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TOPICAL REVIEW

Federated Learning Meets Intelligence Reflection Surface in Drones for Enabling 6G Networks: Challenges and Opportunities

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ABSTRACT The combination of drones and Intelligent Reflecting Surfaces (IRS) have emerged as potential technologies for improving the performance of six Generation (6G) communication networks by proactively modifying wireless communication through smart signal reflection and manoeuvre control. By deploying the IRS on drones, it becomes possible to improve the coverage and reliability of the communication network while reducing energy consumption and costs. Furthermore, integrating IRS with Federated Learning (FL) can further boost the performance of the drone network by enabling collaborative learning among multiple drones, leading to better and more efficient decision-making and holding great promise for enabling 6G communication networks. Therefore, we present a novel framework for FL meets IRS in drones for enabling 6G. In this framework, multiple IRS-equipped drone swarm are deployed to form a distributed wireless network, where FL techniques are used to collaborate with the learning process and optimize the reflection coefficients of each drone-IRS. This allows drone swarm to adapt to changing communication environments and improve the coverage and quality of wireless communication services. Integrating FL and IRS into drones offers several advantages over traditional wireless communication networks, including rapid deployment in emergencies or disasters, improved coverage and quality of communication services, and increased accessibility to remote areas. Finally, we highlight the challenges and opportunities of integrating FL and IRS into drones for researchers interested in drone networks. We also help drive innovation in developing 6G communication networks.

INDEX TERMS 6G, drones, drone swarm, federated learning, IoT, IRS, smart environment.

I. INTRODUCTION

Recently, the fifth Generation (5G) addresses the significant rise of the Internet of Things (IoT) and users by providing creative communication options. Due to the capability to improve the capacity of mobile infrastructure and expand coverage, drones are expected to play a vital role in enhancing communication reliability of upcoming wireless networks and the attainable spectral efficiency [1]. Additionally, drones were essentially designed to play a crucial part in

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data distribution to IoT devices [2]. Drones must adopt cutting-edge communication paradigms to fulfil the rising need for high data speeds, but this is difficult given their size and power constraints [3]. To support six Generations (6G), it is very difficult to characterize system models and ensure strict Quality of Service (QoS) requirements in such complex and dynamic network environments. 6G wireless networks are expected to provide various services, combining terrestrial, aerial, and space networks for universal coverage. Most earlier efforts have generally concentrated on communications between ground devices and ground Base Station (BS) in the context of the tiny data-packet transmission regime. Non-line-of-sight (NLoS) wireless networks on the ground can sometimes handle many mobile devices while upholding strict mURLLC criteria. Drone can enable several enormous access strategies by significantly improving Line-of-Sight (LoS) while guaranteeing various QoS criteria. The benefits of deployment capabilities and high mobility inspired this idea. Intelligent Reflecting Surface (IRS) technology-empowered drone network systems, which have recently been introduced to resolve these problems by avoiding obstructions and enhancing connection in drone systems [4]. According to the IRS-assisted drone design, IRSs are in an open network environment to facilitate communication between drones and smart devices or users. By using the IRS to enable multiple LoS connections, which significantly decrease channel attenuation, a blocked NLoS transmission channel may be addressed.

The idea of an IRS has recently come to light as a disruptive technology expected to completely transform wireless communications by giving wireless system engineers complete control over the propagation environment while the wireless transmission is in progress [5]. In particular, IRS is a surface that enables the manipulation of the impinging communication signals to accomplish one of the following goals [6]: (i) extending the coverage to a dead zone, (ii) Physical layer security, (iii) extensive Device to Device (D2D) communication, and (vi) wireless data and power transfer. IRSs have an advantage in flexible IoT ecosystems' energy efficient because they do not employ active components. As a result, IRS-assisted drone communications can offer IoT networks energy-efficient communications [1].

Drones fly closer to the implicated battery-limited IoT devices to accomplish energy efficiency, which enables IoT devices to transmit at lower power in the uplink, eventually resulting in decreased energy consumption and extended battery lives [7], [8], [9], [10]. Additionally, the employment of IRS-assisted drones to increase network coverage [11] and channel capacity significantly reduces the number of cellular BS, creating greener networks, smarter, and consuming less energy [12]. The possible use of IRS in cellular communications with drones that have weak signals was examined [13]. In such a scenario, IRS are placed on walls and controlled by a Base Station (BS) to direct reflected signals toward drones. By coordinating the reflections, signal strengths are boosted for the drones, enhancing the wireless communication quality. The symbol error rate and outage probability of multi-layer drone-powered wireless communications provided by the IRS [14]. The authors of [4] examined the integration of drones and IRS by illuminating the uses for IRS and the benefits of drones and outlining the benefits of doing so in combination with the wireless network. The drone trajectory, the transmit beamforming at the BS, and the passive beamforming in IRS are jointly optimized [15].

A potential way to deploy over-the-air intelligent reflection and increase wireless coverage is by merging IRS and drones. IRS-drone integrated systems can drastically lower drone energy consumption and increase operating time because of the attractive benefits of passive IRS. Due to drones' relatively high heights and adaptable 3D mobility, IRS-drone-integrated systems are more likely than terrestrial IRS to establish robust LoS linkages with ground equipment. Additionally, IRS-drone integrated systems can achieve panoramic full-range reflection, considerably expanding the number of mobile users supported. Compared to terrestrial IRS systems, several new difficulties exist, including durability, stability, and controllability. Particularly, low-complexity IRS-drone-integrated 3D wireless channel models are challenging to describe. Additionally, 3D IRS-drone trajectories with user associations must be designed and optimized to enhance system performance. Characterizing the optimization issues for error-rate and delay-bounded QoS is complex due to high-dimensional complexity, evolving environments, and time-varying action spaces, especially when considering massive access applications to support mURLLC.

Despite the benefits of drone communication, the complicated terrain and surroundings may obstruct the Air-to-Ground (A2G) channels. Furthermore, the information security of authorized users could not be assured. IRS can be used in drone-assisted A2G networks to address these problems by creating a favourable propagation environment and enhancing the communication quality of intended users. Furthermore, by appropriately configuring the passive beamforming, the IRS may cancel out the undesired signals to reduce interference and stop aggressive eavesdropping. The performance of A2G networks has recently been improved by experiments fusing drones and IRS [16], [17], [18], [19], [21]. To be more specific, the IRS enables the expansion of drone coverage, supporting a variety of QoS demands from consumers. Furthermore, when mounted on a mobile drone rather than a stationary structure, IRS has more deployment flexibility and a larger range of signal reflection. Recently, research integrating the drone with IRS [22], [23] has emerged to enhance the performance of A2G networks. With the aid of IRS, drone coverage may be increased, and therefore, various QoS requirements of users can be met. When mounted on a mobile drone, IRS has more deployment flexibility and a larger range of signal reflection than when put on a permanent structure. Therefore, the use of drones and

IRS to enhance the performance of A2G networks is still in its early stages and requires more discussion, especially the combination of drones and IRSs with the help of advanced technologies and efficient techniques.

Federated Learning (FL) is a decentralized ML paradigm where models are trained collaboratively across multiple devices or servers while keeping the raw data localized. FL finds applications in scenarios where data privacy, security, and distributed data sources are critical concerns, such as mobile devices, edge computing, and sectors like healthcare and finance. Furthermore, the authors of [24] created a unique framework of resource allocation and device selection for the FL technique by deploying numerous IRSs in the FL. Moreover, in [25], focused on enhancing the over-the-air FL (AirFL) performance while maintaining QoS restrictions. When an IRS facilitates the transmission from users to the BS in the AirFL system, [26] explored the model aggregation process. However, the main aim of our novel framework is to provide a comprehensive and novel approach to enhancing communication network performance by combining the power of FL and IRS in drone technology. The framework addresses the challenges and seizes the opportunities to deploy IRS in drones and integrate it with FL to enable 6G communication networks. The contributions of the framework can be summarized as providing a solution to enhance communication network coverage, capacity, and energy efficiency through the use of FL and IRS in drone technology.

A. RELATED WORK

1) DRONES

Drones represent a transformative technological innovation with diverse applications across various fields. The drones, controlled remotely or autonomously, have gained prominence for their ability to traverse challenging terrains, collect data from inaccessible locations, and perform a wide range of tasks without human intervention [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39]. Drones come equipped with sensors, cameras, and communication capabilities, enabling them to gather real-time information, capture high-resolution imagery, and facilitate remote sensing operations. The versatility spans agriculture, surveillance, disaster response, environmental monitoring, and entertainment [40], [41], [42], [43]. UAVs offer the potential to revolutionize industries by providing cost-effective, efficient, and flexible solutions to address complex challenges that were previously difficult or impossible to tackle.

2) IRS

The IRS was implemented initially in drone systems [16] and demonstrated to increase data rate significantly; however, secrecy performance and power allocation should have been considered. The authors then presented a secrecy rate maximization challenge using IRS in [44], developing multi-antenna access points for transmit beamforming and the IRS's reflect beamforming. Furthermore, the authors of [45] investigated the secrecy rate maximization issue using IRS with an eavesdropper and a single receiver. When the genuine receivers' channel response was highly associated with that of the eavesdroppers, the IRS was used to offer extra communication lines [46]. In [47], the authors examined the relevance of generated noise in IRS-aided wireless communication networks. In addition, a unique deep reinforcement learning-based secure beamforming technique is provided for the first time in IRS-aided wireless secure communication to obtain the best beamforming policy against eavesdroppers [48]. The first flying IRS was suggested to protect the terrestrial transmission in the availability of an eavesdropper [18], with the IRS phases, user association, trajectory, and transmit power all optimized together. However, direct communications between the BS and the users were believed to be prevented. Motivated by the advantages of both the drone and the IRS, the authors of [49] proposed a secure IRS-aided drone to support wireless communication situations such as concerts where large crowds and heavy communication traffic are required temporarily.

3) IRS IN DRONE

The combination of drones with IRS for sky reflection was researched in [16] and [50]. These pieces may generally be divided into two groups. Terrestrial IRS-assisted drone communications are one, while drone IRS-assisted communications are the other [16], [22], [51]. To increase the average attainable rate for the ground user, a hybrid drone trajectory and terrestrial IRS passive beamforming design were examined in [16]. By concurrently designing the drone movement, the terrestrial IRS phase shift, and the power allocation strategy, the authors in [51] used the decaying deep Q-network to reduce the energy consumption of ground users. Using passive beamforming at the terrestrial IRS, a drone was developed to aid the terrestrial IRS in reflecting its signals to the BS and improve drone transmission [22].

The transmitter and receiver are on the ground for combining drone and IRS-assisted communications, resulting in A2G channels. Additionally, the drone and IRS location combination defines array response in the LoS passive signal reflections. The combination of drones and IRS was used to increase the worst-case signal-to-noise ratio in a given region [52]. However, the authors did not consider A2G LoS linkages. Neglected were the NLoS connections affected by the combination of drone and IRS location. Furthermore, only single-user beamforming was considered when the worst-case SNR was maximized. Maximizing the drone trajectory and the combination of drone and IRS phase shift, transmit power, and user association motivated the authors of [53] to explore secure up-link communications with the combination of drone and IRS assistance. The NLoS A2G links and several antennae at the BS were ignored, and the combination of drone and IRS height was fixed [53].

Due to the considerable far-field double route loss (i.e., the attenuation or loss of a wireless signal's strength as it travels over a long distance through two distinct propagation paths), the combination of drone and IRS placement design is essential for the combination of drone and IRS-assisted communications [54]. In [52], the optimal LoS A2G route was presumed, and the deployment of a combination of drones and IRS was considered. The combination of drone and IRS placement between destination nodes and the fixed source was the main emphasis [50]. However, the random geographical distribution of users must be considered while evaluating performance. Notably, single drone networks focused on previous efforts that combined drones with IRS. The numerous drone-enabled combinations of drone and IRS systems need to be looked into since the swarm network of drones they generate makes passive signal reflections more effective at increasing aperture gain. References [55] and [56] regarded as relay BSs for multi-drone 3D deployment, with the Point-to-Point (P2P) signal transmissions occurring over the G2A or A2G channels. However, transmissions encounter cascading G2A and A2G channels when drones are outfitted with IRS to reflect signals.

4) FL MEETS IRS IN DRONE

The combination of FL and IRS has been used in several previous works, including [57] and [58]. By carefully choosing users and allocating resources, the developers of [57] reduced the FL loss function and established an explicit link between packet error rate and FL performance. Ni et al. [58] created a unique resource allocation framework and selected a smart device for the FL system by deploying numerous IRSs in the FL system.

