Drones' Edge Intelligence Over Smart Environments in B5G: Blockchain and Federated Learning Synergy

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***Abstract*—Edge Intelligence is an emerging technology which has attracted significant attention. It applies Artificial Intelligence (AI) closer to the network edge for supporting Beyond fifth Generation (B5G) needs. On the other hand, drones can be used as relay station (mobile drone edge intelligence) to gather data from smart environments. Federated Learning (FL) enables the drones to perform decentralized collaborative learning by developing local models, sharing the model parameters with neighbors and the centralized unit to improve global model accuracy in smart environments. However, drone edge intelligence faces challenges such as security and decentralization management, limiting its functions to support green smart environments. Blockchain is a promising technology that enables privacy-preserving data sharing in a distributed manner. There are several challenges that still need to be addressed in blockchain-based applications, such as scalability, energy efficiency, and transaction capacity. Motivated by the significance of FL and blockchain, this survey focuses on the synergy of FL and blockchain to enable drone edge intelligence for green sustainable environments. Moreover, we discuss the combination of FL and blockchain technological aspects, motivation, and framework for green smart environments. Finally, we discuss the challenges and opportunities, and future trends in this domain.**

***Index Terms*—Smart environment, federated learning, blockchain, tethered drone, energy harvesting, sustainable, privacy, drone edge intelligence, green environment, energy efficiency, connectivity, QoS, B5G.**

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I. Introduction

RECENTLY, driven by Beyond fifth-generation (B5G) networks, the tremendous growth of the Internet of Things (IoT) in many smart environments leads to maturity with heterogeneous and widespread smart devices improving people's daily life quality. However, the increasing number of distributed smart IoT devices in smart environments cause several challenges in terms of data processing, storage, and transfer which demands considerable computation resources, energy, and radio bandwidth [1]. Intelligence can address some of these challenges by bringing Artificial Intelligence (AI) closer to smart environments [2], [3] that can offer critical demands of smart environments in terms of connectivity, security, and real-time analysis, energy efficiency, etc. Drones can be used as a relay station (mobile drone edge intelligence) to gather data from low-power short-range IoT devices in smart environments, and enhance energy efficiency. Unique features such as easy deployment, 3D mobility, and a higher chance of line-of-sight communication have made drones an essential technology for network coverage extension, enhancing the Quality of Service (QoS) of smart IoT devices while moving the computation capabilities closer to these devices [4]–[6]. Due to the above benefits, drones can offer a promising solution for various B5G applications in smart environments [7]–[14], where the drone can be utilized as an intelligent edge node to assist in data gathering, provide efficient computing capability, and train data models locally [15]. Therefore, drones make environments smarter and greener [8]. However, drone-aided IoT in smart environments faces security and energy challenges. Limited energy leads to a limited network access lifetime. Fig. 1 shows few used cases of using drones in smart environments with the help of B5G technologies.

Traditionally, Machine Learning (ML) techniques are deployed in a cloud which involves data to be sent and processed in a centralized way. ML can equip drones with data processing and decision-making capabilities in many smart environments. However, such ML-based decision-making techniques involve heavy computations at the drones to process the gathered data. On the other hand, transferring the collected data to the central station for processing can involve various privacy and security threats. This way is not efficient for drone networks due to several reasons. These reasons are private data inaccessibility, stream raw data transfer, and centralized latency. Therefore, moving toward decentralized learning represents an efficient solution for drone applications that require autonomous monitoring, real-time decision making, as well as virtual reality applications. Federated Learning (FL) is a critical technology that enables edge devices, i.e., drones, to collaboratively train a global model based on their captured data from smart environments while preserving data privacy [16]. Google first introduced Federated Deep Learning (FDL) to train the models locally rather than sending raw data to the cloud [16], [17]. In FL implementation, only some parameters of the locally trained model need to be transferred to the FL server for aggregation [18]. FL techniques are also vulnerable to the single-point failure when a drone fails or is under attack. Furthermore, FL-based data aggregation models often cannot reward local drones for participation in the model training process. Therefore, the local processing of a huge amount of data results in high energy consumption at drones during the training model. Blockchain has the potential to support high-level security by enabling decentralization to facilitate on-drone FL in IoT smart environments, as shown in Fig. 1. The authors of [19] discussed how blockchain could be used in energy efficiency and make energy efficiency markets transparent and safer. However, the authors of [20] proposed blockchain-based infrastructure to control drone operation with improving energy-efficient and security for all drones in networks.

The authors introduced blockchain for building computing frameworks within FL [21], [22]. In [23], the authors presented on-device ML using blockchain with consensus algorithms in decentralized training data. Furthermore, blockchain offers many benefits, including reducing costs, improving resources management efficiently, data authentication, and protecting privacy. However, blockchain faces many issues, including scalability, transaction capacity, and fault tolerance [24]. Utilizing blockchain and FL for securing data sharing among multiple parties was introduced in [25]. The authors of [26] discussed the combination of blockchain and FL to share data between industries with a high-security, and therefore, they can collaborate to accomplish optimal results efficiently. This paper provides a comprehensive survey on blockchain and FL synergy in drone edge intelligence for making smart environments smarter, greener, and sustainable. We first review the drone edge intelligence for green and sustainable environments, and then discuss the current work related to FL and blockchain in drone edge intelligence within B5G networks in smart environments.

