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SURVEY

IRS-Empowered 6G Networks: Deployment Strategies, Performance Optimization, and Future Research Directions

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ABSTRACT The performance of the envisioned 6G network is fundamentally constrained by the uncontrollable and random wireless communication channel. Intelligent reflecting surfaces (IRSs) have emerged as one of the potential solutions to overcome this challenge by smartly controlling the incident signal to enhance the energy efficiency and spectrum efficiency of the 6G network. In addition, the future 6G network will incorporate several enabling technologies, including artificial intelligence and machine learning (AI/ML), integrated terrestrial and non-terrestrial (TNT) networks, multi-access edge computing (MEC), non-orthogonal multiple access (NOMA), and terahertz/millimeter wave (THz/mmWave) communication techniques. Therefore, this paper provides a contemporary and comprehensive overview of the envisioned IRS-empowered 6G networks from the perspective of its architecture, deployment strategy, integration of IRS technology with other 6G-enabling technologies, and physical layer security (PLS). Finally, we highlight design challenges and future research directions aimed at improving the 6G network performance.

INDEX TERMS Intelligent reflecting surfaces, terahertz communication, terrestrial and non-terrestrial (TNT) networks, unmanned aerial vehicles, 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], [2], [3]. In this context, 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]. The key performance indicators (KPIs) of 6G networks are summarized as follows: [1], [3], [5], [6], [7].

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1) **Bandwidth:** 6G networks will need to support frequencies of up to 100 GHz in the visible frequency and terahertz (THz) bands and frequencies up to 10 GHz in the millimetre-wave (mmWave) frequency bands.
2) **Peak data rate:** It is expected to have a speed of $\geq$1 terabit per second (Tbps), which is 100-1000 times faster than 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:** To achieve a green communication network, the energy efficiency of 6G should be 10 to 100 times greater than 5G.

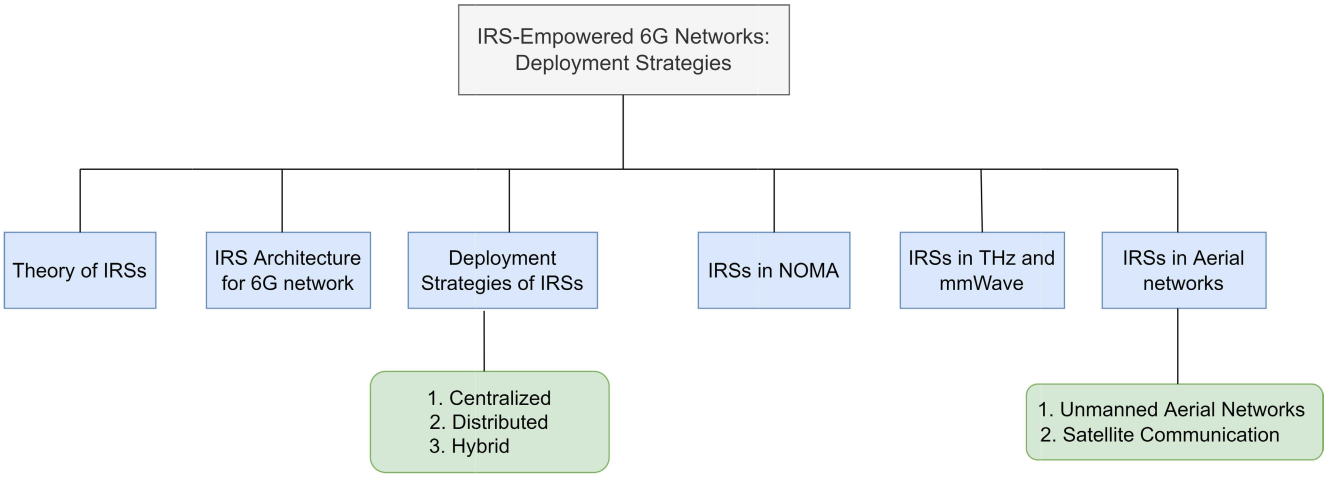

FIGURE 1. Organization of the paper.

6) **Latency:** For applications such as AR, MR, and VR, the 6G has a more stringent enhanced URLLC requirement to support $\leq 100\ \mu$s.

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

For 6G environments, the time-varying and random wireless channels are the fundamental challenges that hinder high capacity, and ultra-reliable communications [13]. Intelligent reflecting surfaces (IRSs) have emerged as a promising paradigm to reconfigure the random radio/channel propagation environment to satisfy the targeted KPIs for 6G [7], [14], [15]. 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 [15], [16], [17]. IRSs can be densely deployed in the wireless system in order to reconfigure their reflections intelligently to achieve the desired distributions and gains. The IRS-assisted network enables the propagation environment to be controlled dynamically, resulting in a quantum leap in reliability and capacity. Moreover, the wireless channel interference and fading can also be mitigated in IRS-assisted 6G networks [9].

Moreover, future networks are also expected to support aerial users in highly mobile and dynamic wireless environments [18]. In this context, the IRSs deployment for aerial communications has shown promising results by creating stronger line-of-sight (LOS) channel conditions that enhance the coverage and capacity of the 6G network compared to the terrestrial network.

TABLE 1. List of main acronyms.

Acronym	Definitions
5G	Fifth generation
B5G	Beyond fifth generation
uRLLC	Ultra-reliable and Low-Latency communications
mMTC	Massive Machine-Type Communications
eMBB	Enhanced mobile broadband
IRSs	Intelligent reflecting surfaces
UAV	Unmanned aerial vehicle
UAV-IR	Unmanned aerial vehicle enabled Intelligent reflector
NOMA	Non-orthogonal multiple access
SIMO	Single-input multiple-output
MISO	Multiple-input single-output
MIMO	Multiple-Input Multiple-Output
ML	Machine learning
PLS	Physical layer security
DRL	Deep reinforcement learning
D3QN	Dueling double deep Q-network
FL-DRL	Federated learning deep reinforcement learning
EA-DDPG	Exploration attenuated deep deterministic policy gradient
QoS	Quality of service
KPIs	Key performance indicators
BS	Base station
LoS	Line-of-sight
SNR	Signal-to-noise ratio
SER	Symbol-error-rate

Recent studies have investigated the impact of IRS deployment on performance improvement in 6G networks [18], [19], [20], [21], [22]. In particular, the IRS-assisted communication systems have shown promising results for 6G applications, including terahertz (THz) [23], non-orthogonal multiple access (NOMA) [24], physical layer security (PLS) [25], and aerial networks [13]. However, one of the key

TABLE 2. 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 addresses the design aspects of IRS deployment strategies for 6G applications and the benefits of jointly optimizing IRS technology with other 6G-enabling technologies.
[9]	Outlines the design and applications aspects of IRSs in wireless systems.	
[10]	Explores deep learning (DL) architectures, especially for channel estimation, beam-forming and signal detection in IRS-assisted communication.	
[11]	Focuses on channel estimation, capacity analysis, and reliability analysis of 6G networks.	
[12]	Summarizes the applications, principles, and future research directions for 6G.	

challenges is investigating the IRS deployment designs tailored for 6G applications. This paper investigates the design aspect of IRSs in NOMA, THz, PLS, and aerial networks by employing optimization and ML techniques.

A. MOTIVATIONS AND CONTRIBUTIONS

Unlike recent works summarized in Table 2, this survey is the first to provide comprehensive literature on IRS deployment strategies in 6G applications, as well as the benefits of associating IRS technology with other 6G-enabling technologies. The key contributions of the paper are summarized as follows.

1) The paper presents a comprehensive survey on IRS-assisted communication, covering the design aspects of IRSs in perspective applications of 6G networks.
2) We also investigate IRS deployment and integration with other 6G-enabling technologies, including AI/ML, NOMA, THz/mmWave, PLS and integrated terrestrial and non-terrestrial networks, including UAV and satellite networks.
3) Finally, this paper suggests promising future research directions and open issues related to the IRS-aided 6G network design.

The remainder of the paper is organized as follows: The theory and architecture of IRS are discussed in Section II. Section III proposes an IRS-assisted framework for the 6G applications scenario. Then, Section IV investigates different IRS deployment strategies in 6G networks. Sections V, VI, VII, and VIII explore the deployment optimization of IRSs in NOMA, THz, UAVs, and satellite systems, respectively. Lastly, open research issues and future research directions of IRS-empowered 6G systems are discussed in Section IX.