B. MOTIVATION AND CONTRIBUTIONS

Integrating FL and IRS in drones can support the demands of emerging applications in the next generation of wireless communication, such as autonomous drones, aerial photography and delivery services, environmental monitoring, disaster response, and infrastructure inspection. These are just a few examples of the potential applications of FL and IRS for drones. Integrating these technologies can bring new capabilities and opportunities to drones' next generation of wireless communication. The integration of FL and IRS in drones is motivated by the need to improve communication performance, security, and efficiency in the next generation of wireless communication for drones.

The motivation behind combining FL and IRS in drones to enable 6G networks is to address some critical challenges and opportunities in the next generation of wireless communication for drones. With the increasing use of drones for various applications, there is a growing demand for new solutions to handle the increasing traffic and improve communication performance. FL and the IRS have the potential to address these challenges by providing a decentralized and efficient way of training Machine Learning (ML) models and dynamically controlling the wireless environment for drones. By combining FL and IRS for drones, 6G networks can leverage the benefits of both technologies to create a more intelligent and efficient communication infrastructure for drones. Using FL can allow for the decentralized and distributed training of ML models, taking advantage of the large and diverse data generated by drones in the network. In addition, the use of IRS can improve communication performance and security by dynamically controlling the wireless environment and reducing interference. In this framework, we introduce FL meets IRS in drones to enable 6G networks and discuss the state-of-the-art research and development in this area. In addition, we summarize the current work and identify the key challenges, opportunities, and future directions for this integration. The contributions of the summaries are as follows:

1) We provide an overview of the current status of the research and development of FL and IRS in drones for enabling 6G networks. The combination of FL and IRS in drone technology to enhance 6G communication networks is highlighted. Then, we identify the key technical and implementation issues that must be addressed to deploy the framework and achieve its potential benefits successfully.
2) We introduce a novel framework that can overcome the challenges of combining FL and IRS in drones to enable 6G networks, providing insights into the design and development of FL and IRS integration in drones.
3) We identify the critical challenges, opportunities and future trends in integrating FL and IRS in drones for enabling 6G networks.

C. PAPER STRUCTURE

The paper structure is shown as shown in Fig.1. The rest of the paper is organised as follows. Section II discusses the preliminaries, while Section III introduces IRS-Drones. Section IV presents a framework for FL meets IRS in drones to support 6G. Section V addresses the challenges and future trends. Finally, the conclusion of this paper is given in Section VI.

II. PRELIMINARIES

A. 6G

6G is the sixth generation of wireless communication technology expected to succeed in the current 5G networks. It is envisioned as a transformative technology that will revolutionize the way we communicate and interact with technology. 6G networks are expected to be faster, more efficient, and more reliable than the existing wireless networks, with the ability to support many devices and applications. Some of the key features and capabilities that are expected to define 6G networks include higher data rates, ultra-low latency, greater energy efficiency, higher spectrum efficiency, improved security and privacy, and the ability to support new emerging applications and technologies such as augmented reality, virtual reality, and the IoT [59].

One of the main challenges in developing 6G networks is the need for a new wireless spectrum that can support the high-speed and high-frequency transmissions required by 6G networks. Another challenge is the need for new and innovative network architectures and technologies to support the massive amounts of data and traffic generated by 6G devices and applications. Despite these challenges, the potential benefits of 6G are immense, and it is expected to drive innovation and growth in various industries such as healthcare, transportation, manufacturing, and entertainment. However, the development of 6G networks is still in its early stages, and it is expected to take several years before the technology is commercially available.

B. FL

FL is a relatively new ML paradigm that allows multiple parties to train a model collaboratively without sharing their data. The basic mechanism of FL involves the distribution of the ML model to multiple devices or clients, each of which trains the model using its local data. The model updates are then sent to a central server for aggregation, and the aggregated model is sent back to the devices for further training. This process is repeated multiple times until the model achieves the desired accuracy. The pros of FL include improved data privacy and security since the data never leaves the device, the ability to train models on decentralized data, and the potential for faster training times since the data does not need to be transmitted to a central server. However, the cons of FL include increased complexity in model optimization, potential communication latency and bandwidth limitations, and the need for careful design and implementation to ensure privacy and security. Table 1 illustrates the cons and pros of FL based on different parameters.

1) LOCAL MODEL TRAINING

The local model training step can involve using gradient-based optimization algorithms, such as Stochastic Gradient Descent (SGD) or its variants.

2) GRADIENT COMPUTATION

For a model with weights W and biases &b&, the gradient of the loss function L with respect to W and b can be computed as:

$$\nabla L(W, b) = \frac{\partial L}{\partial W}, \frac{\partial L}{\partial b} \quad (1)$$

This equation represents the gradient of the loss function L concerning the weights W and biases b of a model. The notation $\partial L/\partial W$ and $\partial L/\partial b$ indicate the partial derivatives of the loss function concerning W and b, respectively.

3) WEIGHT AND BIAS UPDATES

The weights and biases can be updated using the computed gradients:

$$W' = W - \eta \nabla L(W, b) \quad (2)$$

$$b' = b - \eta \nabla L(W, b) \quad (3)$$

where η is the learning rate that controls the step size of the updates, and $\nabla L(W, b)$ is the gradient of the loss function L with respect to W and b.

4) FL AGGREGATION

The FL aggregation process can involve weighted averaging or other aggregation techniques, which can be represented mathematically.

5) WEIGHTED AVERAGING

For the model updates received from each drone, the global model can be computed as a weighted average of the local model updates, where the weights represent the contribution of each local model update:

$$Global_{model} = \frac{\sum_{i}^{N}(w_i * Local_{model_i})}{\sum_{i}^{N} w_i} \quad (4)$$

where w_i represents the weight assigned to the i-th local model update, which is determined based on various factors such as the performance or reliability of the local model.

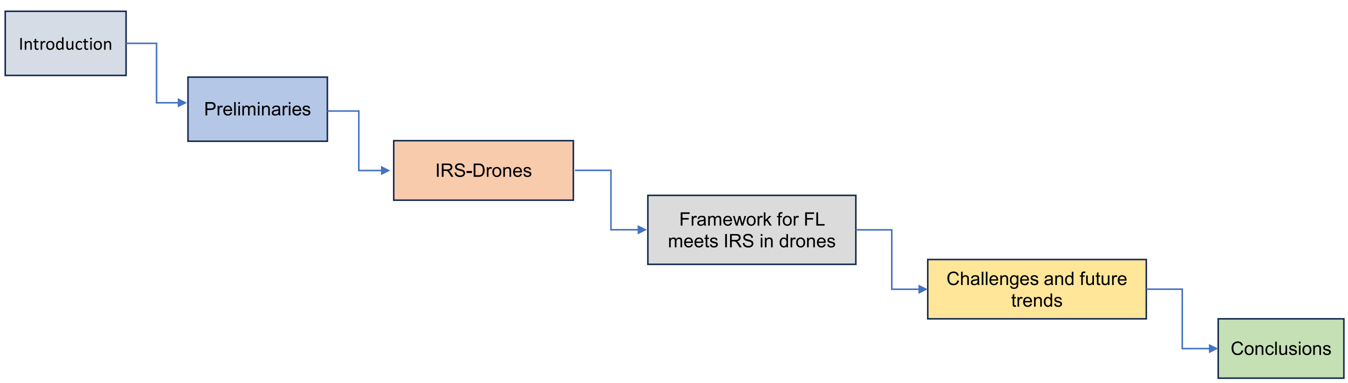

FIGURE 1. Paper structure.

TABLE 1. Cons and pros of FL for support framework.

Parameter	Pros	Cons
Data Privacy	Data is kept on devices, reducing the risk of data breaches Protects sensitive personal data	Increased complexity in implementing privacy-preserving techniques Possible vulnerabilities
Decentralized Data	Allows for training on data that is distributed across different devices Improving model generalization and accuracy	Increased communication overhead between devices Possible limitations in network bandwidth and latency
Speed	Reduced training time by training models in parallel on different devices Reduces the need for transmitting large amounts of data to a central server	Increased complexity in model optimization Limited by the computing resources available on individual devices
Security	Reduces the risk of a single point of failure Improving security by not transmitting data to a central server	Increased complexity in securing communications between devices Possible vulnerabilities
Robustness	Continuing to function even if some devices drop out or fail Adapting to changes in the network environment	Increased complexity in aggregating model updates from multiple devices Possible reduction in accuracy

6) REFLECTION COEFFICIENT OPTIMIZATION

The reflection coefficient optimization can involve mathematical optimization techniques, such as convex optimization or heuristic algorithms, depending on the specific approach used in the proposed framework.

C. IRS

Intelligent Reflecting Surfaces (IRS) are a new and innovative technology being actively researched and developed for future wireless communication systems. An IRS consists of many passive reflecting elements, each of which can be controlled individually to manipulate the wireless signal that passes through it. By adjusting the phase and amplitude of the reflected signal, an IRS can enhance signal strength, improve signal quality, and reduce interference and noise. IRS technology has several advantages over traditional wireless communication technologies. First, it is much more energy-efficient, as it only requires passive elements to manipulate the signal. Second, it can provide higher data rates and improved coverage, especially in environments with obstacles and interference. Third, it can be easily integrated into existing wireless communication systems and coexist with other wireless technologies.

IRS technology has many potential applications, including indoor and outdoor wireless communication, Internet of Things (IoT) networks, 5G and beyond 5G cellular networks, and satellite communication systems. IRS can also be used in conjunction with other technologies, such as drones and artificial intelligence, to enhance the performance of wireless communication systems further. Despite its many advantages, some challenges still need to be addressed before the IRS can be fully integrated into wireless communication systems. These challenges include the design and optimization of IRS structures, the development of efficient control algorithms, and the development of cost-effective and scalable manufacturing processes.

D. FL MEETS IRS

Integrating IRS and FL involves combining the benefits of both technologies to improve the efficiency and effectiveness of wireless communications and machine learning. There are several critical steps involved in this integration:

Incorporating IRS into the wireless communication system: The first step is to incorporate IRS into the wireless communication system by placing the reflecting surfaces strategically to optimize signal strength and reduce interference [60], [61]. Therefore, it involves modelling the wireless propagation environment and using optimization algorithms to determine the optimal placement of the reflecting surfaces.

Using FL to train the ML models: The second step is to use FL to train ML models that can optimize the use of the wireless communication system. This can involve distributing the training process across multiple devices and aggregating the results to create a global model that can be used to optimize the wireless communication system.

Combining the IRS and FL components: The final step is to combine the IRS and FL components to optimize the wireless communication system using ML models. This can involve using the global model to control the phase shifts of the reflecting surfaces to optimize signal strength and reduce interference. The ML models can also optimize allocating resources such as bandwidth and power to different users based on their specific needs.

Summary: The Integrating IRS and FL improve wireless communication systems' efficiency and effectiveness by optimizing resource use and reducing interference. The combination of these technologies can also enable new applications such as smart transportation systems, remote healthcare, and industrial automation. However, careful consideration must be given to data privacy and security issues to ensure this integration's benefits are realized without compromising individual rights and freedoms.

Figure 2 shows the steps involved in the FL algorithm for optimizing reflection coefficients, including data collection from the communication environment, local model training at each IRS, local model updates, FL aggregation, global model update, and model distribution.

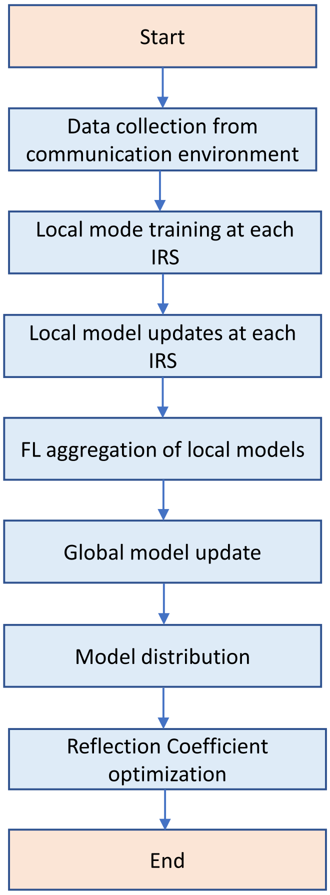

FIGURE 2. FL algorithm for optimizing reflection coefficients.

Algorithm 1 Processing Flowchart

1: Initialization: The ensemble process initialises the IRS reflection coefficients to a random value and the global model weights to zero.

2: Local model training: Each drone in the swarm trains a local model on its data using FL. The local model is updated using the gradient descent algorithm with the learning rate. The loss function used for optimization is a weighted average of the mean squared error (MSE) of each drone's data, with weights determined by their performance or reliability.

3: Model aggregation: The local models are sent to the central controller, aggregating them using a weighted average. The weights assigned to each local model are determined by their performance or reliability.

4: IRS reflection coefficient optimization: The central controller then uses the aggregated model to optimize the IRS reflection coefficients. This is done by minimizing the loss function using the gradient descent algorithm with the learning rate.