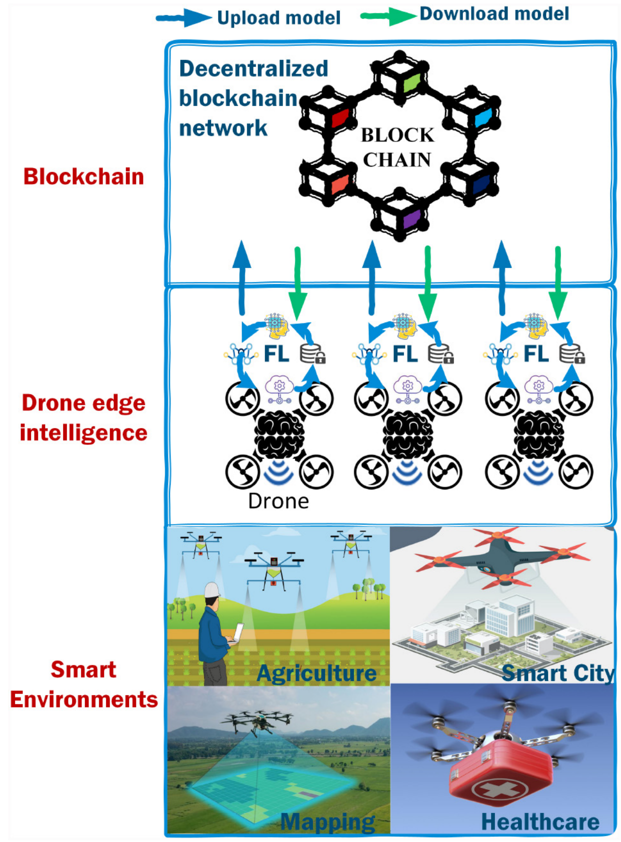

Fig. 1. Blockchain assisted FL in drone edge intelligence for smart environments.

A. Motivation and Contributions

Blockchain has unique features and great potential to enhance the FL security in drone edge intelligence networks. Decentralized blockchain helps eliminate the need for a centralized FL center [23]. Model aggregation decentralization does not fully mitigate the risk of single-point failure but it decreases the burden posed by a global model aggregation to the center. Therefore, blockchain allows all drones to verify the training process and progress to ensure high-level security and privacy. The architecture of blockchain and FL integration was first introduced in [15] in which FL was utilized to train ML models, exchange them, and upload to the blockchain. Moreover, the integration of blockchain and FL at mobile edge intelligence base IoT user coordination to solve the optimization of data relaying issue [27], [28]. The authors in [29] introduced a framework for integrating AI and blockchain. Furthermore, AI and blockchain integration were applied to improve clinical operation in healthcare environments [30]. The authors of [31] introduced a decentralized and asynchronous FL that offered a decentralized FL based on blockchain, which depicted FL with asynchronous convergence, it asynchronously permits a global aggregation with a staleness coefficient. Furthermore, the authors in [32] proposed a blockchain enabling FL for disaster response on drones in B5G networks. The focus of this work is to reduce the blockchain latency and improve the energy efficiency in the drone network.

While there exist several studies on the application of blockchain and FL in edge computing, there is no existing work to review the synergy of blockchain and FL in drone edge intelligence to the best of the our knowledge. To fill this gap, we provide a comprehensive survey on the FL and blockchain synergy to enable drone edge intelligence networks connectivity and energy efficiency, starting with an overview of drone edge intelligence and using FL and blockchain in drone edge intelligence. Then, we discuss the framework of how blockchain and FL can improve drone edge intelligence in smart environments, especially in improving connectivity and energy efficiency. We outline the possible challenges and opportunities with the proposed solution for future research using blockchain and FL in smart environments. In this context, the main contributions are highlighted as follows.

1) We provide a brief discussion on drone edge intelligence as well as blockchain and FL in drone edge intelligence for smart environments. We discuss the existing work in blockchain and FL for green and smart environments.
2) We discuss the blockchain and FL synergy framework in drone edge intelligence to improve the smartness of the IoT environment based on connectivity and energy efficiency. This conceptual framework aims to provide a comprehensive grasp on how drone edge intelligence can benefit from the integration of blockchain and FL in smart environments. We particularly study the potential of this technology to improve energy efficiency, QoS, and security for green and sustainable smart environments.
3) We outline the challenges and opportunities brought by blockchain and FL in drone edge intelligence in smart environments.

B. Related Work

There are many research attempts on IoT, blockchain, FL, edge computing, and technical aspect issues related to these technologies. Furthermore, there many works have been done based on the convergence of blockchain and IoT, ML, and edge computing in B5G Networks. The authors of [33] discussed the synergy of blockchain and B5G networks with exploring the blockchain opportunities to enable B5G services such as network slicing, edge computing, etc. The authors of [34] discussed the IoT challenges and potential blockchain solutions to B5G networks in order to improve industrial applications. Moreover, the authors of [35] introduced a combination of blockchain and cloud to manage decentralization by improving system implementation security and privacy in many applications.