II. IRS 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 [26]. 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 the meta-surface elements can be controlled accordingly. The IRS architecture mostly used in the literature is passive, in which the incident signals are reflected without amplification. However, in 6G networks, there can be scenarios where the direct LOS between the sender and receiver is not weak, and high capacity gain often cannot be achieved. Thus, passive IRSs can lead to the negative effect of *multiplicative fading*, and the path losses of the transmitter-IRS and receiver-IRS can be larger than the unobstructed direct link. A massive number of IRS elements will be required to compensate for the effect of large path loss and achieve a higher capacity gain in 6G. To overcome the performance bottleneck issue due to the *multiplicative fading* effect of passive IRSs, active IRSs have been proposed to reflect the incident signals and further amplify the reflected signals [27]. Moreover, active IRSs have shown substantial capacity gain and overcome the limitation of ‘‘multiplicative fading’’. The typical architecture of the IRS consists of three layers connected to an intelligent controller. The first layer consists of many reconfigurable metallic patches printed on a substrate to control the incident signal intelligently [21]. The second layer is based on a copper plate to minimize energy leakages during the reflection phase. In the third layer, a control board tunes and excites the phase shifts and reflection amplitude in real-time. The field-programmable gate array (FPGA)-based intelligent controller is attached to the third layer and is used to regulate the configuration and reflection. The intelligent controller acts as a gateway to communicate with the user terminals and BSs using a wireless or wired network.

III. IRS-ASSISTED ARCHITECTURE FOR APPLICATION SCENARIOS IN ENVISIONED 6G 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 will lead to novel paradigm shifts in network

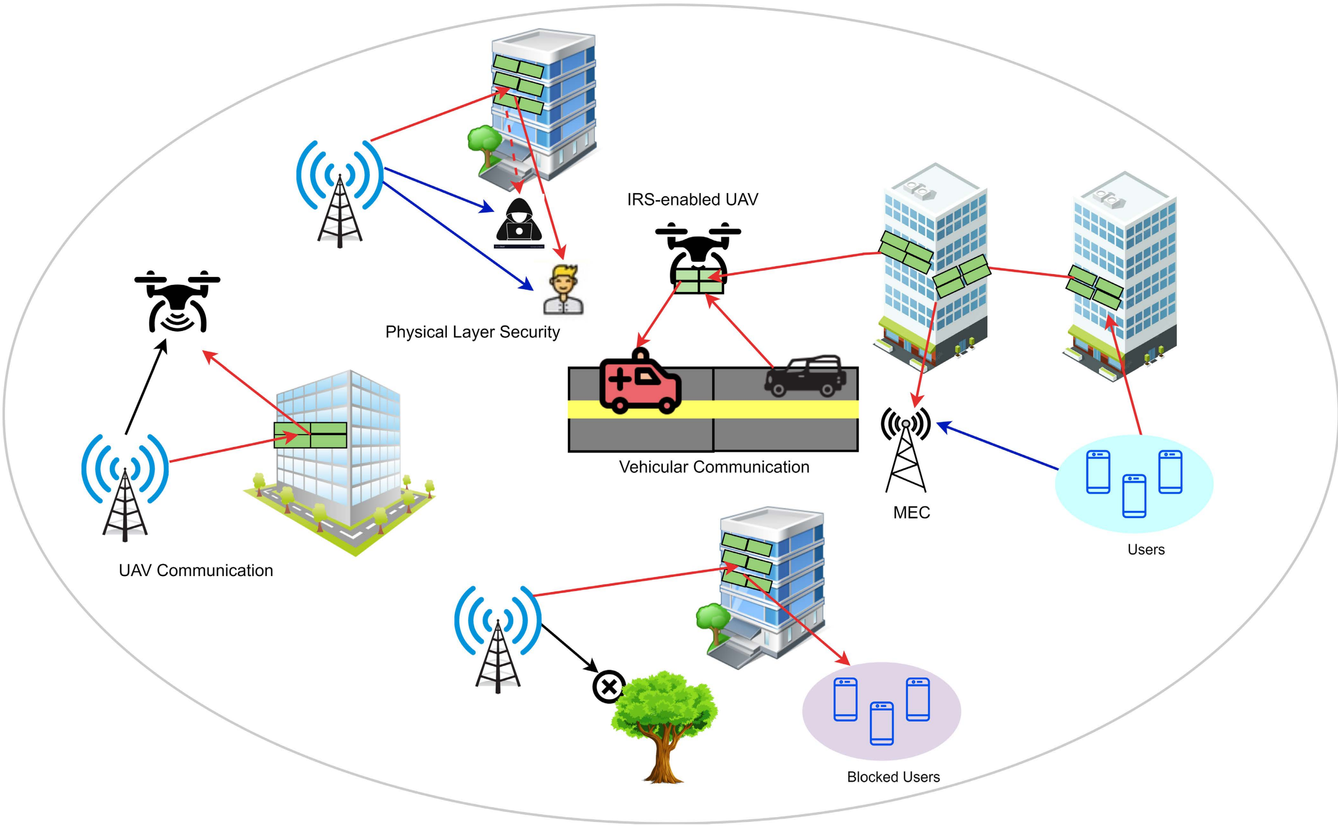

FIGURE 2. Deployment scenarios of IRSs in future 6G networks.

architectures, as illustrated in Fig. 2. Future IRS-aided wireless networks are expected to support applications such as mMTC, uRLLC, and eMBB. For instance, IRSs can be deployed to bypass obstacles and establish a LOS link between the AP and users located in a dead service zone. Moreover, IRSs can be deployed at the edge of the cell to suppress the co-channel interference from adjacent cells and improve the desired signal strength at the users in the dead service zone. This application of IRSs enhances the coverage in THz and mmWave communications, which are highly vulnerable to blockage. Moreover, in an indoor environment, IRSs can be deployed on the walls, ceiling, and furniture to enhance the capacity and coverage, which are essential for satisfying stringent application requirements. On the other hand, IRSs can also be placed on high-speed vehicles, UAVs, satellites, and buildings in an outdoor environment to achieve high spectral efficiency. Another deployment strategy for IRSs involves installing them at the BS end. This strategy helps minimize the product-distance path-loss and is identical to conventional reflect-array [28]. Deploying IRSs at the user-side or BS side can also be made based on key factors, including channel conditions, network coverage, passive beamforming, and signalling overhead. However, some design challenges may be considered before the deployment, such as the IRS-user association and transmission mode selection. Consequently, deploying IRSs at optimal locations can make wireless environments intelligent to support various applications in the future 6G networks. In addition, IRS-assisted aerial networks have also emerged as a promising solution to boost the performance of future 6G networks by providing proactive control of the wireless communication channel through IRSs and manoeuvre 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 to communicate with ground terminals [29], [30].

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 [28], [31].

Furthermore, although UAVs create LOS links with ground nodes due to their high altitudes, the terrestrial communication channels 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 integrating IRSs with UAVs has been considered in recent works, a comprehensive investigation of their deployment strategies and corresponding advantages for 6G applications is still lacking.

