gateway to communicate with the user terminals and BSs by using a wireless or wired network. IRS elements can be deployed on buildings, indoor ceilings, transmitter/receiver, UAVs, and walls to smartly reconfigure the phase shift of the incident signals to increase the capacity in IRS-assisted wireless networks [23]. IRS creates a strong LOS link towards the receiver and improves channel condition to improve the spectral efficiency, signal power, and network capacity. The reflection coefficients of the IRS elements are configured based on the channel state information (CSI), which is necessary for IRS optimization. However, due to the highly mobile and random mobile wireless propagation environment, adaptive placement of IRS elements is a challenging task and needs further investigation [11]. The following section discusses the architecture, emphasizing deployment strategies of IRSs for future terrestrial and non-terrestrial networks.

TABLE II: List of main acronyms

Acronyms	Definitions
5G	Fifth generation
B5G	Beyond fifth generation
IRSs	Intelligent reflecting surfaces
UAV	Unmanned aerial vehicle communication
RL	Reinforcement learning
ML	Machine learning
QoS	Quality of service
uRLLC	ultra-reliable and Low-Latency communications
mMTC	massive Machine-Type Communications
eMBB	enhanced mobile broadband
KPIs	Key performance indicators
BS	Base station
NOMA	Non-orthogonal multiple access
LoS	Line-of-sight
MISO	Multiple-input single-output
SNR	Signal-to-noise ratio
SER	Symbol-error-rate
UAV-IR	Unmanned aerial vehicle enabled Intelligent reflector
SIMO	Single-input multiple-output

III. Deployment Strategies of IRSs in future 6G-enabled terrestrial and non-terrestrial networks

A fundamental design challenge for 6G-enabled terrestrial and non-terrestrial networks lies in the dynamic and uncontrollable signal propagation environment in achieving ultra-reliable and high capacity requirements. It is envisioned that IRSs will be massively deployed in future wireless systems and lead to novel paradigm shifts in network architectures, from existing heterogeneous wireless systems to novel IRS-assisted wireless networks, as illustrated in Fig. 3. Future IRS-aided wireless networks are expected to support various applications such as mMTC, uRLLC, and eMBB. For instance, the users can be located in a dead service zone, and IRSs can be deployed to create a LOS link between the AP and users to bypass obstacles between them. This application of the IRS is useful to improve the coverage in THz and mmWave communications in 6G, which will be highly vulnerable to blockage. A hybrid IRS deployment strategy is shown in Fig. 3, where IRS elements are placed at the edge of the cell in the UAVs to suppress the co-channel interference from adjacent cells and improve the desired signal strength at the users in the dead service zone. Moreover, in an indoor environment, the IRS can be deployed on the walls, ceiling, and furniture to enhance the capacity and coverage, which are essential for satisfying stringent applications requirements. Meanwhile, the IRS can be placed on high-speed vehicles, UAVs, and buildings in an outdoor environment to achieve high spectral efficiency. Consequently, properly deploying the IRS elements can make wireless environments intelligent to support various

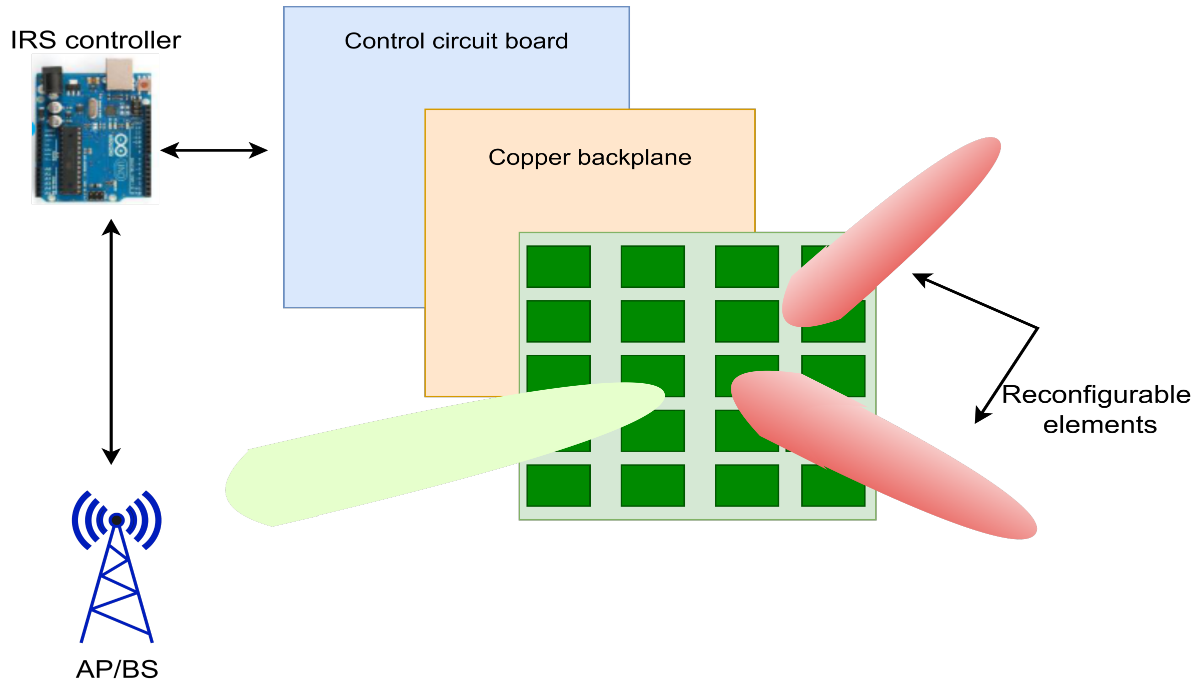

Fig. 2: Architecture of IRS

applications in the future 6G networks.

Another deployment strategy for IRSs involves installing at the BS end. This strategy helps minimize the product-distance path-loss and is very similar to conventional reflect-array [24]. Deploying IRSs at the user-side or BS side can also be made based on key metrics, including the channel conditions, network coverage, passive beamforming improving the channel conditions, and signaling overhead. However, some design challenges may need to be considered before the deployment, such as the IRS-user association and transmission mode selection.