Furthermore, authors in [36] discussed how blockchain could secure and support data storage in edge computing. In [37], the authors investigated the convergence of ML and blockchain to improve model development and data sharing in a decentralized way with enhancing the privacy and scalability of blockchain. The above studies focused on the convergence of ML, blockchain, and edge computing. Blockchain plays a vital role in offering a valuable solution to FL future applications in smart environments. Blockchain as a distributed decentralized ledger that shares information in Peer to Peer (P2P) networks with high-level security was discussed in [38]–[40]. Moreover, blockchain enables decentralized computing instead of traditional centralized computing while assuring high-level security [41]–[43]. The authors of [44] discussed the integration of B5G and drones. Distributed heterogeneous computing of integration of terrestrial stations and drones were considered by utilizing the collaborative communication capability and cashing. FL is used for predicting the cashing placement.

However, to the best of our knowledge, there is no existing work on the convergence of blockchain and FL synergy for drone edge intelligence. This survey investigates blockchain and FL synergy for improving drone edge intelligence in smart environments.

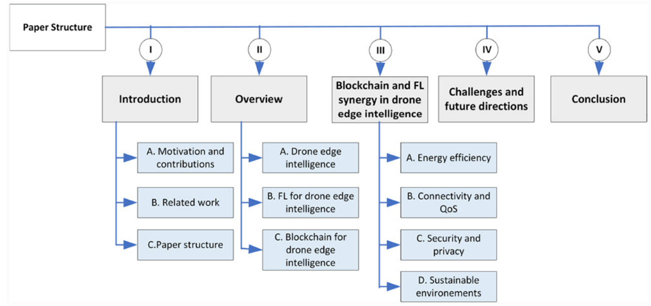

Fig. 2. Paper structure.

C. Paper Structure

The remainder of the paper is organized as follows, and shown in Fig. 2. Section II gives an overview of drone edge intelligence with support of FL and blockchain. Section III discusses the convergence of blockchain and FL to support drone edge intelligence for green and sustainable smart environments. In Section IV, the discussion of challenges and opportunities is provided followed by the conclusion in Section V.

II. OVERVIEW

A. Drone Edge Intelligence

Drone can be considered as an intelligent flying relay station which flies closer to the smart environments for data gathering and processing locally in real-time. Drone edge intelligence offers several unique features, including mobility, flexibility, ease of deployment, line of sight communication, and ease of maintenance. These features can contribute to extending the coverage of cellular and IoT networks as well as improving communications. Drone edge intelligence enables several industries 4.0 such as telecommunications, delivering goods, monitoring, surveillance, etc. The authors of [45] presented and discussed the importance of drones for traffic monitoring, such as road vehicle features, constructing databases, visualization, analysis, and movement properties.

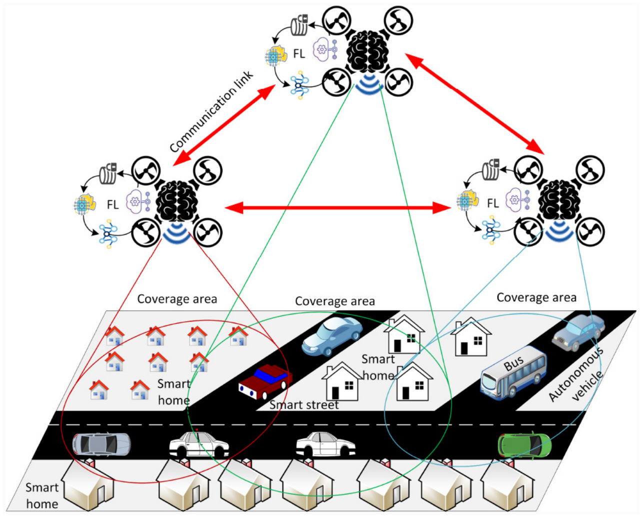

Fig. 3. Drones edge intelligence over smart environments.

Recently, many studies have been devoted to improving smart environments in smart cities, smart healthcare, smart homes, smart agriculture, smart transportation, etc. [7], [9], [46]. However, few studies have considered drones as an edge intelligence node for supporting green and sustainable smart environments [47]. The authors of [48] discussed drone-aided mobile crowdsourcing to improve the energy efficiency of drones in sensing tasks and trajectories. Zhang *et al.* [49] applied deep reinforcement learning techniques to improve the priority of data sensing in dynamic smart environments, where smart cars were used for recharging the drone battery. Furthermore, Zhang *et al.* [50] studied drone's trajectory and power optimization over cellular networks to offer real-time data transmission. Moreover, the authors in [51] developed a Long Short-Term Memory (LSTM)-based optimization policy for drones to optimize the data gathered ratio to reduce energy consumption during sensing tasks.

Drone edge intelligence can be very useful in administering B5G networks due to Line of Sight (LoS) connections with numerous smart devices, mobile users and terrestrial BSs. Fig. 3 illustrates several drones edge intelligence nodes covering smart environments without the need for connecting directly to BSs. Furthermore, drone edge intelligence can collaborate over smart environments to maintain the connectivity, increase the network performance, assist with load balancing, and managing energy consumption. Thanks to the LoS communication link between the drone edge intelligence and users within the coverage area, drones edge intelligence can offer intelligent real-time decision-making at IoT and cellular devices in smart environments [52]. In networking, drone edge intelligence can serve as a learning agent to monitor the condition of terrestrial networks in terms of resource availability, QoS , Quality of Experience (QoE) needs, mobility and link quality.