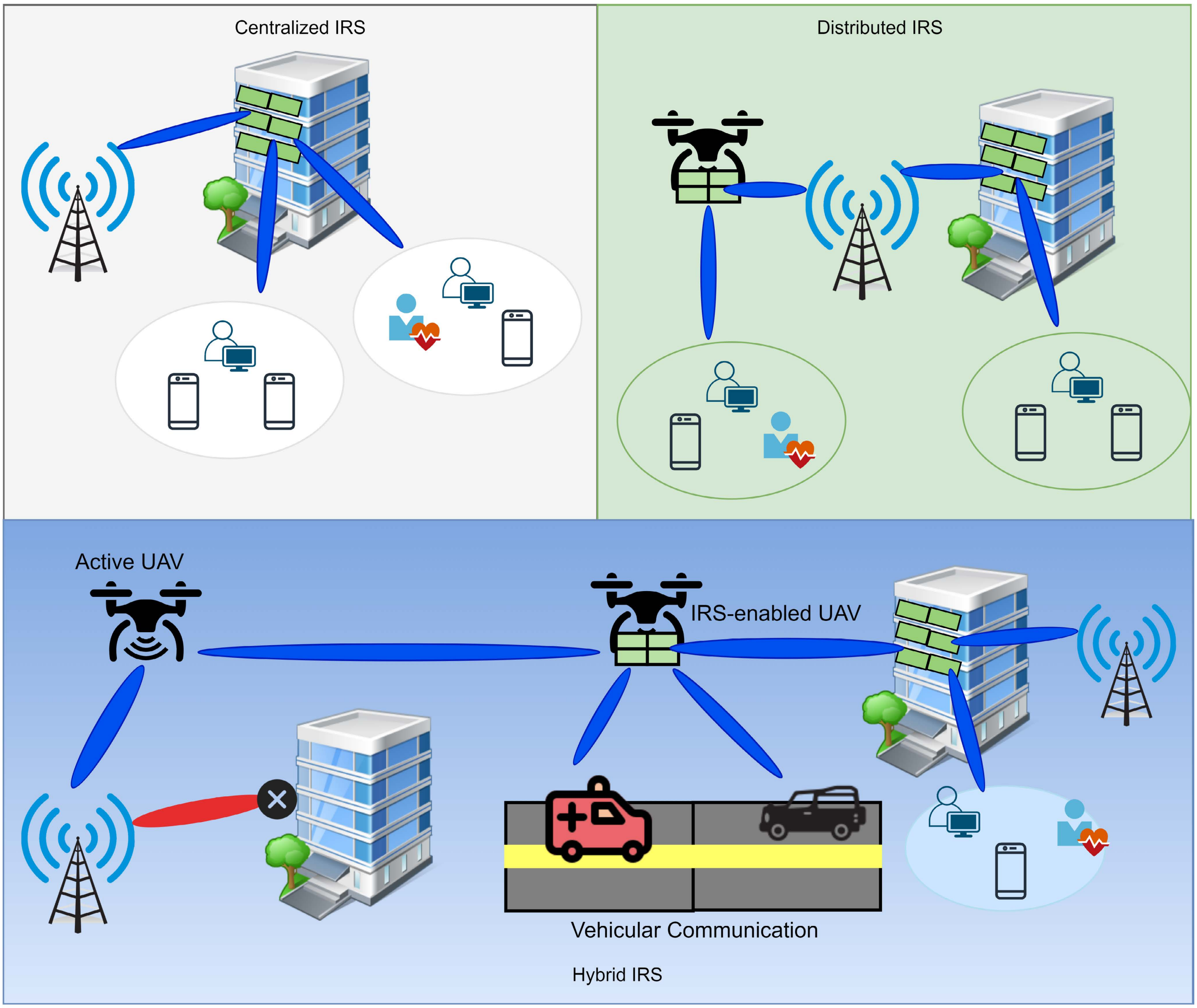

FIGURE 3. IRS deployment strategies: Centralized vs Distributed vs Hybrid.

IV. DEPLOYMENT STRATEGIES OF IRSs IN 6G NETWORKS

Practically, there are three IRS deployment strategies: single IRS or centralized deployment, where all the reflecting elements are mounted on a single reflecting surface; multi-IRS decentralized design, also known as cooperative networks, where multiple IRSs are deployed in the wireless system to enhance the system capacity; and a hybrid configuration [12], [32], [33], as shown in Fig. 3.

1) **Centralized IRS Design:** The centralized IRS approach deploys a passive IRS centrally to achieve a high beamforming gain. This centralized IRS design is a promising approach for 6G, specifically for cluster-based networks. This deployment strategy is useful for the scenarios in which there is a NLOS communication between the BS and users (e.g., in THz, multiple-input multiple-output (MIMO), NOMA and mmWave communications). The centralized IRS design has outperformed the distributed IRS setup under practical channel setup [34]. However, one of the disadvantages of the centralized deployment configuration is that a massive number of IRS elements will be required to achieve a high gain. Moreover, obtaining an accurate channel state information (CSI) of the network is challenging when the number of IRS elements and users is high. One potential solution is to employ artificial intelligence (AI) techniques such as reinforcement learning (RL) in the BS to learn the optimal IRS beamforming, phase shift, and BS-IRS user link for an imperfect CSI based on the feedback of the IRS-assisted 6G network.
2) **Decentralized IRS Design:** This deployment strategy for the 6G network deploys IRSs in a distributed configuration close to different clusters. More specifically, each IRS in the cluster can improve the performance

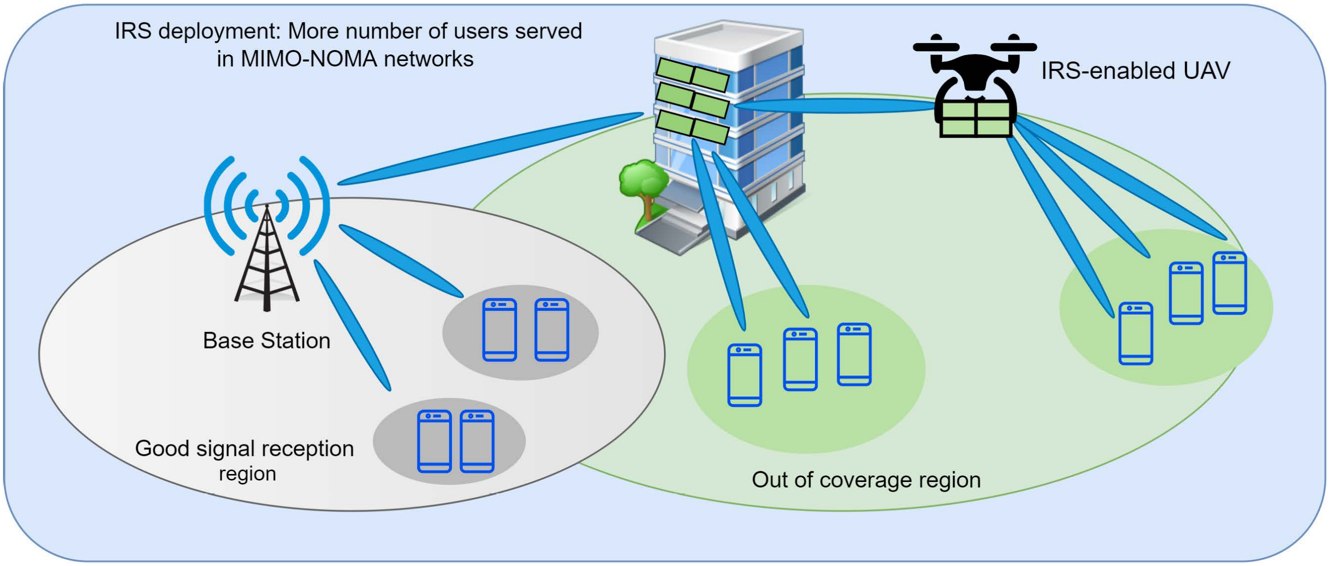

FIGURE 4. Deployment scenarios of IRSs in MIMO-NOMA.

of a specific user based on its QoS requirements. The research in [35] proposed a distributed IRS strategy and established the fact the distributed IRS deployment can learn the available CSI intelligently to achieve a higher data rate even if the user rate is asymmetric. Moreover, the optimal placement of IRSs and UAVs in the distributed approach can create strong LoS communication paths and achieve better channel conditions between the BS and users as compared to the centralized IRS deployment. However, the distributed deployment design can exchange a massive amount of data between the IRSs and BS, which creates new challenges in learning the optimal IRS configuration. One potential solution is to utilize the concept of federated learning (FL), where the model parameters are shared with the BS instead of the complete information.

3) **Hybrid IRS Design:** The centralized and distributed IRS design cannot satisfy the stringent performance requirements of the heterogeneous 6G network. Alternatively, a hybrid IRS deployment design can improve the capacity and signal strength in the 6G [36]. In such design, a centralized IRS is deployed near the BS to achieve a high passive beamforming gain, while distributed strategy where multiple aerial IRSs and static IRSs are deployed near the users to create a stronger LOS communication channel. The UAVs can also optimize their 3D trajectory by incorporating AI techniques to enhance the coverage by utilizing efficient dynamic 3D beamforming, which is essential to enable massive access in ultra-dense 6G networks. Moreover, another critical consideration in the hybrid deployment strategy is to allocate the number of reflecting elements to the user-side, BS-side and UAV-side to achieve higher capacity in a target area. The number of reflecting elements of IRSs in the deployment can be determined by several constraints, such as QoS requirements, locations and user channel conditions. To achieve better performance for 6G applications, a hybrid IRS strategy implementing AI techniques such as FL and RL is preferable.