When it comes to IRS-user association and mode selection, some essential practical factors to take into account include the user's QoS requirements, co-channel interference levels, channel condition, and deployment strategy [25]. Moreover, the associated BS might remain unchanged for a mobile user within a cell, but the associated IRS and communication mode might need to be adaptively adjusted. In this context, the optimal resource allocation policy in deploying IRSs remains a challenging task since it requires complete CSI information of all communication links, which is very difficult to obtain in practice. This becomes more challenging with the coexistence of BS and user side IRS, resulting in complex channels having multiple reflection links and multiple user communication modes. Moreover, since IRSs are coupled with active/passive beamforming in a complex and mobile environment, it cannot be solved with the CSI information only [26], [27]. A possible solution to this problem is *surface partitioning* where the IRS can be partitioned into multiple sub-surfaces by assigning a sub-surface to a user based on QoS requirements instead of the entire IRS.

Integrating IRS with UAVs has also emerged as a promising solution to boost the performance of future 6G networks by providing proactive control of the wireless communication channel through IRS and maneuver control via UAVs. Leveraging the controllable mobility of UAVs in the 3D space, the trajectory of UAVs can be adjusted to create a LOS channel to bypass the ground obstacles, such as high-rise buildings with ground terminals [28], [29]. However, both IRSs and UAVs suffer from limitations that need to be considered in future works to implement IRS-assisted UAV communications practically. For example, UAVs have stringent weight, power, and size constraints, which impose limitations on their flight time and endurance, further affecting the communication performance [30], [31]. Furthermore, UAVs create LOS links with ground nodes due to their high altitudes; however, the channels in terrestrial communication can be blocked by obstacles, such as buildings and trees, which can degrade the communication performance. Terrestrial IRS deployments on high-rise buildings can help solve this problem by establishing LOS links with the UAVs. Although the integration of IRSs with UAVs has been considered in recent works, a comprehensive investigation of their deployment strategies and corresponding advantages for future wireless networks is still lacking.

IV. Traditional Optimization Based Approaches for IRS-Deployment

The deployment of IRSs is a crucial consideration for achieving higher capacity in future communication systems since it can intelligently reconfigure the reflected signals to construct a favorable wireless propagation environment. Many works in the literature focus on improving the network's energy and spectral efficiency, and IRS deployment is one of the key factors in performance improvement since the future wireless environment becomes controllable. We divide the deployment strategies of IRSs into two subsections: terrestrial

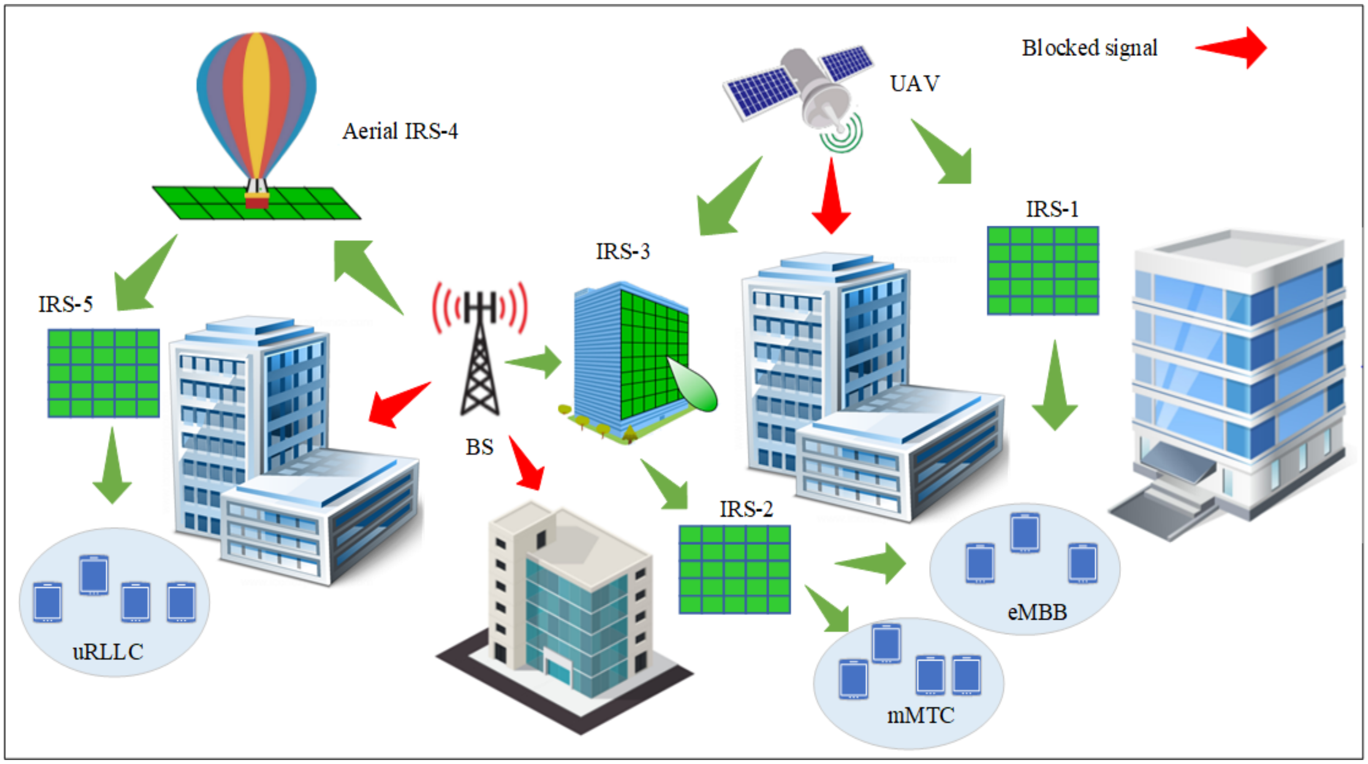

Fig. 3: Deployment scenarios of IRSs in future 6G networks

and non-terrestrial networks. The deployment strategies and their pros and cons are detailed below.

A. IRS-deployment for terrestrial networks

Practically there are two IRSs deployment strategies: single IRS deployment, where all the reflecting elements are mounted on a single reflecting surface, and multi-IRS deployment, where multiple IRSs are deployed in the wireless system to enhance the system capacity. Single IRS deployment benefits from reduced hardware cost since a single IRS controller needs to be installed instead of separate controllers for sub-IRS.