Summary: We believe that drone edge intelligence-based FL training offers several advantages. First, it can be deployed anywhere to participate in model training. Second, it can establish short-distance LoS connections with training clients, which can significantly speed up the training process. Third, it covers many smart devices or users and enlist them into the training. Finally, compared to their terrestrial equivalents, drones edge intelligence equipped with smart IoT devices flying in the sky can capture more data, including monitoring photos and videos with high resolution. However, designing energy-efficient training techniques for FL model training at drones is very desirable because their energy resources are limited, the drones consume considerable energy during the flight in addition to the energy required for computing and communication. Furthermore, drone-based surveillance missions are still vulnerable to several privacy and security threats during data sharing with other drones or the ground station. Relying on recent advances of B5G, edge computing and model development at drones can facilitate several applications such as autonomous driving, smart cities and industry 4.0.

B. FL for Drone Edge Intelligence

The implementation of ML techniques at drones can enhance their decision making capabilities, while it can raise several issues regarding resource consumption, privacy, and security. FL is a promising technique to enable drones to collaboratively train shared global models without sharing local sensing data. FL techniques have attracted the attention of industry and academia in many applications of smart environments. Wang *et al.* [53] introduced adaptive FL in edge computing systems to balance the training of local models and the aggregation of a global model. The authors of [54] introduced a FL technique for joint optimization of power consumption and resource allocation of vehicle networks in B5G to enable low latency. The authors of [55] explored FL opportunities for Industry 4.0 networks and collaboration of smart components in smart manufacturing. Recently, FL has introduced ML to the edge, closer to smart devices [56]. The authors of [57] introduced federated deep learning for drone-based wireless networks to solve several challenges.

Fig. 4 shows how FL helps drones edge intelligence in training gathered datasets locally and send only updated models instead of raw data to the server. The cloud carries the aggregation task and sends global models to drones edge intelligence to facilitate task collaboration. Therefore, FL techniques can result in reducing the transmission overhead in B5G networks, reducing the computation complexity, and providing privacy and security.

The authors of [58] discussed optimizing FL performance with the goal of minimizing delay and enhancing resource allocation. Furthermore, in [59], the introduced strategy for FL was implemented in a wireless network to improve bandwidth allocation and energy efficiency. Moreover, the authors in [60] discussed scheduling policies' impact on FL performance. However, these techniques could not be applied in drones due to mobility and the limited lifetime of batteries. Due to limited battery challenges in B5G mobile users, FL plays an important role in solving such issues.

Noting the mobility of drones, optimizing their operation involves optimizing the transmission time, power control, bandwidth, and location to maximize the energy efficiency

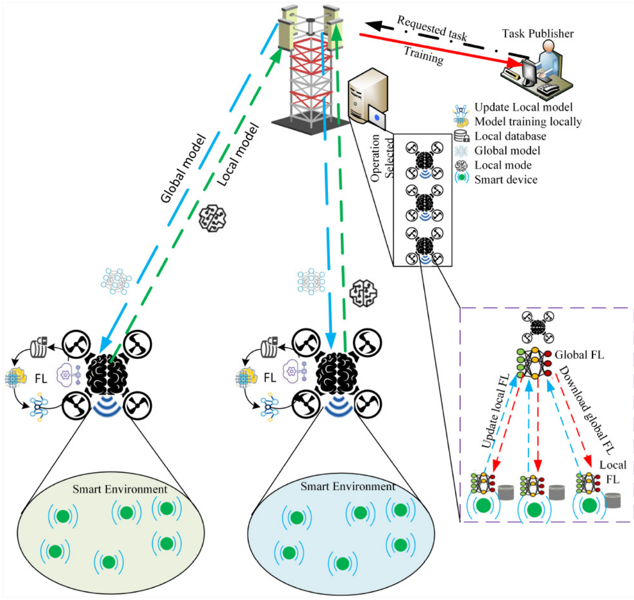

Fig. 4. FL function in drones edge intelligence over smart environments.

of drones. The authors of [61] proposed a FL-based model to enable power transfer and support sustainable wireless networks. The results showed significant improvement in drone energy efficiency. The drone needs ML for task recognition in real-time. Furthermore, implementing centralized ML is also challenging to maintain continuous connectivity between the drone and center. The authors of [62] proposed a framework for leader-follower UAV swarms where FL is implemented at each drone. Each drone processes the collected data locally and creates a model according to its gathered data and then sends its model to a cluster-head drone that is able to aggregate and generate a global model. The findings of the proposed approach showed the effectiveness of FL analysis in improving energy efficiency and delay.

To enable privacy among independent drones as a service, the authors of [63] proposed an FL approach to address the trade-off between the age of information and service latency. In [64], the authors introduced FL for privacy to enable drone-based mobile computing for pandemic and disaster emergency communications. Furthermore, the authors of [65] focused on controlling massive drones, while FL was used to share model parameters of neural networks among the drones. There are very limited works considering the convergence of FL and drone technology applications in smart environments [54], [66]. In [66], the authors proposed an aggregation technique for data collected from the only edge in-vehicle networks. The main challenges of using a FL in drone edge intelligence environments include transmission overhead, delay, drone mobility, dynamic environments, privacy and security, and resource management.