5: Global model update: The central controller updates the global model weights using the aggregated local models and the optimized IRS reflection coefficients. This is done using the formula

$$W' = W - *L(W), \tag{5}$$

where W is the global model weights and $L(W)$, is the gradient of the loss function concerning W.

6: Repeat: The ensemble process is repeated for multiple iterations until convergence is achieved.

E. FL IN UAV-ENABLED NETWORKS

FL in UAV-enabled networks involves multiple UAVs collaboratively improving machine learning models while keeping data local [62], [63]. Each UAV collects data from its environment and trains its model on the device. Instead of sharing raw data, UAVs transmit model updates to a central coordinator, aggregating these updates to create an improved global model. The model is then returned to UAVs for integration into their local models. The approach preserves data privacy, reduces communication overhead, and adapts to diverse environments, aligning well with UAV networks' distributed nature and limited communication capabilities.

Compared to traditional centralized learning, FL offers distinct advantages. It safeguards sensitive data by avoiding data transmission and ensuring privacy. Communication efficiency is enhanced since only model updates are shared, reducing bandwidth demands. The decentralized nature improves resilience and scalability, accommodating the dynamic UAV network. Moreover, FL allows UAVs to adapt models locally to context-specific conditions, resulting in more accurate insights. The energy-efficient approach caters to UAVs' limited power resources and facilitates real-time decision-making. Table.2 provides a simplified comparison comparison table between FL and traditional centralized learning in the context of UAV-enabled networks

1) WILDLIFE CONSERVATION AND MONITORING

UAVs equipped with cameras and sensors can be deployed to monitor wildlife habitats. Each UAV collects data on animal behavior, habitat conditions, and ecological changes. Federated Learning enables UAVs to collaboratively train models to identify animal species, track migration patterns, and detect unusual behavior without sharing sensitive location data. This approach ensures data privacy, as raw images and locations remain localized while contributing to a global model that improves species protection and conservation efforts.

2) DISASTER RESPONSE AND RECOVERY

In disaster-stricken areas, UAVs can rapidly assess damages and identify survivors. Federated Learning empowers UAVs to develop models for damage detection, survivor identification, and emergency resource allocation. Each UAV processes images and sensor data locally to enhance situational awareness while respecting individuals' privacy. These models can quickly adapt to changing conditions and

TABLE 2. Comparison between FL and traditional centralized learning in the context of UAV-enabled networks.

Items	FL	Centralized Learning
Data Privacy	Preserves privacy by keeping data on UAVs	Raises privacy concerns due to central data storage
Communication Efficiency	Minimizes communication by transmitting only model updates	Demands substantial data transmission to a central server
Decentralization	Aligns with the UAV network's distributed structure	Centralizes data, potentially leading to single points of failure
Adaptability	Adapts models to local UAV environments	Lacks adaptability to diverse contexts without continuous data updates
Scalability	Scales naturally as more UAVs join	face scalability issues as data volume grows
Energy Efficiency	Energy-efficient with local training and lightweight updates	May strain energy resources due to data transmission
Resilience	Enhances network resilience by removing central dependency	Vulnerability to server failures impacting the entire network
Real-time Decision-making	Supports real-time updates due to lightweight communication	Might experience latency in model updates due to data transfers

improve disaster response efficiency by facilitating accurate decision-making without centralized data accumulation.

3) PRECISION AGRICULTURE

UAVs play a vital role in precision agriculture by monitoring crop health, irrigation needs, and pest infestations. Federated Learning enables UAVs to train models that provide real-time insights to farmers. Each UAV collects data on crop conditions and environmental factors, allowing models to optimize irrigation, pest control, and crop yields. Privacy is preserved since raw data, such as field images, remains on UAVs, ensuring sensitive farming practices stay confidential.

4) TRAFFIC MONITORING AND CONTROL

UAVs can manage traffic by monitoring road conditions, congestion, and accidents. Federated Learning allows UAVs to develop models that predict traffic patterns, optimize traffic flow, and detect road hazards. Each UAV gathers traffic data from its vantage point while avoiding data centralization. This approach enhances urban mobility while addressing privacy and data security concerns.

5) ENVIRONMENTAL SURVEILLANCE

UAVs are essential for monitoring environmental changes such as pollution, deforestation, and climate-related events. Federated Learning enables UAVs to build models that analyze air quality, vegetation health, and natural disaster impacts. Each UAV gathers data specific to its location, contributing to global insights while preserving data confidentiality. This approach enhances our understanding of environmental trends without compromising sensitive geographic information.

III. IRS-DRONES

IRS and drones are two emerging technologies that have gained significant attention recently. For example, IRS is a passive and intelligent radio environment that can manipulate radio waves through many low-cost, low-power, and controllable phase shifters. On the other hand, drones can fly autonomously or be remotely controlled. Integrating IRS and drones presents a promising solution for various communication and networking applications, such as enhancing network coverage [64], increasing network capacity [64], and reducing energy consumption [65], [66]. In particular, the deployment of IRS in drones can allow on-demand radio environment control and dynamic adjustments to communication links, leading to improved network performance. Additionally, by integrating IRS into drone technology, it is possible to increase the network coverage area and provide communication support to remote or difficult-to-reach areas. The IRS-drone integration represents a novel approach to enhancing communication networks and is expected to impact the development of 6G communication networks significantly.

A smart IRS may be able to intellectually manipulate the FL-aware IRS Task Scheduling (FL-IRSTS) approach to extend flag concentration attained at the objective [67]. This is frequently contrasted to earlier practices that improved distant communications by modifying the recipient or sender. An IRS is composed of many IRS, each of which is capable of speaking to the occurrence flag at various points. In IRS-assisted communications, the remote connection from the source to the IRS optimized the objective. Such a communication strategy is invaluable when there is no clear LoS between the origin and destination or a weak distant channel due to borders or poor natural circumstances [68].Many experts in remote communications anticipate that the IRS will significantly enhance 6G systems by effectively tailoring remote communication scenarios.

The IRS is known as metasurfaces [6] and is an emerging technology that can help wireless data transmission networks work more efficiently. IRS' major goal is to increase the quality of wireless communications by raising their total energy by managing the propagation medium. Because of its tremendous influence on energy and spectral efficiency, IRS technology is predicted to play a vital role in enhancing 6G networks. The IRS consists of passive antenna elements capable of adjusting the phase of wireless signals before reflecting them to the intended targets. To optimize transmission efficiency, multiple reflectors are employed for a given target, each with chosen phase shifts that align the reflected signals coherently in the channel. The wireless signal propagation environment is intentionally altered by manipulating numerous small reflecting elements, making IRS a potential candidate for improving diverse aspects of forthcoming wireless communication. While individual nodes within the IRS gain empowerment, the central node's involvement remains vital for decision-making and data learning during the IRS process. IRS is a new reflecting radio technology that has gotten much buzz recently [69]. Furthermore, IRS has a 2D artificial structure such as an array of reflective elements that can be strategically configured to control signal propagation and enhance wireless communication, with many passive reflective elements whose electromagnetic properties, such as reflection, scattering, and refraction, can be controlled electronically and independently in real-time by applying various control signals.

The reflected signal's direction may be precisely regulated for a particular receiver [70], allowing for a fully programmable radio environment. The ability to program the radio space in such a way has enormous potential for wireless networks. For example, IRS can enhance the received SNR and improve the throughput and coverage of wireless communication networks by reflecting signals from a transmitter (TX) to the receiver (TR) [71]. Furthermore, the SNR improves significantly, allowing high modulation orders to be used to enhance spectral efficiency. Holographic MIMO surfaces, which may shape electromagnetic waves to meet specific goals, has recently received a lot of interest [72]. Similarly, by regulating the propagation of radio waves in a specified region of interest, IRS may be used to cancel or decrease hazardous wireless interference [73]. The authors of [74] consider merging IRS with Simultaneous Wireless Information and Power Transmission (SWIPT). In [75], the authors proposed a solution for joint optimization issues to adjust transmit and reflection beamforming to achieve the minimal weighted received signal strength to interference plus noise ratio at users with transmit power limits. IRS is utilized in [76] to improve the coverage of network by using multi-hop transmission with numerous IRS panels and deep reinforcement learning to create the beamforming matrices.

IRS may change the amplitude and phase of incident signals using many low-cost passive reflecting pieces, making it a viable technology for reconfiguring propagation conditions and improving network performance [6]. IRS consumes significantly less energy than current systems like active relay and backscattering communication, and it can be installed on building facades, walls, and ceilings. IRS has recently been studied in terrestrial networks to improve energy efficiency, capacity, and security [44], [77], and [78]. The phase shifts of reflecting components can be adjusted in conjunction with the transmission control of transceivers in various network configurations to achieve various communication goals. IRS has recently been touted as a possible method for quicker and more reliable data transfer [79]. In the last few months, a slew of novel research has been committed to the IRS due to its controllability, energy efficiency, and environmental adaptability. Three more features of the IRS are critical to implementing the utilities mentioned above and their widespread deployment. First, IRS comprises energy-efficient, cost-effective passive devices such as printed dipoles [78]. Second, IRS can be made in a high-density configuration [80]. Third, the IRS may be controlled electronically with a rapid switching rate between states, allowing real-time reconfiguration of reflected waves.

A. IRS-ENABLE DRONE

The use of IRS is a potential technique for 6G networks. The IRS's cutting-edge technology controls wireless propagation and directs the signal in a specific direction using passive reflecting components. To improve spectrum efficiency, some contemporary literary works have suggested fitting drones with IRSs and using the IRS to reflect the signal in the direction of drones flying BSs. However, Figure 3 depicts these two various IRS-drone coupling scenarios: (i) drones for IRSs, where the drones carrying the reflective surfaces can function as a passive relay in both downlink and uplink communications between ground users and terrestrial BSs, and (ii) IRSs for drones, where IRS-equipped buildings aid the drone's communication.

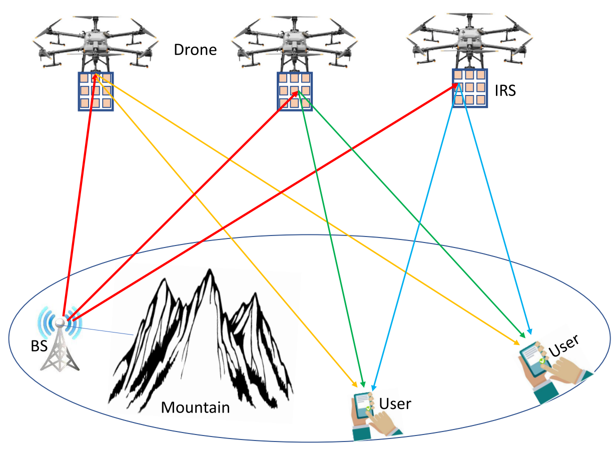

FIGURE 3. Empowering Drone Communication Networks with Drone-IRS and IRS-Enhanced Infrastructure.

The authors of [18] presented an effective deployment of IRS-equipped drones to service a mobile user who does not reach LoS with the BS in supporting mmWave technology. IRS collects energy from the drone and reflects mmWave signals. The deep Q network is utilized to define the location of the drone, and the IRS reflecting parameters to maximize the capacity of the downlink. The same authors discussed using IRS-equipped drones for numerous users to get through the bottleneck caused by the buildings [18]. The position of the drone, the BS precoding matrix, and the reflection parameters are optimized using distributional reinforcement learning. In contrast to [18], the study [51] focused on reducing drone energy usage rather than considering energy harvesting. The position, IRS phase shift, and power distribution to mobile users are all optimized in the research on increasing drone-IRS's service quality. In addition, a non-orthogonal multiple access approach is employed to increase downlink communication efficiency. Compared to the traditional Q-learning technique, the degrading deep Q network converges and prevents oscillations when used to alter the drone's location dynamically.

The authors of [82] investigated the application of the drone-IR as a passive relay for transmitting smart devices to BS from the viewpoint of uplink. To reduce the average age of the information, deep reinforcement learning is used to optimize the location of the drone-IRS, the transmission timing, and the phase shift. In contrast to the works mentioned above, which focus on IRS-equipped drones, the authors of [83] discussed how a drone-IRS is positioned on the top of nearby buildings to enhance the channel condition between the drone and multiple users. Drone trajectory, data throughput, and IRS phase changes are just a few of the variables optimized in this arrangement. The findings showed two distinct types of solutions for the reinforcement learning technique: (i) a continuous action space utilizing the deep deterministic policy gradient (DDPG) technique and (i) a discrete action space based on a deep Q network.

