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Review

A Survey on Energy-Efficient Design for Federated Learning over Wireless Networks

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Abstract: Federated learning (FL) has emerged as a decentralized, cutting-edge framework for training models across distributed devices, such as smartphones, IoT devices, and local servers while preserving data privacy and security. FL allows devices to collaboratively learn from shared models without exchanging sensitive data, significantly reducing privacy risks. With these benefits, the deployment of FL over wireless communication systems has gained substantial attention in recent years. However, implementing FL in wireless environments poses significant challenges due to the unpredictable and fluctuating nature of wireless channels. In particular, the limited energy resources of mobile and IoT devices, many of which operate on constrained battery power, make energy management a critical concern. Optimizing energy efficiency is therefore crucial for the successful deployment of FL in wireless networks. However, existing reviews on FL predominantly focus on framework design, wireless communication, and security/privacy concerns, while paying limited attention to the system's energy consumption. To bridge this gap, this article delves into the foundational principles of FL and highlights energy-efficient strategies tailored for various wireless architectures. It provides a comprehensive overview of FL principles and introduces energy-efficient designs, including resource allocation techniques and communication architectures, tailored to address the unique challenges of wireless communications. Furthermore, we explore emerging technologies aimed at enhancing energy efficiency and discuss future challenges and opportunities for continued research in this field.

Keywords: federated learning (FL); decentralize learning; energy efficiency; wireless network; internet of things (IoT)

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1. Introduction

The rapid growth of Internet of Things (IoT) applications, coupled with the increasing computational power of smart devices such as smartphones, wearables, and autonomous vehicles, has generated unprecedented amounts of data within modern distributed networks [1,2]. For instance, IoT devices produced an estimated 1.1 zettabytes of data in 2023 alone, underscoring the urgent need for efficient data-driven machine learning approaches [3,4]. Traditional centralized learning techniques, which have typically been used to process and analyze data, rely on aggregating data at central cloud servers for storage and training [5]. While effective in certain contexts, this method faces significant limitations in handling vast data generated by modern IoT ecosystems. The reliance on central servers not only results in communication bottlenecks, high transfer costs, and latency issues but also makes it unsuitable for real-time applications like smart healthcare, smart cities, and autonomous driving systems [6–8]. Additionally, transferring sensitive user data to centralized servers increases the risk of data breaches and malicious exploitation [9,10], underscoring the limitations of conventional learning methods in distributed networks.

Federated learning (FL) offers a promising alternative by decentralizing the training process. FL technique operates by having a central server distribute global model parameters to remote devices, whereas each device uses its local dataset to update the model [11,12]. Instead of transferring raw data, which is typically vast and sensitive, these devices send only their locally updated model parameters back to the server [13]. The server then aggregates these updates, refines the global model, and repeats the process until a desired level of accuracy is reached. This significantly reduces the amount of data exchanged over the network, improving communication efficiency [14]. The size of model updates is often much smaller than the raw data, which is particularly advantageous for reducing network traffic and latency. Furthermore, FL enhances privacy by keeping sensitive data on local devices, minimizing the risk of data theft or breaches during transmission [15,16]. In this way, FL provides an efficient, scalable, and privacy-preserving solution for machine learning in distributed environments like IoT networks [17].

Although wired networks are known for their stability and reliability, wireless networks offer distinctive benefits that enhance the efficiency and scalability of FL, especially in the context of IoT [18]. Specifically, wireless networks allow devices to connect and disconnect seamlessly as they move in and out of coverage areas, which is essential for accommodating the vast and dynamic ecosystem of IoT devices. This adaptability ensures that new devices can be easily integrated into the FL process without significant infrastructure changes. Moreover, the use of wireless networks enables FL to reach remote or hard-to-wire locations and offers a diverse range of devices and datasets in the learning process [19]. This diversity can lead to the development of more generalized and robust models that perform better across diverse environments and use cases. Additionally, wireless protocols can be readily optimized for energy efficiency, ensuring battery-powered devices participate in FL without excessive energy consumption [20]. By leveraging the flexibility of wireless networks, FL can maximize the potential of distributed IoT devices, facilitating scalable and efficient machine learning in diverse, real-world environments, while preserving data privacy [18]. This powerful combination makes FL an optimal solution for training machine learning models in vast, dynamic, and geographically dispersed networks.

Despite its advantages, deploying FL over wireless networks presents challenges, particularly in latency, reliability, scalability, and energy efficiency [21–23]. Among these challenges, the limited battery life of IoT devices emerges as a well-documented barrier to deploying FL effectively. To achieve high accuracy in the global model, service operators require IoT devices to engage in frequent local model training and update model parameters through wireless links. This process, while essential for improving the performance of the FL system, results in substantial energy consumption for UEs [21]. Moreover, as IoT devices are typically deployed in environments with limited access to charging infrastructure, the energy constraints become even more critical. Consequently, ensuring energy-efficient operation while maintaining the efficiency and effectiveness of the FL process is critical for practical FL implementation over wireless networks [24].

Existing surveys on FL primarily focus on technical optimizations, such as model compression, hyperparameter tuning, and training algorithm improvements. However, implementing FL over wireless networks introduces additional complexities, including resource allocation, bandwidth limitations, fluctuating channel conditions, and energy constraints. With the rapid evolution of wireless technologies driven by 5G and the anticipated shift to 6G, new architectures are emerging to help solve the issues in deploying FL over wireless networks [25]. For instance, nonorthogonal multiple access (NOMA) can be leveraged in both the power domain [26] and code domain [27]. In the spatial domain, advanced techniques like massive multiple-input multiple-output (MIMO) [28], reconfigurable intelligent surface (RIS) [29], and unmanned aerial vehicles (UAVs) [30] can be integrated further to enhance the performance and efficiency of wireless networks. These advancements serve as the primary motivation for our survey, which aims to provide a comprehensive review of cutting-edge wireless network architecture designs for energy-efficient FL. From this point of view, our survey highlights critical research challenges, explores promising solutions, and outlines the future vision for efficient deployment of FL over wireless networks.

The main contributions of this paper can be summarized as follows:

- First, we provide a brief overview of the fundamental principles behind deploying FL in general wireless networks. Then, we introduce a resource allocation optimization problem for minimizing overall energy consumption composed of computation and communication energy consumption.
- Next, we present a comprehensive survey of the latest wireless network architectures with energy-efficient designs for FL. These architectures are systematically categorized based on the distinct characteristics of the FL process, including centralized federated learning (CFL) and decentralized federated learning (DFL), offering a clear understanding of their respective strengths and use cases.
- To enhance energy efficiency in deploying FL over wireless networks, this paper provides an overview of emerging advanced technologies that can be integrated into wireless architectures to boost system performance. Technologies such as SWIPT, IRS, and NOMA are explored for their significant potential to address the challenges of implementing FL in wireless environments effectively.
- Finally, we discuss the challenges, opportunities, and potential research directions, considering emerging advanced technologies and future wireless network architectures.

2. Basic Principles of FL over Wireless Networks

In this section, we provide a brief overview of the fundamental principles governing FL in a general wireless network, with a focus on understanding the associated energy consumption model during the FL process. FL is broadly classified into two main categories: centralized federated learning (CFL) and decentralized federated learning (DFL). These approaches differ in how they coordinate and aggregate model updates from participating devices, aligning closely with specific wireless network architectures based on their communication patterns and infrastructure requirements.

The overarching concept of FL, encompassing both CFL and DFL, is to collaboratively derive a global model, denoted as $\mathbf{q}$, by aggregating contributions from all participating local models. The primary objective of FL is to determine the optimal parameters $\mathbf{q}$ for the global model by minimizing the global loss function, expressed as

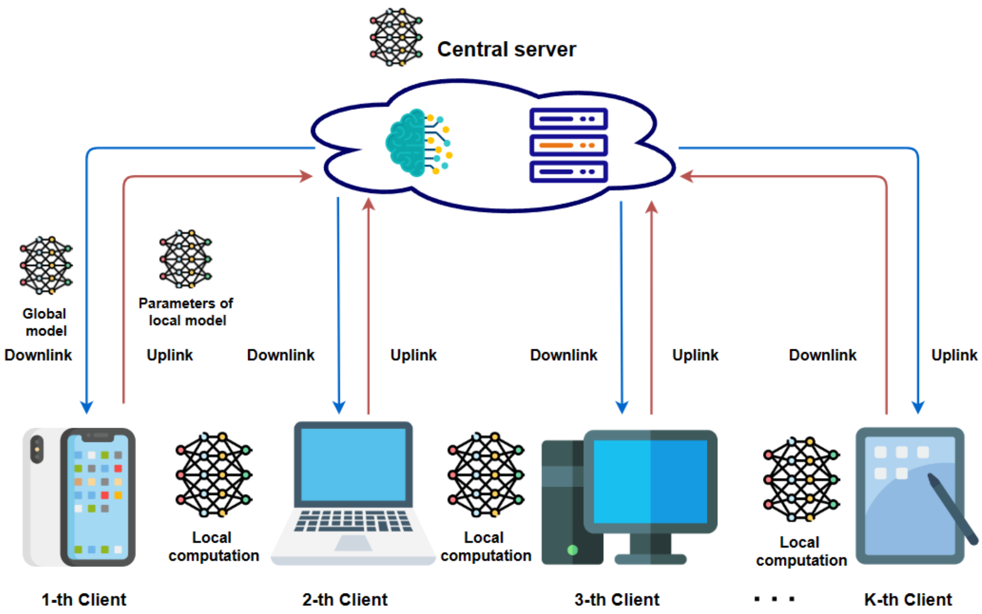
$$\min_{\mathbf{q}} F(\mathbf{q}) \triangleq \sum_{k=1}^{K} \frac{D_k}{D} F_k(\mathbf{q}), \tag{1}$$

where $F_k(\mathbf{q}) = \sum_{i=1}^{D_k} \mathrm{f}(\mathbf{q}, x_{k,i}, y_{k,i})$ represents the local loss function for the k-th client over its local dataset $\mathbf{D}_k$ with size D_k, and $D = \sum_{k=1}^{K} D_k$ denotes the total dataset size across all participating devices. Here, $\mathrm{f}(\mathbf{q}, x_{k,i}, y_{k,i})$ denotes the loss function for an individual data sample pair $(x_{k,i}, y_{k,i})$ from the local dataset $\mathbf{D}_k$. To solve the optimization problem (1) for both CFL and DFL, we introduce the foundational FL algorithm, federated averaging (FedAvg), initially proposed in [31].

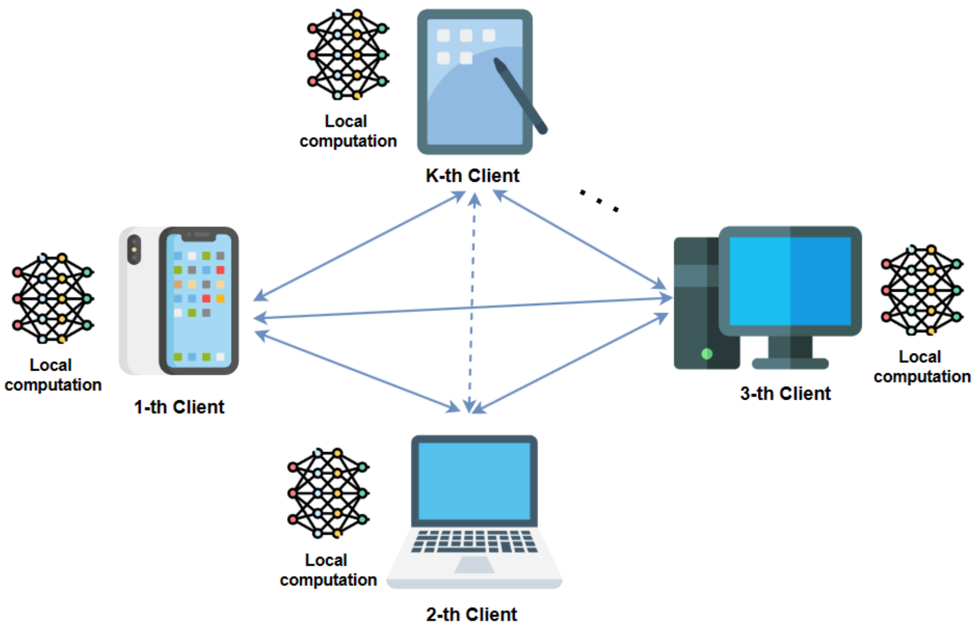
2.1. Overview of FL Models

2.1.1. Overview of the CFL Strategy

As illustrated in Figure 1a, a basic CFL system relies on a central server, such as a cloud server, serving K clients (e.g., sensor IoT devices and smartphones). In wireless communication contexts, the central server is often situated at a base station (BS), which facilitates communication with and coordination of clients over wireless links. The CFL approach involves the central server aggregating local models from K clients to construct a global model $\mathbf{q}$, which is subsequently disseminated back to the clients for further iterations.



(**a**) Centralized federated learning



(**b**) Decentralized federated learning

Figure 1. Federated learning strategies.

This architecture is particularly well suited for traditional wireless networks, such as 4G and 5G, where the BS or cloud serves as the central hub for client communication. CFL benefits from the stability and reliability of such centralized systems, enabling efficient aggregation and low-latency synchronization of models.

The CFL process addresses the optimization problem in (1) iteratively through three key phases: local computation, communication, and global computation. During the j-th global iteration, the following steps are performed: Step 1 (Global downlink training updates): At the start of the CFL process ($j = 0$), the central server initializes the global model, which is typically a machine learning model, such as a deep neural network, composed of multiple layers and interconnected nodes designed to capture complex patterns in data. The initialization of the model often involves setting the model parameters (weights) to random values or pretrained values, depending on the specific application and prior knowledge available. Then, the central server broadcasts the global model $\mathbf{q}^{(j)}$ to K clients over wireless downlink channels.

Step 2 (Local computation): During the j-th iteration, the k-th client retrieves the global model $\mathbf{q}^{(j)}$ from the central server, and uses it as the initial local model. The k-th client then trains its local dataset $\mathbf{q}_k^{(j)}$ using its dataset, $\mathbf{D}_k$, by minimizing the loss function $F_k(\mathbf{q})$. Optimization methods such as gradient descent (GD) and stochastic gradient descent (SGD) [21] can be used to solve this optimization problem. After completing a predetermined number of local iterations, the clients transmit their locally updated models to the server via wireless uplinks.

Step 3 (Global uplink training updates): The central server collects the locally updated models, $\mathbf{q}_k^{(j)}, k = 1, 2, \cdots, K$, from the K clients and computes a new global model $\mathbf{q}^{(j+1)}$, using the FedAvg algorithm:

$$\mathbf{q}^{(j+1)} := \sum_{k=1}^{K} \frac{D_k}{D} \mathbf{q}_k^{(j)}. \tag{2}$$

The CFL training process iterates until the global model achieves the desired level of accuracy.