Summary: The integration of FL techniques at drones as edge intelligent devices and improving the performance metric including improving the QoS, enhancing energy efficiency, ensuring high-level security and privacy, and assuring the reliability has recently given extraordinarily research attention. FL plays a vital role in swarm drones to train each drone locally based on its gathered data and create a model. The created model can be shared with other drones by using advanced communication technologies such as B5G. Therefore, drones can reach a consensus on managing their trajectory and avoid collision during flying and performing tasks. However, there are several issues such as transmission delay, drone mobility to be investigated further.

C. Blockchain for Drone Edge Intelligence

Recently, the role of blockchain technology in securing drone operations in B5G networks has been the subject of several research. Qiu *et al.* [67] introduced blockchain for securing spectrum sharing of drones in cellular networks. The authors of [68] developed a blockchain-based solution for mobile edge computing in a scenario where the drone serves as an aerial base station. The authors of [69] discussed blockchain-enabled drone edge intelligence for supporting edge computing in 5G to meet dynamic applications. The authors of [70] introduced blockchain for securing data gathered from IoT networks, where drones operate as relay stations for authentication before data is sent to mobile edge computing. Reference [71] proposed a blockchain approach for decentralized data sharing among air-to-ground IoT networks. Moreover, Li *et al.* [72] introduced blockchain for decentralizing multi-drone in high-level security in ad hoc networks. Alsamhi *et al.* [43] discussed the framework of blockchain for decentralized multi-drone collaboration to perform tasks in a decentralized way to avoid a collision.

Kang *et al.* [73] adopted a decentralized blockchain for achieving reputation management efficiently. In contrast, the authors of [74] proposed a blockchain-based model for securing the system of energy trading. Recently, blockchain has been also proposed for asynchronous decentralized FL [17], [56], [73]. The authors of [75] introduced the integration of blockchain and FL to enhance privacy and security in 5G network applications, considering learning quality and energy consumption. In [76], the authors proposed the architecture of FL with blockchain, which included numerical evaluation and selected participant devices in each group of FL training.

Recently, many efforts have focused on leveraging blockchain technology to enhance drone networks' security. Qiu *et al.* [67] introduced blockchain for securing spectrum sharing for drone-assisted wireless networks. Islam and Shin [70] introduced a secure framework for data gathering by mobile edge computing enabled smart environment, in which drones operate as a relay station for authentication before information is sent to mobile edge computing. The authors of [68] utilized blockchain as a service integrated with mobile edge computing for smart environments, where drones as Arial stations to facilitate blockchain task offloading. Furthermore, in [71], the authors proposed a decentralized blockchain for sharing data in a drone to ground smart environment. Moreover, Li *et al.* [72] developed a private blockchain for key distribution for ad hoc UAV networks.

Summary: The integration of blockchain and FL techniques has not been extensively investigated yet. The ever-growing application of massive IoT devices calls for new mobile access points such as drones to be deployed in smart environment. Therefore, blcokchain can be used in B5G networks to meet the dynamic demands via decentralized services, and support drone edge intelligence with a high-level security.

III. Blockchain and FL Synergy in Drone Edge Intelligence

The communication network of Industry 4.0 is mainly focused on autonomous and digitalization of industrial components such as drones, vehicles, robots, IoT devices, and machines. These communication networks require fast and reliable communication with low latency while assuring resource energy efficiency, and high QoS. FL techniques can improve the learning and communication reliability of industry 4.0 components in smart environments. Noting the increasing demand for autonomous vehicles and therefore the fast growing number of smart devices in smart streets, the Internet of Vehicles (IoV) needs FL to preserve the users' privacy in IoV. However, FL suffers from a single point of failure of communication when a continuous model is required to maintain synchronously. The authors of [77] proposed drones as flying relay stations to facilitate high connectivity in IoV with the help of FL for improving data processing accuracy. In [78], the authors proposed an FL technique to enable the privacy of independent drones as a service for IoV applications, such as predicting the traffic and managing car parking in high occupancy. The finding showed that the proposed FL guaranteed profit efficiency. The authors of [79] developed an integrated blockchain and FL system for a constellation of satellites. This approach was applicable to drones. In [80], the authors proposed a blockchain approach to secure FL framework in drone-assisted mobile crowd sensing to exchange local models and authenticate the verification.

Blockchain can also assist FL for drone edge intelligence computing and reduce the risk of failure in smart environments. Moreover, the combination of blockchain and FL provides privacy and ensures model updating [81]. In [23], the authors described blockchain-based FL techniques for edge devices collaboration with providing rewards to the training sample. The authors of [82], introduced blockchain for ensuring reliable reputation-based incentive techniques. The incentive technique could host updated learning models efficiently and improve learning model accuracy.

Blockchain enables digital twins wireless networks to increase edge intelligence accuracy and efficiency with better performance [28]. Moreover, the authors of [83] discussed the combination of blockchain and FL closer to end-nodes. Blockchain was used to store the local learning model, and then the aggregation model could be provided to the edge nodes. Decentralized FL techniques can coordinate local learning updates and verify them by a‘ smart contract in the blockchain. Such Chain FL is used to store and update aggregation of the model [84]. Blockchain assisted FL in solving the single point of failure issue and providing reliable learning smart environments [85], [86]. Table I summaries the combination of FL and blockchain synergy for smart environments.