The authors in [32] investigated the data detection problem in a single IRS deployment and achieved improved BER results without the need for pilot signaling. The authors provided an improved methodology for performance improvement in a single IRS deployment setup. The authors in [34] considered joint active and passive beamforming in a single IRS-aided MIMO system to show significantly reduced transmit RF chains. The IRS-assisted multiple-input single-output (MISO) system is exploited to study the performance improvements in terms of energy efficiency in a single IRS deployment. The researchers in [35] proposed two efficient channel estimation schemes to optimize passive beamforming gains of a single IRS element deployed in a broadband communication system with multiple users employing Orthogonal Frequency Division Multiple Access (OFMDA).

In light of the above mentioned, recent works reveal that multi-IRS deployment strategies outperform single IRS deployments by increasing the LOS communication channel of the BS/IRS and IRS/user links [24]. Also, multi-IRSs deployment achieves a higher capacity than single IRS deployments when the total number of reflecting elements is large. This is due to achieving higher passive beamforming gain of multi-reflection links compared to single reflection links [38]. In addition, further gains are possible in terms of increased signal strength, spatial multiplexing gain, and beamforming gain as compared to single IRS deployments [37], [39].

Authors in [36] use a double-IRS deployment and propose a channel estimation scheme to achieve significant rate enhancements compared to a single IRS deployment. Similarly, [40] investigates a wireless network with multiple IRSs to cooperatively assist communication between a multi-antenna BS and single-antenna cell-edge users. By jointly optimizing the BS transmit beamforming and IRS phase shifts, weighted sum-rate maximization is achieved for all cell-edge users.

The authors considered an indoor wireless environment in [41]–[46], where multiple IRSs are deployed to reconfigure the electromagnetic waves that undergo free space path loss, signal absorption, reflection, refraction, and diffraction caused by physical objects within the indoor environment. These studies aimed to increase users' data, secrecy, and wireless charging. Furthermore, [41]–[43] evaluated the ability of IRSs to mitigate path loss and indoor multi-path fading effects. In [21], [47], [48], the authors used a multi-IRS setup to enhance signal strength for the cell-edge users and to mitigate inter-cell interference.

The authors considered the joint optimization of reflection coefficients and deployment of IRSs in [49] considering three multiple access schemes: non-orthogonal multiple access (NOMA), Frequency Division Multiple Access (FDMA), and Time Division Multiple Access (TDMA). The problem for TDMA is optimally solved by leveraging the time-selective

TABLE III: Summary of optimization techniques for IRS Deployment in terrestrial communication

Ref.	IRS Type	Environment	System Model	Metric	Contributions
[32]	Single IRS	Outdoor	Single device downlink MISO IRS system	BER, least squares (LS), minimum mean square error (MMSE), imperfect CSI,	Proposed DeepRIS for detec ting and estimating signals transmitted through the IRS.
[33]	Single IRS	Outdoor	Multi-input-single-output (MISO) based downlink communication framework	BER, CSI, computational complexity	Proposed the maximum likelihood detection (MLD) based approach for detecting and estimating downlink for multiple UEs
[34]	Single IRS	Outdoor	Single and multi-user system with single AP (MIMO) in 3D system for active and passive beamforming.	Data rate (bps/hz), transmit power (dBm),	Proposed a novel approach for enhancing energy and spectrum efficiency by active beamforming at the AP and passive reflect beamforming at IRS.
[35]	Multi IRS	Outdoor	Single MIMO AP with multiple users in OFDM uplink system	MSE, singal fading, user intensity, complexity	Proposed two channel estimation approaches for multi-user IRS assisted broadband systems using OFDMA.
[36]	Double IRS	Indoor	Single user single AP with two IRSs (single antenna) indoor cooperative communication system in uplink.	Transmit power, MSE, data rate, SNR	Proposed channel estimation and passive beamforming for double IRS enabled cascaded single user and single AP cooperative systems.
[37]	Double IRS	Indoor	Single and multiple users with MIMO communication	Transmit power, MSE, data rate, SNR, IRS subsurfaces, user intensity	Proposed channel estimation and beamforing for double IRS enabled MIMO communication systems.
[24]	Multi-IRS	Outdoor, indoor	IRS aided single cell hybrid system with 3 single antenna users and 40 antenna BS in uplink system.	Avg. rate (bps/Hz)	Studied the energy efficiency of user, BS, and hybrid IRS deployment strategies along with beamforming.
[38]	Single/ Multi-IRS	Outdoor	Single and multi user IRS aided system for optimal beamforing in downlink systems.	Rate (bps/Hz), No. of reflecting elements,	Proposed an IRS enabled decode and forward relaying system and studied the capacity of such systems.
[39]	Mulit-IRS	Outdoor	Single BS with two coopeative IRS aided system in the 3D setup with one user.	Received SNR(dB), elements on IRS,	Proposed a joint deployment and beamforming of multi IRS in a cooperative system.
[40]	Multi-IRS	Outdoor	Four IRSs with 8 users with single BS in 2D downlink system.	Weighted sum rate (bps/Hz), transmit power, IRS-BS distance	Studied cooperative system for increasing weighted sum-rate in multi-IRS.

nature of IRSs. However, non-convex optimization problems are obtained for NOMA and FDMA and are solved by leveraging monotonic optimization and semi-relaxation to find a performance upper bound. The authors revealed significant performance gains by optimizing the asymmetric and symmetric deployment strategies for NOMA and FDMA/TDMA. On the other hand, the work in [50] focuses on enhancing the spatial throughput of a single-cell multi-user system with multiple IRSs deployed. The authors concluded that the throughput is maximized by adopting different deployment strategies for IRS. Furthermore, the spatial throughput can also be increased by deploying fewer IRSs with more reflecting elements; however, this comes at the cost of more spatially varying user rates. Recent studies have also used stochastic geometry-based solutions to optimize the IRS deployment [51], [52]. Specifically, [51] studied the effect of large-scale IRS deployments on a terrestrial network by exploiting and modeling blockages in a cell using a Boolean line model. On the other hand, [52] used a stochastic geometry-based approach to randomly distribute IRSs and BSs in a hybrid wireless network with both active BSs and passive IRSs to characterize the spatial throughput in the network. The results showed gains in signal strength and sub-optimal throughput at the cost of marginally increased interference in the network. Table III shows the summary of existing optimization techniques for the IRS deployment in terrestrial networks.