Summary: By integrating IRS into drones, the quality of the drone and other network nodes can be improved, leading to better connectivity and more reliable communication. For example, IRS can be used to mitigate the impact of obstacles and reflections, providing clear line-of-sight communication between the drone and the other nodes, reducing communication latency, and increasing the communication data rate. IRS can also be used to offload computation tasks from the drone to the edge devices, reducing the computation load on the drone and extending its battery life. This enables the drone to perform more computation-intensive tasks like real-time data analysis and decision-making. Additionally, IRS can enhance the security of the drone network by providing a secure communication channel between the drone and the other nodes. IRS dynamically controls the reflection of the signals, enabling the secure transmission of sensitive data without being intercepted by unauthorized nodes. IRS enable drones to achieve enhanced communication and computation capabilities, improving connectivity, reliability, security, and performance. Integrating IRS into drones is a promising direction for future drone networks, enabling more advanced and efficient drone applications.

B. HARNESSING IRS FOR ENHANCED DRONE COMMUNICATION NETWORK

IRS installations are not confined to indoor and outdoor contexts, but when placed over drones for wireless coverage extension, they considerably boost capacity. IRS-integrated drone-based wireless networks have two types of IRSs: (a) IRS for drone-enabled data communication, where drones gather data from scattered nodes, and (b) IRS for drone-aided ubiquitous coverage, where IRSs are installed in drone networks to increase ubiquitous coverage area, (c) IRS for information transfer and energy in SWIPT networks with drones, (d) IRSs can be placed near customers as a gateway to boost backhaul capacity in cases when drones cannot be deployed near consumers owing to insufficient wireless capacity, (e) IRS for drone-aided secrecy communication, here the IRS may be used to improve security in the drone by weakening eavesdropper communication channels, and (f) IRS for cellular-connected in drone communication networks, where IRS passive beamforming may be improved to enhance drone communication downlink and uplink [64]. However, drone communications may be blocked and eavesdropped because of the enormous hurdles and high node mobility in a wireless network. In this regard, IRS installations can improve the performance of future non-terrestrial networks by creating a favourable and controlled wireless environment by managing drones' trajectory.

The IRS mounted on buildings can help the drone-based integrated A2G network, where the drone trajectory can be tuned and combined with passive and active beamforming to increase the secrecy rate. The main problem, however, is optimizing the drone's trajectory in conjunction with the IRS passive beamforming. The IRS components' location is a significant aspect of enhancing reflection efficiency. Thus, it must be determined appropriately [4]. Multiple drones are used in recent research [84] to plan the IRS deployment to optimize the average attainable rate. The authors of [19] used a downlink NOMA to optimize the position of the drone-IRSs to increase the user rate while keeping the weak user rate constant. Optimizing the received power at the user is defined by maximizing active beamforming at the drone, passive beamforming at the IRSs, and the drone's trajectory during a certain flight period. The authors developed a semi-definite relaxation iterative technique to improve the IRS phase shifts and transmit beamforming.

Drone-IRS trajectory optimization with passive beamforming to maximize capacity is one of the most critical design elements for IRS deployment. However, the two biggest hurdles to optimizing the drone's trajectories are low power consumption and consistent user communication. To overcome the problem, the authors of [16] propose using IRSs to improve the signal quality of communication between a drone and its users. In addition, the authors of [85] investigated IRS deployment for achieving high gains from the drone-IRS arrangement for user connections. The findings showed that the IRS-assisted cellular system might significantly enhance SINR throughout the area where drone trajectory can be adjusted [13], [14]. Moreover, the authors of [18] presented the influence of phase compensation error on the IRS ergodic capacity aided by drone communications. As a result, successful IRS deployment in the non-terrestrial network can assist in enhancing connection quality and offer flexibility in A2G networks.

Summary: IRS deployment in drones involves integrating IRS components into the drone's hardware and software architecture. The deployment process consists of design, implementation, and testing. The deployment of IRS in drones is a complex process that requires a comprehensive understanding of the IRS technology, the drone hardware and software architecture, and the communication and computation requirements. The deployment process can be optimized using advanced design tools, simulation platforms, and testing frameworks, enabling IRS's efficient and effective drone integration. The deployment of IRS in drones involves integrating IRS components into the drone architecture, facilitating enhanced communication and computation capabilities. The deployment process requires a comprehensive understanding of IRS technology, drone architecture, and advanced design and testing tools.

C. DRONE-IRS FOR COMMUNICATION

A novel network architecture, drone-IRS, was developed to expand the service region [86], where the IRS is installed on a drone to implement over-the-drone IRS. Due to the comparatively higher altitude of the drone, drone-IRS is likely to establish more robust LoS linkages with the ground nodes than terrestrial IRS, minimizing the likelihood of blockage. Drone-IRS can achieve 360 panoramic full-range reflections, i.e., one drone IRS may help communicate between any nodes within the coverage area, considerably boosting the number of serviceable users. Furthermore, the drone-IRS coverage area can be expanded further by utilizing its high mobility to move closer to multiple area-separated users sequentially to enhance their communication performance by utilizing short-range LoS channels and minimizing the IRS-reflected link product distance. On the other hand, terrestrial IRS can improve drone-ground communication performance by reducing signal reflections [13], [16].

The literature has also looked at the integration of the IRS with drones. For example, Lu et al. [86] recommended that terrestrial users be served by flying platforms such as balloons or drones outfitted with IRS. Because of the capacity to reposition the IRS to maximize specific system characteristics, such as maximizing the SNR, the reported findings indicate that flying the IRS has an additional degree of freedom. Furthermore, it is demonstrated that, as compared to terrestrial IRS, flying IRS requires fewer parts to produce a given benefit. The IRS was utilized to guide the drone's signal to boost its received signal intensity [13]. The results demonstrate that by optimizing the IRS position and phase of the reflected signals, considerable signal enhancement may be achieved with a limited number of reflectors. A system in which a single drone broadcasts to numerous terrestrial IRS was investigated [23]. The research focused on the best beamforming architecture for the drone, IRS, and trajectory to optimize the received power for ground users. The authors of [21] introduced the downlink of a multi-antenna BS using an IRS-drone platform to connect with a single antenna user.

The work assesses the IRS's ability to maximize the system's total energy efficiency by beamforming the optimization vector at BS and the IRS's phase shift matrix. Many optimisation strategies are used under the premise of efficient channel state information. Several additional publications have looked at using an integrated IRS-drone to reduce transmitting power, increase SNR, improve spectral efficiency, or increase the sum rate [16], [50], [87], [88]. However, they did not consider the risk of a mistake or outage or the consequence of an inadequate phase estimate and control method. The capability of IRS-based drone communications with unsatisfactory phase adjustment is assessed [77].

The IRS technology offers a promising yet low-cost solution to this problem since it can simulate significant MIMO gain with active antennas [89]. Therefore, single-antenna drone-assisted communications have received a lot of research [90], [91]. Nonetheless, by intelligently modifying its reflection coefficients, an IRS may provide a high passive beamforming gain without needing many antennas on a drone. As a result, one of the critical reasons for this effort is to "recycle" some of the dissipated signals by reflecting them on the targeted consumers. IRS in drone-enabled communication systems can increase the freedom to design a drone's trajectory. For example, if a user is far from the drone but near an IRS, the drone does not need to change trajectory and fly close to the end user to establish strong communication linkages, which takes energy and time in consideration. Instead, an IRS can work with the drone to conduct beamforming on the reflected signals to boost the received signal strength at the remote ground user, allowing for reasonable data throughput.

Incorporating an IRS into drone-enabled communication systems presents possibilities and problems in determining its combined trajectory and resource allocation. The composite channel power gain combining the direct link from the drone to ground users and the reflected link through the IRS is a complex function of the drone's trajectory because of the IRS. Furthermore, properly scheduling users for IRS assistance is still unclear, and it is worth our time to investigate. Finally, because broadband communications are widely used in today's cellular networks, the reflected path of IRS results in a frequency- and spatial-selective fading channel, posing a significant challenge for drone trajectory design that has previously been overlooked by works based on frequency-flat channel models [91], [92], [93]. Although [94] developed a multi-carrier channel model for IRS-assisted communications, it is irrelevant to drone communication systems since it ignores the drone's mobility. The authors of [18] outfitted a drone with an IRS to increase the dependability of terrestrial millimetre-wave communication networks. An RL strategy was used to optimize the location of a drone and the IRS reflection coefficients to maximize the system sum rate.

Summary: Drones integrated with IRS can significantly enhance communication capabilities compared to traditional drone networks. IRS are smart surfaces that can dynamically control the reflection of radio frequency (RF) signals, enabling the manipulation of the propagation environment and improving communication quality. By integrating IRS into drones, the communication quality between the drone and other network nodes can be improved, leading to better connectivity and more reliable communication. Additionally, the IRS can enhance the security of the drone-IRS communication network by providing a secure communication channel between the drone and the other nodes. IRS can dynamically control the reflection of the signals, enabling the secure transmission of sensitive data without being intercepted by unauthorized nodes. As a result, drone-IRS communication networks can significantly enhance communication capabilities, providing better connectivity, reliability, security, and performance. Integrating IRS into drones is a promising direction for future drone networks, enabling more advanced and efficient drone applications.

D. APPLICATIONS OF IRS-DRONE

Combining IRSs and drones can be advantageous in various communications and networking applications. This section discusses how combining both technologies may affect coverage, interference, security, and SWIPT.

1) COVERAGE

A drone offers this capacity by carrying the Intelligent Omni Surface (IOS) below it and flying at an appropriate altitude to produce reflecting RF surfaces when necessary. IRS-assisted drone technology increases the range of incident signal SNR at the periphery of a BS coverage area. As shown in Figure 4, the initial cell coverage is effectively extended in the required direction by optimizing the drone trajectory and phase shift vectors to reach the intended end users, whether static or mobile. Mahmoud et al. [95] introduced the use of IRS in drone-powered communications networks to increase coverage and boost dependability regarding spectral efficiency while considering the IoT paradigm. The research investigated the ergodic capacity and outage probability after first deriving tractable analytical formulations.

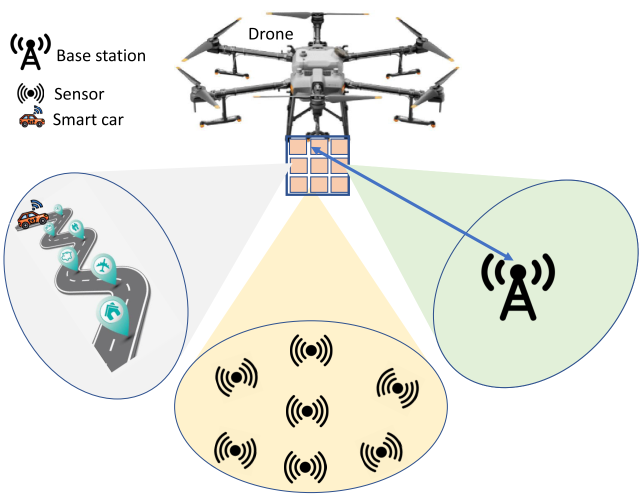

FIGURE 4. **Drone-IRS coverage areas.**

The deployment of IRS on drones can significantly enhance the coverage of wireless communication networks. With IRS, the signal quality can be improved by reflecting the radio waves in a desired direction, reducing the impact of obstacles and reflections, and increasing the coverage range. IRS on drones can also provide an alternative to traditional wireless communication networks, such as cellular networks. In areas with limited or no network coverage, IRS-equipped drones can be deployed to create a communication network that provides coverage in these areas. In addition, IRS drones can provide temporary coverage in emergency response situations, such as disaster zones, urban canyons, and remote locations. IRS-equipped drones can be deployed quickly to provide communication coverage in these areas, improving the efficiency and reliability of emergency response efforts. The integration of IRS into drones has the potential to revolutionize wireless communication networks, providing improved coverage, quality, and reliability.

2) CAPACITY

In contrast to half-duplex mode, the IRS typically operates in full-duplex mode, increasing spectral efficiency. IRS is passive, in which any antenna self-interference and noise amplification are eliminated by its relaying technique, resulting in lower power consumption and less computation than active full-duplex relays. Under the premise of knowing CSI at the IRS controller, interference cancellation can be accomplished by adjusting the phase shifts of particular IRS parts to invert the interference signal and eliminate or lessen it.

Additionally, by maximizing the phase shifts of the antenna components, the IRS may work with the drone to create rich dispersion of LoS connections for many ground end users. The IRS properties and the LoS capabilities made possible by the drone will cause the spectral efficiency to outperform the other capacity-increasing methods. Where available, multiple drones paired with static IRS can be used to provide scalability. It is important to note that aerial-IRS can enable LoS connections with strong channel quality (high SNR) to increase spectral efficiency by implementing spatial multiplexing and/or multi-user MIMO.