To better understand the differences between CFL and DFL, Table 1 highlights their key characteristics across multiple dimensions, such as architecture, communication overhead, scalability, fault tolerance, energy efficiency, privacy, and use case suitability. This comparison provides a clear understanding of how these two paradigms differ in terms of their operational models and practical applications.

Table 1. Comparison of CFL and DFL.

Characteristic	**CFL**	**DFL**
Architecture	Central server aggregates updates from devices	Peer-to-peer communication without a central server
Communication Overhead	High, as all devices communicate with the server	Lower, as communication is localized among peers
Scalability	Limited by central server capacity	High, as no central bottleneck exists
Fault Tolerance	Vulnerable if the central server fails	More resilient, as no single point of failure exists
Energy Efficiency	May require more energy due to server-device interactions	Typically more energy-efficient due to localized operations
Privacy	Relies on the server's privacy measures	Offers better privacy as data exchanges are localized
Use Case Suitability	Suitable for scenarios with robust infrastructure	Ideal for distributed systems with limited infrastructure

2.1.2. Overview of the DFL Strategy

In contrast to CFL, DFL, illustrated in Figure 1b, eliminates the need for a central server to manage the learning process [32,33]. Instead, each client exchanges model parameters directly with other clients to update its local model. The final model is obtained on an edge device by aggregating local updates from the connected edge clients. In the context of wireless systems, DFL is particularly well suited for wireless systems that utilize device-to-device (D2D) communications [34]. Like CFL, the primary goal of DFL is to optimize the global parameters $\mathbf{q}$ by minimizing the global loss function in (1).

The DFL process during the j-th iteration involves the following steps:

Step 1 (Local computation): At the beginning of the DFL process ($j = 0$), all K clients initialize their local models with the same structure. During the j-th iteration, the k-th client updates its local model, $\bar{\mathbf{q}}_k^{(i)}$, using its dataset, $\mathbf{D}_k$, and optimization algorithms such as SGD [35,36].

Step 2 (Model aggregation via D2D communications): After completing the local computation, each client shares its trained model with neighboring clients over the wireless links. Using the FedAvg method in [31], the k-th client updates its local model by aggregating the models received from other clients:

$$\mathbf{q}_k^{(i)} := \sum_{k'=1}^{K} \alpha_{k,k'} \beta_{k,k'} \bar{\mathbf{q}}_k^{(i)}, \tag{3}$$

where $\beta_{k,k'}$ is the aggregation weight between clients k and k', with values ranging from 0 to 1 [32], and $\alpha_{k',k} = \{0, 1\}$ indicates the presence or absence of a D2D link between the two clients. The DFL process iterates until a global consensus is reached, yielding an optimized model.

2.2. Signal Transmission Models

During the local model uploading process, the transmit uplink signal from the k-th client is given by $x_k = \sqrt{p_k} s_k$, where s_k, with $\mathbb{E}\{|s_k|^2\} = 1$, denotes the desired data symbol, and p_k denotes the uplink power of the k-th client. In a CFL setup, this signal is transmitted to the central server, while in DFL, it is transmitted to other clients. Two common schemes for uplink transmission are time division multiple access (TDMA) and frequency division multiple access (FDMA).

2.2.1. TDMA-Based Uplink Transmission

In the TDMA scheme, each client is assigned a distinct, orthogonal time slot of length t_k to communicate with the central server (CFL) or with other clients (DFL), ensuring interference-free transmission. The achievable uplink rate for the k-th client (in bps) is given by

$$R_k^{\mathrm{u}} = \frac{B_{\mathrm{u}} t_k}{T} \log_2\left(1 + \frac{|h_k^{\mathrm{u}}|^2 p_k}{\sigma_{\mathrm{noise}}^2}\right), \tag{4}$$

where $\frac{|h_k^{\mathrm{u}}|^2 p_k}{\sigma_{\mathrm{noise}}^2}$ represents the signal-to-noise ratio (SNR) of the k-th client during uplink transmission. $|h_k^{\mathrm{u}}|^2$ captures the uplink channel gain between the k-th client and the central server (CFL) or other clients (DFL). $\sigma_{\mathrm{noise}}^2$ represents the variance of the background noise. $T \triangleq \sum_{k=1}^{K} t_k$ is the total time resource, B_{u} denotes the total uplink bandwidth allocated for local model transmission.

2.2.2. FDMA-Based Uplink Transmission

In the FDMA scheme, each client is allocated a distinct, nonoverlapping frequency band to communicate with the central server (CFL) or other clients (DFL), avoiding interference. The uplink rate of the k-th client (in bps) in this case is expressed as

$$R_k^{\mathrm{u}} = B_k \log_2\left(1 + \frac{|h_k^{\mathrm{u}}|^2 p_k}{\sigma_{\mathrm{noise}}^2}\right), \tag{5}$$

where B_k denotes the bandwidth allocated to the k-th client, and $B_{\mathrm{u}} \triangleq \sum_{k=1}^{K} B_k$ is the total uplink bandwidth.

2.3. Energy Consumption Model

2.3.1. Computation Energy Consumption

The number of CPU cycles required by the k-th client to process a single data sample is denoted as $N_{c,k}$. This parameter is typically determined offline by analyzing the execution time of local computation in FL, along with the CPU clock speed and the number of input bits [37]. For a dataset of size D_k at the k-th client, the total CPU cycles required for a single local computation round are $N_{c,k}D_k$, leading to the computation time:

$$tcmp_k = \frac{N_{c,k}D_k}{f_k}, \tag{6}$$

where $f_k \in [f_{\min}, f_{\max}]$ is the CPU frequency of the k-th client, adjustable to meet specific performance objectives. According to [38], the power consumption of the mobile CPU processor at the k-th client is modeled as $Pcmp_k = \zeta_k f_k^3$ (Joule/s), where ζ_k is the effective capacitance coefficient dependent on the processor architecture. Thus, the total computation energy consumption (in Joule) at the k-th client during each local round is calculated as

$$Ecmp_k = Pcmp_k tcmp_k = \zeta_k N_{c,k} D_k f_k^2. \tag{7}$$

2.3.2. Communication Energy Consumption

Let N_s denote the size of the model parameters transmitted during each communication round. The transmission time between the k-th client and the central server (CFL) or other clients (DFL) is computed as

$$tcom_k^\mathrm{u} = \frac{N_\mathrm{s}}{R_k^\mathrm{u}}, \tag{8}$$

where R_k^u is the uplink rate for the k-th client , derived in (4) or (5). Consequently, the total communication energy consumption for the k-th client in one round is expressed as

$$Ecom_k^\mathrm{u} = E\{|x_k|^2\} \times tcom_k^\mathrm{u} = \frac{p_\mathrm{u}^{\max} \mathrm{w}_k^2 N_\mathrm{s}}{R_k^\mathrm{u}}. \tag{9}$$

From (9), the communication energy consumption at each client depends on the uplink power and rate. While higher uplink power improves the uplink rate, reducing latency in the FL update process, it also increases energy consumption, which is a concern in resource-constrained environments. Therefore, power control strategies are considered to optimize transmission power, striking a balance between signal quality and energy efficiency. Additionally, bandwidth allocation strategies are also crucial for reducing communication latency and improving uplink efficiency by assigning resources based on client requirements or network conditions, thus ensuring both reduced delays and fairness. Consequently, resource allocation strategies, such as bandwidth and power control, are essential for enhancing communication energy efficiency in FL over wireless networks. These strategies can be efficiently optimized using advanced techniques such as convex optimization or reinforcement learning, as referenced in several studies.

2.3.3. Total Energy Consumption Minimization Problem

The total energy consumption by clients (in Joules) during a CFL or DFL training round can be decomposed into the energy for the local computation process and that for the communication process, which can be expressed as

$$Etotal = \sum_{k=1}^{K} (Ecom_k^\mathrm{u} + NcmpEcmp_k), \tag{10}$$

where $Ncmp$ represents the number of local computation rounds per global iteration.

To enhance energy efficiency in FL over wireless networks, resource allocation must be optimized to minimize total energy consumption over N_0 global training rounds. This challenge can be formulated as the following optimization problem:

$$\underline{\mathrm{P}:} \quad \min_{p_k, f_k, B_k, \alpha_{k,k'}} \quad N_0 \sum_{k=1}^{K} (Ecom_k^{\mathrm{u}} + NcmpEcmp_k) \tag{11a}$$

$$s.t. \quad 0 \leq p_k \leq P_{\max}, \quad \forall k \in \mathcal{K}, \tag{11b}$$

$$f_{\min} \leq f_k \leq f_{\max}, \quad \forall k \in \mathcal{K}, \tag{11c}$$

$$\sum_{k=1}^{K} B_k \leq B_{\mathrm{u}}, \tag{11d}$$

$$\alpha_{k,k'} \in \{0,1\}, \quad k, k' \in \mathcal{K}, \tag{11e}$$

where constraints (11b) and (11c) ensure appropriate uplink power and CPU frequency for each client, respectively. Constraint (11d) ensures that the total bandwidth does not exceed the available uplink bandwidth B_u (FDMA), while constraint (11e) enforces link selection criteria for DFL strategies.

Effective resource allocation for wireless transmission and local computation is critical for reducing energy consumption in FL. Tailored strategies are needed for different wireless network architectures to achieve optimal energy efficiency. Advanced wireless networks, continually evolving, offer innovative approaches to further improve energy efficiency for FL at the edge. The next two sections explore these architectures in detail.

3. Wireless Network Architectures for Energy-Efficient CFL

3.1. Terrestrial-Based Architectures

3.1.1. CFL in Centralized Wireless Networks

Centralized wireless networks, illustrated in Figure 2, are systems where a central entity (e.g., a BS, access point, or central server) oversees resource management and operation decision-making. The central controller manages communication tasks, including user access, data routing, resource allocation, and security, providing stable connectivity for edge devices.

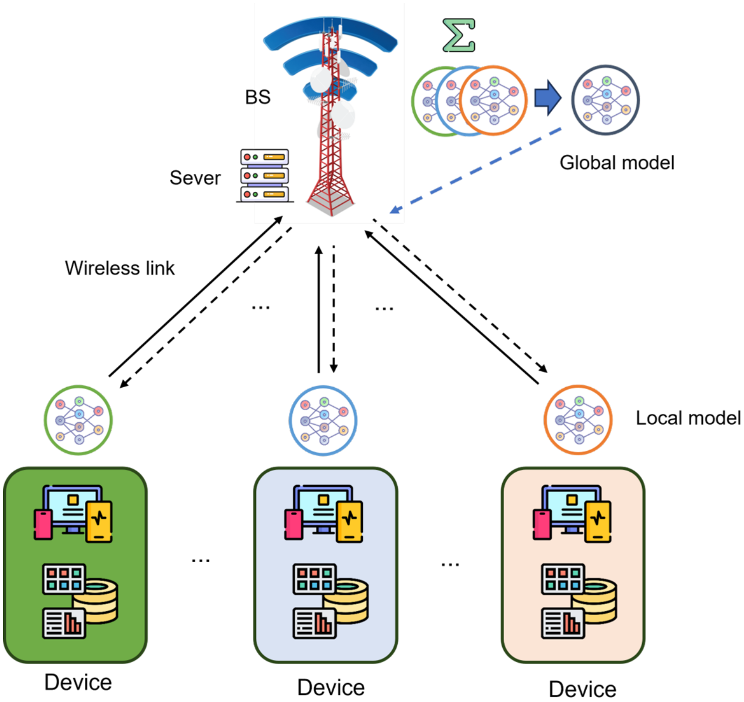


Figure 2. CFL over a centralized wireless network.

As the adoption of machine learning and deep learning grows within centralized wireless networks, there is an increasing demand for privacy-preserving and resource-efficient methods. Transmitting raw data to a central server often proves impractical due to bandwidth and privacy constraints. However, the structure of centralized networks aligns well with CFL, enabling decentralized training of machine learning models without sharing raw data [18,39–42].

- CFL in Cellular Networks: A cellular network is a type of centralized system, providing wireless communication services over wide geographical areas. Several studies on energy-efficient CFL in cellular networks were presented in [21,39,43–46]. In [39], the authors examined strategies to improve overall energy efficiency in CFL over 5G+ mobile devices by analyzing energy consumption trade-offs between local computation and wireless communication.
  Building on this, Ref. [45] introduced a joint design for wireless transmission and weight quantization to enhance energy efficiency on mobile devices. Similarly, Ref. [21] tackled energy-efficient transmission challenges for CFL in wireless networks.
- CFL in IoT Network: Centralized network architectures have been widely applied in IoT networks to manage large-scale deployments, optimize communication, and streamline data processing. With the rapid proliferation of IoT devices, coupled with the integration of machine learning in IoT applications, CFL has emerged as a promising solution to address these challenges [11,47–49]. In [48], the author proposed a multiagent federated reinforcement learning algorithm to optimize energy-efficient CFL while ensuring the quality of service (QoS) for IoT nodes, fairness, and UAV trajectory planning. The authors in [49] explored resource allocation and energy-efficient CFL schemes for relay-assisted IoT networks, focusing on minimizing the overall energy consumption of IoT devices while meeting latency constraints for training and transmission.
- CFL in Fog-Cloud RAN: Fog–cloud radio access networks (F-RAN or C-RAN) represent another centralized architecture, especially for 5G and beyond. Energy-efficient CFL in such networks is highly promising [50,51]. The authors in [51] developed an energy-efficient CFL framework for C-RAN with strict energy constraints.
- Resource Allocation for CFL: Resource allocation plays a critical role in CFL-based systems, as it directly impacts communication efficiency, energy efficiency, model convergence speed, and overall system performance. By strategically managing resources like bandwidth, power, and computational capacity, CFL can operate more effectively in centralized networks [52–57]. Ref. [55] incorporated a simultaneous wireless information and power transfer (SWIPT) system with multicarrier NOMA to improve CFL energy efficiency. In [56], the authors proposed an energy-efficient CFL framework for wireless networks by employing a joint computation-and-communication resource management strategy. Leveraging intelligent reflecting surfaces (IRS), Ref. [57] optimized resource allocation for CFL in centralized wireless networks.
- MIMO/mMIMO Technology for CFL: CFL has been applied to enhance performance in large-scale cellular and IoT networks. To further address communication challenges posed by wireless channel fading in centralized networks, recent studies have explored CFL along with multiple-input multiple-output (MIMO)/massive multiple-input multiple-output (mMIMO) technology as a promising approach for efficient parameter transmission between multiple wireless devices and servers. This integration enables communication-efficient CFL by improving both spectral and energy efficiency, thereby addressing key requirements for scalable and sustainable wireless communication [58–60]. Studies like [60] proposed synchronous, asynchronous, and session-based designs for energy-efficient CFL in mMIMO networks. However, research in this area remains limited.

3.1.2. CFL in Distributed Wireless Networks

In this subsection, we analyze the design of distributed wireless network architectures that support CFL and present recent studies addressing the energy efficiency challenges in these networks. Cell-free massive MIMO (CFMM) system can be interpreted as a combination of massive MIMO, distributed antenna systems [61], and network MIMO, which is considered the most advanced distributed wireless network.