V. DEPLOYMENT OPTIMIZATION OF IRSs IN NOMA SYSTEMS

NOMA and MIMO are key enabling technologies for achieving massive connectivity in 6G networks [24]. A massive MIMO-NOMA can achieve remarkable performance improvement in terms of spectral efficiency in URLLC applications. However, the uncontrollable and stochastic characteristics of the wireless propagation environment can degrade its performance. One of the critical challenges in traditional MIMO-NOMA systems is their poor performance in crowded environments with many users with diverse performance requirements and different channel gains. It is also challenging in conventional MIMO-NOMA networks to provide uniform signal coverage to users far away from the BS or users who suffer from poor signal reception due to heavy blockage. This issue becomes more challenging in 6G networks due to the short wavelengths of the THz and mmWave communication, resulting in strong signal attenuation.

On the other hand, the widescale deployment of multiple cooperative IRSs can provide multiple independent beams to each user and achieve pervasive coverage. Fig. 4 shows that by deploying IRSs in the MIMO-NOMA network, channel gains can be tuned considering the phase-shift, amplitude and location of IRSs to meet the capacity requirements of both near and far users [37]. This approach can cluster small NOMA groups in a crowded wireless environment to achieve ubiquitous signal coverage in the out-of-coverage area, massive access, and ultra-high data rates. The deployment of multiple UAVs as aerial BSs is also a promising approach to improve the signal coverage in MIMO-NOMA networks, as depicted in Fig. 4. The communication architecture based on multiple UAVs combined with IRSs deployed on high-altitude locations can improve the coverage region and serve multiple users by optimizing a single 3D beamforming. From a design perspective of IRSs in MIMO-NOMA for future wireless networks, the hybrid design can be implemented where some UAVs are considered active, and others function as smart reflective devices. This UAV-enabled IRS framework combines active and passive 3D beamforming for MIMO-NOMA networks and can provide more extended signal coverage even to MIMO-NOMA users far from the active UAVs.

In the next sections, we provide a review of optimization techniques and AI-empowered techniques developed to enable the deployment of IRS-empowered NOMA systems in future 6G applications, such as telepresence and augmented holographic reality.

A. TRADITIONAL OPTIMIZATION TECHNIQUES FOR IRS DEPLOYMENT IN NOMA

The envisioned IRS-NOMA 6G network will have formidable performance requirements such as high throughput, power efficiency and energy efficiency.

1) SUM RATE MAXIMIZATION IN IRS-NOMA SYSTEMS

To address the sum rate, the authors in [51] considered the joint optimization of reflection coefficients and deployment of IRSs for three multiple access schemes: NOMA, Frequency Division Multiple Access (FDMA), and Time Division Multiple Access (TDMA). The optimization problem for TDMA is solved by leveraging the time-selective nature of IRSs. However, monotonic optimization and semi-relaxation are used to tackle non-convex optimization issues for NOMA and FDMA in order to discover a performance upper bound. The authors revealed significant performance gains by optimizing the asymmetric and symmetric deployment strategies for NOMA and FDMA/TDMA. Similarly, the researchers in [43] proposed an alternating optimization technique for optimizing the active and passive beamforming in a multiple-input-single-output (MISO) IRS-NOMA. Analytical results show an improved sum rate assuming both perfect and imperfect scenarios. Moreover, researchers in [39] proposed two-phase shift adjustment techniques (namely, one-time phase adjustment and dynamic phase adjustment) to maximize the sum rate in an IRS-assisted multi-user downlink system. Simulation results show that the average sum rate of NOMA empowered by IRSs outperforms the conventional OMA networks. Similarly, the researchers in [40] proposed a semi-definite relaxation technique in an IRS-based NOMA system for uplink communication to increase the performance of wireless networks. Numerical results show that NOMA systems employing IRS's achieve a higher sum rate than OMA schemes.

2) THROUGHPUT MAXIMIZATION IN IRS-NOMA SYSTEMS

A novel optimization for the NOMA-IRS in a multi-user uplink communication system was proposed in [41] to address the imperfect successive interference cancellation (SIC) issue. The proposed framework exploits the polarization capability of the IRSs in a dual MIMO-NOMA environment to achieve a higher throughput. Moreover, [38] proposed an optimization technique for the multi-channel downlink communications IRS-NOMA framework to optimize the decoding order and channel assignment to maximize the throughput. On the other hand, the work in [52] focuses on enhancing the spatial throughput of a single-cell multi-user system with multiple IRSs. The authors concluded that the spatial throughput could 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 [53], [54]. Specifically, [53] studied the effect of large-scale IRS deployments on a terrestrial network by exploiting and modelling blockages in a cell using a Boolean line model. On the other hand, [54] 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. Simulation results showed gains in signal strength and sub-optimal throughput at the cost of marginally increased interference in the network.

3) ENERGY EFFICIENCY OPTIMIZATION IN IRS-NOMA SYSTEMS

The authors in [42] studied the energy efficiency (EE) problem for a multi-user IRS-NOMA environment and proposed a beamforming and semi-definite relaxation (SDR) based phase shift optimization techniques that maximized the EE compared to OMA. Similarly, the researchers in [44] investigated the performance of traditional OMA and IRS-assisted NOMA. Simulation results show that deploying IRSs in NOMA minimizes power transmission. The paper proposed a novel difference-of-convex (DC) optimization technique for the design of phase shifts and beamforming to minimize the transmission power in a single cell IRS-NOMA wireless system. In another work, [45], the authors investigated the IRS-NOMA in a multi-cluster MISO environment. The problem of minimizing the transmission power is formulated as an alternating direction method of multipliers (ADMM) and second-order cone programming (SOCP) optimization problem [46]. Finally, the authors jointly optimized the power efficiency of NOMA users, phase shifts of IRSs and beamforming of the BS to minimize the transmission power. In addition, the researchers in [55] 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). The proposed scheme

TABLE 3. Summary of Traditional Optimization techniques for IRS deployment in NOMA Systems.

Reference	Model	Objective	Contribution
[38]	SISO multi-user downlink	Maximize sum rate	Optimize the decoding order and channel assignment to maximize the throughput
[39]		Maximize data rate	Proposed two phase shift adjustment technique to achieve higher sum rate.
[40]	SISO multi-user uplink	Maximize throughput	A semi-definite approach to provide near-optimal throughput.
[41]	SISO NOMA-MIMO downlink	Data rate maximization	The dual polarized IRS approach achieves polarization diversity.
[42]	MISO multi-user downlink	Energy efficiency maximization	Provides a phase shift and beamforming optimization technique to maximize EE.
[43]		Maximize data rate	Proposed an alternative optimization technique to optimize active and passive beamforming.
[44]		Minimize transmission power	Optimize the phase shift and beam form via DC method to minimize transmit power.
[45]		Minimize transmission power	A SOCP-ADMM based technique is proposed to minimize the transmission power.
[46]		Reduce transmission power	Provides a joint optimization of the phase shift, beamforming, and the power allocation for multi-IRS.

TABLE 4. Summary of AI-empowered techniques for IRS deployment in NOMA Systems.

Reference	Model	Algorithm	Objective	Contribution
[47]	Indoor downlink IRS MISO	FL-DDPG	Throughput and sum rate	Proposed a FL-DRL based NOMA to improve the capacity for users
[48]	Downlink MISO communication	D3QN	Energy efficiency	Developed a DRL for IRS-NOMA to improve energy efficiency of users.
[49]	Multi-user downlink	EA-DDPG	Throughput	Proposed EA-DDGP in NOMA to increase the throughput of users.
[22]	Multi-user uplink	RL	Data rate	Proposed a DRL in NOMA to increase the data rate of the users.
[50]	Downlink multi-user	DDPG	Sum rate	A DDPG algorithm is proposed to increase the sum-rate in NOMA network.

showed significant performance improvement compared to benchmark schemes.

A summary of classical optimization techniques for IRS deployment in NOMA systems is presented in Table 3.

B. AI-BASED OPTIMIZATION TECHNIQUES FOR IRS DEPLOYMENT IN NOMA NETWORKS

The 6G networks will be highly complex, and traditional techniques such as successive convex approximation (SCA) and SDR do not perform well for resource allocation problems in IRS-NOMA. To address this issue, researchers have proposed AI-based techniques such as supervised learning, unsupervised learning, and RL to smartly address the resource allocation issue in uncertain and dynamic IRS-NOMA environments. The researchers in [56] explored the performance improvement of IRS in a multi-robot network. Particularly, they proposed a novel AI framework where the IRS and NOMA are deployed at the AP to serve 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 the 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 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. Numerical analysis showed that the proposed D3QN algorithm for the NOMA-enabled IRS environment outperforms the benchmarks and achieves higher energy efficiency compared to the OMA-enabled IRS system. In [22], a hybrid RL-based framework is proposed for NOMA networks in a multi-IRS multi-user uplink network. Similarly, simulation results show an improved sum rate compared to the OMA scheme.