3) MASSIVE MULTIPLE ACCESS

The difficulties of large access may be successfully overcome by combining IRS technology with the drone's dynamics and improving the IRS phase shift vectors to increase system capacity [95]. Communications systems supported by the IRS direct indoor wireless channels in favour of users with distinct needs from typical users. However, the practicality of outdoor Virtual Reality (VR) applications using IRS-assisted drone communications systems may increase.

Three main issues are anticipated to affect indoor and outdoor VR users: multi-link communications, energy consumption brought on by massive data transfers, and interference from nearby VR equipment [96]. When drones are an essential component of IRS communication systems, these problems may be successfully solved. In [16], the authors use this technique to optimize the IRS jointly with the drone height and trajectory phase shift vectors to improve coverage and capacity and enable widespread connection.

4) SPECTRUM SHARING

The energy consumption of drone systems is crucial to the system's long-term performance. Thus, IRS-assisted drone systems can use spectrum sharing to increase system capacity in hot locations. The viability and benefits of IRS providing spectrum sharing for indoor smart environments have been demonstrated [73]. In this case, the capacity is maximized by allowing the multi-user to access the shared spectrum. In contrast, user interference is managed by IRS optimization of phase shifters. The authors of [97] introduced the IRS-aided spectrum-sharing method to boost secondary users' capacity while ensuring primary users' QoS by channel diagonalization and phase shift optimization. The natural continuation of these studies is spectrum sharing facilitated by IRS-assisted drones, where the parameters characterizing the drone mechanics will play a significant part in real-time wireless networking performance optimization under dynamic user settings. A cooperative multiple-task reallocation problem with target precedence constraints for heterogeneous UAVs was addressed [98], [99], utilizing a combination of fuzzy C-means clustering and ant colony optimization algorithms. To increase the system capacity with IRS installed on drones, it is crucial to understand how altitude, latitude, and longitude coordinates affect the performance of the IRS phase shifters.

5) SECURITY

Drones have been suggested to enhance terrestrial cellular networks' Physical Layer Security (PLS). The dominating LoS connections that may be made between an aerial and ground node make this possible. PLS assistance comes in various forms, from drones. Drones, for example, can serve as an AR between authorized users to maximize transmission power and reduce the data rate for eavesdroppers. Drones can also be used as friendly jammers to broadcast powerful artificial noise that can reach potential attackers and shield the data and privacy of genuine users. In normal wireless contexts, the aforementioned drone functions enhancing PLS have shown tremendous promise [20]. The development of wireless threats and assaults, on the other hand, has led to the creation of complex and challenging situations that can impair the functioning of wireless networks even when the suggested safety measures are used. For example, an eavesdropper can carefully place himself to acquire a high SNR, possibly greater than the destination node. To combat cunning attackers, IRSs placed on drones can be used. Prior studies have demonstrated that when the distance between peers reduces, the secrecy rate among legal users rises. As a result, the free movement paradigm of drones reduces the transmission source's distance from the target user. The IRS phase shifts can then be adjusted so that the original signal and the reflected signal at the authorized user combine positively to increase the SNR. To reduce the received SNR in particular areas and reduce the likelihood of eavesdropping, some of the IRS reflecting units, on the other hand, can use various phase shifts to generate a destructive reflected signal, as shown in Figure 4.

E. IRS FOR ENABLING DRONE SWARM

In this section, we discuss the importance of IRS for enabling drone swarm. There are various uses for drone swarm in wireless networks, including traffic offloading in hotspots, surveillance, IoT networks, drone swarm networks in catastrophes, Vehicle-to-Everything (V2X) communications helped by drones, and the creation of smart cities. drone swarm cooperating to complete a task better than one drone. Drones are frequently used for military purposes, but interest in their civilian applications has recently grown. By creating optimum reflector coefficients, the passively reflecting IRS may amplify signals at receivers and lessen interference. IRS has minimal power consumption without active transmitters due to its passive nature. Therefore, despite the ground IRS deployment, the drone-enabled aerial IRS may be effectively deployed and offer panoramic reflections for ground communications [9].

The swarm of drone-IRS systems provides the following benefits over drone-IRS: (i) raising the drone count to enhance aperture gain; (ii) ensuring drone flight stability and adaptability by allowing each drone to have a moderate-sized IRS, particularly in adverse weather or air turbulence; (iii) offering a rich scattering environment with various drones' placements, which facilitates spatial multiplexing for a large number of users; (iv) the production cost of IRS can be lowered, and the flight time of the drone can be increased thanks to the smaller IRS size of each drone. In [7], the authors introduced the trade-offs between energy consumption, latency, and dependability in drone swarm networks with random network coding.

The benefits of a swarm of drone-enabled IRSs are enumerated as follows:

1) A more significant gain in the aperture It has been demonstrated in earlier publications [78] that IRS obtains a power gain via reflection-beamforming and captures a power gain by gathering the incoming signal energy.
2) Collaborative communication: Future wireless networks will allow a drone swarm to operate together in civic and military applications, including surveillance, video streaming, and combat monitoring. As a result, drones with various features (such as drone BS, drone, and drone user) may work together to offer reliable wireless communication.
3) Ensuring flight path Stability and adaptability: A drone has several reflected components, and it is challenging to provide flying flexibility and stability, especially in adverse weather or turbulent air. Furthermore, an additional payload would need more energy from

the drone, which would shorten its lifespan, given the limited battery capacity. To guarantee flexible mobility and a longer lifespan, each drone can carry fewer reflected components when more drones are present. Additionally, drone swarm follows moving automobiles in vehicular networks, supporting reliable communication with their adaptable mobility.

4) Reduced IRS costs: A large IRS has more expensive manufacturing since it has vast integrated electric components. A sizable IRS's internal control is also challenging. In contrast to a single large IRS, several moderate-sized IRSs can lower production and control costs.

Drones offer two key benefits: a) variable positioning and b) dependable A2G communication linkages. As a result, drones may be deployed swiftly in disaster zones or hotspots to enable dependable wireless connectivity. In Figure 5, we consider a situation in which the combination of drone swarm and IRS is positioned to serve ground users in a circular area. Users may be present in hotspots or disaster areas, but impediments may prevent communication between the BS and users. Figure 5 shows how drone swarm -IRS can help in the disaster area for presentation and mitigate the impact of the disaster.

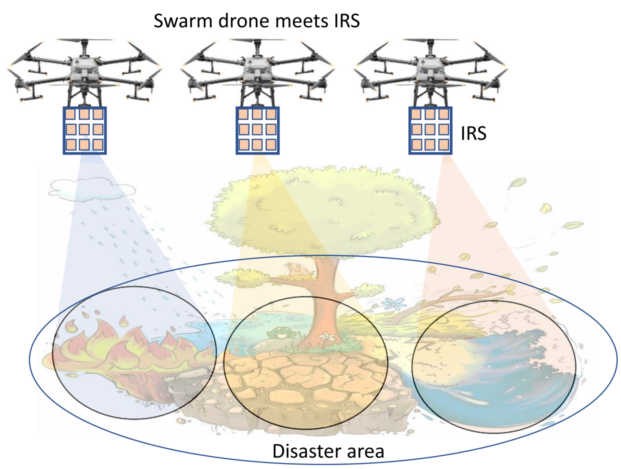

FIGURE 5. **Drone swarm meets IRS for large disaster area.**

F. APPLICATION OF DRONE S.WARM

This section discusses the applications of drone swarm enabled IRS.

1) MULTIPLE REFLECTIONS FOR REMOTE IoT

It is challenging for the present cellular network to reach outlying locations like forests, enormous oceans, volcanic lands, and other challenging conditions. IoT devices may be widely used for specialized activities requiring data transfers, such as integrating sensor data with high-definition sound and video information. Future wireless networks can use the combination of drone swarm and IRS to offer ubiquitous wireless connections and reliable data flow for distant IoT. Due to the significantly increased signal attenuation, pure multiples of the combination ofdrone swarm and IRS reflections are ineffective, according to the product distance-based path loss (i.e., twice path loss) model in IRS communication. Fortunately, drones with various characteristics may work together as a drone swarm to provide data transfers for distant IoT. As an illustration, the combination of drone and IRS can reflect the signal to a drone relay, which then decodes and transmits the signal to a second combination of drone and IRS. In this manner, BS and distant IoT devices are connected over a dependable wireless network as needed.

2) A2A REFLECTION FOR DISASTER AREAS

Ground-based small cell BSs are often installed in densely populated regions like downtown, stadiums, and public spaces in cellular networks. Users in disaster areas can communicate wirelessly, in this case, thanks to the integration of IRS and drone swarm system. For instance, swarm drone-IRS reflects wireless signals from drone BS to users with a significant aperture gain. The signal strength under such A2A reflection is greatly increased compared to traditional BSs because of the dependable A2G pathways. A similar A2A reflection technology can also be used in disaster zones if the infrastructure on the ground is damaged.

3) SIGNAL ENHANCEMENT IN DRONE SWARM

For information-sharing purposes, such as exchanging flight control signals, training an autonomous flight model, and offloading computing duties, the drone swarm may occasionally need to connect to BS. Therefore, it is vital to guarantee a reliable wireless connection between the drone swarm and the BS. The integration of IRS and drone swarm can fly synchronously next to drone swarm users to deliver a reliable reflected signal for drone swarm users. The beamforming design for this application must consider the drones' velocity and movement.

IV. FRAMEWORK FOR FL MEETS IRS IN DRONES TO SUPPORT 6G

The goal of FL meeting IRS in drones' framework to enable 6G is to provide a novel solution for wireless communication networks. The framework for integrating FL and IRS in drones aims to increase the coverage area, enhance the quality of wireless communication services, provide reliable and efficient deployment of wireless communication services, and improve communication in dynamic environments. Briefly, the aim of the framework for FL meets IRS in drones for enabling 6G is to provide a highly optimized solution for wireless communication networks that offers improved coverage, quality, and reliability [100]. Due to the investigation of statistical training models directly on remote devices, FL has emerged as the focal point in the large-scale area of distributed optimization [101]. Figure 6 illustrates a framework for combining FL and IRS in drones for supporting 6G. Combining IRS with drones offers a high potential for improving drone connection in various applications. Because drones have more flexibility and mobility, they can help optimize the IRS link by determining the best location for the IRS-drone. Nonetheless, the accuracy of the phase estimate and co-phasing operations is critical to getting the final benefit from the IRS. In practice, both activities are imperfect, so the IRS technology's eventual benefit may not be assured, which is especially important for IRS-drone setups. In this paper, we combine drone-IRSs and swarm drone-IRS to improve the performance of 6G networks. We highlight the desirable advantages of fusing IRS and drones. Then, we discuss the drone-IRS and swarm drone-IRS applications. In addition, the practical limits of the IRS and drone and the transmission architecture must be considered for efficient IRS-drone deployment.

The FL no longer has a problem with personal data being accessible. In allocated networks, the FL approach is learned closer to devices. Because it protects privacy, the FL model may be used to create various IRS networks. IRS functions as a distributed trainer in this network to train the data generated and then create a model that transmits to an aggregating unit. In this fashion, decentralized FL learning for deployment and policy design is possible. Figure 7 illustrates an FL-based IRS networking system. Each thing in a smart environment has a local ML model that receives the learned parameter from the drone after being trained on a local dataset. The real-world applications that leverage the combination of FL and IRS in drone-enhanced communication networks are:

Emergency response: In disaster-stricken areas, drones equipped with IRS can provide communication and sensing services, improving the coverage and reliability of the communication network. Edge devices, such as smartphones and laptops, can use FL to collaborate and learn a shared model, providing critical information and support to the rescue teams.

Agriculture: IRS can be used to enhance the connectivity and reliability of IoT devices in agriculture, such as sensors and drones, allowing them to communicate effectively and collect data from the fields. FL can be used to learn a shared model for IoT devices, providing insights and recommendations for improving crop yield and reducing waste.

Transportation: IRS can improve the connectivity and reliability of vehicles and communication infrastructure in transportation, such as traffic lights, road signs, and communication towers. FL can be used to learn a shared vehicle model, providing information and insights for improving the traffic flow, reducing accidents, and enhancing energy efficiency [102].

Industrial automation: IRS can be used to improve the connectivity and reliability of industrial automation systems, such as robots and sensors. FL can be used to learn a shared system model, providing information and insights for improving efficiency, reducing downtime, and enhancing safety. These are just a few examples of the potential applications of the combination of FL and IRS in drone-enhanced communication networks. The combination can benefit various domains, including communication, computation, sensing, and more, by providing a flexible and scalable solution for communication and computation.

To boost the data rate in a single antenna with massive users, the authors [103] presented an IRS-assisted optimum beam reflection-FL. The experimental findings imply that the attainable rate is comparable to other centralized ML models and that changing the receiver number has no appreciable impact on the rate. To address resource allocation and device selection issues for aggregation accuracy and coverage rate improvements, the authors of [58] introduced an air FL system. The findings show that the suggested model can converge faster and with less training loss. A MIMO system was created using the suggested FL-convolutional neural network model. The received signals were utilized as an ML model to contribute to the application of drone trajectory [104].