CFMM is recognized as a key enabler for 6G networks, as it effectively addresses significant propagation losses and enhances the quality of service, particularly for cell-edge UEs [62]. Figure 3 illustrates a CFMM system with M access points (APs) and K UEs. These distributed APs collaborate to serve UEs without geographic limitations.

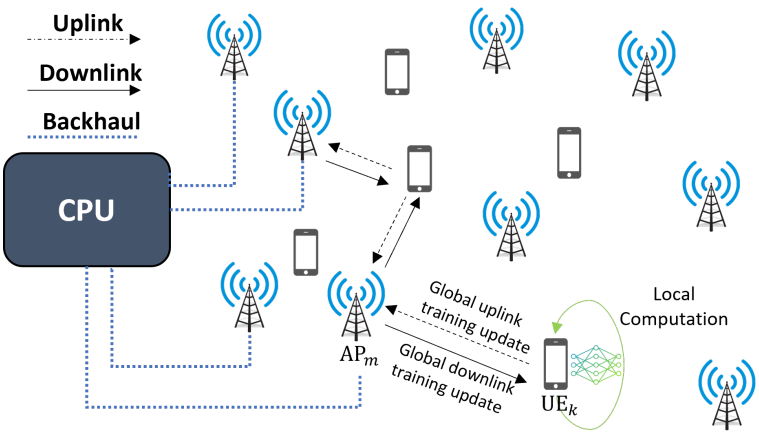


Figure 3. CFL over a CFMM system.

In the context of FL, CFMM enables the accommodation of a large number of served UEs compared with other wireless architectures owing to the support of the mMIMO technique. Additionally, recent studies demonstrate that CFMM can achieve a five-fold gain in spectral efficiency and a ten-fold improvement in energy efficiency compared with small-cell and cellular massive MIMO systems [63]. Moreover, the distinctive features of CFMM systems, particularly their ability to leverage the cooperative nature of distributed APs, position them as an ideal platform for implementing CFL with energy-saving techniques.

Recent studies have introduced several strategies to reduce energy consumption in these systems. For instance, the authors of [64] focused on minimizing energy consumption in UEs during the FL training phase by optimizing key parameters such as transmit power, frequency allocation, communication time, and computation time. They proposed an iterative algorithm based on the inner approximation method, transforming the original nonconvex optimization problem into a series of convex problems. This approach identifies at least one locally optimal solution, thereby reducing energy expenditure during training. Similarly, Ref. [65] proposed a novel uplink power allocation scheme tailored for CFL in CFMM systems. This scheme simultaneously minimizes energy consumption and latency during CFL training by optimizing users' uplink transmission powers. By utilizing the coordinate gradient descent method, the algorithm accounts for the impact of each user's power on overall energy consumption and latency experienced by other users, leading to more efficient resource allocation within the CFMM framework.

In [66], the authors presented an over-the-air CFL scheme for CFMM systems, formulating a joint optimization problem that integrates device scheduling and power scaling while adhering to energy consumption constraints. They conducted a convergence analysis and applied the Lyapunov method to simplify the long-term problem into a manageable short-term one. An alternating optimization approach is utilized to tackle the mixed-integer nonlinear programming problem. In [67], the authors highlighted CFMM's potential for federated edge learning, offering uniform coverage and high spectral efficiency. They introduced over-the-air CFL (OTA-FL), which reduces communication overhead by allowing clients to send updates simultaneously over shared resources. The study also provided practical implementation insights for OTA-FL in CFMM environments. Similarly, Ref. [68] focuses on energy-efficient CFL in IoT networks, proposing an optimization problem to minimize energy consumption in IoT devices. It addresses challenges like power limitations and straggler effects, demonstrating the adaptability of CFMM for diverse scenarios. Collectively, these studies underscore the CFMM's potential to enhance CFL energy efficiency. They pave the way for future research to explore advanced optimization techniques and broaden the application of CFMM in diverse network environments.

3.2. Non-Terrestrial-Based Architectures

Aerial access networks (AANs) have emerged as a pivotal technology in 5G and beyond networks [69]. These networks play a versatile role across a range of wireless applications, including IoT data collection, wireless backhaul support, emergency response operations, and wireless-powered communication systems. Owing to their distinctive attributes, such as high flexibility, mobility, and adjustable altitude, AANs can function as dynamic BSs, enhancing the capacity and coverage of wireless networks while optimizing energy efficiency [70].

Driven by these advantages, integrating aerial networks with FL presents significant potential to enhance system performance [71]. By deploying aerial platforms, FL training can be extended across devices in remote or dynamic locations, supporting applications like smart agriculture, disaster response, and environmental monitoring [71,72]. ANNs not only provide ubiquitous coverage but also contribute to energy efficiency, a critical factor in FL systems. However, since aerial platforms often operate with limited energy resources, it is essential to optimize energy use in communication, flight, and processing to maintain sustainable FL operations.

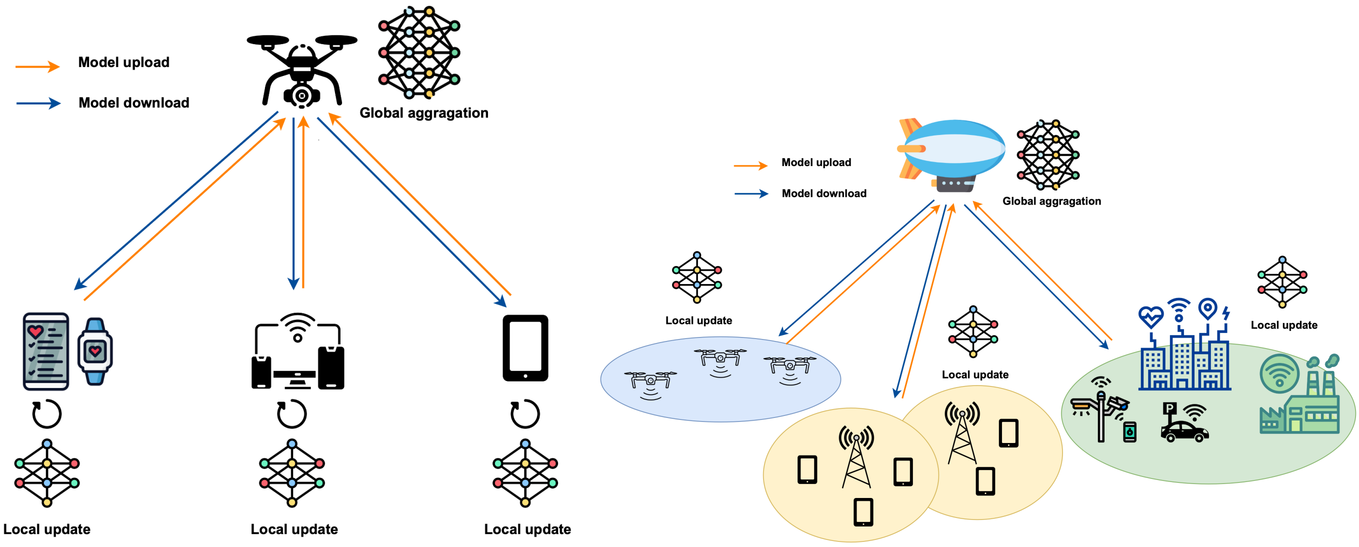
This subsection delves into three key aerial platforms for FL: UAVs, high-altitude platform systems (HAPSs), and low Earth orbit (LEO) satellites highlighting their roles, associated challenges, and optimization strategies for promoting energy efficiency.

3.2.1. CFL in UAV Communication Networks

UAVs are highly adaptable platforms that support FL training by collecting and aggregating data from devices across diverse locations. With their dynamic mobility and ability to fly autonomously, UAVs are particularly well-suited for scenarios requiring on-the-fly connectivity. Their ability to access remote and hard-to-reach areas makes them essential for CFL tasks where localized data needs collaborative processing, such as in agriculture monitoring, disaster management, and environmental sensing. However, the energy-constrained nature of UAVs necessitates careful planning to balance efficient flight operations with CFL communication demands. This subsection reviews existing research on UAV-based CFL and highlights strategies to optimize energy use while maintaining system performance.

One of the first CFL frameworks within UAV networks, as illustrated in Figure 4a, was introduced in [73]. This study analyzed the impact of wireless factors, such as fading, transmission delay, and UAV antenna deviations, on CFL convergence. It proposed a joint power allocation and scheduling strategy to optimize the convergence rate while accounting for energy consumption and system delay constraints. Similarly, the work in [74] provided an overview of FL applications in UAV-enabled wireless networks, emphasizing the suitability of FL to address various challenges.

Optimization of the placement and movement of UAVs is critical to achieving high communication quality and energy efficiency, as evidenced by numerous studies. For instance, research in [75–80] introduced various strategies incorporating UAV placement optimization. A novel approach in [75] proposed deploying UAVs with edge computing capabilities, functioning as both aerial energy sources and servers for FL aggregation. Using a block decomposition method, the study demonstrated the energy efficiency of this solution compared with benchmarks. Similar to the work in [76], Ref. [78] addressed joint UAV location and resource allocation optimization to reduce energy consumption in air-ground integrated FL systems. Meanwhile, Ref. [77] proposed a hybrid split and federated learning framework for UAV networks, allowing users to choose between split and federated training. To further improve energy efficiency while maintaining performance, a user scheduling algorithm was developed within this framework. Regarding UAV trajectory, the investigation in [81] addressed energy efficiency optimization for FL in UAV communication networks, proposing an alternating optimization approach to solve the nonconvex problem and evaluate UAV trajectories for better performance. The study in [82] explored the concept of covert federated learning in UAV-enabled networks, ensuring FL operations remain hidden from adversarial surveillance. This framework optimized UAV trajectory, jamming power, and communication scheduling to achieve covert learning while maintaining model convergence.



(**a**) CFL over a UAV communication network (**b**) CFL over a HAPS communication network

Figure 4. CFL over non-terrestrial-based wireless architectures.

Efficient resource allocation remains a critical challenge for energy-efficient UAV-FL. In addition to the articles previously mentioned [75–80], the study in [83] presented a multiagent federated reinforcement learning algorithm for resource management in UAV-assisted mobile edge computing (MEC) systems. By tackling power control and user association, the algorithm demonstrated comparable performance to centralized schemes while enhancing operational efficiency and ensuring privacy protection. Although the results appear promising, further research is necessary to completely comprehend the implications of this algorithm in various contexts. The study in [84] addressed battery-constrained FL in UAV-enabled IoT networks, optimizing energy consumption and latency using a deep deterministic policy gradient-based algorithm, prolonging UAV battery life, and ensuring uninterrupted FL training. The study in [72] proposed a fairness-enhanced scheduling mechanism based on a multiarmed bandit algorithm, where device selection was guided by a weighted reward function that balances model freshness and energy consumption. This multicriteria scheduling promotes fair participation among ground devices, optimizing long-term system performance and preventing drained energy.

In the context of UAV-MEC networks, navigation policies must consider UAVs' diverse capabilities to ensure energy efficiency and service quality. The study in [85] proposed a decentralized navigation solution based on the soft hierarchical deep reinforcement learning network and dual-end federated reinforcement learning. These methods not only enhance task-offloading energy efficiency but also reduce waiting times. These studies collectively emphasize the importance of advanced optimization techniques in UAV-enabled FL systems to enhance energy efficiency and system performance.

3.2.2. CFL over HAPS Communication Networks

HAPSs, positioned 20 to 50 km above Earth, offer extensive coverage and reliable line-of-sight (LOS) communication [86], making them an ideal candidate for integrating CFL into aerial networks, as depicted in Figure 4b. Their stable positioning, broad connectivity, and ability to act as mega-cells are particularly valuable for 6G networks, addressing energy efficiency and latency sensitivity in CFL. This subsection explores HAPS-enabled CFL architectures, focusing on energy-efficient resource management, hierarchical model optimization, and integration with other aerial platforms to boost CFL energy efficiency.

Energy efficiency is vital for enhancing HAPS performance in CFL scenarios. The research in [87] underscores dynamic resource allocation strategies tailored to the fluctuating demands of HAPS-enabled CFL networks. Similarly, Ref. [88] delves into CFL techniques for task and resource allocation in wireless high-altitude balloon networks, which are equally relevant to HAPSs. The study proposed a support vector machine (SVM)-based CFL algorithm to minimize energy and time consumption. These studies underscore HAPSs' potential for sustainable CFL operations while acknowledging the complexity and need for further optimization research.

The synergy between HAPSs and UAVs enhances CFL frameworks by improving data aggregation and model training efficiency. For instance, Ref. [87] outlined a collaborative framework integrating HAPSs and UAVs, while [89] introduced a hierarchical aerial computing framework that leverages these platforms for efficient IoT data processing. Privacy-preserving CFL is another avenue explored in [90], where a federated deep reinforcement learning model is used for HAPS-supported multi-UAV deployment. In this architecture, the HAPS aggregates model updates from various UAVs operating autonomously, reducing data transmission and preserving privacy. The collaboration between HAPSs and UAVs demonstrates their combined effectiveness in enhancing energy efficiency within CFL settings.

The integration of HAPSs with other aerial platforms, such as LEO satellites, presents additional opportunities for energy optimization in CFL systems. For example, Ref. [91] introduced a sparse channel estimation scheme tailored for CFL in nonterrestrial networks (NTNs), including HAPSs. This approach enhances channel estimation accuracy, crucial for efficient uplink and downlink CFL parameter transmission, significantly improving spectral and energy efficiency. By leveraging HAPS as a central node in NTNs, CFL systems benefit from more consistent performance, especially in dynamic and high-mobility scenarios.