B. IRS-deployment in non-terrestrial networks

IRS deployments are not limited to indoor and outdoor environments but significantly improve the capacity when deployed over UAVs for wireless coverage extension. Typical use cases for IRS-integrated UAV-based wireless networks involve (a) IRS for UAV-enabled data communication, where the data is collected by UAVs from distributed ground nodes (b) IRS for UAV-assisted ubiquitous coverage, this is for the scenarios, where the IRSs are deployed in the UAV networks to improve the ubiquitous coverage (c) IRS for energy and information transfer for UAV-enabled simultaneous wireless information and power transfer (SWIPT) networks, (d) IRS for UAV-assisted relaying, for the scenarios where the UAVs cannot be deployed near to users due to limited wireless backhaul capacity, IRSs can be deployed near the users as a ground gateway to improve the backhaul capacity (e) IRS for UAV-enabled secrecy communication, where the IRS can be deployed to enhance the physical layer security in UAV networks by weakening the communication channel of ground eavesdropper and (f) IRS for cellular-connected UAV communication, where the IRS passive beamforming can be optimized to improve the uplink and downlink communication via UAVs [14]. However, UAV communications may suffer from blockage and eavesdropping due to the large obstacles and high mobility of nodes in a wireless environment. In this context, given their ability to construct a favorable and controllable wireless environment by controlling the trajectory of UAVs, IRS deployments can enhance the performance of future non-terrestrial communication systems.

IRS deployed on buildings can assist the UAV-based integrated air-ground network, where the UAV trajectory can be jointly optimized with active and passive beamforming to maximize the secrecy rate. However, the vital challenge is to optimize the UAVs trajectory jointly with the IRS passive beamforming. The placement of the IRS elements is a critical factor to improve the reflection efficiency and thus needs to be carefully chosen [53]. The recent study [54] considers multiple UAVs to design the deployment of IRSs in order to maximize the average achievable rate. The authors in [55] considered a downlink NOMA network to optimize the location of the UAV-IRSs in order to maximize the rate of the users while maintaining the target rate for the weak user. The authors proposed a penalty-based Block Coordinate Descent (BCD) algorithm to design the active and passive beamforming for maximizing the instantaneous minimum rate. This is formulated by jointly optimizing active beamforming at the UAV, passive beamforming at the IRSs, and UAVs trajectory over a given flying time to maximize the received power at the ground. The authors also designed a semi-definite relaxation iterative algorithm to optimize the IRSs transmit beamforming and phase shifts.

One of the most important design aspects for IRS deployment is to optimize the UAV trajectory with IRS passive beamforming jointly to improve the capacity. However, the main challenges in optimizing the UAV trajectory include reliable user connectivity and low power consumption. To address the issue, the authors in [56] consider IRSs for enhancing the communication signal quality between a UAV and ground users. Furthermore, authors in [15] demonstrate that deployment of IRSs is essential for attaining high gain from the UAV-IRS setup for ground user communications. The authors also proved that the IRS-aided cellular system could remarkably improve the SINR over the entire area where the trajectory of the UAVs can be optimized [57], [58]. In their system model, the authors deployed the IRS on buildings and remotely configured the installed IRSs from the BS to transmit the reflected signal toward the UAV. The authors concluded that IRS deployment placed at optimal locations could significantly improve the signal strength at the UAVs. The work in [58] studies the effect of phase compensation error on the ergodic capacity for IRS's assisted by UAV communications. Hence, the effective deployment of IRSs in the non-terrestrial network can help improve the communication quality and provide more flexibility for air-ground networks. The existing literature employing optimization techniques for the IRS placement can be seen summarized in Table IV.

There still exist some challenging issues in UAV networks from the IRS deployment perspective to enhance the network performance. For example, accurate channel estimation is critical in highly mobile IRS-assisted non-terrestrial communication. Moreover, the above-discussed optimization techniques cannot accurately formulate the dynamic and complex characteristics of IRS-assisted terrestrial and non-terrestrial networks for achieving higher capacity. As a result, the following section investigates the recent model-free RL techniques in the literature for learning the IRS deployment strategies in complex and dynamic future wireless networks.

V. Reinforcement learning techniques for IRS-deployment

IRS-assisted terrestrial and non-terrestrial wireless networks are more complex to model and design due to complex and mobile characteristics than conventional wireless networks [61]. Therefore, it is challenging to develop accurate models that account for the dynamic nature of smart radios and that once plugged into the wireless network, are adaptive for network optimization. Moreover, the computational complexity of deploying, programming, and controlling IRS-aided wireless networks rises significantly with increased network-to-infrastructure and user-to-network interactions. This requires more efficient and on-demand network intelligence in IRS networks to cope with the complex deployment planning and dynamic control for service provisioning [62]. Reinforcement learning (RL) techniques have recently been proposed as a potential solution for the effective deployment and optimization of IRS networks in complex terrestrial cellular and UAV-enabled wireless networks [63].

RL is a model-free approach that interacts with an environment and performs actions to learn the optimal policy in a complex and dynamic environment [62]. Though RL

TABLE IV: Summary of optimization techniques for IRS Deployment in non-terrestrial communication