TABLE I
Blockchain and FL Synergy for Smart Environments

Ref	**Highlighted**	**Synergy**	**Blockchain function**
[24] (2019)	Enable decentralized training data	Block-FL	Edge devices collaboration
[85] (2019)	Introduced high reputation devices for participating in learning and training model		Ensuring high reliable reputation
[29] (2020)	Blockchain-enabled FL for digital twins collaborative in wireless Computing networks	DTWN	Sharing the information models
[86] (2020)	Bring blockchain and FL to edge intelligence at the end nodes	iFL-BC	Storing the shared model
[87] (2020)	ChainFL is used as decentralized FL technique that uses blockchain for transferring stored models between between nodes .	Chain-FL	Aggregating the updated model and storing it Heterogeneous
[88] (2019)	Blockchain network for improving FL collaboration of secure data computation	Fl-chain	Storing the local model of each aggregation
[89] (2020)	Developing a novel blockchain-enabled FL for solving edge intelligence inefficiency subsequent	FL-Block	Verifying global model
[84] (2021)	Presenting a blockchain for FL crowdsourcing to ensure high-level security and privacy.		Model aggregate
[76] (2020)	Introduced blockchain for reliable FL in reputation management		Storing the reputation update opinion

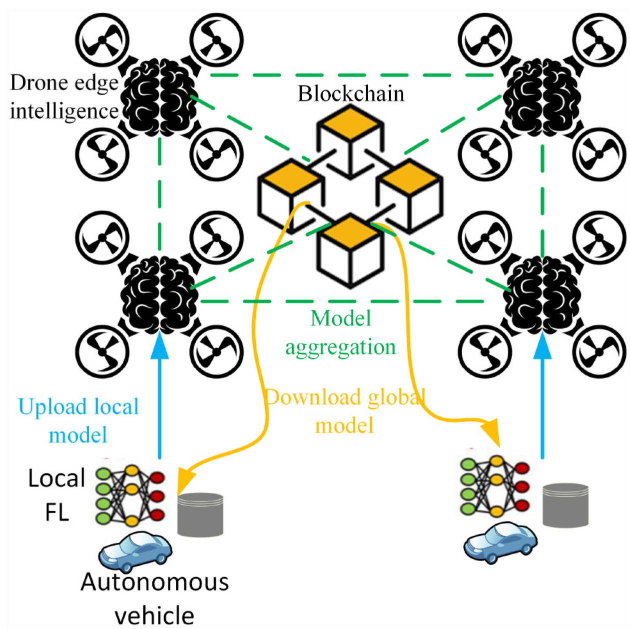

Fig. 5. FL and blockchain synergy.

Blockchain can assist the FL model by replacing the center processing for obtaining a global model among drones edge intelligence; as shown in Fig. 5.

Fig. 6 illustrates the convergence of blockchain and FL for sustainable and green smart environments. The proposed framework is divided into three layers, i.e., smart environment

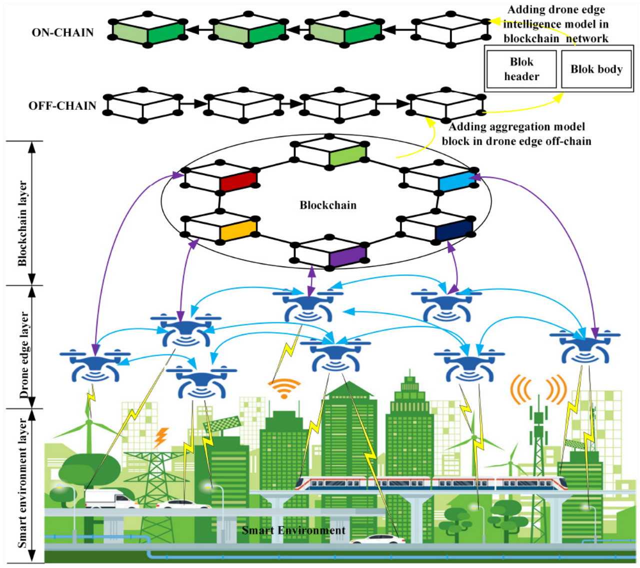

Fig. 6. Blockchain and FL enabling drone edge intelligence in smart environments.

layer, drone edge intelligence layer, and blockchain layer. The environments layer contains the actual location of smart devices that are used to gather data from surrounding smart environments. These smart devices are used to sense the environment and send data to closer drone edge intelligence. The data gathered from a smart environment is vital and sensitive for the training model in drone edge intelligence, in which drone edge intelligence can perform decision-making with a great accuracy rate based on local data. The drone edge intelligence layer consists of many drones connected with each other in the blockchain network. Each drone edge intelligence has been used as a minor node to validate and aggregate the transaction. Furthermore, each drone has its own off-chain for training the gathered data, storing the training model, and generating an aggregation model using FL. The cloud layer generates a global model trained based on a selected training model sent by the drone edge intelligence layer.