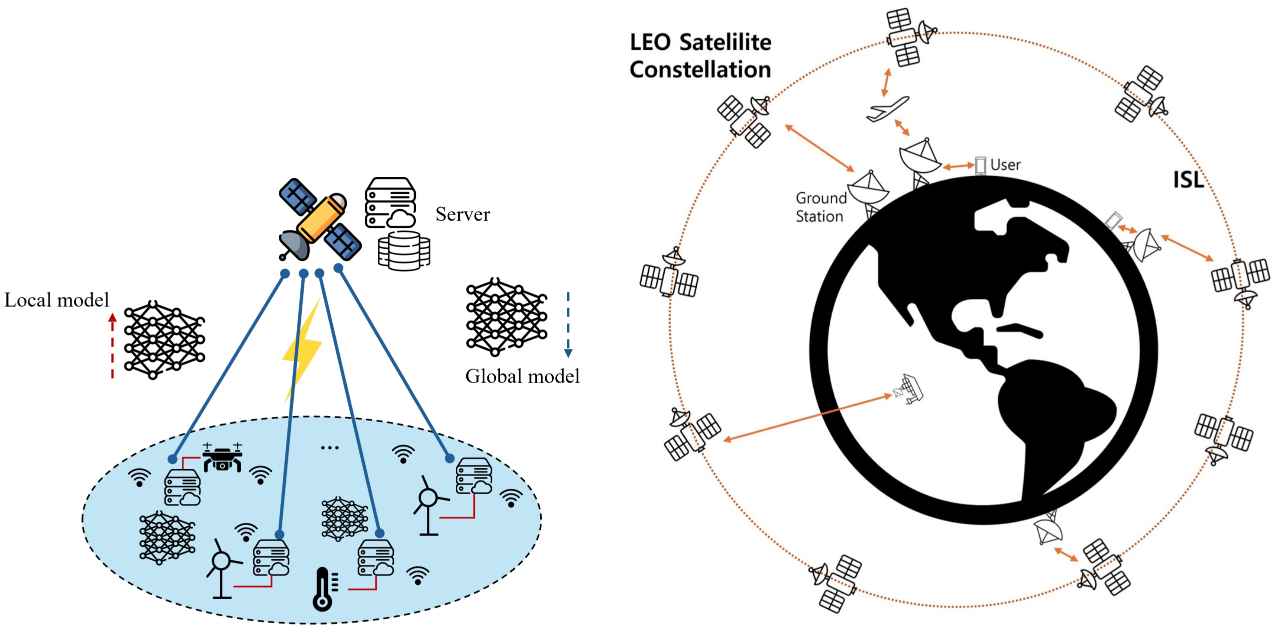
HAPSs also play a critical role in air-ground integration for CFL in intelligent transport systems and edge intelligence networks. Refs. [92,93] highlighted HAPSs' ability to combine aerial and terrestrial networks, distributing CFL processes efficiently across 3D networking architectures. Through proper network selection and optimal offloading, these platforms reduce latency and energy consumption in vehicle-to-everything and IoT applications, demonstrating their potential to empower edge intelligence and streamline communication between network nodes.

Integrating HAPSs into CFL architectures boosts energy efficiency by centralizing aggregation and coordinating resources across UAV and LEO layers, reducing device energy consumption and enabling scalable CFL. Future research could explore hybrid aerial systems combining UAVs and HAPSs with energy-harvesting technologies to extend operation in energy-constrained environments. Additionally, the development of CFL protocols tailored for aerial networks could further optimize energy usage and processing speed, enhancing resilience and adaptability [94].

3.2.3. CFL in Satellite Communication Networks

Satellite-based federated learning (SFL) provides global coverage and high scalability, making it ideal for large-scale operations in remote or underserved areas. Satellites excel in fault tolerance and offer persistent connectivity, overcoming limitations such as the restricted battery life of UAVs and the limited coverage of HAPSs. Unlike these platforms, satellites are not constrained by energy limitations or geographical boundaries, making them the most reliable choice for wide-area communication [95]. SFL is particularly valuable in applications like disaster response, environmental monitoring, and secure global communication, where real-time data processing and privacy are paramount [96]. In a typical SFL setup, multiple satellites gather data from edge devices while a central server, located on Earth or in orbit, aggregates and processes the model updates [97], as illustrated in Figure 5a. This system enables distributed learning across satellites and ground stations, with each satellite or device conducting local computations and sharing updates with the central server.

Energy efficiency is a cornerstone of SFL due to the power constraints of satellites, which rely on limited onboard energy sources. Various strategies have been proposed to address this challenge, tailored to specific use cases. For low-power IoT devices in LEO satellite systems, [98] proposed selective device participation to minimize energy consumption. By balancing computational and communication loads, the approach aligns with power-aware scheduling principles and leverages dynamic resource allocation to enhance efficiency. The authors in [99] suggested satellite grouping and the use of inter-satellite links (ISLs) to address data heterogeneity and communication challenges. This strategy includes caching frequently accessed data onboard satellites and optimizing transmission power and computing frequency, effectively reducing redundant transmissions and conserving energy. Focusing on satellite–terrestrial integration, Ref. [100] proposed caching mechanisms to offload traffic from terrestrial networks, improving energy efficiency. By storing frequently accessed data onboard satellite, energy consumption is significantly reduced, aligning with conservation principles. All the studies focused on optimizing energy consumption while preserving system performance, employing techniques like dynamic resource management, caching, and ISL optimization as key strategies.



(**a**) CFL over a satellite communication network (**b**) DFL over a satellite constellations communication network

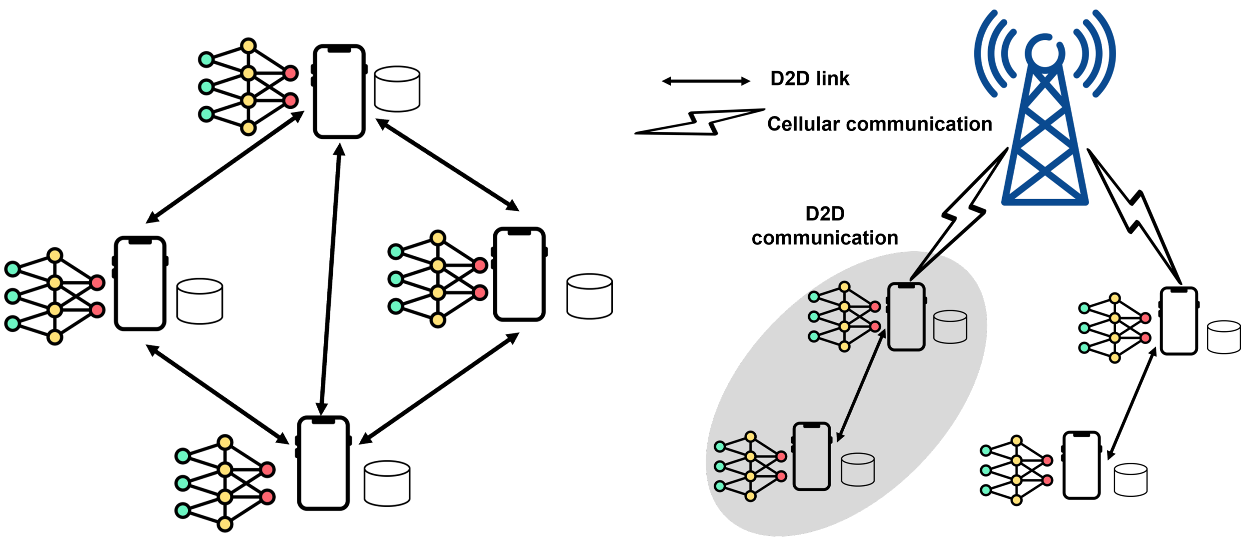
Figure 5. FL strategies over a satellite communication network.

Energy efficiency is further enhanced through hybrid systems that combine satellites, UAVs, and HAPSs in FL [101,102]. UAVs are well suited for localized tasks due to their proximity to the ground, while HAPSs and satellites offer broad, continuous coverage for large-scale operations. This complementary arrangement highlights the potential for collaborative frameworks that balance localized and global learning tasks. In particular, the integration of UAVs and HAPSs with FL has garnered significant attention for leveraging their nonterrestrial network capabilities to provide dynamic, scalable, and energy-efficient communication platforms, especially in environments with limited terrestrial infrastructure.

4. Wireless Network Architectures for Energy-Efficient DFL

4.1. DFL in D2D Communication Networks

D2D communication plays a pivotal role in DFL within wireless networks. By enabling direct peer-to-peer model updates without a BS, D2D communication aligns with the decentralized nature of FL, optimizing energy usage by shortening transmission distances and reducing communication costs. In densely populated mobile networks, D2D allows nearby devices to efficiently exchange model updates, thereby saving energy and eliminating the need for intermediary nodes [103]. To illustrate the different operational modes of D2D communication, Figure 6 presents two modes: (a) Standalone D2D, which operates independently of any infrastructure, and (b) Network-assisted D2D, which leverages existing network resources. Additionally, Table 2 briefly summarizes key studies on energy-efficient DFL in D2D environments, which will be discussed further in this subsection.



(**a**) Standalone D2D (**b**) Network-assisted D2D

Figure 6. Operational modes of D2D communications.

Table 2. Summary of key studies on energy-efficient FL in D2D environments.

Reference	Design Variables	Method	Mode
[104]	Resource allocation	Deep reinforcement learning (DRL)	(a)
[105]	Computing power allocation and dataset correlation into FL scheduling	Graph learning and DRL	(b)
[106]	The selection of LAs and the scheduling of devices to LAs/RRBs	A low-complexity graph-theory algorithm	(b)
[107]	Device selection, offloading ratios	Graph convolutional networks (GCN)	(b)
[108]	Devices participating in the training, the offloading destination, the set of sampled data points, and the transmission power level of each device at each round	Deep neural network (DNN)	(b)
[109]	The clustering selection, CH-device scheduling, and frequency computation allocation	FL-EOCD	(b)
[110]	Local training periods, consensus rounds	Two timescale hybrid FL (TT-HF)	(b)
[111]	Participation vector, link selection matrix	A FL framework involving a one-side matching theory-based incentive mechanism to select and encourage users to take part in the process	(b)
[34]	Power adjustment, wireless resource allocation, link selection, and aggregation weight adaptation mechanism	Alternating optimization algorithm, semidefinite programming (SDP), tabu search-based meta-heuristic algorithm	(a)

(a) Standalone D2D, which operates independently of any infrastructure, (b) Network-assisted D2D, which leverages existing network resources.

When it comes to optimizing energy-efficient DFL in D2D environments, numerous studies have proposed various methods. For example, the study in [104] optimized resource allocation using deep reinforcement learning (DRL) to maximize network capacity and minimize energy consumption, while ensuring the QoS for both cellular and D2D users. In contrast, Ref. [105] combined DRL with graph learning to exploit the relationships between datasets during model aggregation, which helps improve DFL accuracy and reduce model errors within the energy constraints of edge servers. Graph-based methods have gained prominence in optimizing DFL systems, particularly in heterogeneous and energy-constrained environments. These methods are effective in modeling complex relationships between devices, data, and network attributes. For instance, Ref. [106] presented a low-complexity graph-theoretic algorithm to optimize parameters such as local aggregator selection and device scheduling within a DFL system. By incorporating D2D communication for model aggregation, this approach reduces energy consumption while maintaining convergence rate, minimizing the need for central server communication and achieving substantial energy savings in resource-limited environments. Similarly, Ref. [107] utilized graph convolutional networks (GCNs) to optimize device selection and offloading ratios within a D2D-enabled DFL framework, making it particularly suitable for environments with diverse device capabilities and network topologies. This model enhances DFL accuracy and reduces data processing and energy overhead by learning complex interdependencies between devices and local data distributions, outperforming traditional sampling methods.

Another energy-focused approach was introduced in [108], which proposed a D2D-assisted DFL framework that minimizes the global loss of a deep neural network (DNN) model while respecting device energy constraints and edge server bandwidth limitations. By using auxiliary graphs to solve weighted maximum matching problems, this method optimizes local model uploads, leverages the energy resources of neighboring devices, and improves communication efficiency during the training process. To further improve resource utilization, Ref. [109] proposed a DFL-EOCD scheme, which integrates D2D communications and overlapped clustering for decentralized aggregation. This approach reduces the energy consumption of devices while maintaining a satisfactory convergence rate. The DFL-EOCD algorithm outperforms traditional DFL schemes by optimizing energy consumption, latency, and convergence rate, offering a promising direction for DFL in decentralized networks.

The study in [110] proposed a two-timescale hybrid DFL (TT-HF) framework that combines conventional device-to-server communication with D2D communications, enabling devices to perform multiple local gradient descent iterations and participate in a cooperative D2D consensus within clusters at each global aggregation interval. The authors introduced a novel definition of gradient diversity to analyze the TT-HF's convergence behavior, establishing new bounds to minimize network resource demands during distributed learning. An incentive-driven DFL framework was proposed in [111], which integrates a one-sided matching theory-based mechanism to encourage user participation. By utilizing D2D communications and forecasting channel conditions with echo state networks at each user site, this framework optimizes the trade-off between energy consumption and convergence time, thus enhancing the DFL process in communication-challenged environments. Finally, Ref. [34] proposed a decentralized learning mechanism that optimizes computing power, wireless resource allocation, link selection, and aggregation weight adaptation. Using alternating optimization, semidefinite programming, and a tabu search-based algorithm, this framework minimizes total learning costs, including latency and energy consumption, while improving energy and communication efficiency in D2D-enabled DFL systems. These methods, which leverage graph-based models, address key challenges in DFL by reducing energy use, enhancing accuracy, and improving convergence rates, demonstrating the effectiveness of graph-theoretic and D2D strategies in enhancing the performance and sustainability of DFL systems.

4.2. DFL in UAV Communication Networks

While CFL employs distributed topologies for model parameter exchange, it remains centralized, relying on a central server for model aggregation. In contrast, the server-based DFL approach faces a single point of failure in UAV networks [73]. For example, in a UAV DFL framework, a leading UAV typically serves as the central server for model aggregation, with other UAVs sending their local models to this server. However, if the central UAV becomes unreachable due to issues with air-to-air links, attacks, or battery depletion, the system may fail. To mitigate this risk, Ref. [112] proposed a DFL framework for UAV networks (DFL-UN), as shown in Figure 7. In this framework, each UAV trains its local model and integrates models from neighboring UAVs, eliminating the need for a central aggregation entity. Recognizing the importance of aggregation methods for enabling model sharing and combining updates among UAVs, the authors in [113] proposed two novel aggregation methods within a DFL framework tailored for UAV networks.

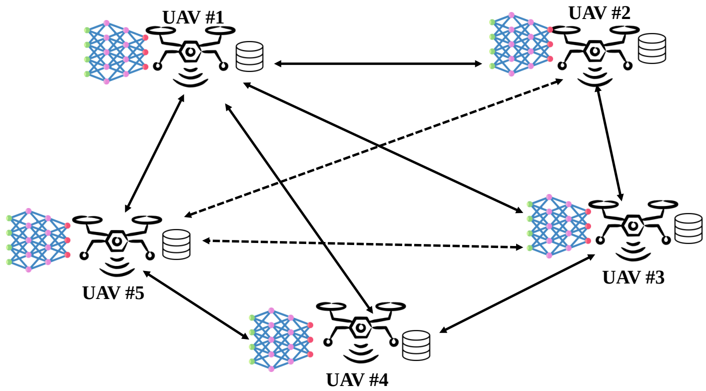


Figure 7. DFL over UAV networks.

These methods address server dependency, energy consumption, and communication costs by optimizing local training and communication rounds.

To address security challenges in DFL-UN, such as unreliable connections, high mobility, and energy inefficiency, authors in [114] proposed the use of peer-to-peer trust policies, asymmetric encryption, and an intrusion detection mechanism to detect hijacking attempts. Additionally, they integrated location-based energy-efficient routing to predict link breakage and optimize routing paths. In [115], the authors extended the UAV systems into a coordinated swarm, using natural swarm behavior algorithms and introducing a leader election-assisted, spiking neural networks-driven DFL framework. This approach optimizes FL model training while minimizing energy consumption and training time.