Ref	Deployment Strategy	Environment	System Model	Metric	Contributions
[15]	IRS aided multi-cell downlink communication for aerial users	Outdoor	Multi-cell downlink communication system	Mean SINR, SINR improvement rate	Proposed an optimal IRS placement strategy that maximizes the contribution of the IRS in mitigating the interference between aerial users.
[53]	IRS mounted on Mobile UAV	Outdoor	Terrestrial communication network enhanced by UAV-IRS	Average achievable rate, average secrecy rate	Joint design of transmission UAV trajectory, and reflecting phase shifts to maximize the average achieve secrecy rate.
[54]	Multiple UAVs in IRS network	Outdoor	Millimeter wave multicast system with UAV-IRS	Minimum achievable rate,average objective value	Penalty based BCD algorithm proposed to jointly optimize the beamformers of multiple IRSs and the mmWave BS for maximizing the instantaneous achievable rate.
[55]	Single UAV equipped with IRS as a relay node	Outdoor	UAV-assisted MISO with NOMA downlink network	Data rate, transmit power	Proposed an iterative algorithm to optimize the transmit beamforming and phase shift of the IRS.
[56]	Downlink transmission system with a mobile UAV	Outdoor/Urban	IRS-assisted UAV communication System	Average rate, UAV trajectories	Proposed a joint UAV trajectory and IRS passive beamforming optimization algorithm to improve the communication quality of UAV-enabled networks.
[59]	Single UAV-IR deployment for downlink mmWave transmission	Outdoor	Millimeter wave network	Average data rate, harvested power,transmit power	Deep RL algorithm for optimal placement of UAV-IRS in the downlink mm-wave transmission to mobile users.
[57]	IRS deployed on building walls configured by cellular base stations to optimize UAV trajectory	Outdoor/Building mounted IRS	IRS-assisted downlink cellular communication system	IRS gain vs. UAV height, signal gain vs. IRS location	Signal gains were analyzed at the UAV due to the IRS deployment as a function of UAV height including IRS size, altitude, and distance from the base station.
[58]	Optimizing multiple unmanned aerial vehicles trajectory in an IRS network	Outdoor	UAVs assisted by IRS network	Symbol error rate, outage probability	SER and outage performance of IRS assisted UAV-UAV communications are investigated when phase compensation at the reflectors are imperfect
[60]	Single UAV with multiple IRSs deployed on buildings	Outdoor	UAV-IRS assisted downlink transmission system	Fairness, overall rate, overall reward	Proposed a joint optimization of trajectory of UAV and passive phase shift of the reflection elements in an IRS-assisted UAV communication system, while maximizing the geographical fairness and data rate of all the UEs served by the UAV

had great success in solving a variety of small decision-making problems; however, its performance degrades in large and continuous networks. Thus, deep reinforcement learning (DRL), where the states are approximated by using a neural network. This is also what, in contrast to classical RL, makes the agent perform well in unseen and massive networks [64].

Inspired by the potential of reinforcement learning approaches, several works have attempted to utilize RL algorithms, particularly DRL, to deploy intelligent reflecting surfaces in various state-of-the-art systems effectively. The next subsection reviews these works

A. Reinforcement learning techniques for IRS-deployment in non-terrestrial networks

Future B5G networks will rely on high-frequency millimeter wave (mmWave) communications to meet the growing capacity requirements [1]. However, enabling reliable mmWave links under blockage (caused by buildings, trees, and other objects) is a major design aspect for deploying mmWave bands into wide-scale commercial uses. Passive reflectors have been proposed to address the issue of blockage links to increase the strength of the electromagnetic wave [77]. Specifically, implementing multiple reflectors creates a higher probability of LOS, thus significantly reducing the mmWave

TABLE V: Articles employing RL techniques for IRS deployment in non-terrestrial communication

Ref.	System Model	Algorithm	State	Action	Metric	Contributions
[59]	UAV-IR downlink transmission	DQN,MDP	UE's location,CSI	Identification of optimal location of UAV-IR,	Average data rate, LOS probability	A RL technique is proposed for optimal deployment of the UAV-IR in downlink mmWave transmissions
[65]	UAV-IR MISO downlink transmission	Distributional RL, MDP	received signal power at each UE	Variation in UAV-IR location	Average data rate, LOS probability	A DRL technique is proposed for optimal placement of IRS element in an UAV environment over downlink mmWave frequencies in a multi-user scenario
[66]	Downlink NOMA-MISO-IL IRS network	Decaying deep Q-network	UAV's trajectory, IRS's phase shifts, power allocation	Trajectory of the UAV and phase shift of IRS elements	Average energy consumption	Proposed a NOMA architecture in IRS-assisted UAV wireless networks
[67]	IoT wireless network	PPO	SNR	Adjustment of the UAV's altitude	Expected sum Age-of-Information (EAoI)	Proposed a new relaying system for Internet of Things (IoT) by integrating the UAV and the reconfigurable intelligent surfaces (IRS)
[68]	Uplink SIMO UAV-IRS system	Combination of PPO and DDQN	UAVs current location, data rate and AAOI of users	The position of UAVs, phase shift and angle of IRS, power allocation, and sub-carrier assignment	Average Age of Information (AAoI)	Proposed a PPO based technique for IRS-enabled UAV environment to improve the uplink channel reliability.
[69]	SIMO IRS-assisted UAV network	SAC	positions of the BS and UAV	The coordinates of UAV in the x-axis, y-axis and z-axis	Data rate	An IRS assisted UAV framework to provide reliable communication services for high speed trains (HSTs)
[60]	IRS downlink transmission	DQN, DDPG	UAV 's current coordinate and current energy level	UAV's flying direction,distance	Fairness, reward, data rate	Proposed an RL-based solution for the joint optimization of trajectory and passive phase shift of reflection elements in an IRS-assisted UAV communication system

channel attenuation. Considering this, several studies [77]–[79] have proposed deploying IRSs in mmWave communications; however, these works rely on placing the passive reflectors at a random and fixed location, which results in suboptimal given with the random changes in the mmWave channels.

Due to the random nature of mmWave channels, mobile reflectors, such as UAV-carried intelligent reflector IR (UAV-IR), are believed to be more appropriate to enhance mmWave communications than stationary IRs. In this regard, Zhang et al [59] proposed an IR-enabled UAV strategy to create a LOS channel between a mobile node with a terrestrial base station. Specifically, a novel framework is proposed to deploy a UAV-enabled IR environment to assist mmWave downlink transmission in a highly dynamic and mobile environment. The authors proposed a RL technique to learn the optimal placement and reflection coefficient of the UAV-IR to improve the downlink transmission capacity. Meanwhile, the authors proposed a RF energy harvesting framework to self-power the IR. Simulation results showed a significant performance improvement in achievable downlink LOS probability and average data rate using an IR-assisted framework with a UAV environment compared to a static IR environment.