A deep learning design method was developed to create the IRS configuration matrix, which used the sampled channel state information for the training of IRS [44]. However, preserving user privacy throughout the communication process has not received enough attention in earlier works to be considered a critical concern. Therefore, FL has been suggested as a fresh approach to dealing with distributed learning's data privacy concerns in recent years. For instance, FL created low-latency Vehicle-to-Vehicle connections while safeguarding the users' private information [25]. The CSI between a user and the IRS, an IRS-assisted B5G system, is a class of private data closely tied to a user's location data. To accomplish high-speed communication with the CSI, optimum beam reflection based on FL is presented in [103].

FL is needed in IRS-enabled drone systems to enable local training of ML models without compromising data privacy and security. In drones, FL improves the performance and reliability of wireless communication by allowing each drone to train its model on local data, reducing the need to transmit sensitive data to a central server, which improves data privacy and reduces the risk of data breaches. FL features are helpful in IRS-enabled drones, including the ability to train ML models on local data, aggregate the model updates from multiple drones, and protect sensitive data through secure and privacy-preserving techniques. In addition, FL improves wireless communication's performance and reliability by enabling real-time decision-making and reducing the need for data transmission.

In IRS-enabled drones using FL, sensitive data such as surveillance data or personal information needs to be protected to ensure privacy and prevent data breaches. Additionally, model parameters must be protected to avoid unauthorized access and ensure that the models are trained on accurate and representative data. The model information is exchanged through a central server on an IRS-enabled drone using FL. Each drone trains its local model on local data and sends the updated model parameters to the central server.

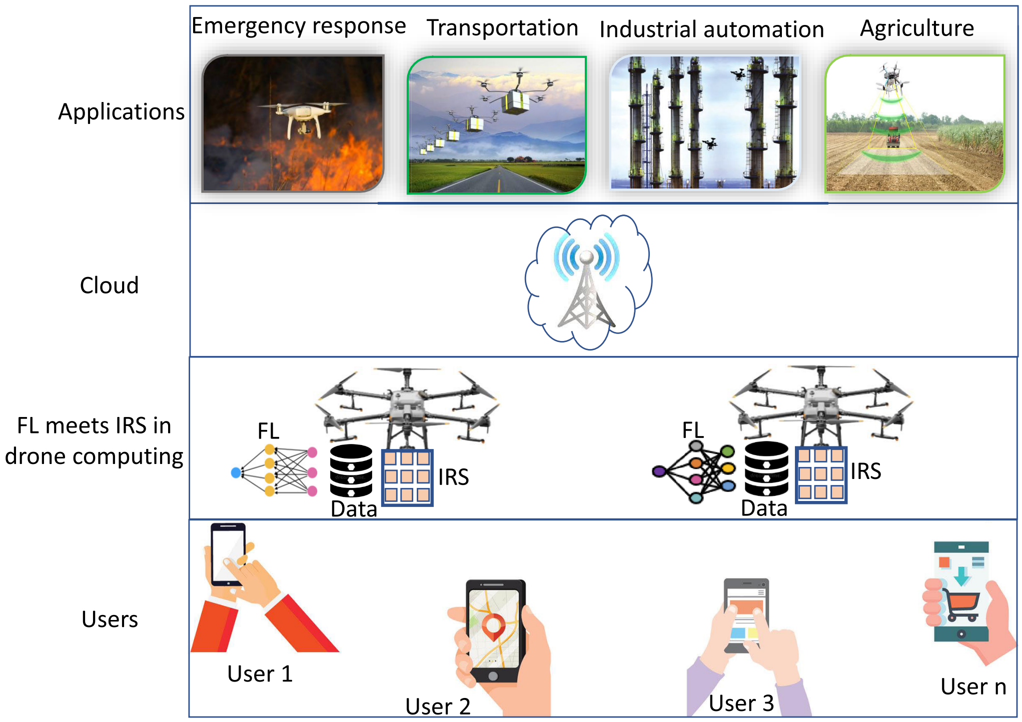

FIGURE 6. Framework for FL meets IRS in drones for enabling 6G network.

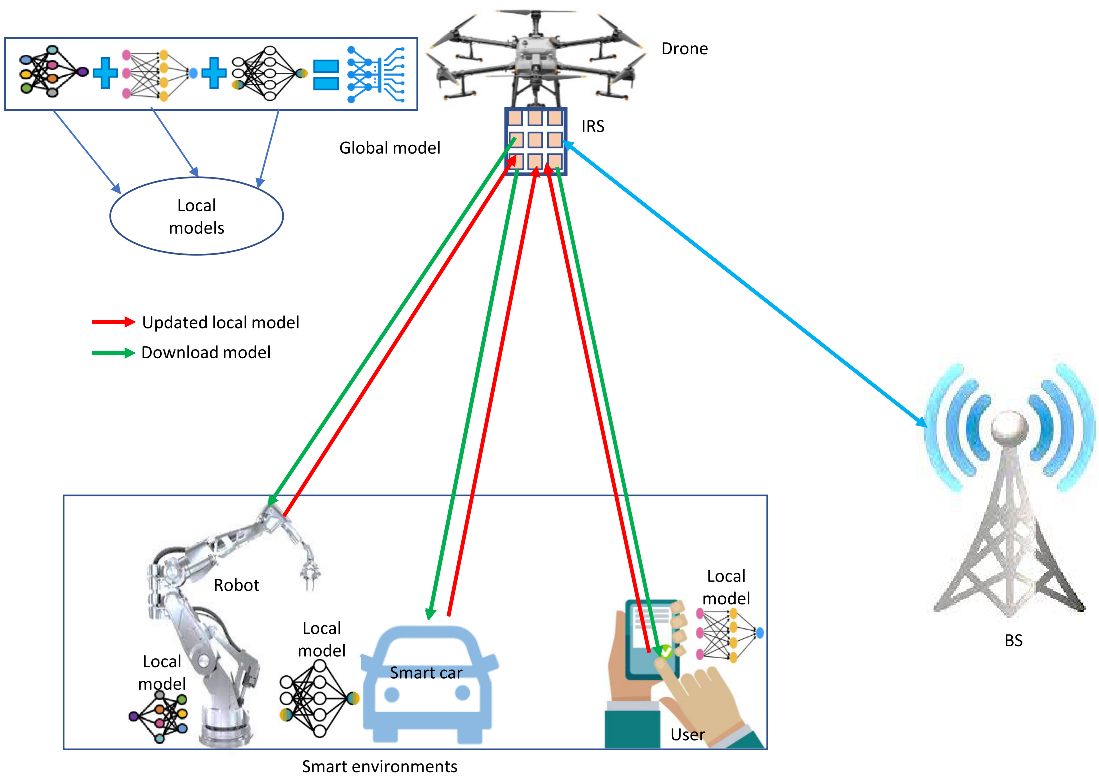

FIGURE 7. Covergence of FL and IRS for efficient 6G network with drone help.

The central server aggregates the model updates and sends the updated global model back to the drones. The local data can include information about the wireless communication environment, such as signal strength, interference, and other factors affecting communication performance. By using IRS to reflect and manipulate the signal, the proposed FL meets

IRS in drones, adapts to the changing environment, and optimizes wireless link quality, improving performance and reliability. The framework's effectiveness depends on several factors, including the system's complexity, the learning speed of FL, and the dynamic environment in which the drone system is used. The framework's effectiveness improves through careful design and implementation and the development of appropriate security and privacy techniques. Additionally, the learning speed of FL improves through advanced optimization algorithms and hardware acceleration techniques.

FL for IRS deployment in UAV computing To address the increased capacity needs, future 6G will rely on high-frequency millimeter wave [105]. However, a fundamental design challenge for implementing mmWave bands into wide-scale commercial usage is permitting reliable mmWave connectivity under the obstruction. To solve the issue of blocking connections and boosting the power of the electromagnetic wave, passive reflectors have been proposed [106]. Specifically, using numerous reflectors increases the likelihood of LoS, lowering mmWave channel attenuation substantially. Several research [106], [107] have advocated using IRSs in mmWave. Still, these studies depend on the passive reflectors in a fixed and random position, which is unsatisfactory, provided the unpredictable changes of mmWave channels.

Mobile reflectors, such as drone-carried IRS, are ideal for enhancing mmWave than stationary IRS because of the random nature of mmWave channels. The authors of [18] developed an IRS-enabled drone for establishing a LoS channel between BS and mobile users. In particular, a novel architecture for deploying a drone-enabled IRS to aid the transmission of mmWave downlink in a mobile and dynamic environment. Meanwhile, the scientists presented a framework for self-powering the IRS via radio-frequency energy harvesting. Simulation results indicated a considerable improvement in average data rate and attainable downlink LoS probability when employing an IR-aided framework in a drone compared to a static IRS environment. In [18] introduced drone-IRS deployment for mmWave channels with radio-frequency energy harvesting using reinforcement learning. However, downlink transmission only examines a single user and ignores the more complex topic of multi-user connections. In [108] simulated a multi-user IRS-carried drone, a distributional reinforcement learning approach was presented to optimize the reflection parameters, drone placement, and precoding matrix at BS. In a multi-user setting, deep reinforcement learning techniques are used to discover the best deployment of a drone-IRS for effective downlink transmissions across mmWave frequencies. Compared to non-learning drone-IRS, IRS, and direct transmission, the findings demonstrated that deep reinforcement learning could learn the appropriate placement of the drone-IRS and achieve greater downlink capacity and an achievable rate.

Unlike [18], Liu et al. [51] ignored energy harvesting and presented the challenge of reducing drone energy consumption as a decaying deep Q-network method. The NOMA for an IRS-empowered drone framework was implemented to improve user QoS. The challenge of minimizing energy consumption is defined as a combination of drone trajectory, power allocation strategy from drone to users and IRS phase shift. The energy dissipation of the drone may be significantly lowered by deploying drone-IRSs by adding NOMA and using 11.7% less energy than in the IRS-OMA scenario, according to numerical data.

The authors of [82] investigated IoT traffic uplink transmission in a drone-IRS system. To decrease the information average age, deep reinforcement learning based on protocol optimization was used to learn the unpredictability of IoT device activation patterns and manage the phase-shift, height of the drone, and communication scheduling of IRS. The authors established the drone's schedule and altitude in [82]. However, this study used only one drone, and trajectory optimization was not considered. The NOMA approach examined that it did not require a LoS channel between users and BS. Hariz et al., [109] investigated multiple drones' sub-carrier distribution and trajectory to increase user coverage. NOMA examined the LoS link between the receiver and users, while NLoS was between the drone and users. The adopted double deep Q network approach is used to tackle the presented problem. The drone-IRS system may be used in IoT networks by adjusting power, sub-carrier, trajectory, and phase shift. Furthermore, the suggested technique reduces users' average information age while maintaining maximum transmit power and drone mobility limits. According to numerical data, the suggested technique outperforms the random-trajectory and matching algorithms by 15% and 10%, respectively. Regarding IRS deployment in cutting-edge networks, writers in [110] introduced high-speed trains and recommended a drone-IRS to offer high-speed trains robust and dependable communication services. The authors looked at the combined design of a phase shift and a drone trajectory and devised an actor-critic method to optimize high-speed trains' least feasible data rates. Compared to the IRS's random and fixed phase shift, the proposed method learns the best drone trajectory and IRS phase shift and achieves high data rates.

FL meets IRS in drone swarm: FL and IRS in drone swarm enable 6G networks, a promising approach for improving wireless communication service coverage and quality. Multiple IRS-equipped drones are deployed in the communication environment to reflect incoming signals and form a wireless communication network. FL is used to continuously learn from the communication environment and optimize the reflection coefficients of each IRS. This allows the network to adapt to changing communication environments and improve the coverage and quality of wireless communication services. Furthermore, by integrating FL and IRS in drone swarm deployment, the framework enables the development of 6G networks, which provide higher data rates, lower latency, and more reliable communication services. As a result, this framework has the potential to transform wireless communication and provide new opportunities for communication-intensive applications and services, such as drone-based remote sensing, delivery, and inspection services.

Let W be the weight vector representing an IRS's reflection coefficients, and let L(W) be the loss function that measures the error between the desired signal and the received signal after reflection from the IRS. Federated learning aims to optimize the weight vector W across multiple devices (i.e., drones) without sharing the raw data. This is achieved through local model updates and global model aggregation. In each local model update, a device (i.e., a drone) computes the gradient of the loss function concerning its local data and sends it to the server. The server then aggregates the gradients from all devices and computes the global gradient. The weights of the IRS are updated using the computed global gradient as follows:

$$W' = W - \eta \cdot \nabla L(W) \tag{6}$$

where is the learning rate that controls the step size of the updates and $\nabla L(W)$ is the global gradient of the loss function concerning the weight vector W. To ensure privacy, each device only sends the gradient of the loss function and not the raw data. The server updates the weights of the IRS without accessing the raw data. The algorithm flowchart process is given in the algorithm.2.