4.3. DFL in Satellite Constellations Communication Networks

CFL relies on a central server to aggregate model parameters, which is impractical for distributed LEO satellite constellations due to the difficulty in selecting a suitable central satellite. Moreover, reliance on ground stations introduces latency and limits operational flexibility due to the intermittent visibility of satellites. With the increasing deployment of LEO constellations by organizations such as SpaceX, OneWeb, and Amazon, there is a growing need for solutions like SFL that integrate scalability, efficiency, and robustness into satellite-based operations [116].

To address these challenges, a DFL framework for LEO satellite constellations was proposed in [94], as shown in Figure 5b. This framework enables efficient model aggregation across LEO satellite networks without requiring a central server, thereby mitigating reliability concerns and communication bandwidth limitations inherent in CFL approaches. Optimizing energy efficiency in DFL over satellite constellations involves enhancing ISLs to minimize communication overhead, utilizing energy-aware data exchange protocols, and applying dynamic resource allocation strategies to reduce power consumption. The study in [117] introduced a novel decentralized SFL framework for Walker Delta, where satellites communicate via ISLs across orbital planes. This approach addresses a mixed combinatorial optimization problem by jointly optimizing power control, bandwidth allocation, and routing to minimize energy consumption. The authors in [118] leveraged decentralized operations and energy-aware communication strategies to reduce communication congestion and improve fault tolerance, aligning with DFL principles to optimize energy consumption while maintaining system performance. The authors in [119] focused on minimizing convergence time in satellite-based DFL by optimizing the number of satellites per orbit and the number of orbits. This approach balances energy constraints, communication distance, and DFL performance, ensuring efficient and reliable operation. These studies highlighted the innovative strategies for enhancing energy efficiency in DFL-enabled satellite constellation systems.

Table 3 summarizes the research issues and limitations of the existing energy-efficient FL-enabled wireless network architectures, providing a comprehensive reference for the topics discussed in Sections 3 and 4.

Table 3. Summary of the research issues and limitations of the existing energy-efficient FL-enabled wireless network architectures.

Wireless Network Architectures	Limitations	Research Issues
Centralized Wireless Networks	Constrained resources such as bandwidth, processing time; high latency due to the need to aggregate and process data at a central server; poor performance in scenarios with poor channel conditions or when devices are located far from the central server.	Managing interference from neighboring cells; scalability issues as the number of devices increases; optimizing the constrained resource allocation; requiring highly accurate channel estimation in MIMO/mMIMO systems.
Distributed Wireless Networks	High backhaul energy costs; uneven energy usage and synchronization between APs during FL; pilot contamination for channel estimation.	Handling large-scale networks including a large number of devices; managing the heterogeneity of data across different devices or access points, minimizing interference when multiple devices operate simultaneously; optimizing the selection of APs to ensure efficient data routing and model aggregation.
UAV Communication Networks	UAV mobility challenges in maintaining stable FL training; high latency in UAV-server communications; limited battery life constraints; synchronization of UAV collaboration.	Optimizing the UAV placement and trajectory for energy efficiency; managing UAV mobility to maintain stable communication links and ensure FL model update consistency; managing the limited computational power and battery life of UAVs, addressing the consensus and synchronization in collaboration of multiple UAVs.
HAPS Communication Networks	Limited energy resources in HAPSs; inconsistent communication quality in harsh weather conditions; HAPS mobility challenges; low latency due to long-distance communication; energy constraints	Improving the accuracy of channel models for HAPS communication in harsh environments; optimizing HAPS placement for maximum coverage and FL task efficiency; challenges of maintaining a stable communication and synchronization link between the HAPS and ground stations or devices;
Satellite Communication Networks	High latency, especially with geostationary satellites in the FL updating process; limited bandwidth, unstable links between the satellite and ground stations or edge devices due to atmospheric conditions and satellite movement.	Optimizing resource allocation between devices and satellites; building robust systems to address the FL disruptions due to satellite movement and atmospheric conditions; addressing the challenges of multisatellite coordination, such as seamless handoff, interference, synchronization, and orbits.
D2D Communication Networks	Interference management due to overlapping D2D communications, limited participation as short-range links exclude distant devices, reducing diversity; synchronization as the number of participating devices increases.	Optimization of resource allocation, computing power, and FL scheduling; selection of local agents (LAs); management of offloading ratios; CH-device scheduling; adaptation of aggregation weights and link selection matrices.

5. Improving Energy Efficiency in FL Using Emerging Technologies

This section provides an in-depth look at the latest technologies designed to enhance wireless system performance. Specifically, we highlight advancements in FL-enabled wireless systems that leverage these emerging technologies to improve energy efficiency.

5.1. Simultaneous Wireless Information and Power Transfer

SWIPT has emerged as a vital technology in the IoT era, enabling simultaneous data and energy transmission over a single wireless medium. This innovation benefits energy-constrained devices by eliminating the need for separate power sources [120]. SWIPT is becoming increasingly important in FL-enabled wireless systems, as it allows devices to harvest energy from RF signals while simultaneously receiving control information or updates [121]. The harvested energy supports local computations and facilitates uplink transmissions throughout the FL process. As a result, the integration of SWIPT into FL-enabled wireless systems has garnered significant attention in recent studies.

In [122], the use of SWIPT in IoT with FL is explored, where devices simultaneously transmit model data and harvest energy. The study investigated the trade-off between communication rounds and time, ensuring that energy harvesting offsets energy expenditure. Additionally, SWIPT was shown to enable efficient model learning with minimal communication rounds while extending device battery life. The authors in [123] proposed the use of SWIPT in FL to address the energy limitations of edge devices. The central parameter server, co-located with the BS, uses SWIPT to transmit both the model and power to edge devices, which then train local models and send updates via NOMA. Similarly, Ref. [124] presented a SWIPT-assisted FL network and minimized long-term energy consumption while ensuring FL convergence through dynamic resource allocation and UE scheduling.

SWIPT also provides significant benefits for FL-enabled UAV systems by addressing energy scarcity, particularly in micro-UAV swarm networks. Studies in [125,126] tackle this issue using SWIPT for FL, where the BS broadcasts both the model and power to UAVs, which use the harvested energy to train and upload models. The research optimizes UAV scheduling and resource allocation, with results showing that the proposed suboptimal algorithm outperforms existing baselines. Furthermore, [127] introduced a UAV-based communication model for IoT in areas without ground BSs. This model uses SWIPT to transmit both information and energy to IoT devices, optimizing UAV trajectory, power splitting ratio, and communication scheduling to maximize energy efficiency through DRL.

5.2. Intelligent Reflecting Surfaces

IRS is an innovative technology that is set to revolutionize wireless communication networks by enabling intelligent and adaptive control over electromagnetic wave propagation [128,129]. IRS utilizes a reconfigurable array of metamaterial elements to dynamically enhance signal strength, extend network coverage, mitigate interference, and enhance spectral efficiency, all while being energy-efficient and cost-effective. When integrated with FL, IRS amplifies its capabilities, creating a synergistic framework that enables secure, energy-efficient, and reliable communication in wireless networks [130,131]. This combination has attracted significant attention from researchers, particularly in developing energy-efficient FL systems supported by IRS [56,132–134].

In [132], the authors introduced a HAPS communication system that utilizes rate-splitting multiple access and UAVs equipped with IRS as relay nodes to enhance the performance of integrated satellite–aerial–terrestrial relay networks. To optimize system energy efficiency, a multiobjective optimization problem was formulated, and the challenging nonconvex nature of the problem was tackled using an approach called access-free federated deep reinforcement learning. In [133], the authors proposed a scheme combining wireless power transfer, information transmission, and solar energy harvesting in IoT units, supported by UAVs and IRS. They introduce a multiagent federated reinforcement learning algorithm to optimize parameters and maximizes energy efficiency. Furthermore, in [134], the authors investigated an indoor millimeter-wave (mmWave) downlink communication system, where a wireless AP is supported by multiple IRSs. To adapt to the indoor environment, they developed an energy-efficient FL framework that enables the parallel configuration of multiple IRSs.

5.3. Nonorthogonal Multiple Access

NOMA is a technique that enhances bandwidth efficiency and interoperability in future networks, especially for 6G IoT systems [135,136]. Unlike orthogonal multiple access, NOMA enables multiple users to share the same time-frequency resources simultaneously, significantly boosting wireless system performance. The integration of NOMA into FL has demonstrated significant potential for improving FL frameworks in wireless networks, particularly when paired with emerging approaches such as resource allocation strategies [137], dynamic user selection [138], IRS [139], and CSI techniques [140]. Moreover, with a focus on energy-efficient FL, studies in [102,141–143] have provided comprehensive insights into implementing energy-efficient FL within NOMA networks, highlighting their ability to significantly enhance FL performance.

In [142], the authors proposed a joint resource allocation scheme using a two-dimensional search algorithm and an efficient bisection algorithm to minimize the total energy consumption in wireless-powered FL networks utilizing NOMA. The study in [141] presented energy minimization in IoT-based CFL by combining WPT, NOMA, and IRS. The proposed method utilizes semidefinite programming and a bisection algorithm, outperforming benchmark schemes in terms of energy efficiency. Integrating NOMA into the UAV systems demonstrated substantial improvements in energy-efficient FL. For instance, the authors in [143] investigated energy reduction strategies in MEC systems leveraging NOMA with UAVs, overcoming challenges posed by dynamic 5G and beyond networks, such as frequent changes in task requests and device positions that would typically increase energy consumption with stationary edge deployments.

NOMA techniques also proved effective in satellite communications, facilitating rapid, bandwidth-efficient model transmissions among satellites, and thus accelerating the FL training process. In [102], the authors introduced NomaFedHAP, a novel approach for integrating NOMA into satellite communications NOMA to speed up CFL in LEO satellites. By utilizing HAPSs as parameter servers, the approach mitigates mitigates Doppler shifts and optimizes model aggregation. Simulations showed that NomaFedHAP achieves faster and more accurate CFL convergence compared with existing methods.

6. Challenges, Opportunities, and Research Directions

This section provides a comprehensive overview of the critical challenges in deploying FL over wireless systems. Based on these challenges, we identify potential research opportunities for future advancements.

6.1. Limitation of Analyzed Designs

The energy-efficient design models in the analyzed studies rely on ideal assumptions, such as perfect channel estimation and stable network conditions, which may not accurately reflect real-world environments characterized by fading and mobility. The energy models focus on computational and communication energy but exclude hardware inefficiencies and environmental factors. Assumptions of homogeneous devices overlook the real-world heterogeneity in device capabilities, which can impact energy consumption and convergence. Moreover, the results derived from the considered studies lack validation in practical deployments, where issues like hardware limitations and unexpected delays may arise. Additionally, the trade-offs between energy efficiency and other metrics, such as latency and accuracy, were not extensively quantified. Addressing these limitations provides valuable directions for future work to refine energy-efficient FL frameworks.

6.2. Channel Estimation Challenges

Channel estimation plays a crucial role in ensuring reliable communication in FL over wireless networks. Accurate estimation of the wireless channel state is essential for effective resource allocation, beamforming, and interference management, all of which directly influence FL performance [144]. In architectures like IRS-assisted and UAV-supported networks, channel estimation faces additional challenges due to multihop channels and dynamic environments. For example, IRS-assisted systems require the estimation of both direct and indirect channels, making the process computationally demanding [145]. Similarly, UAV mobility leads to rapid changes in channel conditions, causing outdated channel state information. This, in turn, degrades the QoS, slows FL convergence, and significantly increases energy consumption [146].

While numerous studies have explored enhancing channel estimation in wireless systems using various techniques, FL-enabled wireless systems require robust and adaptive estimation methods that can operate under low-latency constraints. Additionally, these methods must strike a balance between estimation accuracy and computational efficiency, especially for energy-constrained devices. Therefore, a comprehensive evaluation of channel models is necessary to understand the impact of various factors across different wireless system architectures. Furthermore, developing channel estimation algorithms that can withstand external disturbances will be crucial for the continued success of FL in wireless environments.

6.3. Physical Layer Security Challenges

Physical layer security (PLS) is an emerging concern in FL over wireless networks due to the open and shared nature of the communication medium [147]. FL training involves frequent transmission of model updates between the central server and user devices, making it susceptible to various eavesdropping and jamming attacks. PLS offers a promising solution by providing perfect security without the need for complex key distribution or encryption algorithms, thus reducing communication overhead and enhancing security without increasing energy consumption [148,149].

Innovative PLS methods tailored for FL over wireless systems will leverage wireless characteristics, such as secure beamforming and cooperative jamming, to safeguard FL transmissions without compromising performance. Recent studies [150–153] have proposed various methods for integrating PLS into FL systems. However, several unresolved challenges persist in deploying PLS for FL over wireless networks. A primary challenge lies in designing lightweight, real-time, adaptive PLS techniques capable of responding to dynamic network conditions, such as fluctuating channel quality and varying user participation, while maintaining the robustness and reliability of FL systems. Additionally, balancing the overhead introduced by PLS mechanisms with the need for energy-efficient FL operations remains a critical issue. Moreover, addressing the trade-off between ensuring robust security and accommodating the resource constraints of edge devices, without compromising FL training efficiency, continues to be a significant area for further research and development.

6.4. UAV Energy Consumption Challenges

One of the most significant barriers to implementing FL in UAV communication systems is the limited energy available to UAVs. Many studies overlook this critical issue, often assuming that UAVs have sufficient energy for operations. However, in practice, UAVs must carefully manage their remaining energy to ensure a safe return to base [154]. Thus, accounting for UAV energy constraints is essential for the efficient deployment of FL.

Although some studies have attempted to address this issue by using advanced technologies like SWIPT to recharge UAVs, most fail to provide a comprehensive energy consumption model [125,126]. These studies often neglect important practical factors such as payload weight, flight speed, weather conditions, and temperature fluctuations, all of which can significantly impact energy usage [155]. To effectively deploy FL with UAVs, it is crucial to develop more realistic and practical energy models that take these factors into account. Addressing this gap presents a promising research direction for optimizing UAV performance and ensuring efficient energy management in FL systems.

We have explored various aspects of energy-efficient FL in wireless networks; however, there remain significant opportunities for further research. One promising avenue involves the application of advanced machine learning and reinforcement learning techniques to address complex optimization challenges in FL. For example, as highlighted in [156], machine learning-based approaches such as linear regression and DNNs have shown effectiveness in predictive modeling. Similarly, Ref. [157] demonstrated the potential of hybrid frameworks that integrate metaheuristics with Q-learning to solve urban traffic light scheduling problems. These methodologies could be adapted to develop efficient resource allocation strategies and improve network orchestration in FL systems, particularly in large-scale and heterogeneous network environments.