The work in [59] claims to be the first paper that proposes a reinforcement learning-based deployment of UAV-IRs for mmWave communications with RF energy harvesting. However, it considers a single user in downlink transmission and does not look into the more challenging consideration of multi-user communications. The same authors simulated an IRS-equipped UAV environment for multiple users in [65] and a distributional RL technique was proposed to optimize the reflection coefficients, UAV's location, and precoding matrix at the base station. The authors consider a UAV-IR-enabled downlink framework to assist a mmWave BS for multi-user communications. The authors proposed a DRL

TABLE VI: Summary of RL techniques for IRS deployment in terrestrial communication

Ref.	Environment	System Model	Algorithm	State	Action	Metric	Contributions
[70]	Cooperative networks	SISO hybrid relay-IRS network	Double deep Q-Learning	Phase shift and reflection amplitude	Vary the phase shift and reflection amplitude	Throughput	Proposed DRL-based relay selection in IRS-assisted cooperative networks (DRL-RI) to maximize the throughput with the discrete phase shifts and practical phase-dependent amplitude model
[71]	Cooperative networks	Two hop IRS network	Multi-agent DRL (MA-DRL) algorithm	Secrecy rate and channel capacity	Controllable reflection amplitudes and phase shifts .	Average secrecy rate, through-put	Proposed a multi-agent DRL-based buffer-aided relay selection scheme for an IRS-assisted secure cooperative network in the presence of an eavesdropper
[72]	NOMA	Downlink IRS-aided multi-robot NOMA network	D3QN algo-rithm	IRS phase shift, robot po-sition,current set of allocation power from the AP to all the robots	Varying phase shifts, the moving direction and distance for the IRS	Throughput	Employed RL algorithms to plan trajectories for the robots and design the IRS phase shift matrix
[73]	NOMA	Downlink MISO com-munication	D3QN algo-rithm	IRS phase shift, power allocated to each MU, IRS and MU coordinates	Changing positions, IRS phase shifts variation, variation in allocated power	Energy ef-ficiency	Proposed a novel frame-work for the deployment and passive beamforming design of an IRS with the aid of NOMA technology
[74]	NOMA	Indoor downlink IRS MISO	FL-DDPG	User position, IRS position, fading matrix	Motion, IRS phase shift, power allocation	Throughput, sum rate	Proposed a NOMA en-hanced wireless network model with the aid of mo-bile IRSs that can pro-vide NOMA craved chan-nel conditions and improve the channel quality for users
[75]	THz com-munication networks	Multi-hop IRS MISO, IL	DDPG	CSI, beamforming and IRS phase configuration matrix	Beamforming and IRS phase configuration	Throughput	Proposed a hybrid beamforming framework for multiuser IRS-assisted wireless THz communication networks
[76]	THz com-munication networks	Multi-hop IRS MISO, IL	DDPG	CSI, beamforming and IRS phase configuration matrix	Beamforming and IRS phase configuration	Throughput	Employed DRL techniques for the joint design of dig-ital and analog beamform-ing at the IRSs to combat the propagation loss

technique to learn the optimal deployment of a UAV-IR for efficient downlink transmissions over mmWave frequencies in a multi-user environment. Simulation results showed that the proposed DRL can learn the optimal location of the UAV-IR and achieves higher downlink capacity and achievable rate compared to the non-learning UAV-IR, static IR, and direct transmission schemes.

Unlike [59], Liu et.al [66] did not take energy harvesting into account and formulated the problem of minimizing the energy consumption of UAV as a decaying deep Q-network (D-DQN) algorithm. Their framework incorporated the NOMA for an IRS-enabled UAV framework for enhancing the QoS of users. The energy consumption minimization problem is formulated as a joint IRS phase shift, UAV trajectory, and power allocation policy from the UAV to mobile users (MUs). Numerical results demonstrated that the energy dissipation of the UAV can be significantly reduced by deploying IRSs in the UAV environment by incorporating NOMA and consumes 11.7% less energy than the IRS-OMA case.

The authors in [67] studied the uplink transmission of IoT traffic in a UAV-IR system. The DRL framework based on proximal policy optimization (PPO) is used to learn the randomness of the internet of things devices (IoTDs) activation patterns and control the altitude of the UAV, the phase-shift, and communication scheduling of IRS to minimize the average age of the information (AoI). Numerical results demonstrated that the proposed algorithm can significantly minimize the AoI compared to other baselines, such as random walk and heuristic greedy algorithms. In [67], the authors determined the scheduling and altitude of the UAV. However, this work considered only one UAV, and trajectory optimization is not considered. Moreover, the authors considered an OMA technique with no LOS communication channel between the BS and users.

To address the above-mentioned issues, Hariz et al., [68] considered the sub-carrier allocation and trajectory of multiple UAVs to improve the coverage of the users. Moreover, besides the non-line-of-sight (NLOS) communication between the user and AP, they considered NOMA with a direct link between users and the receiver. The authors used the double deep Q-network (DDQN) method to solve the proposed problem. They investigated applications of the UAV-IRS system on the IoT networks via optimizing sub-carrier, power, phase shift, and trajectory. Furthermore, the objective of the proposed technique is to minimize the average age of information (AAoI) of the users satisfying a maximum transmit power and UAV's movement constraints. Numerical results showed that the proposed approach improves 15% and 10% than the random-trajectory and matching algorithm.

Regarding IRS deployment in state-of-the-art networks, authors in [69] considered high-speed trains (HSTs) and proposed a UAV environment with IRS deployment to provide stable and reliable communication services for HSTs. The authors investigated the joint design of phase-shift and UAV trajectory and formulated an actor-critic (SAC) algorithm to maximize the minimum achievable data rates of HSTs. The proposed algorithm learns the optimal trajectory of the UAV and phase shift of the IRS and achieves 4% and 19.9% higher data rates, respectively, compared with the fixed IRS and random phase shift of the IRS.

The study in [80] employed a RL framework to optimize the beamforming and learn the optimal placement of the UAV to maximize the user's received signal power in UAV-IRS. The proposed RL technique was able to accurately learn the optimal position of the UAV that can provide stronger LOS to the mobile user. It is expected that the beamforming service can be improved using a combination of IRS and UAV, thus providing a potential way to complement the limitations of the current 5G systems.

In recent work, Wang et al [60] considered a dynamic multi-IRS configuration for improving the LOS channel model between a UAV and a set of ground users. They aimed to maximize all UEs geographical fairness and data rate by optimizing the IRSs phase shifts and UAVs trajectory jointly. However, since the IRS-assisted UAV environment is highly mobile and dynamic, and traditional optimization methods fail to perform well, the authors proposed a deep Q-network by discretizing the phase shift and trajectory, which is suitable for practical systems with discrete phase-shift control. Furthermore, they proposed a DDPG-based solution to tackle the case with continuous trajectory and phase shift design. The experimental results proved that the proposed solutions achieve better performance than benchmarks. Table V summarizes the shortlisted articles employing RL for IRS deployment in UAV-based communication networks.