Algorithm 2 Processing Flowchart

1: Initialize the weight vector W of the IRS.
2: Repeat until convergence:
a. Randomly sample a subset of devices.
b. For each device i, compute the gradient $L_i(W)$ of the loss function concerning its local data.
c. Send $L_i(W)$ to the server.
d. At the server, aggregate the gradients from all devices to compute the global gradient $L(W)$.
e. Update the weight vector W using the computed global gradient: $W' = W - *L(W)$
3: Return the optimized weight vector W.

FL in IRS in swarm drones has two major goals: reduce signal distortion and increase FL convergence rate. In addition, IRS has been acknowledged as a revolutionary method to deftly change the complicated radio signal propagation environment by putting passively reflecting components in drone swarm on programmable surfaces [111]. In particular, even when IRSs in drone swarm are taken into account, IRSs can proactively adjust the wireless channels between the drone and smart devices by carefully managing each reflecting element's amplitude and phase shift in real-time [112]. FL jointly improves model synchronization and the device employing IRSs in drone swarm to decrease propagation error while accelerating the convergence rate. IRSs are crucial in converting wireless channels into a usable computer to achieve FL's desired weighted sum feature. Furthermore, to effectively improve parameter aggregation from smart devices, drone swarm equipped with IRSs are used. Many unresolved concerns, such as the joint design of transmit reflect and receive in IRSs in drone swarm -assisted smart device networks, must still be resolved since FL in IRSs in drone swarm technology is still in its infancy. As illustrated in Figure 8, the FL satisfies IRS requirements for drones to gather data from smart devices and process that data locally in drones. The selection of devices to take part in the model uploading process, rather than averaging all local parameters

FL and IRS in a drone swarm is a novel framework for enhancing the coverage and quality of wireless communication networks. In this framework, multiple IRS-equipped drones are deployed as a swarm in the communication environment to form a distributed wireless network. FL algorithms coordinate the learning process among the drones and optimize the reflection coefficients of each IRS. This allows the swarm to adapt to changing communication environments and improve the coverage and quality of wireless communication services. Integrating FL and IRS technology in a drone swarm offers several advantages over traditional wireless communication networks. For example, the swarm rapidly deploys in disasters or emergencies, providing communication services to affected areas. The swarm offer communication services to remote or underserved areas where traditional communication infrastructure is unavailable or unreliable. The framework of FL and IRS in a drone swarm has the potential to revolutionize wireless communication and enable new opportunities for communication-intensive applications and services.

FL has emerged as a promising approach to enable ML on edge devices without sharing raw data. Combined with IRS, it can significantly enhance the performance and efficiency of 6G communication networks, especially in the context of drones. In this integration, FL can enable drones to learn collaboratively from their local data and improve their performance and efficiency in real-time. This can improve drones' communication performance and security, allowing for more efficient and secure data exchange. Additionally, IRS can reflect incoming signals to enhance the signal quality and reduce interference, further improving the communication performance of drones. The integration of FL and IRS in drones can bring several benefits for 6G communication networks, including:

Improved communication performance: By enabling collaborative learning and intelligent signal reflection, integrating FL and IRS in drones can significantly improve the communication performance and reliability of 6G networks.

Increased security: FL can help protect users' privacy by keeping the raw data on edge devices and only sharing the models. IRS can also enhance communication security by reducing the possibility of eavesdropping and interference.

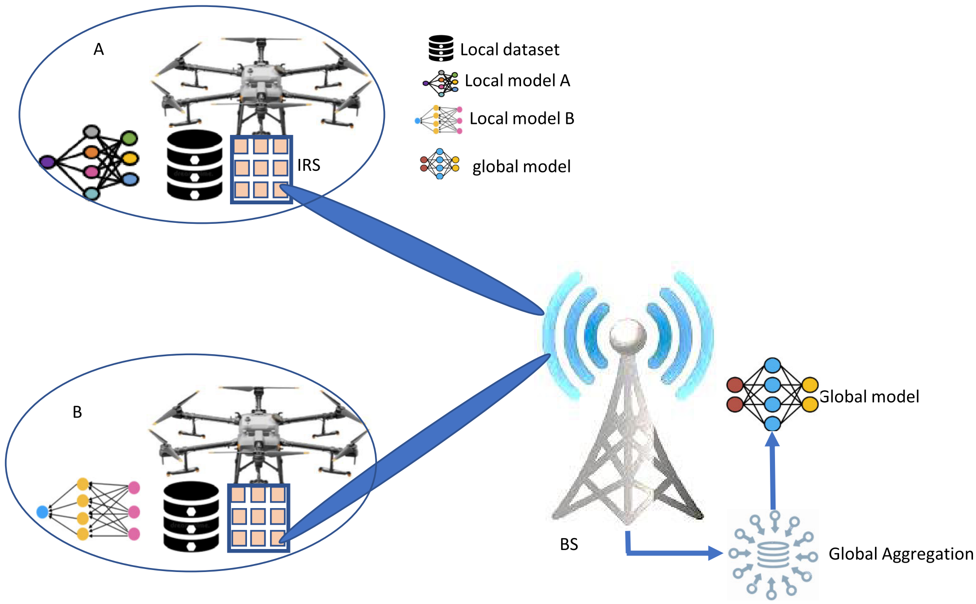

FIGURE 8. FL in Multi-IRS in drones enabling 6G.

Reduced latency: By enabling real-time learning and adaptation, FL and IRS integration in drones can significantly reduce the latency of 6G communication networks, making them more suitable for latency-sensitive applications such as autonomous drones.

Increased energy efficiency: By reducing the communication overhead and improving the signal quality, integrating FL and IRS in drones can significantly increase the energy efficiency of 6G communication networks, making them more sustainable and environmentally friendly.

The integration of FL and IRS in drones has the potential to significantly enhance the performance and efficiency of 6G communication networks. Furthermore, this integration can bring new opportunities and capabilities for various applications, such as autonomous drones, aerial photography and delivery services, environmental monitoring, disaster response, and infrastructure inspection. The algorithm flow charts for FL optimize the reflection coefficients is shown in algorithm 3.

Mathematical expression for the loss function: The loss function can be defined as the sum of the mean squared error (MSE) between the received signal at each device and the desired signal, weighted by a regularization term:

$$L = \sum_{i=1}^{N} w_i \cdot \mathrm{MSE}(y_i, \hat{y}_i) + \lambda \cdot |\boldsymbol{w}|_2^2$$

where N is the number of devices, y_i is the desired signal at device i, $\hat{y}_i$ is the received signal at device i after reflection from the IRS, $\boldsymbol{w}$ is the vector of IRS reflection coefficients, w_i is the weight assigned to device i, and λ is the regularization parameter. The loss function can be defined as the sum of the mean squared error (MSE) between the received signal at each device and the desired signal, weighted by a regularization term.

Algorithm 3 Algorithm Flow Chart for Optimizing the Reflection coefficients

1: Initialize the IRS reflection coefficients randomly.
2: Partition the devices into groups and send the IRS reflection coefficients to each group.
3: Each device uses its local data to compute the gradient of a loss function concerning the IRS reflection coefficients.
4: Each device sends the computed gradients to a central server.
5: The central server aggregates the gradients and computes the average gradient.
6: The central server updates the IRS reflection coefficients using the average gradient.
7: Repeat steps 2-6 until convergence.

Mathematical expression for the gradient of the loss function: The gradient of the loss function concerning the IRS reflection coefficients can be computed as follows:

$$\nabla \mathcal{L} = \sum_{i=1}^{N} w_i \cdot \mathrm{MSE}(\mathbf{y}_i, \hat{\mathbf{y}}_i) \cdot \mathbf{a}_i + 2\lambda \cdot \mathbf{w}$$

where $\boldsymbol{a}_i$ is the vector of the complex amplitudes of the signals the IRS reflects at device i. Including these details in the paper would provide a more detailed explanation of how FL optimizes the reflection coefficients of IRS in swarm drones.

The proposed framework of FL meets IRS in drones for enabling 6G communication networks has several potential advantages and limitations. These can be summarized as follows:

A. ADVANTAGES OF PROPOSED FRAMEWORK

1) ENHANCED WIRELESS COMMUNICATION

The integration of FL and IRS in drones can significantly enhance wireless communication in 6G networks. FL allows drones to collaboratively train ML models while keeping their data locally, preserving privacy and data ownership. IRS units strategically placed in the environment can manipulate the propagation of wireless signals, improving coverage, reliability, energy consumption, or costs. This combined approach can optimize wireless communication services and improve the overall performance of the communication network.

2) DISTRIBUTED AND SCALABLE

The proposed framework is distributed, with drones acting as data collectors, model trainers, and aggregators. This distributed approach allows for scalability, as more drones can be deployed in the network to increase coverage and capacity. FL enables drone collaboration without a centralized server, reducing communication overhead and enabling efficient communication in a large-scale network. This makes the framework suitable for dynamic and evolving environments like 6G communication networks.

3) COST-EFFECTIVE

The use of drones and IRS units in the framework has the potential to be cost-effective. Drones can be deployed flexibly and dynamically in the communication network, eliminating the need for fixed infrastructure. IRS units are passive and do not require active power consumption, making them energy-efficient and cost-effective compared to traditional communication infrastructure. This can result in cost savings in the communication network's deployment, operation, and maintenance.

4) IMPROVED PRIVACY AND SECURITY

FL allows drones to train ML models locally without sharing raw data, preserving privacy and data ownership. This can address privacy concerns associated with data sharing in wireless communication networks. Additionally, IRS units do not require data transmission or storage, reducing the risk of data breaches or cyber-attacks. This can result in improved privacy and security of communication within the framework.

Summary: Integrating FL and IRS technology in drones offers a robust solution for enhancing wireless communication in 6G networks. The integration optimizes coverage, reliability, and energy efficiency by allowing drones to collaboratively train machine learning models while maintaining data privacy and leveraging IRS units to manipulate wireless signals strategically. The decentralized and scalable nature of the framework accommodates dynamic environments with the cost-effective deployment of drones and passive IRS units. Additionally, the combined approach enhances privacy and security by preserving data ownership, reducing data transmission risks, and presenting a compelling solution for advancing wireless communication systems.

B. LIMITATIONS OF THE PROPOSED FRAMEWORK

1) COMPUTATIONAL AND ENERGY CONSTRAINTS OF DRONES

Drones may have limited computational and energy resources, affecting the performance of FL and IRS operations. Training ML models locally on drones can be computationally intensive and may require significant energy consumption, leading to reduced battery life and operational time. This can impact the scalability and performance of the framework.

2) REGULATORY AND LEGAL CHALLENGES

Integrating drones with IRS in 6G communication networks may face regulatory and legal challenges, such as spectrum allocation, licensing, and compliance with aviation regulations. Regulatory frameworks for the operation of drones and IRS units may vary across different regions or countries, which can affect the deployment and operation of the proposed framework.

3) PROPAGATION ENVIRONMENT LIMITATIONS

The performance of IRS units in manipulating the propagation of wireless signals depends on environmental conditions, such as the placement of IRS units, obstacles, and interference. If the propagation environment is not conducive to IRS operations, the performance improvement in coverage, reliability, energy consumption, or costs may be limited. Coordination and Communication Overhead: The proposed framework may require coordination among drones and communication with the centralized server for model aggregation, which can introduce communication overhead and latency. Efficient coordination and communication among drones may be challenging in dynamic and changing environments, and communication delays or failures may impact the framework's performance.

Summary: Implementing FL and IRS technology in drones encounters various challenges. Drones' limited computational and energy resources can hinder FL and IRS operations, potentially decreasing battery life and scalability due to intensive local model training. Regulatory and legal hurdles, including spectrum allocation, licensing, and compliance with aviation regulations, pose obstacles to integrating drones and IRS units in 6G networks, especially given regional variations. Coordinating drones and communication for model aggregation introduces overhead and latency, with communication challenges in dynamic environments potentially impacting the framework's efficiency.

V. CHALLENGES AND FUTURE TRENDS

This section outlines challenges and future trends of leveraging IRS-drone for a 6G wireless network.

A. FUTURE DIRECTIONS

1) ROBUSTNESS AND ADAPTABILITY

Future research could explore techniques to make the proposed IRS-enabled drone system more robust and adaptable to changing communication environments, weather conditions, and mission requirements. This could involve developing algorithms or mechanisms that dynamically adjust the reflection coefficients of the IRS based on real-time feedback from the environment or incorporating ML techniques for improved adaptation and performance.