7. Conclusions

This paper provided a comprehensive review of FL concepts across various wireless network architectures, with a particular emphasis on energy efficiency challenges. We outlined the fundamental principles of FL architectures, including CFL and DFL, along with their detailed implementation steps. The energy efficiency optimization problem in FL deployment over wireless systems was examined, covering both local computation and communication energy models. We presented an overview of wireless network architectures designed to support energy-efficient FL, focusing on networks tailored for both CFL and DFL. We also explored emerging technologies such as SWIPT, IRS, and NOMA, assessing their potential to enhance FL-enabled wireless networks. Moreover, integrating hybrid technologies, such as combining SWIPT with IRS or NOMA, could significantly boost. Enhanced cooperation between UAVs and ground infrastructure, facilitated by robust channel estimation and power control mechanisms, also has the potential to improve FL scalability and reliability. These advancements could pave the way for a new era of FL-enabled wireless networks. Finally, we discussed key challenges in implementing FL over wireless networks, including channel estimation, PLS, and UAV energy consumption, while identifying promising directions for future research to address these challenges and optimize FL performance in wireless environments. Addressing the research challenges and limitations of the current energy-efficient FL-enabled wireless frameworks, as discussed in this study, holds the potential to substantially enhance both the performance and practicality of deploying FL over wireless networks.

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References

1. Khang, A.; Abdullayev, V.; Hahanov, V.; Shah, V. *Advanced IoT Technologies and Applications in the Industry 4.0 Digital Economy*; CRC Press: Boca Raton, FL, USA, 2024.
2. Houssein, E.H.; Othman, M.A.; Mohamed, W.M.; Younan, M. Internet of things in smart cities: Comprehensive review, open issues, and challenges. *IEEE Internet Things J.* **2024**, *11*, 34941–34952. [CrossRef]
3. Xu, H.; Sun, Z.; Cao, Y.; Bilal, H. A data-driven approach for intrusion and anomaly detection using automated machine learning for the internet of things. *Soft Comput.* **2023**, *27*, 14469–14481. [CrossRef]
4. Quy, V.K.; Nguyen, D.C.; Van Anh, D.; Quy, N.M. Federated learning for green and sustainable 6G IIoT applications. *Internet Things* **2024**, *25*, 101061. [CrossRef]
5. Sirohi, D.; Kumar, N.; Rana, P.S.; Tanwar, S.; Iqbal, R.; Hijjii, M. Federated learning for 6G-enabled secure communication systems: A comprehensive survey. *Artif. Intell. Rev.* **2023**, *56*, 11297–11389. [CrossRef]
6. Liu, S.; Yu, G.; Yin, R.; Yuan, J.; Qu, F. Communication and computation efficient federated learning for Internet of vehicles with a constrained latency. *IEEE Trans. Veh. Technol.* **2024**, *73*, 1038–1052. [CrossRef]
7. Lan, G.; Liu, X.Y.; Zhang, Y.; Wang, X. Communication-efficient federated learning for resource-constrained edge devices. *IEEE Trans. Mach. Learn. Commun. Netw.* **2023**, *1*, 210–224. [CrossRef]
8. Nguyen, T.A.; Lee, J. Using Long Short-term Memory to Estimate the Two-dimensional Interference of Bit-patterned Media Recording Systems. *IEEE Trans. Magn.* **2024**, *60*, 3100605. [CrossRef]
9. Dhinakaran, D.; Sankar, S.; Selvaraj, D.; Raja, S.E. Privacy-preserving data in IoT-based cloud systems: A comprehensive survey with AI integration. *arXiv* **2024**, arXiv:2401.00794.
10. Alzu'bi, A.; Alomar, A.; Alkhaza'leh, S.; Abuarqoub, A.; Hammoudeh, M. A review of privacy and security of edge computing in smart healthcare systems: Issues, challenges, and research directions. *Tsinghua Sci. Technol.* **2024**, *29*, 1152–1180. [CrossRef]
11. Khan, L.U.; Saad, W.; Han, Z.; Hossain, E.; Hong, C.S. Federated learning for internet of things: Recent advances, taxonomy, and open challenges. *IEEE Commun. Surv. Tutor.* **2021**, *23*, 1759–1799. [CrossRef]
12. Chen, S.; Yu, D.; Zou, Y.; Yu, J.; Cheng, X. Decentralized wireless federated learning with differential privacy. *IEEE Trans. Ind. Inform.* **2022**, *18*, 6273–6282. [CrossRef]
13. Zhang, C.; Xie, Y.; Bai, H.; Yu, B.; Li, W.; Gao, Y. A survey on federated learning. *Knowl.-Based Syst.* **2021**, *216*, 106775. [CrossRef]
14. AbdulRahman, S.; Tout, H.; Ould-Slimane, H.; Mourad, A.; Talhi, C.; Guizani, M. A survey on federated learning: The journey from centralized to distributed on-site learning and beyond. *IEEE Internet Things J.* **2020**, *8*, 5476–5497. [CrossRef]
15. Mothukuri, V.; Parizi, R.M.; Pouriyeh, S.; Huang, Y.; Dehghantanha, A.; Srivastava, G. A survey on security and privacy of federated learning. *Future Gener. Comput. Syst.* **2021**, *115*, 619–640. [CrossRef]
16. Yazdinejad, A.; Dehghantanha, A.; Karimipour, H.; Srivastava, G.; Parizi, R.M. A robust privacy-preserving federated learning model against model poisoning attacks. *IEEE Trans. Inf. Forensics Secur.* **2024**, *19*, 6693–6708. [CrossRef]
17. Gugueoth, V.; Safavat, S.; Shetty, S. Security of Internet of Things (IoT) using federated learning and deep learning—Recent advancements, issues and prospects. *ICT Express* **2023**, *9*, 941–960. [CrossRef]
18. Beitollahi, M.; Lu, N. Federated learning over wireless networks: Challenges and solutions. *IEEE Internet Things J.* **2023**, *10*, 14749–14763. [CrossRef]
19. Duan, Q.; Huang, J.; Hu, S.; Deng, R.; Lu, Z.; Yu, S. Combining federated learning and edge computing toward ubiquitous intelligence in 6G network: Challenges, recent advances, and future directions. *IEEE Commun. Surv. Tutor.* **2023**, *25*, 2892–2950. [CrossRef]
20. Yao, J.; Xu, W.; Yang, Z.; You, X.; Bennis, M.; Poor, H.V. Wireless federated learning over resource-constrained networks: Digital versus analog transmissions. *IEEE Trans. Wirel. Commun.* **2024**, *23*, 14020–14036. [CrossRef]
21. Yang, Z.; Chen, M.; Saad, W.; Hong, C.S.; Shikh-Bahaei, M. Energy efficient federated learning over wireless communication networks. *IEEE Trans. Wirel. Commun.* **2020**, *20*, 1935–1949. [CrossRef]
22. Zhao, Z.; Xia, J.; Fan, L.; Lei, X.; Karagiannidis, G.K.; Nallanathan, A. System optimization for federated learning networks with a constrained latency. *IEEE Trans. Veh. Technol.* **2022**, *71*, 1095–1100. [CrossRef]
23. Zhou, Y.; Shi, Y.; Zhou, H.; Wang, J.; Fu, L.; Yang, Y. Toward scalable wireless federated learning: Challenges and solutions. *IEEE Internet Things Mag.* **2023**, *6*, 10–16. [CrossRef]
24. Salh, A.; Ngah, R.; Audah, L.; Kim, K.S.; Abdullah, Q.; Al-Moliki, Y.M.; Aljaloud, K.A.; Talib, H.N. Energy-efficient federated learning with resource allocation for green IoT edge intelligence in B5G. *IEEE Access* **2023**, *11*, 16353–16367. [CrossRef]
25. Yeh, C.; Jo, G.D.; Ko, Y.J.; Chung, H.K. Perspectives on 6G wireless communications. *ICT Express* **2023**, *9*, 82–91. [CrossRef]
26. Dang, X.T.; Le, M.T.P.; Nguyen, H.V.; Chatzinotas, S.; Shin, O.S. Optimal user pairing approach for NOMA-based cell-free massive MIMO systems. *IEEE Trans. Veh. Technol.* **2022**, *72*, 4751–4765. [CrossRef]
27. Xie, Z.; Chen, P.; Fang, Y.; Chen, Q. Polarization-aided coding for non-orthogonal multipleaccess. *IEEE Internet Things J.* **2024**, *11*, 27894–27903. [CrossRef]
28. Ali, E.; Ismail, M.; Nordin, R.; Abdulah, N.F. Beamforming techniques for massive MIMO systems in 5G: Overview, classification, and trends for future research. *Front. Inf. Technol. Electron. Eng.* **2017**, *18*, 753–772. [CrossRef]
29. Ahmed, M.; Raza, S.; Soofi, A.A.; Khan, F.; Khan, W.U.; Abideen, S.Z.U.; Xu, F.; Han, Z. Active reconfigurable intelligent surfaces: Expanding the frontiers of wireless communication-a survey. *IEEE Commun. Surv. Tutor.* **2024**. [CrossRef]

30. Banafaa, M.; Pepeoğlu, Ö.; Shayea, I.; Alhammadi, A.; Shamsan, Z.; Razaz, M.A.; Alsagabi, M.; Al-Sowayan, S. A comprehensive survey on 5G-and-beyond networks with UAVs: Applications, emerging technologies, regulatory aspects, research trends, and challenges. *IEEE Access* **2024**, *12*, 7786–7826. [CrossRef]
31. McMahan, B.; Moore, E.; Ramage, D.; Hampson, S.; y Arcas, B.A. Communication-efficient learning of deep networks from decentralized data. In Proceedings of the Artificial Intelligence and Statistics, PMLR, Fort Lauderdale, FL, USA, 20–22 April 2017; pp. 1273–1282.
32. Xing, H.; Simeone, O.; Bi, S. Decentralized federated learning via SGD over wireless D2D networks. In Proceedings of the 2020 IEEE 21st International Workshop on Signal Processing Advances in Wireless Communications (SPAWC), Atlanta, GA, USA, 26–29 May 2020; pp. 1–5.
33. Beltrán, E.T.M.; Pérez, M.Q.; Sánchez, P.M.S.; Bernal, S.L.; Bovet, G.; Pérez, M.G.; Pérez, G.M.; Celdrán, A.H. Decentralized federated learning: Fundamentals, state of the art, frameworks, trends, and challenges. *IEEE Commun. Surv. Tutor.* **2023**, *25*, 2983–3013. [CrossRef]
34. Liu, S.; Yu, G.; Wen, D.; Chen, X.; Bennis, M.; Chen, H. Communication and energy efficient decentralized learning over D2D networks. *IEEE Trans. Wirel. Commun.* **2023**, *22*, 9549–9563. [CrossRef]
35. Sundhar Ram, S.; Nedić, A.; Veeravalli, V.V. Distributed stochastic subgradient projection algorithms for convex optimization. *J. Optim. Theory Appl.* **2010**, *147*, 516–545. [CrossRef]
36. Xin, R.; Kar, S.; Khan, U.A. An introduction to decentralized stochastic optimization with gradient tracking. *arXiv* **2019**, arXiv:1907.09648.
37. Miettinen, A.P.; Nurminen, J.K. Energy efficiency of mobile clients in cloud computing. In Proceedings of the 2nd USENIX Workshop Hot Topics Cloud Comput. (HotCloud 10), Boston, MA, USA, 22–25 June 2010.
38. Burd, T.D.; Brodersen, R.W. Processor design for portable systems. *J. VLSI Signal Process. Syst. Signal Image Video Technol.* **1996**, *13*, 203–221. [CrossRef]
39. Shi, D.; Li, L.; Chen, R.; Prakash, P.; Pan, M.; Fang, Y. Toward energy-efficient federated learning over 5G+ mobile devices. *IEEE Wirel. Commun.* **2022**, *29*, 44–51. [CrossRef]
40. Xia, Z.; Du, J.; Jiang, C.; Han, Z.; Ren, Y. Latency constrained energy-efficient underwater dynamic federated learning. *IEEE/ACM Trans. Netw.* **2024**, 1558–2566. [CrossRef]
41. Yang, Z.; Chen, M.; Wong, K.K.; Poor, H.V.; Cui, S. Federated learning for 6G: Applications, challenges, and opportunities. *Engineering* **2022**, *8*, 33–41. [CrossRef]
42. Marnissi, O.; El Hammouti, H.; Bergou, E.H. Adaptive sparsification and quantization for enhanced energy efficiency in federated learning. *IEEE Open J. Commun. Soc.* **2024**, *5*, 4307–4321. [CrossRef]
43. Chen, R.; Wan, Q.; Zhang, X.; Qin, X.; Hou, Y.; Wang, D.; Fu, X.; Pan, M. EEFL: High-speed wireless communications inspired energy efficient federated learning over mobile devices. In Proceedings of the 21st Annual International Conference on Mobile Systems, Applications and Services, Helsinki, Finland, 18–22 June 2023; pp. 544–556.
44. Beitollahi, M.; Lu, N. Multi-frame scheduling for federated learning over energy-efficient 6g wireless networks. In Proceedings of the IEEE INFOCOM 2022-IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS), Virtual, 2–5 May 2022; pp. 1–6.
45. Chen, R.; Li, L.; Xue, K.; Zhang, C.; Pan, M.; Fang, Y. Energy efficient federated learning over heterogeneous mobile devices via joint design of weight quantization and wireless transmission. *IEEE Trans. Mob. Comput.* **2022**, *22*, 7451–7465. [CrossRef]
46. Kim, M.; Saad, W.; Mozaffari, M.; Debbah, M. Green, quantized federated learning over wireless networks: An energy-efficient design. *IEEE Trans. Wirel. Commun.* **2023**, *23*, 1386–1402. [CrossRef]
47. Nguyen, V.D.; Sharma, S.K.; Vu, T.X.; Chatzinotas, S.; Ottersten, B. Efficient federated learning algorithm for resource allocation in wireless IoT networks. *IEEE Internet Things J.* **2020**, *8*, 3394–3409. [CrossRef]
48. Jabbari, A.; Khan, H.; Duraibi, S.; Budhiraja, I.; Gupta, S.; Omar, M. Energy maximization for wireless powered communication enabled IoT devices with NOMA underlaying solar powered UAV using federated reinforcement learning for 6G networks. *IEEE Trans. Consum. Electron.* **2024**, *70*, 3926–3939. [CrossRef]
49. Al-Abiad, M.S.; Hassan, M.Z.; Hossain, M.J. Energy-efficient resource allocation for federated learning in NOMA-enabled and relay-assisted internet of things networks. *IEEE Internet Things J.* **2022**, *9*, 24736–24753. [CrossRef]
50. Shi, Y.; Xia, S.; Zhou, Y.; Mao, Y.; Jiang, C.; Tao, M. Vertical federated learning over cloud-RAN: Convergence analysis and system optimization. *IEEE Trans. Wirel. Commun.* **2023**, *23*, 1327–1342. [CrossRef]
51. Wang, J.; Mao, Y.; Wang, T.; Shi, Y. Green federated learning over cloud-RAN with limited fronthaul capacity and quantized neural networks. *IEEE Trans. Wirel. Commun.* **2023**, *23*, 4300–4314. [CrossRef]
52. Xu, J.; Wang, H. Client selection and bandwidth allocation in wireless federated learning networks: A long-term perspective. *IEEE Trans. Wirel. Commun.* **2020**, *20*, 1188–1200. [CrossRef]
53. Dinh, C.T.; Tran, N.H.; Nguyen, M.N.H.; Hong, C.S.; Bao, W.; Zomaya, A.Y.; Gramoli, V. Federated learning over wireless networks: Convergence analysis and resource allocation. *IEEE/ACM Trans. Netw.* **2021**, *29*, 398–409. [CrossRef]
54. Li, R.; Zhang, G.; Xu, H.; Chen, Y.; Chen, X. A novel energy-efficient FL resource allocation scheme based on NOMA. *Wirel. Pers. Commun.* **2023**, *132*, 2023–2040. [CrossRef]
55. Ho, M.C.; Tran, A.T.; Lee, D.; Paek, J.; Noh, W.; Cho, S. A DDPG-based energy efficient federated learning algorithm with SWIPT and MC-NOMA. *ICT Express* **2024**, *10*, 600–607. [CrossRef]