Blockchain for IoT applications is discussed in [87]. The implementation of IOTA Tangle and DAG-based distributed ledger are discussed in [88] without examining the IOTA tangle's flaws. In [88], IOTA Tangle presented the random and the random-walk-based Monte Carlo Markov Chain (MCMC) selection algorithms. The authors of [89] improved IOTA Tangle, however, it is still vulnerable to the parasite chain attack, which may compromise the ledger's immutability and irreversibility. Therefore, IOTA Tangle requires significant enhancements to fulfil the fault tolerance and high-security criteria of IoT applications.

Federated blockchain platforms include Stellar [90]. The network is divided into smaller groups known as federates [91], with each federate maintaining local consensus. Thus, local consensus can be transmitted across the network, and global consensus can be established under specific conditions. In addition, the federates that run in parallel enhance throughput. CAPER [92] went on to develop three global consensus techniques. CAPER, interestingly, uses a DAG structure for its distributed ledger. In addition, Herlihy's [93] atomic cross-chain swaps, which are represented in a directed graph topology, allow for asset exchange across several (unrelated) blockchains. Another well-known technique is to delegate the processing of some transactions from the main blockchain to a series of sidechains [94]. A node-clustering technique was presented in a recent paper [95] on the multi-chain structure in the context of the industrial Internet to decrease cross-chain interactions and increase throughput. Hellings and Sadoghi [96] developed a delayed-replication method to increase the efficiency of handling read-only workloads. Dang *et al.* [97] proposed a sharding-based scalable blockchain with a throughput of over 3000 transactions per second. Sharma *et al.* [98] effectively used transaction reordering, a well-known database method, to boost the throughput of completed transactions by a factor of 12x while cutting the average delay in half. Table II provides a summary of techniques recently proposed to enhance blockchain scalability.

TABLE II
SUMMARY OF TECHNIQUES TO ENHANCE BLOCKCHAIN SCALABILITY

Ref	Scalable technique
[91] [92]	DAG
[93]	Stellar
[96] [97] [98] [99]	Multiple chain
[101]	Transaction recording
[95]	CAPER
[93] [94]	Fedrated blcockhain
[100]	Sharding

Summary: The integration of blockchain with FL can improve the performance of drone edge intelligence in smart environments. The Storage of the trained model will be off-chain instead of on-chain to solve the storage issue of blockchain. Deployment of drone edge intelligence closer to smart devices in a smart environment will improve their energy efficiency and reduce delay. This paper focuses mainly on discussing the combination of blockchain and federated learning for drone edge intelligence in smart and green environment and highlighting the research gaps.

A. Energy Efficiency

Besides the security and privacy concerns,drone-assisted IoT in a smart environment faces several other issues such as energy efficiency, mobility, and connectivity. The limited battery lifetime at drones results in a limited network access lifetime. To address these challenges, the authors of [99] introduced blockchain technology for drone-assisted IoT in a smart environment to secure data collection and improve energy efficiency. The simulation results showed that the proposed system could effectively improve the security and energy efficiency of data gathered from IoT in smart environments. The authors in [100] represented a blockchain technology for authentication and verification of the marine vehicles when drones performed smart surveillance. The findings show that blockchain supported less energy consumption.

Furthermore, in an untrusted environment, energy transfer of drones present various security and privacy challenges.

The authors of [101] introduced a blockchain and direct acyclic graph-based approach to secure drone-assisted power transfer while different consensus were created to verify macro energy transactions. The numerical results showed the high security level of drones-assisted power transfer. Reference [102] addressed a drone base station placement problem and proposed an ML-based approach for optimized deployment of drones to reduce energy consumption. The authors in [103] discussed the framework of drones in delivery systems with improving security and energy efficiency. Furthermore, the authors of [104] discussed a reliable and secure energy trading method among drones and the charging station. The proposed model allowed drones to pay tokens or borrow tokens for buying energy from charging stations. The proposed model results provided an increasing utility for charging stations and drones with a high level of security.

Collaboration of multi-drone has shown significant enhancement in achieving complex tasks effectively and efficiently. Due to security issues, the authors of [105] proposed a blockchain-based approach for distributed key management in ad hoc UAV networks to identify malicious UAVs. The findings showed imprudent energy efficiency and resistance against internal and external attacks. The authors of [106] introduced blockchain to secure IoT data via drones to improve connectivity and energy efficiency.

Drones are used for supporting various smart environments, including smart cities, smart homes, smart agriculture, surveillance etc. Due to the limited time of drone operation, the authors of [107] introduced scheduling drone chagrining-based consensus in the multi-drone network with a limited charging stations. The battery capacity of drones has an upper limit. The limited energy of drones has become the most significant limitation of drone applications. Research on blockchain and mobile edge computing has put forward practical IoT security and drone energy efficiency [15], [108], [109]. These researches can effectively improve the trustworthiness of data and the efficiency of drones. However, there is still a lack of integrated solutions real-world drone-assisted IoT scenarios to provide secure and efficient data collection. Reference [110] introduced a FL and dynamic digital twin for the drone to ground networks, in which drones are used for data aggregation captured by digital twins for clients. The results showed a significant enhancement in energy efficiency and accuracy. The authors of [111] discussed drone deployment energy efficiency and user association. Furthermore, the authors used FL to predict the illumination distribution for minimizing drones total transmission power. The results showed a significant reduction in drone transmission power.