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 this issue, the authors in [47] proposed a mobile IRS model where IRSs are mounted on intelligent robots to achieve flexible deployment. The deep deterministic policy gradient (DDPG) framework is used in the IRS-assisted NOMA network to optimize the power allocation. 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 IRSs 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. Lastly, 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 compared to the independent training framework. In [49], the authors proposed an exploration attenuated deep deterministic policy gradient (EA-DDPG) technique for a multi-user IRS environment to increase the throughput in NOMA networks. The results showed an improved capacity compared to the OMA network. Similarly, the authors in [50] proposed a DDPG algorithm for a downlink IRS-assisted environment and achieved a higher sum rate than the conventional OMA networks.

A summary of AI-empowered optimization techniques for IRS deployment in NOMA systems is presented in Table 4.

VI. DEPLOYMENT OPTIMIZATION OF IRSs IN THz AND mmWave SYSTEMS

As mentioned earlier, one of the shortcomings in THz and mmWave communication is that communication signals suffer a strong molecular absorption effect and extremely high propagation attenuation due to their ultra-high frequency. Furthermore, due to THz's high band frequency characteristics, it experiences poor diffraction, which is sensitive to the blockages [65]. In particular, when THz and mmWave communication is implemented in indoor scenarios, the communication LOS signal can easily experience blockage from human bodies, complex interior structures, and furniture, leading to severe communication interruption. Thus, ubiquitous coverage and coverage holes are issues that need to be addressed in 6G-assisted THz communication.

In order to tackle this challenge, IRSs has been envisioned as a promising paradigm to improve the coverage in 6G, as depicted in Fig. 5. In particular, IRSs can smartly reconfigure the direction of propagation waves in THz and mmWaves to create a strong LOS signal and mitigate the blockage vulnerability. Hence, IRSs can be deployed in places such as hospitals, offices, and classes where obstacles block the LOS link between the transmitter and receiver.

A. CLASSICAL OPTIMIZATION TECHNIQUES FOR IRS DEPLOYMENT IN THz AND mmWave SYSTEMS

Massive deployment of IRSs is required to guarantee seamless communications of dense networks in the higher frequency spectrum domain. In this regard, the deployment strategies of IRSs at different locations (either transmitter side, receivers side, and/or different locations between a transceiver pair) play a crucial role in determining the performance of a network. However, a densely arranged network with multiple IRSs requires the optimization of factors that are not considered in single IRS systems. These factors include the number of IRSs per cell, the practical wireless constraints, and channel estimation due to radio turnaround time.

In this regard, the authors in [57] analyzed the effect of the number of IRS elements on the system ergodic capacity in an IRS-assisted THz communications architecture by optimizing the phase shift of the IRS elements using a swarm-based algorithm. Based on their findings, the system ergodic capacity increases as the number of IRS elements increases. Similarly, the ergodic capacity, outage probability, and the average bit error rate were also studied in [58]. Here, the authors showed that increasing the number of IRS elements will result in a system diversity gain. The authors implemented multiple reflectors to create a higher probability of LOS to reduce the mmWave channel attenuation significantly. Considering this, several studies [59], [60], [66] 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 solutions given the random changes in the mmWave channels.

In a different approach, to extend the short-range nature of the higher frequencies, the authors in [67] leveraged IRS in a THz system to reflect the significant impact on the system performance due to the deployment of IRS in the network. Moreover, the authors in [61] investigated the distributed and centralized strategies of IRS deployment. Based on these scenarios, the overall system capacity is derived. In addition, the authors in [53] investigated the massive deployment of IRSs on randomly located blockages to determine if dense locations can be used to create many virtual LOSs. The authors utilized stochastic geometry to derive the radio of blind spots and then identified the required IRSs density to increase the network's coverage.

B. AI-BASED OPTIMIZATION TECHNIQUES FOR IRS DEPLOYMENT IN THz AND mmWave SYSTEMS

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 studied much in the existing literature [62]. In this context, the works [62], [63] studied the problem of maximizing the total achievable rate of multi-hop multi-user IRS-aided wireless THz communication systems in the infinite blocklength regime. They proposed a hybrid beamforming architecture to improve the network's capacity. Afterwards, a deep reinforcement learning (DRL) algorithm is proposed to learn the optimal beamforming. The proposed scheme increased the coverage range of THz communications by 50%. In [64], a novel DRL framework is proposed for a multi-hop IRS network for THz communication.

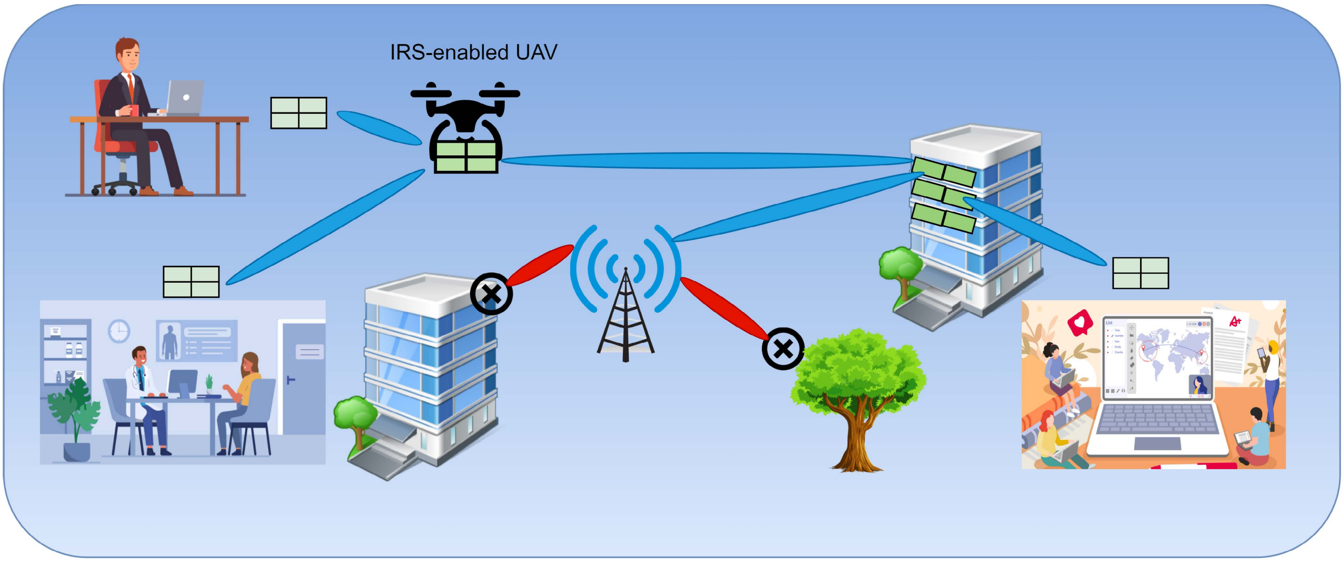

FIGURE 5. Deployment scenarios of IRS-enabled THz and mmWave networks.

TABLE 5. Summary of Classical Optimization and AI-empowered Techniques for IRS Deployment in THz and mmWave Systems.

Reference	Optimization strategy	Model	Algorithm	Objective	Contribution
[57]	Classical	Single-user downlink IRS	SIO	Outage probability and ergodic capacity	Utilises swarm intelligence optimization to derive an analytical expression for outage probability and ergodic capacity.
[58]		Single-user downlink IRS	Analytical	Outage probability, ergodic capacity, and average bit error rate	Analytical expressions for the outage probability and average BER for several modulation schemes are derived.
[59]		Reflector based mmWave	PO method	Coverage range	Designed passive-reflectors using PO method to increase the coverage range.
[60]		Multi-user downlink IRS	SDR	Receive SNR	Distributed algorithm adjusting transmit beamforming and the phase shifts until convergence.
[61]		Two-user uplink IRS	AO	Capacity/achievable rate	Demonstrated performance of centralized and distributed deployment of IRS.
[53]	ML	Uplink multi-IRS	Stochastic geometry	Coverage range	Presented performance of the cellular network with blockages of IRS.
[62]		Multi-hop IRS MISO	DDPG	Throughput	Proposed a DDPG beamforming framework for multiuser IRS-assisted THz system.
[63]		Two hop IRS network	MA-DRL	Average secrecy rate and throughput	A multi-agent DRL-based IRS selection for secure cooperative network in the presence of an eavesdropper.
[64]		Multi-hop IRS MISO	DDPG	Throughput	Proposed a DDPG beamforming framework for multiuser, multi-hop IRS-assisted THz system.