56. Zeng, Q.; Du, Y.; Huang, K.; Leung, K.K. Energy-efficient resource management for federated edge learning with CPU-GPU heterogeneous computing. *IEEE Trans. Wirel. Commun.* **2021**, *20*, 7947–7962. [CrossRef]
57. Zhang, T.; Mao, S. Energy-efficient federated learning with intelligent reflecting surface. *IEEE Trans. Green Commun. Netw.* **2021**, *6*, 845–858. [CrossRef]
58. Mu, Y.; Garg, N.; Ratnarajah, T. Federated learning in massive MIMO 6G networks: Convergence analysis and communication-efficient design. *IEEE Trans. Netw. Sci. Eng.* **2022**, *9*, 4220–4234. [CrossRef]
59. Jeon, Y.S.; Amiri, M.M.; Lee, N. Communication-efficient federated learning over MIMO multiple access channels. *IEEE Trans. Commun.* **2022**, *70*, 6547–6562. [CrossRef]
60. Vu, T.T.; Ngo, H.Q.; Dao, M.N.; Ngo, D.T.; Larsson, E.G.; Le-Ngoc, T. Energy-efficient massive MIMO for federated learning: Transmission designs and resource allocations. *IEEE Open J. Commun. Soc.* **2022**, *3*, 2329–2346. [CrossRef]
61. Choi, W.; Andrews, J.G. Downlink performance and capacity of distributed antenna systems in a multicell environment. *IEEE Trans. Wirel. Commun.* **2007**, *6*, 69–73. [CrossRef]
62. Ngo, H.Q.; Ashikhmin, A.; Yang, H.; Larsson, E.G.; Marzetta, T.L. Cell-free massive MIMO versus small cells. *IEEE Trans. Wirel. Commun.* **2017**, *16*, 1834–1850. [CrossRef]
63. Ngo, H.Q.; Tran, L.N.; Duong, T.Q.; Matthaiou, M.; Larsson, E.G. On the total energy efficiency of cell-free massive MIMO. *IEEE Trans. Green Commun. Netw.* **2017**, *2*, 25–39. [CrossRef]
64. Dang, X.T.; Shin, O.S. Energy efficiency optimization for federated learning in cell-free massive MIMO systems. In Proceedings of the 2024 Tenth International Conference on Communications and Electronics (ICCE), Las Vegas, NV, USA, 5–8 January 2024; pp. 60–65.
65. Mahmoudi, A.; Zaher, M.; Björnson, E. Joint energy and latency optimization in federated learning over cell-free massive MIMO networks. *arXiv* **2024**, arXiv:2404.18287.
66. Wang, H.; Zhao, H.; Xia, W.; Wang, Q.; Zhu, H. Energy-efficient optimization for over-the-air federated learning in cell-free massive MIMO. In Proceedings of the 2023 IEEE 23rd International Conference on Communication Technology (ICCT), Wuxi, China, 20–22 October 2023; pp. 635–639.
67. Sifaou, H.; Li, G.Y. Over-the-air federated learning over scalable cell-free massive MIMO. *IEEE Trans. Wirel. Commun.* **2023**, *23*, 4214–4227. [CrossRef]
68. Zhao, T.; Chen, X.; Sun, Q.; Zhang, J. Energy-efficient federated learning over cell-free IoT networks: Modeling and optimization. *IEEE Internet Things J.* **2023**, *10*, 17436–17449. [CrossRef]
69. Dao, N.N.; Pham, Q.V.; Tu, N.H.; Thanh, T.T.; Bao, V.N.Q.; Lakew, D.S.; Cho, S. Survey on aerial radio access networks: Toward a comprehensive 6G access infrastructure. *IEEE Commun. Surv. Tutor.* **2021**, *23*, 1193–1225. [CrossRef]
70. Zeng, Y.; Wu, Q.; Zhang, R. Accessing from the sky: A tutorial on UAV communications for 5G and beyond. *Proc. IEEE* **2019**, *107*, 2327–2375. [CrossRef]
71. Pham, Q.V.; Zeng, M.; Huynh-The, T.; Han, Z.; Hwang, W.J. Aerial access networks for federated learning: Applications and challenges. *IEEE Netw.* **2022**, *36*, 159–166. [CrossRef]
72. Zhu, C.; Shi, Y.; Zhao, H.; Chen, K.; Zhang, T.; Bao, C. A fairness-enhanced federated learning scheduling mechanism for UAV-assisted emergency communication. *Sensors* **2024**, *24*, 1599. [CrossRef] [PubMed]
73. Zeng, T.; Semiari, O.; Mozaffari, M.; Chen, M.; Saad, W.; Bennis, M. Federated learning in the sky: Joint power allocation and scheduling with UAV swarms. In Proceedings of the ICC 2020-2020 IEEE International Conference on Communications (ICC), Dublin, Ireland, 7–11 June 2020; pp. 1–6.
74. Brik, B.; Ksentini, A.; Bouaziz, M. Federated learning for UAVs-enabled wireless networks: Use cases, challenges, and open problems. *IEEE Access* **2020**, *8*, 53841–53849. [CrossRef]
75. Pham, Q.V.; Le, M.; Huynh-The, T.; Han, Z.; Hwang, W.J. UAV-enabled wireless powered communication for energy-efficient federated learning. In Proceedings of the ICC 2022-IEEE International Conference on Communications, Seoul, Republic of Korea, 16–20 May 2022; pp. 1–6.
76. Jing, Y.; Qu, Y.; Dong, C.; Shen, Y.; Wei, Z.; Wang, S. Joint UAV location and resource allocation for air-ground integrated federated learning. In Proceedings of the 2021 IEEE Global Communications Conference (GLOBECOM), Madrid, Spain, 7–11 December 2021; pp. 1–6.
77. Do, Q.V.; Pham, Q.V.; Hwang, W.J. Deep reinforcement learning for energy-efficient federated learning in UAV-enabled wireless powered networks. *IEEE Commun. Lett.* **2021**, *26*, 99–103. [CrossRef]
78. Pham, Q.V.; Le, M.; Huynh-The, T.; Han, Z.; Hwang, W.J. Energy-efficient federated learning over UAV-enabled wireless powered communications. *IEEE Trans. Veh. Technol.* **2022**, *71*, 4977–4990. [CrossRef]
79. Jing, Y.; Qu, Y.; Dong, C.; Ren, W.; Shen, Y.; Wu, Q.; Guo, S. Exploiting UAV for air–ground integrated federated learning: A joint UAV location and resource optimization approach. *IEEE Trans. Green Commun. Netw.* **2023**, *7*, 1420–1433. [CrossRef]
80. Pham, Q.V.; Zeng, M.; Ruby, R.; Huynh-The, T.; Hwang, W.J. UAV communications for sustainable federated learning. *IEEE Trans. Veh. Technol.* **2021**, *70*, 3944–3948. [CrossRef]
81. Dang, X.T.; Shin, O.S. Optimization of energy efficiency for federated learning over unmanned aerial vehicle communication networks. *Electronics* **2024**, *13*, 1827. [CrossRef]
82. Hou, X.; Wang, J.; Jiang, C.; Zhang, X.; Ren, Y.; Debbah, M. UAV-enabled covert federated learning. *IEEE Trans. Wirel. Commun.* **2023**, *22*, 6793–6809. [CrossRef]

83. Nie, Y.; Zhao, J.; Gao, F.; Yu, F.R. Semi-distributed resource management in UAV-aided MEC systems: A multi-agent federated reinforcement learning approach. *IEEE Trans. Veh. Technol.* **2021**, *70*, 13162–13173. [CrossRef]
84. Tang, S.; Zhou, W.; Chen, L.; Lai, L.; Xia, J.; Fan, L. Battery-constrained federated edge learning in UAV-enabled IoT for B5G/6G networks. *Phys. Commun.* **2021**, *47*, 101381. [CrossRef]
85. Wang, P.; Yang, H.; Han, G.; Yu, R.; Yang, L.; Sun, G.; Qi, H.; Wei, X.; Zhang, Q. Decentralized navigation with heterogeneous federated reinforcement learning for UAV-enabled mobile edge computing. *IEEE Trans. Mob. Comput.* **2024**, *23*, 13621–13638. [CrossRef]
86. Abbasi, O.; Yadav, A.; Yanikomeroglu, H.; Dao, N.D.; Senarath, G.; Zhu, P. HAPS for 6G networks: Potential use cases, open challenges, and possible solutions. *IEEE Wirel. Commun.* **2024**, *31*, 324–331. [CrossRef]
87. Li, Z.; Wang, Z.; Wang, Z.; Zhou, Y. Energy-efficient federated learning over hierarchical aerial wireless networks. In Proceedings of the 2023 IEEE 34th Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC), Toronto, ON, Canada, 5–8 September 2023; pp. 1–6.
88. Wang, S.; Chen, M.; Yin, C.; Saad, W.; Hong, C.S.; Cui, S.; Poor, H.V. Federated learning for task and resource allocation in wireless high-altitude balloon networks. *IEEE Internet Things J.* **2021**, *8*, 17460–17475. [CrossRef]
89. Jia, Z.; Wu, Q.; Dong, C.; Yuen, C.; Han, Z. Hierarchical aerial computing for Internet of Things via cooperation of HAPs and UAVs. *IEEE Internet Things J.* **2022**, *10*, 5676–5688. [CrossRef]
90. Liu, L.; He, H.; Qi, F.; Zhao, Y.; Xie, W.; Zhou, F.; Feng, L. HAP-assisted multi-aerial base station deployment for capacity enhancement via federated deep reinforcement learning. *J. Cloud Comput.* **2023**, *12*, 136. [CrossRef]
91. Zhang, H.; Meng, X.; Qi, F.; Chai, Y.; Li, P.; Liu, X. Sparse channel estimation aided federated learning assisted non-terrestral network. In Proceedings of the 2024 5th International Conference on Geology, Mapping and Remote Sensing (ICGMRS), Wuhan, China, 12–14 April 2024; pp. 74–78.
92. Shinde, S.S.; Tarchi, D. Joint air-ground distributed federated learning for intelligent transportation systems. *IEEE Trans. Intell. Transp. Syst.* **2023**, *24*, 9996–10011. [CrossRef]
93. Qu, Y.; Dong, C.; Zheng, J.; Dai, H.; Wu, F.; Guo, S.; Anpalagan, A. Empowering edge intelligence by air-ground integrated federated learning. *IEEE Netw.* **2021**, *35*, 34–41. [CrossRef]
94. Zhai, Z.; Wu, Q.; Yu, S.; Li, R.; Zhang, F.; Chen, X. FedLEO: An offloading-assisted decentralized federated learning framework for low earth orbit satellite networks. *IEEE Trans. Mob. Comput.* **2023**, *23*, 5260–5279. [CrossRef]
95. Matthiesen, B.; Razmi, N.; Leyva-Mayorga, I.; Dekorsy, A.; Popovski, P. Federated learning in satellite constellations. *IEEE Netw.* **2023**, *38*, 232–239. [CrossRef]
96. Wang, Y.; Zou, C.; Wen, D.; Shi, Y. Federated learning over LEO satellite. In Proceedings of the 2022 IEEE Globecom Workshops (GC Wkshps), Rio de Janeiro, Brazil, 4–8 December 2022; pp. 1652–1657.
97. Chen, H.; Xiao, M.; Pang, Z. Satellite-based computing networks with federated learning. *IEEE Wirel. Commun.* **2022**, *29*, 78–84. [CrossRef]
98. Zhou, A.; Wang, Y.; Zhang, Q. Energy-efficient resource management for federated learning in LEO satellite IoT. In Proceedings of the 2024 IEEE Wireless Communications and Networking Conference (WCNC), Dubai, United Arab Emirates, 21–24 April 2024; pp. 1–6.
99. Xiong, T.; Xu, X.; Du, P.; Zhang, Y.; Zhang, R.; Liu, J. Energy-efficient federated learning for earth observation in LEO satellite systems. In Proceedings of the 2024 IEEE Wireless Communications and Networking Conference (WCNC), Dubai, United Arab Emirates, 21–24 April 2024; pp. 1–6.
100. Li, J.; Xue, K.; Wei, D.S.; Liu, J.; Zhang, Y. Energy efficiency and traffic offloading optimization in integrated satellite/terrestrial radio access networks. *IEEE Trans. Wirel. Commun.* **2020**, *19*, 2367–2381. [CrossRef]
101. Mao, B.; Tang, F.; Kawamoto, Y.; Kato, N. Optimizing computation offloading in satellite-UAV-served 6G IoT: A deep learning approach. *IEEE Netw.* **2021**, *35*, 102–108. [CrossRef]
102. Elmahallawy, M.; Luo, T.; Ramadan, K. Communication-efficient federated learning for LEO satellite networks integrated with HAPs using hybrid NOMA-OFDM. *IEEE J. Sel. Areas Commun.* **2024**, *42*, 1097–1114. [CrossRef]
103. Pekka, J.; Chia-Hao, Y.; Klaus, D.; Cássio, R.; Carl, W.; Klaus, H.; Olav, T.; Visa, K. Device-to-device communication underlaying cellular communications systems. *Int. J. Commun. Netw. Syst. Sci.* **2009**, *2009*. [CrossRef]
104. Guo, Q.; Tang, F.; Kato, N. Federated reinforcement learning-based resource allocation in D2D-enabled 6G. *IEEE Netw.* **2022**, *37*, 89–95. [CrossRef]
105. Li, Z.; Zhang, K.; Zhang, Y.; Liu, Y.; Chen, Y. D2D-assisted adaptive federated learning in energy-constrained edge computing. *Appl. Sci.* **2024**, *14*, 4989. [CrossRef]
106. Al-Abiad, M.S.; Hossain, M. Minimizing energy consumption for decentralized federated learning using D2D communications. In Proceedings of the 2023 IEEE 97th Vehicular Technology Conference (VTC2023), Florence, Italy, 20–23 June 2023; pp. 1–6.
107. Wang, S.; Morabito, R.; Hosseinalipour, S.; Chiang, M.; Brinton, C.G. Device sampling and resource optimization for federated learning in cooperative edge networks. *IEEE/ACM Trans. Netw.* **2024**, *32*, 4365–4381. [CrossRef]
108. Li, Y.; Liang, W.; Li, J.; Cheng, X.; Yu, D.; Zomaya, A.Y.; Guo, S. Energy-aware, device-to-device assisted federated learning in edge computing. *IEEE Trans. Parallel Distrib. Syst.* **2023**, *34*, 2138–2154. [CrossRef]
109. Al-Abiad, M.S.; Obeed, M.; Hossain, M.J.; Chaaban, A. Decentralized aggregation for energy-efficient federated learning via D2D communications. *IEEE Trans. Commun.* **2023**, *71*, 3333–3351. [CrossRef]