B. Reinforcement learning techniques for IRS-deployment for terrestrial Communication

Some researchers also worked on the deployment of IRSs in cooperative networks. In this regard, Huang et al [70] proposed the DRL technique for relay selection to maximize the throughput in IRS-assisted cooperative networks (DRL-RI) with the discrete phase shifts and practical phase-dependent amplitude model. Furthermore, the authors proposed the joint relay selection and optimization of IRS reflection coefficients for cooperative networks while considering the discrete phase shifts. The DRL algorithm was introduced to solve the complicated non-convex optimization problem and improve optimization performance in massive wireless networks. Simulation results showed that the proposed DRL-based algorithm significantly improves the throughput compared to random relay selection and random reflection coefficients methods.

Motivated by this, Huang et al., [71] proposed a multi-agent deep reinforcement learning-based buffer-aided relay selection scheme for an IRS-assisted secure cooperative network in the presence of an eavesdropper. They considered a practical scenario where both phase shift and reflection amplitude of the IRSs are optimized to improve the wireless network's performance. Furthermore, the buffer-aided relay is introduced to enhance the secrecy performance, but the use of buffer leads to a delay cost. Thus, the paper aimed to maximize the average secrecy rate with a delay constraint or the throughput with both delay and secrecy constraints by optimizing the buffer-aided relay selection and IRS reflection coefficients. The proposed optimization problems were divided into two sub-tasks. A distributed multi-agent reinforcement learning scheme is developed for the two cooperative sub-tasks; each relay node represents an agent in the distributed learning. Next, they applied the distributed reinforcement learning scheme to optimize the IRS reflection coefficients and then utilized an agent on the source to learn the optimal relay selection based on each iteration's optimal IRS reflection coefficients. Simulation results showed that the proposed learning-based scheme used an iterative approach to learn from the environment to approximate an optimal solution by exploring multiple agents, which outperforms benchmark schemes. However, this paper [71] only considered a single untrusted relay as an eavesdropper in the proposed network. This can be further extended to consider multiple eavesdropper scenarios.

Sparked by the advantages of NOMA and IRS, Gao et al [72] explored the performance improvement of IRS in a multi-robot network. Particularly, they proposed a novel framework where the IRS is deployed, and NOMA is employed at the AP for serving multiple robots. The sum-rate maximization problem is formulated by jointly optimizing the power allocation at the AP, reflection coefficients of the IRS, trajectories, and NOMA decoding orders of robots subject to QoS constraint of robots. The dueling double deep Q-network (D3DN) was proposed to learn the optimal robot locations and IRS-element phase shifts. Simulation results showed that the proposed D3DN technique for IRS-aided NOMA networks achieves significant gains compared to the IRS with OMA and without-IRS-assisted schemes.

The problem of jointly optimizing the phase shift, power allocation, and deployment of IRS was formulated as a decaying double deep Q-network (D3QN) to maximize energy efficiency while satisfying the QoS constraints. The numerical analysis showed that the proposed D3QN algorithm for the NOMA-enabled IRS environment outperforms the benchmarks and achieves higher energy efficiency than the OMA-enabled IRS system. However, IRSs are deployed on fixed locations in most existing research contributions. Therefore due to the fixed deployment, IRSs may not be able to obtain LoS paths and optimal channel enhancement, especially in an environment with obstructions. To address the issue, the authors in [74] proposed a mobile IRS model where IRSs are mounted on intelligent robots to achieve flexible deployment. The DDPG framework is used in the IRS-assisted NOMA network to optimize the power allocation, and the phase shift is formulated. To further increase the agent's exploration capability and training efficiency, federated learning is used in the DDPG framework. Simulation results showed that the network with mobile IRS achieved three times higher data rates than the static IRS environment. Moreover, NOMA can achieve a sum-rate gain of 42% compared to the OMA scheme. Finally, the simulations were performed assuming a multi-cell environment, which showed that the proposed FL enhanced DDPG (FL-DDPG) algorithm has a superior convergence rate and optimization performance to the independent training framework.

Furthermore, most existing works consider single IRS-enabled wireless systems, where only one IRS is deployed between the AP and the users. In practice, multiple IRSs can increase the probability of creating a LOS between the BS and users to achieve better service coverage. However, multi-hop IRS assisted systems have not been that much studied in the existing literature [75]. In this context, the works [75], [76] studied the problem of maximizing the total achievable rate of multi-hop multi-user IRS-aided wireless terahertz (THz) communication systems in the infinite blocklength regime. They proposed a hybrid beamforming architecture for a multi-user IRS-enabled wireless system to improve the network's capacity. The DRL algorithm is proposed to learn the optimal beamforming in a multi-user IRS wireless scenario. The proposed scheme can result in a 50% increase in the coverage range of THz communications. Table VI summarizes the literature employing RL techniques for IRS deployment in terrestrial networks.

The above-discussed studies showed that RL techniques for IRS deployment are gaining research attention. However, the research in this area is still in its infancy. More studies are needed to effectively employ RL algorithms to achieve optimal IRS deployment in future terrestrial and non-terrestrial networks.

VI. Challenges and Future Research Directions

In the following, we list some of the challenges and future directions that arise for placement strategies of IRSs in the future wireless network. Table VII shows the summary of the challenges in the deployment of IRSs with their possible research direction.

A. CSI Acquisition

Accurate channel estimation is critical for optimizing the beamforming gain and phase-shifts in IRS-assisted wireless communication, specifically for the UAV-IRS networks where the UAVs will have high mobility and random channel conditions. Furthermore, deploying more IRSs will result in additional IRS-user links, UAV-IRS channels, additional phase shifts, and more channel coefficients are required to be estimated. The challenges mentioned above can significantly reduce the system performance due to the frequent pilot transmissions for accurate CSI estimation. Therefore, accurate channel estimation becomes a critical issue for viable communication because of the IRSs inherent passive nature of lacking RF chains. One potential solution to address the above challenges is to employ advanced ML techniques such as federated learning, transfer learning, and deep neural networks to obtain an accurate CSI with a lower overhead in future wireless netoworks.