Simulation results showed that the DRL framework achieved an improved performance coverage in addressing the NP-hard beamforming problems in a multi-hop scenario. Furthermore, to analyze the optimal deployment strategy for IRSs in dense networks, the authors in [68] detailed a two-step machine learning approach, where an LSTM and double deep Q-network are utilized to solve the joint problem of IRSs deployment and design. By doing so, a systematic framework is developed to maximize the energy efficiency of the network by deriving optimal deployment designs for IRS-assisted networks. Nevertheless, the deployment strategies of the IRSs in THz and mmWave communication are still not well explored for 6G networks and are considered a paucity of studies. Some essential factors need to be considered for the deployment of IRSs in 6G THz communication, such as wireless conditions, number of IRSs, deployment costs, and building distribution.

A summary of classical and AI-empowered optimization techniques for IRS deployment in THz and mmWave systems is presented in Table 5.

VII. DEPLOYMENT OPTIMIZATION OF IRSs IN UAV SYSTEMS

IRSs can significantly improve the network's capacity and provide coverage extension when deployed over UAVs as shown in Fig. 6.

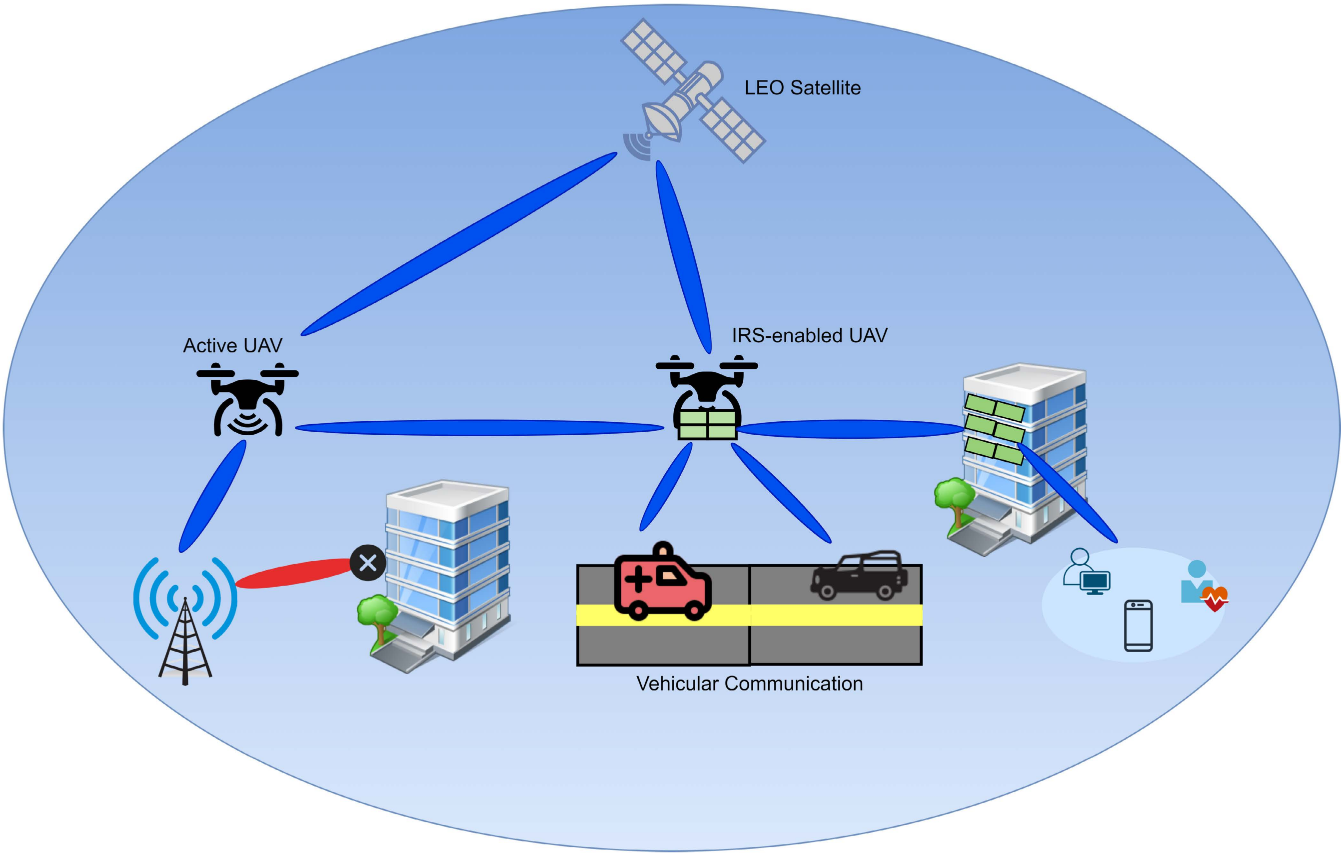

FIGURE 6. Deployment scenarios of IRSs in Aerial Networks.

Typical use cases for IRS-integrated UAV wireless networks involve (a) IRS for UAV-enabled data communication, where UAVs collect the data from distributed ground nodes, (b) IRS for UAV-assisted 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 PLS in UAV networks by weakening the communication channel of a 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 [13].

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 favourable 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. Nevertheless, it it still challenging to jointly optimize the UAV'a trajectory with passive beamforming to maximize the secrecy rate. Moreover, the placement of the IRS elements is a critical factor in improving the reflection efficiency and thus needs to be carefully chosen [69].

A. CLASSICAL OPTIMIZATION TECHNIQUES FOR IRS DEPLOYMENT IN UAV SYSTEMS

The recent study [70] proposed an IRS-aided communication system with multiple UAVs to maximize the average achievable rate. The authors in [71] 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 to maximize the instantaneous minimum rate. This is formulated by jointly optimizing the UAV's active beamforming, 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 beamforming and phase shifts.

One of the most important design aspects for IRS deployment is to jointly optimize the UAV's trajectory with IRS passive beamforming to improve the capacity. However, the main challenges in optimizing the UAV trajectory include reliable user connectivity and low power consumption. To address this issue, the authors in [72], [73], [74], and [75] considered IRSs to enhance the communication signal quality between a UAV and ground users. Furthermore, the authors in [18] demonstrated that deployment of IRSs is essential for attaining high gain from the UAV-IRS setup for ground user communications. The authors also proved that an IRS-aided cellular system could remarkably improve the SINR over the entire area when the UAV's trajectory is optimized [76], [77]. In their system model, the authors deployed the IRS on buildings and remotely configured them 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 [77] studies the effect of phase compensation error on the ergodic capacity for IRS's assisted by UAV communications. The authors in [78] and [79] proposed a synergetic UAV-IRS communication system where a UAV is equipped with a highly directional antenna aimed at the IRS. The authors provided a link budget analysis as well as a closed-form expression of the outage probability and the average outage duration. Furthermore, the authors showed that their proposed system improved the system performance compared to systems where the UAV is equipped with an omnidirectional antenna or the highly directional antenna is steered towards the ground node. Moreover, the authors in [80] and [81] proposed a throughput maximization algorithm for IRS-assisted UAV-enabled communication systems where the IRS and ground users (GUs) can harvest energy from the UAV. The authors jointly optimized the phase shift of IRS, the transmit power and time allocation of GUs, and the path planning of the UAV. Afterwards, the non-convex optimization problem is decomposed into three sub-problems using the BCD resource optimization method. The proposed system achieved superior performance compared to benchmark algorithms.