2) SCALABILITY AND COMPLEXITY

The scalability and complexity of the proposed framework could be further investigated. This could include exploring approaches to manage many drones and IRS units efficiently, optimizing the communication and coordination between drones and IRS units, and addressing challenges related to system complexity, computational overhead, and communication overhead.

3) INTEROPERABILITY WITH OTHER GENERATIONS OF NETWORKS

The proposed IRS-enabled drone system could be integrated with networks of other generations, such as 5G or future 6G networks. Future research could investigate techniques to enable seamless interoperability between the IRS-enabled drone system and other communication networks, such as cross-network resource management, network slicing, or inter-network coordination.

4) ENERGY EFFICIENCY AND SUSTAINABILITY

Energy efficiency and sustainability are essential for drone systems. Future research could explore techniques to optimize the energy consumption of the IRS-enabled drone system, such as energy-aware routing, power control, and energy harvesting. Additionally, investigating the system's environmental impact, such as carbon footprint and sustainability, could be relevant in future research.

5) SECURITY AND PRIVACY

Security and privacy are critical aspects of any communication system. Future research could focus on developing robust security mechanisms to protect the IRS-enabled drone system against potential cyberattacks, unauthorized access, and privacy breaches. This could include encryption, authentication, and access control mechanisms tailored to the unique characteristics of the IRS-enabled drone system.

6) REAL-WORLD IMPLEMENTATIONS AND FIELD TRIALS

While the proposed framework may be based on theoretical or simulated evaluations, future research could focus on real-world implementations and field trials to validate the performance, feasibility, and practicality of the IRS-enabled drone system. It involves experimental setups, measurements, and evaluations in real-world scenarios to gain insights into the system's performance and potential limitations.

7) CHANNEL STATE INFORMATION

In particular, drone-IRS networks have variable channel circumstances and high mobility; channel estimation accuracy is essential for improving phase shifts and beamforming gain in IRS-aided communication networks. Additionally, increasing the number of IRSs deployed to increase the number of IRS for user links, phase shifts, drone-IRS channels, and predicted channel parameters. Due to the frequent pilot transmissions required for precise channel state information estimates, the challenges above might considerably lower system performance. Therefore, precise channel prediction becomes a crucial problem for practical communication due to the IRS's intrinsic passive character and lack of RF chains. To overcome the problems of applying advanced ML techniques like FL, deep neural network, and transfer learning to produce accurate channel state information with a lower overhead.

8) THZ COMMUNICATIONS

To handle significant data rates, THz communications are expected to use the bandwidth in higher frequencies effectively. However, the number of RF chains will greatly expand in THz communication, leading to greater hardware and energy costs. Additionally, obstruction and propagation loss are higher on higher frequency channels like the THz channels. To address these complex problems effectively, IRS may be installed at advantageous sites, including BSs, drones, and mobile users, to establish a strong LoS. To accurately predict the channel state information, optimize beamforming signs and phase shift at IRS, and establish LoS to enhance SNR, AI techniques must be developed with the help of the digital twin concept.

9) DRONE COMMUNICATION

In drone-assisted wireless systems, the IRS deployment strategy increases the design freedom of drone trajectories; however, as the actual channel gains between the drone and users rely on drone trajectory and precoding method. The precoding design of the multi-antenna configuration is closely related to the trajectory design of the drone. In actuality, developing an IRS' combined trajectory and precoding design in a drone context presents several difficulties. First, the combined gains of channels from the drone to the users become spatially and frequency-selective due to the numerous reflected propagations provided by IRSs, which complicates the design of drone trajectory. Therefore, more study is still needed into deploying IRSs in complex and dynamic networks while maintaining appropriate fairness and accomplishing the sum-rate target of drones. Further research is required because precise channel tracking detection in THz communication makes compensating for the Doppler spread and delay more difficult.

10) ENERGY CONSUMPTION
Due to the lack of a power amplifier, an IRS needs an energy supply [4]. On the other hand, energy saving is also crucial because of the drone's inadequate battery endurance. Energy is frequently a significant barrier to drone flying length, performance, and battery life. The use of wireless charging for drones while in flight is one remedy. In addition, employing WPT methods can transmit the necessary energy for mission continuity using another drone. Researchers should thus create energy-efficient procedures and appropriate optimization frameworks to lower power consumption without compromising the effectiveness of IRS-assisted drone communication.

11) OPTIMIZATION OF IRS-DRONE OPERATION WITH DIFFERENT WEATHER CONDITIONS
It is crucial to optimise IRS-assisted drone communication when using drones in challenging situations like strong winds or rain. However, non-linear models make it challenging to optimize drone trajectory, IRS phase shift, and resource allocation in particular. Finding innovative design solutions with little complexity and effective performance is therefore advised. In this sense, tools for AI and ML are potential methods for effectively designing and optimizing these networks. These strategies are built on trustworthy, safe, powerful technologies to optimize difficult settings. Furthermore, complex networks may be analyzed for improved secrecy performance using hybrid online and offline methods and data-driven models. However, other variables must be investigated, such as excessive energy usage, latency, and throughput.

12) CSI
For drone-IRS, drones have flexibility, high mobility features and unpredictable channel circumstances; accurate channel prediction is essential for maximizing the phase shifts and beamforming gain in IRS-aided communication networks. The number of IRSs deployed will increase the number of IRSs for user connections, phase shifts, drone-IRS channels, and predicted channel parameters. Due to the channel transmissions required for precise CSI estimates, the challenges above might considerably lower network performance. Therefore, due to the IRS's intrinsic passive character and lack of RF chains, a precise channel estimate becomes a crucial problem for practical communication. To overcome challenges, it is necessary to use cutting-edge ML techniques such as FL, transfer learning, and DNNs to acquire accuracy.

13) DATA GATHERING AND TRAINING MODEL
Data gathering is an essential step in training ML, and the model quality depends on the quality of data [113]. However, data gathering is a barrier to applying ML-based approaches to IRS-based communication since partial data might lead to poor models. The key estimating elements are signal detection, channel estimation, and the receiver's beamforming architecture. Therefore, data-gathering methods may be a future study area for the practical application of ML-based strategies.

14) SECURING DATA COLLECTION
The IRS system should be mobile enough to be mounted on a drone, as was recently investigated [52], to be placed at the ideal location. One significant disadvantage of drone-IRS is that hostile users can create an LoS link using the non-specific nature of the reflected radio signal, compromising the communication's confidentiality. The influence of a drone-IRS system on secure data transmission rates from smart environments was the main emphasis in [114], which sought to maximize the feasible secrecy rates under total transmit power constraints.

15) PERFORMANCE OPTIMIZATION
Further research can be conducted to optimize the performance of IRS-enabled drone systems regarding signal quality, coverage, capacity, and energy efficiency. This can involve exploring novel algorithms, techniques, and architectures for jointly optimizing the operation of drones and IRS in dynamic and changing communication environments.

16) INTEROPERABILITY WITH OTHER NETWORKS
Investigation can be done on how IRS-enabled drone systems can interoperate with other networks of different generations, such as 5G and beyond, to enable seamless communication and networking across heterogeneous networks. This can involve exploring interoperability protocols, handover mechanisms, and network management strategies to ensure smooth integration and operation with other networks.

17) ROBUSTNESS AND RESILIENCE
Research can be conducted to enhance the robustness and resilience of IRS-enabled drone systems against various challenges, such as interference, jamming, mobility, and environmental conditions. This can involve investigating adaptive algorithms, distributed coordination, and fault-tolerant mechanisms to ensure the reliable and resilient operation of the system in dynamic and hostile environments.

18) SECURITY AND PRIVACY
Further investigation can be done on the security and privacy aspects of IRS-enabled drone systems, including protecting against unauthorized access, data breaches, and privacy violations. This can involve exploring encryption, authentication, and access control mechanisms tailored for IRS-enabled drone systems to ensure secure and privacy-preserving communication.

19) REGULATION AND STANDARDIZATION
Research can be conducted on the regulatory and standardization aspects of IRS-enabled drone systems, including

addressing legal, ethical, and policy issues related to their deployment, operation, and management. This can involve studying regulatory frameworks, policy guidelines, and standardization efforts to ensure compliance and harmonization with relevant regulations and standards. These are just generic suggestions, and the specific areas of improvement and future research would depend on the findings, limitations, and contributions of the specific paper you mentioned, as well as the research objectives and context of the proposed framework for IRS-enabled drone systems. It is important for the paper's authors to carefully consider their specific research findings and contributions and provide relevant and meaningful suggestions for future research based on their work.

B. CHALLANGES

The potential challenges and open issues related to integrating IRS with drones in 6G communication are summaries fellow.

1) TECHNICAL CHALLENGES

Integrating IRS with drones in 6G communication may pose various technical challenges. Advanced signal processing algorithms may be required to optimize the reflections from the IRS units to achieve the desired communication performance. Efficient communication protocols need to be designed to enable effective coordination and information exchange between drones and IRS units. Accurate localization and tracking techniques are crucial for the precise positioning and movement of drones and IRS units, especially in dynamic and changing environments. The authors could discuss the technical challenges associated with these aspects, including developing novel algorithms, protocols, and techniques to address them and the potential impact on the overall system performance.

2) REGULATORY CHALLENGES

Integrating IRS with drones in 6G communication may also face regulatory challenges. Spectrum allocation for communication between drones and IRS units may need to be carefully considered, considering the availability, compatibility, and interference issues related to the spectrum bands used. Licensing requirements for operating drones and IRS units, compliance with aviation regulations, and other regulatory considerations may impact the deployment and operation of the system. The authors could discuss the regulatory challenges and requirements associated with integrating the IRS with drones and potential solutions or recommendations to address them.

3) PRIVACY CONCERNS AND SECURITY ISSUES

Privacy and security issues may arise in integrating IRS with drones in 6G communication. The reflections from the IRS units could reveal sensitive information about the environment, infrastructure, or users. Secure communication, authentication, and data privacy mechanisms may be required to protect the communications' integrity, confidentiality, and privacy between drones and IRS units. The authors could discuss the potential privacy concerns and security issues associated with the system and propose appropriate measures or techniques to mitigate them, such as encryption, authentication, and access control mechanisms.

4) INTEROPERABILITY CHALLENGES

Interoperability challenges may arise in integrating IRS with existing networks or coexisting with other wireless technologies. Integration with existing communication networks, such as 5G or legacy networks, may require interoperability mechanisms and protocols to enable seamless communication between drones, IRS units, and other network entities. Coexistence with other wireless technologies or devices, such as Wi-Fi, cellular networks, or other drones, may pose interference or coordination challenges. The authors could discuss the interoperability challenges and potential solutions to ensure smooth integration and coexistence with other communication technologies or networks.

5) PRIVACY AND SECURITY IN FL FOR UAV-ENABLED NETWORKS

Ensuring privacy and security in FL for UAV-enabled networks presents multifaceted challenges. FL's decentralized approach, where UAVs train models locally without sharing raw data, requires addressing data privacy, model confidentiality, and secure communication issues. Safeguarding against potential data breaches during model aggregation, protecting against adversarial attacks, and preventing model poisoning while maintaining the integrity of the learning process are crucial concerns. Additionally, achieving differential privacy across diverse data distributions and complying with regulatory frameworks further complicate the security landscape. Balancing the benefits of FL's decentralized model with robust privacy and security measures is essential for harnessing its potential in UAV-enabled networks while mitigating risks associated with data leakage, adversarial manipulation, and regulatory non-compliance. Leveraging FL to facilitate privacy-preserving collaboration among UAVs is for efficient learning, scheduling, and resource management in dynamic and privacy-sensitive environments [115], [116], [117]

VI. CONCLUSION

The paper has addressed establishing a non-terrestrial network for 6G communications by presenting cutting-edge advancements in IRS and drone communication technologies. A key innovation lies in integrating IRS and FL within drones, offering a compelling avenue for enhancing 6G communication network performance. The proposed framework showcases how the fusion can ameliorate wireless communication services, elevating coverage, reliability, and energy efficiency. The framework fosters collaborative learning among multiple drones, culminating in superior and more streamlined decision-making processes within the network. Amid the evident benefits, challenges like regulatory and security aspects need to be resolved to harness this technology's full potential. Despite the challenges, the convergence of FL and IRS within drones holds substantial promise in catalyzing innovation for the evolution of 6G communication networks and fulfilling the evolving requirements of future wireless communication services. A comprehensive exploration of various FL optimization techniques and algorithms proposed for UAV-enabled networks could offer valuable insights into the technical strategies driving the synergy of FL and IRS, enriching the overall framework's robustness and performance optimization.

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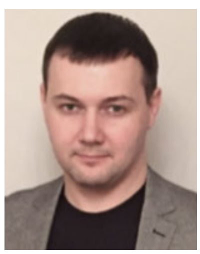

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