B. Interference Management

Future wireless networks will be composed of small cells in ultra-dense environments. As a result, due to random and noisy conditions at the cell edges, power misalignment can enhance the effects of multi-cell interference in wireless networks. Additionally, interference due to multi IRSs can severely degrade the overall system performance in a heterogeneous setting. In some cases, multiple small cells may share the

TABLE VII: Challenges of IRS deployment in future 6G terrestrial and non-terrestrial networks

Challenge	**Description**	**Research directions**
Beamforming design	Accurate estimation of the CSI is required in future 6G networks for achieving optimal phase shift and beamform	Novel ML techniques such as deep learning, graph neural network and transfer learning are needed to accurately estimate the CSI with low complexity
Interference management	Multi-IRSs deployment in random and noisy networks will result in sub-optimal power misalignment's	To develop novel GANs and coordinated multi-agent RL frameworks to address the power management issues in IRS networks.
Physical layer security	Deploying IRSs in cell will result in channel fading and noise in signal and can cause misclassification at the AP side between a legitimate and illegitimate user	To design novel deep learning and federated RL techniques for increasing the privacy of IRS networks
THz and mmWave communications	THz and mmWave communication in deploying IRS elements will experience higher propagation loss and estimating CSI is a challenging task	To propose novel AI based techniques enabled with digital twin to create a digital representation of the physical IRS models for accurately estimating the CSI for optimizing the beamforming.
UAV Communication	UAVs will have high mobility and due to multiple reflected propagation's introduced by deploying IRSs will make difficult to optimize the three dimensional (3D) placement/trajectories of UAVs.	To develop novel RL and federated learning techniques to learn the trajectory of UAVs with optimizing beamforming and phase shift of IRSs.
MAC layer	IRS-assisted network with multiple users will expose to hidden node problems and will result in collisions	Designing multi-agent RL framework to jointly optimize the PHY and MAC layers.

same IRS to serve the cell edge users; however, coordinating the IRS elements for every user in these small cells is a challenging issue. In this regard, the deployment strategy for IRS plays a vital role in reducing the interference in dense networks. Additionally, in a multi-IRSs scenario, the coordination among the dense networks for interference mitigation increases linearly with the number of reflecting elements. Therefore, novel multi-agent RL frameworks such as distributed RL with the generative adverserial networks (GANs) are required to coordinate the IRSs deployment among small cell APs to overcome interference in the wireless network due to the uncontrollable phase angles induced by multiple IRSs in a heterogeneous environment.

C. Privacy and Security

Physical layer security is an effective technique that allows confidential messages to be exchanged wirelessly in the presence of an unauthorized attacker without relying on encryption in the higher layers. By utilizing the inherent randomness of fading noise in communication channels, the amount of information being extracted by an eavesdropper can be limited [81]. However, IRSs optimize their phase angles and amplitudes before initiating communication; the eavesdropper at the other end of the IRS remains at a disadvantage due to the non-reciprocal channel created by the IRS. However, the physical layer security in IRS-assisted wireless networks poses some new research challenges. Depending on the placement of the IRS in the cell, the induced noise and channel fading in a signal will cause misclassification at the AP side between a legitimate and illegitimate user. A strategy to determine the IRS placement that provides freedom for legitimate users to access the AP needs to be developed. Although strategically placing the IRS provides an extra step of authentication during communication, this also increases the risk of a malicious agent providing false information for spoofing attacks hindering the system's performance. Therefore, this requires us to develop the AI techniques such as federated learning for security and privacy protocols under some practical IRS deployment constraints [82].

D. THz and mmWave Communications

THz and mmWave communications promise to support high data rates by utilizing the bandwidth efficiently in the higher frequencies. However, the number of RF chains will be massively increased in THz and mmWave communication, which will result in higher energy and hardware cost than sub-6 GHz wireless systems. Additionally, higher frequency channels, such as the THz and mmWave channels, are more prone to blockage and higher propagation loss. IRS can be deployed at optimal locations such as BSs, UAVs, and users to create a strong LOS link in blockages to tackle these challenging issues efficiently. However, due to the random channel characteristics of the THz and mmWave, it is then crucial to design novel AI techniques assisted with the digital twin concept that can create a virtual representation of the IRS network to accurately estimate the CSI to optimize the phase shift and beamforming design at the AP and IRS to establish a strong LOS links to improve the SNR.

E. UAV Communication

The deployment strategy of IRSs can improve the flexibility in designing UAVs trajectories in UAV-assisted wireless systems. However, the multi-antenna setting's precoding design is directly linked with the UAV's trajectory design, challenging since the practical channel gains between the terrestrial users and UAV depend on its trajectory and precoding strategy. In practice, deploying IRSs into a UAV environment brings many challenges in designing its joint trajectory and precoding design. Due to multiple reflected propagations introduced by IRSs, the composite channel gains from the UAV to terrestrial users becomes both spatial and frequency-selective, which complicates the trajectory design of the UAV. Therefore, the deployment strategies for IRSs with acceptable fairness while achieving the sum-rate objective of UAVs in dynamic and complex wireless networks remain an open research issue. Moreover, accurate detection of tracking the channels in mmWave and THz communication makes the compensation of delay and Doppler spread more challenging and needs further investigation in the future.

F. Medium Access Control Layer

The deployment of IRSs in a multi-user environment will play a vital role in improving the performance of future wireless networks. Specifically, designing AI-assisted medium access control (MAC) solutions for THz and mmWave communications considering the role of the PHY layer is a key challenge that needs to be considered. In addition, the deployment strategy of IRSs in a multi-user environment needs new AI-enabled techniques such as multi-agent RL and transfer learning frameworks for the joint optimization of the MAC and PHY layer.

VII. CONCLUSION

In this paper, we presented a comprehensive survey of the IRS deployment strategies in the future 6G networks. Firstly, we have provided an overview of IRSs from the perspective of deployment strategies in 6G. Then, we focused on a detailed review of traditional optimization techniques used for the placement of IRSs for improving system performance in aerial and terrestrial networks. Afterward, we have presented a survey of model-free RL techniques for the deployment strategies in UAV and terrestrial networks. Finally, we outlined critical challenges and future research directions from the deployment perspective of IRSs in future 6G systems.

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