Due to the energy limitations of the UAVs, energy optimization is vital in IRS-assisted UAV systems, and several solutions have been proposed in the literature, including optimizing the transmission power, implementing energy harvesting systems, and deploying simultaneous wireless information and power transfer (SWIPT) networks [82], [83], [84], [85], [86], [87], [88], [89], [90]. In particular, the authors in [82] proposed a dual power transfer and information transfer system between UAVs and ground IoT devices. In the first phase, the UAVs transfer their harvested power to the IoTs and afterwards, the IoTs transfer their collected information to the UAVs. To maximize the total network sum rate, the authors jointly optimized the UAV's trajectory and power allocation, the energy harvesting scheduling of IoT devices, and the phase-shift matrix of the IRS. Similarly, a SWIPT system was proposed in [83] to maximize the harvested energy while constrained by the QoS requirements. Moreover, an IRS-Assisted UAV IoT data collection platform was studied in [88]. The authors jointly optimize the UAV's deployment and trajectory and the IRS's phase shift to minimize the energy consumption of the UAV and all IoT devices. Afterwards, the authors implemented a competitive learning algorithm to solve the optimization problem. Similarly, The authors in [89] jointly optimized the UAV's trajectory, hovering time and the IRS's phase shift to minimize the total energy consumption of a UAV in a wireless power transfer system. On the other hand, the authors in [90] minimized the total transmit power in a multi-UAV multi-IRS communication system by jointly optimizing the UAV's trajectory, each IRS's phase shift, the subcarrier allocations, and the active beamforming at each base station. Similarly, the authors in [91] optimized the received power at the ground users by optimizing the active beamforming at the UAV, passive beamforming at the IRSs, and UAV's trajectory for a single UAV communicating with multiple IRSs deployed outside building walls.

A summary of classical optimization techniques for IRS deployment in UAV Systems is presented in Table 6.

From the IRS deployment perspective, improving network performance in UAV networks is still challenging. For example, the above-discussed optimization techniques cannot accurately formulate the dynamic and complex characteristics of IRS-assisted terrestrial and non-terrestrial networks to achieve higher capacity. As a result, the following section investigates the recent AI-empowered techniques in the literature for learning the IRS deployment strategies in complex and dynamic future wireless networks.

B. AI-BASED OPTIMIZATION TECHNIQUES FOR IRS DEPLOYMENT IN UAV SYSTEMS

The authors of [93] 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 to enhance the users' QoS. The energy consumption minimization problem was 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 could be significantly reduced by deploying IRSs in the UAV environment by incorporating NOMA and consumes 11.7% less energy than the IRS-OMA case.

Similarly, the authors of [85], [86] jointly optimized the phase shift of IRS and the power allocation of the UAVs to maximize the energy efficiency. Afterwards, a centralized DRL algorithm was proposed to solve the optimization problem with time-varying channels. On the other hand, the study in [87] employed deep reinforcement learning and utilized the Double Deep Q-Network (DDQN) and Deep Deterministic Policy Gradient (DDPG) algorithms to maximize the data rate and minimize the UAV's propulsion energy by optimizing the 3D location of the UAV and the phase shift of the IRS.

The work in [84] 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

TABLE 6. Summary of Classical Optimization Techniques for IRS Deployment in UAV Systems.

Ref	Deployment Strategy	System Model	Metric	Contributions
[18]	IRS aided multi-cell downlink communication for aerial users	Multi-cell downlink communication system	Mean SINR,	Proposed an optimal IRS placement strategy that maximizes in mitigating the interference between aerial users.
[69]	IRS mounted on Mobile UAV	Terrestrial communication network enhanced by UAV-IRS	Average achievable rate and secrecy rate	Joint design of transmission UAV trajectory, and reflecting phase shifts to maximize the average achieve secrecy rate.
[70]	Multiple UAVs in IRS network	Millimeter wave multicast system with UAV-IRS	Minimum achievable rate	Penalty based BCD algorithm to jointly optimize the beamformers of multiple IRSs for maximizing the instantaneous achievable rate.
[71]	Single UAV equipped with IRS as a relay node	UAV-assisted MISO with NOMA downlink network	Data rate and transmit power	Proposed an iterative algorithm to optimize the transmit beamforming and phase shift of the IRS.
[72]	Downlink transmission system with a mobile UAV	IRS-assisted UAV communication System	Average rate	Proposed a joint UAV trajectory and IRS passive beamforming optimization algorithm to improve the communication quality of UAV-enabled networks.
[76]	IRS deployed on building walls configured by cellular base stations to optimize UAV trajectory	IRS-assisted downlink cellular communication system	Capacity	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.
[77]	Optimizing multiple unmanned aerial vehicles trajectory in an IRS network	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.

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 [92], and a distributional RL technique was proposed to optimize the reflection coefficients, UAV's location, and precoding matrix at the base station. Simulation results showed that the proposed DRL could 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.

Furthermore, a DRL framework based on proximal policy optimization (PPO) was 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). The authors in [94] studied the uplink transmission of IoT traffic in a UAV-IR system. 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 [94], 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., [95] considered the sub-carrier allocation and trajectory of multiple UAVs to improve the users' coverage and minimize the average age of information (AAoI) while satisfying a maximum transmit power and UAV's movement constraints. 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 DDQN method to solve the proposed problem. They investigated applications of the UAV-IRS system on the IoT networks via optimizing sub-carrier allocation, power, phase shift, and trajectory. Numerical results showed that the proposed approach achieves 15% and 10% performance improvement compared to the random-trajectory and matching algorithm. Regarding IRS deployment in state-of-the-art networks, the authors in [96] 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 a soft 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 compared to the fixed IRS and random phase shift of the IRS, respectively.

In recent works, Wang et al., [97] considered a dynamic multi-IRS configuration to improve the LOS channel model between a UAV and a set of ground users. They aimed to maximize all UEs geographical fairness and data rates by jointly optimizing the IRSs phase shifts and UAVs trajectory. 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. Experimental results proved that the proposed solution achieved better performance than benchmarks.

TABLE 7. Summary of AI-empowered optimization techniques for IRS deployment in UAV Systems.

Ref.	System Model	Algorithm	Metric	Contributions
[84]	UAV-IR downlink transmission	DQN,MDP	Average data rate, LOS probability	A RL technique is proposed for optimal deployment of the UAV-IR in downlink mmWave transmissions.
[92]	UAV-IR MISO downlink transmission	Distributional RL, MDP	received signal power at each UE	A DRL technique is proposed for optimal placement of IRS element in an UAV environment over downlink mmWave frequencies in a multi-user scenario.
[82]	UAVs and ground IoT devices	DRL	Processing time and network throughput	Two DRL algorithms are proposed to maximize the total network sum-rate.
[93]	Downlink NOMA-MISO-IL IRS network	Decaying deep Q-network	Average energy consumption	Proposed a NOMA architecture in IRS-assisted UAV wireless networks.
[85]	Multi-UAV Single IRS downlink	Centralized DRL	Energy efficiency	A DRL technique was proposed to maximize the energy efficiency with time-varying channels.
[87]	Single RIS-assisted UAV system	DDQN,DDPG	Data rate and the UAV's propulsion energy	Proposed DRL algorithms to maximize the data rate and minimize the UAV's propulsion energy.
[88]	UAV, an IRS and many IoT devices	Competitive learning algorithm	Energy consumption of the UAV and all IoT devices	An IRS-Assisted UAV IoT data collection platform was proposed.
[94]	IoT wireless network	PPO	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)
[95]	Uplink SIMO UAV-IRS system	Combination of PPO and DDQN	Average Age of Information (AAoI)	Proposed a PPO based technique for IRS-enabled UAV environment to improve the uplink channel reliability.
[96]	SIMO IRS-assisted UAV network	SAC	Data rate	An IRS assisted UAV framework to provide reliable communication services for high speed trains (HSTs).
[97]	IRS downlink transmission	DQN, DDPG	Fairness, reward, data rate	Proposed an RL approach for the joint optimization of trajectory and phase shift in an IRS-assisted UAV communication system.
[98]	Single IRS and multiple UAV-user pairs	Deep neural network	SNR, transmit power, and throughput	Proposed a frame-based RIS-assisted transmission protocol.
[99]	Single UAV with attached IRS	RL	Received signal power	A RL technique is proposed for optimal placement of the UAV to maximize the received signal power of a moving user.
[100]	IRS-assisted UAV MIMO communication system	DNN	Spatial cross-correlation functions	A 3D geometry-based stochastic MIMO channel model for IRS-assisted UAV was proposed.