110. Lin, F.P.C.; Hosseinalipour, S.; Azam, S.S.; Brinton, C.G.; Michelusi, N. Semi-decentralized federated learning with cooperative D2D local model aggregations. *IEEE J. Sel. Areas Commun.* **2021**, *39*, 3851–3869. [CrossRef]
111. Fantacci, R.; Picano, B. A D2D-aided federated learning scheme with incentive mechanism in 6G networks. *IEEE Access* **2022**, *11*, 107–117. [CrossRef]
112. Qu, Y.; Dai, H.; Zhuang, Y.; Chen, J.; Dong, C.; Wu, F.; Guo, S. Decentralized federated learning for UAV networks: Architecture, challenges, and opportunities. *IEEE Netw.* **2021**, *35*, 156–162. [CrossRef]
113. Pan, D.; Khoshkholghi, M.A.; Mahmoodi, T. Decentralized federated learning methods for reducing communication cost and energy consumption in UAV networks. In Proceedings of the International Conference on Mobile Computing, Applications, and Services, Messina, Italy, 17–18 November 2022; Springer: Berlin/Heidelberg, Germany, 2022; pp. 18–30.
114. Srinivas, C.; Venkatramulu, S.; Rao, V.C.S.; Raghuram, B.; VinayKumar, K.; Pratapagiri, S. Decentralized machine learning based energy efficient routing and intrusion detection in unmanned aerial network UAV. *Int. J. Recent Innov. Trends Comput. Commun.* **2024**, *11*, 517–527. [CrossRef]
115. Shang, C.; Hoang, D.T.; Hao, M.; Niyato, D.; Yu, J. Energy-efficient decentralized federated learning for UAV swarm with spiking neural networks and leader election mechanism. *IEEE Wirel. Commun. Lett.* **2024**, *13*, 2742–2746. [CrossRef]
116. Razmi, N.; Matthiesen, B.; Dekorsy, A.; Popovski, P. Ground-assisted federated learning in LEO satellite constellations. *IEEE Wirel. Commun. Lett.* **2022**, *11*, 717–721. [CrossRef]
117. Zhou, F.; Wang, Z.; Shi, Y.; Zhou, Y. Decentralized satellite federated learning via intra- and inter-orbit communications. In Proceedings of the 2024 IEEE International Conference on Communications Workshops (ICC Workshops), Denver, CO, USA, 9–13 June 2024; pp. 786–791.
118. Wu, C.; Zhu, Y.; Wang, F. DSFL: Decentralized satellite federated learning for energy-aware LEO constellation computing. In Proceedings of the 2022 IEEE International Conference on Satellite Computing (Satellite), Danang, Vietnam, 4–6 August 2022; pp. 25–30.
119. Yan, Z.; Li, D. Convergence time optimization for decentralized federated learning with LEO satellites via number control. *IEEE Trans. Veh. Technol.* **2024**, *73*, 4517–4522. [CrossRef]
120. Perera, T.D.P.; Jayakody, D.N.K.; Sharma, S.K.; Chatzinotas, S.; Li, J. Simultaneous wireless information and power transfer (SWIPT): Recent advances and future challenges. *IEEE Commun. Surv. Tutor.* **2017**, *20*, 264–302. [CrossRef]
121. Wu, Y.; Dai, M.; Qian, L.; Su, Z.; Quek, T.Q.; Ng, D.W.K. SWIPT-empowered sustainable wireless federated learning: Paradigms, challenges, and solutions. *IEEE Netw.* **2022**, *37*, 206–213. [CrossRef]
122. da Silva, J.M.B.; Ntougias, K.; Krikidis, I.; Fodor, G.; Fischione, C. Simultaneous wireless information and power transfer for federated learning. In Proceedings of the 2021 IEEE 22nd International Workshop on Signal Processing Advances in Wireless Communications (SPAWC), Lucca, Italy, 27–30 September 2021; pp. 296–300. [CrossRef]
123. Wu, Y.; Song, Y.; Wang, T.; Dai, M.; Quek, T.Q. Simultaneous wireless information and power transfer assisted federated learning via nonorthogonal multiple access. *IEEE Trans. Green Commun. Netw.* **2022**, *6*, 1846–1861. [CrossRef]
124. Li, Y.; Wu, Y.; Song, Y.; Qian, L.; Jia, W. Dynamic user-scheduling and power allocation for SWIPT aided federated learning: A deep learning approach. *IEEE Trans. Mob. Comput.* **2022**, *22*, 6956–6969. [CrossRef]
125. Wen, W.; Jia, Y.; Xia, W. Joint scheduling and resource allocation for federated learning in SWIPT-enabled micro UAV swarm networks. *China Commun.* **2022**, *19*, 119–135. [CrossRef]
126. Wen, W.; Jia, Y.; Xia, W. Federated learning in SWIPT-enabled micro-UAV swarm networks: A joint design of scheduling and resource allocation. In Proceedings of the 2021 13th International Conference on Wireless Communications and Signal Processing (WCSP), Changsha, China, 20–22 October 2021; pp. 1–5.
127. Yang, Y.; Liu, X. Deep reinforcement learning based trajectory optimization for UAV-enabled IoT with SWIPT. *Ad Hoc Netw.* **2024**, *159*, 103488. [CrossRef]
128. Vu, B.M.; Dang, T.N.; Shin, O.S. Rate fairness optimization for mixed FSO/RF IRS-assisted UAV communication systems. In Proceedings of the 2023 RIVF International Conference on Computing and Communication Technologies (RIVF), Hanoi, Vietnam, 23–25 December 2023; pp. 200–205.
129. Vu, B.M.; Shin, O.S. Optimization of IRS-assisted OFDMA SWIPT systems with dynamic subcarrier allocation and AC computing. In Proceedings of the 2023 14th International Conference on Information and Communication Technology Convergence (ICTC), Jeju Island, Republic of Korea, 11–13 October 2023; pp. 613–615.
130. Zhong, R.; Liu, X.; Liu, Y.; Chen, Y.; Han, Z. Mobile reconfigurable intelligent surfaces for NOMA networks: Federated learning approaches. *IEEE Trans. Wirel. Commun.* **2022**, *21*, 10020–10034. [CrossRef]
131. Wang, Z.; Zhou, Y.; Zou, Y.; An, Q.; Shi, Y.; Bennis, M. A graph neural network learning approach to optimize RIS-assisted federated learning. *IEEE Trans. Wirel. Commun.* **2023**, *22*, 6092–6106. [CrossRef]
132. Wu, M.; Guo, K.; Lin, Z.; Garg, S.; Kaur, K.; Kaddoum, G. Energy efficiency optimization in RIS-assisted ISATRNs with RSMA: A federated deep reinforcement learning approach. In Proceedings of the 2024 IEEE Wireless Communications and Networking Conference (WCNC), Dubai, United Arab Emirates, 21–24 April 2024; pp. 01–06.
133. Joshi, N.; Budhiraja, I.; Bansal, A.; Garg, S.; Choi, B.J.; Hassan, M.M. Federated learning based energy efficient scheme for IoT devices: Wireless power transfer using RIS-assisted underlaying solar powered UAVs. *Alex. Eng. J.* **2024**, *107*, 103–116. [CrossRef]
134. Li, L.; Ma, D.; Ren, H.; Wang, P.; Lin, W.; Han, Z. Toward energy-efficient multiple IRSs: Federated learning-based configuration optimization. *IEEE Trans. Green Commun. Netw.* **2021**, *6*, 755–765. [CrossRef]

135. Akbar, A.; Jangsher, S.; Bhatti, F.A. NOMA and 5G emerging technologies: A survey on issues and solution techniques. *Comput. Netw.* **2021**, *190*, 107950. [CrossRef]
136. Dang, X.T.; Nguyen, H.V.; Shin, O.S. Optimization of IRS-NOMA-assisted cell-free massive MIMO systems using deep reinforcement learning. *IEEE Access* **2023**, *11*, 94402–94414. [CrossRef]
137. Lin, Y.; Wang, K.; Ding, Z. Sub-channel assignment and power allocation in NOMA-enhanced federated learning networks. In Proceedings of the 2024 IEEE 99th Vehicular Technology Conference (VTC2024), Singapore, 24–27 June 2024; pp. 1–6.
138. Wu, B.; Fang, F.; Wang, X.; Cai, D.; Fu, S.; Ding, Z. Client selection and cost-efficient joint optimization for NOMA-enabled hierarchical federated learning. *IEEE Trans. Wirel. Commun.* **2024**, *23*, 14289–14303. [CrossRef]
139. Le, T.H.T.; Cantos, L.; Pandey, S.R.; Shin, H.; Kim, Y.H. Federated learning with NOMA assisted by multiple intelligent reflecting surfaces: Latency minimizing optimization and auction. *IEEE Trans. Veh. Technol.* **2023**, *72*, 11558–11574. [CrossRef]
140. Ansarifard, M.; Mokari, N.; Javan, M.R.; Saeedi, H.; Jorswieck, E.A. AI-based radio and computing resource allocation and path planning in NOMA NTNs: AoI minimization under CSI uncertainty. *IEEE Trans. Veh. Technol.* **2024**, *73*, 14874–14887. [CrossRef]
141. Alishahi, M.; Fortier, P.; Zeng, M.; Pham, Q.V.; Li, X. Energy minimization for IRS-aided wireless powered federated learning networks with NOMA. *IEEE Internet Things J.* **2024**, *11*, 16339–16350. [CrossRef]
142. Alishahi, M.; Fortier, P.; Hao, W.; Li, X.; Zeng, M. Energy minimization for wireless-powered federated learning network with NOMA. *IEEE Wirel. Commun. Lett.* **2023**, *12*, 833–837. [CrossRef]
143. Sharma, H.; Budhiraja, I.; Consul, P.; Kumar, N.; Garg, D.; Zhao, L.; Liu, L. Federated learning based energy efficient scheme for MEC with NOMA underlaying UAV. In Proceedings of the 5th International ACM Mobicom Workshop on Drone Assisted Wireless Communications for 5G and Beyond, Sydney, NSW, Australia, 17 October 2022; pp. 73–78.
144. Amiri, M.M.; Gündüz, D. Federated learning over wireless fading channels. *IEEE Trans. Wirel. Commun.* **2020**, *19*, 3546–3557. [CrossRef]
145. Zheng, B.; You, C.; Mei, W.; Zhang, R. A survey on channel estimation and practical passive beamforming design for intelligent reflecting surface aided wireless communications. *IEEE Commun. Surv. Tutor.* **2022**, *24*, 1035–1071. [CrossRef]
146. Jung, H.; Ko, S.W. Performance analysis of UAV-enabled over-the-air computation under imperfect channel estimation. *IEEE Wirel. Commun. Lett.* **2021**, *11*, 438–442. [CrossRef]
147. Mitev, M.; Chorti, A.; Poor, H.V.; Fettweis, G.P. What physical layer security can do for 6G security. *IEEE Open J. Veh. Technol.* **2023**, *4*, 375–388. [CrossRef]
148. Shiu, Y.S.; Chang, S.Y.; Wu, H.C.; Huang, S.C.H.; Chen, H.H. Physical layer security in wireless networks: A tutorial. *IEEE Wirel. Commun.* **2011**, *18*, 66–74. [CrossRef]
149. Dang, X.T.; Nguyen, H.V.; Shin, O.S. Physical layer security for IRS-UAV-assisted cell-free massive MIMO systems. *IEEE Access* **2024**, *12*, 89520–89537. [CrossRef]
150. Elbir, A.M.; Papazafeiropoulos, A.K.; Chatzinotas, S. Federated learning for physical layer design. *IEEE Commun. Mag.* **2021**, *59*, 81–87. [CrossRef]
151. Zhang, H.; Yang, C.; Dai, B. When wireless federated learning meets physical layer security: The fundamental limits. In Proceedings of the IEEE INFOCOM 2022 - IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS), Virtual, 2–5 May 2022; pp. 1–6.
152. Ahmed, J.; Nguyen, T.N.; Ali, B.; Javed, M.A.; Mirza, J. On the physical layer security of federated learning based IoMT Networks. *IEEE J. Biomed. Health Inform.* **2023**, *27*, 691–697. [CrossRef] [PubMed]
153. Bartsiokas, I.A.; Gkonis, P.K.; Papazafeiropoulos, A.K.; Kaklamani, D.I.; Venieris, I.S. Federated learning for 6G HetNets' physical layer optimization: Perspectives, trends, and challenges. In *Encyclopedia of Information Science and Technology*, 6th ed.; IGI-Global: Hershey, PA, USA, 2015; pp. 1–28.
154. Thibbotuwawa, A.; Nielsen, P.; Zbigniew, B.; Bocewicz, G. Energy consumption in unmanned aerial vehicles: A review of energy consumption models and their relation to the UAV routing. In *Proceedings of the Information Systems Architecture and Technology: Proceedings of 39th International Conference on Information Systems Architecture and Technology–ISAT 2018: Part II*; Springer: Berlin/Heidelberg, Germany, 2019; pp. 173–184.
155. Thibbotuwawa, A.; Bocewicz, G.; Radzki, G.; Nielsen, P.; Banaszak, Z. UAV mission planning resistant to weather uncertainty. *Sensors* **2020**, *20*, 515. [CrossRef]
156. Giannelos, S.; Bellizio, F.; Strbac, G.; Zhang, T. Machine learning approaches for predictions of CO2 emissions in the building sector. *Electr. Power Syst. Res.* **2024**, *235*, 110735. [CrossRef]
157. Lin, Z.; Gao, K.; Wu, N.; Suganthan, P.N. Scheduling eight-phase urban traffic light problems via ensemble meta-heuristics and Q-learning based local search. *IEEE Trans. Intell. Transp. Syst.* **2023**, *24*, 14415–14426. [CrossRef]