The study in [99] employed an 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. However, accurate channel estimation is critical in highly mobile IRS-assisted non-terrestrial communication [98], [100]. Hence, the study in [98] considered an IRS attached outside a building to assist the communication between multiple UAV-user pairs. The authors developed a transmission protocol based on the channel estimation, transmission strategy, and data transmission. Afterwards, a deep neural network (DNN)-based model was developed to solve the transmission strategy problem. Similarly, the authors in [100] proposed a DL-based channel tracking algorithm in IRS-assisted UAV-enabled communication systems. Firstly, the authors developed a 3D geometry-based dynamic time-variant channel model depending on the blockage parameter, Doppler effects, mobile nodes' velocities, propagation delays, and time delays. Afterwards, the authors developed a channel pre-estimation and channel-tracking DNN to track the time-variant channel model. The proposed system achieved superior performance to benchmark algorithms.

A summary of AI-empowered optimization techniques for IRS deployment in UAV Systems is presented in Table 7.

C. OPTIMIZATION OF IRS-ASSISTED UAV SYSTEMS FOR URLLC APPLICATIONS

IRS-assisted UAV systems have shown performance improvement with the eMBB and URLCC applications in [101] and [102]. The authors jointly optimized the eMBB sum rate and the accepted number of URLLC packets while adhering to the QoS requirements of the eMBB and URLLC using an alternating algorithm. On the other hand, the authors in [103] proposed a UAV-assisted URLLC system to minimize the decoding error probability under block-length and power allocation constraints. In their proposed system, IRS panels are mounted on UAVs to reflect the signals from macro base stations to end users. The authors formulated the optimization problem with respect to the UAVs' deployment, power allocation at the base stations, the phase shift of IRS, and the block length of URLLC. Afterwards, DNNs are proposed to solve the optimal UAVs' deployment. Then, an optimal resource allocation algorithm is proposed to provide the maximal reliability of the considered system with respect to the users' fairness. Their proposed scheme is shown to be superior to other benchmarks.

D. OPTIMIZATION OF IRS-ASSISTED UAV SYSTEMS FOR MEC APPLICATIONS

IRSs can improve the performance of UAVs deployed as aerial mobile edge computing (MEC) servers [104], [105], [106], [107], [108], [109]. For instance, the authors in [104] proposed a dual-IRS MEC-enabled UAV-assisted network architecture to minimize the energy consumption of an Internet of Vehicles (IoV) network. Furthermore, the authors in [105] and [106] utilized the successive convex approximation method to maximize the energy efficiency of the IRS-assisted UAV system by jointly optimizing the UAV's trajectory, resource allocation, and the IRS's phase shift. Similarly, the UAV's trajectory and the IRS's phase shift were jointly optimized in a multi-IRS and multi-UAV system to minimize the UAV's energy consumption, completion time, and maintenance cost in [107] and [108]. Finally, IRSs is proven to improve the UAV's computation capacity of an IRS-enabled UAV-assisted MEC system as presented in [109].

E. SECURITY OPTIMIZATION OF IRS-ASSISTED UAV SYSTEMS

The PLS of the UAV-assisted communication systems can be enhanced by deploying intelligent reflecting surfaces [110], [111], [112], [113], [114], [115], [116], [117], [118], [119], [120], [121], [122], [123], [124], [125]. In particular, the authors in [110] and [111] jointly optimized the UAV's trajectory, the IRS's phase shift, and transmit power to maximize the secure energy efficiency for a communication system where a UAV acts as a relay between the base station and a group of users. Afterwards, the SCA method was applied to solve the optimization problem. The secrecy rate between a UAV base station and a legitimate receiver in the presence of an eavesdropper was maximized by jointly optimizing the UAV's trajectory, transmit power and the IRS's phase shift using an iterative algorithm based on the SCA method. in [112], [113], [114], [115], [116], [117], [118], [119], [120], [121], [122], and [123]. The authors in [124] and [125] extended the previous works by maximizing the secrecy capacity of an IRS-assisted UAV system in the presence of multiple eavesdroppers.

VIII. DEPLOYMENT OPTIMIZATION OF IRSs IN SATELLITE SYSTEMS

The deployment of IRSs in satellite systems has sparked interest from researchers recently [126], [127], [128], [129], [130], [131], [132], [133], and [134]. For instance, the authors in [126] jointly optimized the power allocation and the IRS's phase shift using a Mesh Adaptive Direct Search method to maximize the channel capacity of an IRS-assisted GEO SatCom network. Similarly, an IRS-aided LEO SatCom architecture was proposed in [127], where the IRS elements are deployed on the LEO satellites and the ground nodes. Afterwards, the authors jointly optimized the active and passive beamforming on the LEO satellite and the ground nodes to maximize the channel capacity. On the other hand, the authors in [128] aimed to improve the coverage of an IRS-assisted LEO SatCom network by changing the tilt of the IRS and by increasing the number of IRSs. Furthermore, direct-to-satellite (DtS) channel estimation for different IRS configurations was studied in [129]. A joint beamforming design and optimization algorithm for IRS-aided hybrid satellite-terrestrial relay network was proposed in [130] aiming to minimize the total transmit power of both the satellite and BS while guaranteeing the rate requirements of users. Similarly, the authors in [131] proposed a transmission model for an IRS-assisted LEO IoT network aiming to minimize the transmission power. The authors implemented an alternating optimization scheme by utilizing singular value decomposition and uplink-downlink duality. The outage probability of IRS-assisted satellite-UAV-terrestrial networks was studied in [132]. A rate-adaptive link-switching system design of RIS-UAV-assisted high altitude platform (HAP)-based Satellite-aerial-ground integrated network (SAGIN) using hybrid free-space optics (FSO)/radio frequency (RF) links was proposed in [133]. Lastly, the authors in [134] analyzed an IRS-assisted THz inter-satellite communication and presented the error rate performance.

IX. CHALLENGES AND FUTURE RESEARCH DIRECTIONS

In the following, we list some of the challenges and future directions that arise for deployment strategies of IRSs in 6G networks. Table 8 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

TABLE 8. 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 beamforming.	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	With UAVs having a high degree of mobility and multiple reflected propagation's introduced by deploying IRSs, it will be challenging to optimize their 3D placements/trajectories.	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.

networks to obtain an accurate CSI with a lower overhead in 6G networks.

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 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

PLS 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 [135]. 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 PLS in IRS-assisted wireless networks poses some new research challenges. Depending on the IRS placement in the cell, noise and channel fading in the signal will mis-classify legitimate users from illegitimate users at the AP side. Hence, it is imperative to develop a strategy to determine the IRS placement that allows legitimate users to access the AP. Despite the fact that strategically locating the IRS provides extra level of authentication, it also increases the likelihood that malicious agents will provide false information for spoofing attacks that hinder the performance of the system. Therefore, this requires us to develop AI techniques such as federated learning for security and privacy protocols under some practical IRS deployment constraints [32].

D. THz AND mmWave COMMUNICATIONS

THz and mmWave communications promise to support high data rates by utilizing the bandwidth efficiently in the higher frequencies. The THz and mmWave communication systems will require a larger number of RF chains, which will result in a higher energy cost and hardware cost than sub-6 GHz wireless transceivers. 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 to create a strong LOS link in blockages to tackle these challenging issues efficiently. Since THz and mmWave channels have random channel characteristics, it is then vital to design novel AI techniques assisted with digital twin approach (that can create a virtual representation of IRS network) which can accurately estimate the CSI in order to optimize phase shift and beamforming design at the IRS and AP to establish a strong LOS link to improve the SNR.

E. UAV COMMUNICATION

The deployment strategy of IRSs can improve the flexibility while designing UAVs trajectories in UAV-assisted wireless systems. A challenge to the multi-antenna setting's precoding design is that it is directly dependent on the UAV's trajectory, since the practical channel gains between the UAV and terrestrial users depend on the 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. As a result, the deployment strategy of IRSs in dynamic, complex wireless networks with acceptable fairness while also meeting the sum-rate objective remains an open research issue. Further, accurate channel tracking in mmWave and THz communication makes compensation for delay and Doppler spread more challenging and will require further investigation.

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. Designing AI-assisted medium access control (MAC) solutions for THz and mmWave communications while taking into account the function of PHY layer is a crucial difficulty that needs to be taken into account. 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.

X. CONCLUSION

In this paper, we presented a comprehensive survey of the architecture and deployment strategies of IRSs in the future 6G networks. Firstly, we provided an architectural framework of IRSs from the perspective of deployment strategies in 6G. Then, we investigated the deployment aspect of IRSs in perspective 6G applications incorporating NOMA, THz/mmWave communication techniques, MEC, UAVs, and satellite communication to improve the system performance. We concluded by outlining significant challenges, potential research initiatives, and directions of the envisioned IRS-empowered 6G networks.

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