Summary: Blockchain and FL can play a vital role in improving drones edge intelligence to perform tasks effectively and efficiently in the near real-time. Since in FL approaches, the models are trained locally and the raw collected datasets are no longer shared among the agents, the energy consumption of drones can be significantly reduced. Blockchain technology can facilitate collaboration among multi-drone edge intelligence and reduce energy consumption. The tethered drone can be used to support computing and provide a long operation time and support charging drone edge intelligence, as shown in Fig. 7. Moreover, The collaboration among drones in can result in the system becoming smarter, greener, and more sustainable.

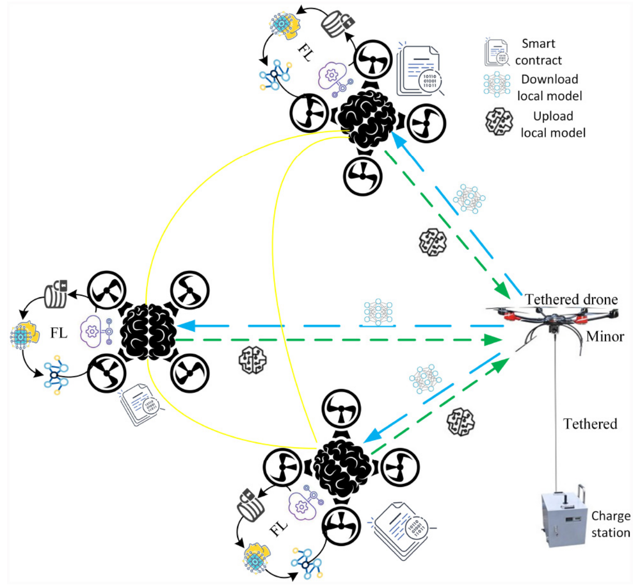

Fig. 7. Tethered drone charging station to support drones edge intelligence using blockchain-aided FL.

1) Energy Harvesting: Energy harvesting equipped the drones with the capability to use available energy sources, i.e., wind, solar, etc. However, because ambient sources are unpredictable and variable, they may not meet QoS requirements. As a result, controlled energy sources from a power plant may be considered to supply energy on demand [112]. Furthermore, the energy consumption of transmitting the acquired drone to drone connectivity data can be reduced by adjusting the drone's wireless transmission power [113]. In addition, energy harvesting may potentially be a viable option for extending drones battery life [114].

Energy harvesting control is challenging to regulate in dynamic and time-varying drone networks. The variable network states at different time epochs necessitate varied power control and energy harvesting control approaches to achieve the best performance. Drones network may be characterized using a Markov decision process [115]. However, collecting correct Markov decision process model information in unknown and dynamic drones networks is challenging. Deep Reinforcement Learning (DRL) technique was suggested to solve the Markov decision process model in drones networks [116]. DRL, in particular, is a trial-and-error learning process that interacts with the drones network environment by watching network states. DRL [116] applys DNNs to estimate state-action values while calculating the potential system cost of each state-action pair.

In enabling energy harvesting drone-assisted IoT, the authors of [117] introduced game theory to improve the power control policy while assuming that smart IoT devices' locations were fixed. In order to reduce the drone's journey time, the authors of [118] developed a protocol to address the joint optimization of task allocation and flying speed

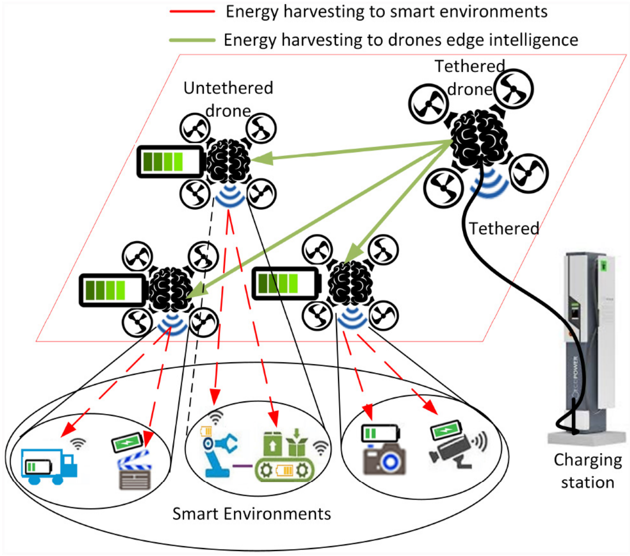

Fig. 8. Energy harvesting of drones edge intelligence.

control in drone networks, which involves the drone generating computing tasks, offloading them to a fog node, and visiting various points of interest.

The use of energy harvesting to charge batteries is a promising technique. The authors of [119] presented a Markov energy model to assess the probability of shortage,energy outage, and service loss for an energy harvesting assisted communication system. Also, the authors of [120] developed an energy-harvesting-aware protocol for IoT networks to extend the IoT devices' lifetime in the face of changing traffic loads and energy availability. For enabling energy-harvesting-assisted IoT networks, the authors of [117] developed a Stackelberg game to motivate the charging station to transfer energy to the IoT devices. Although the energy used by the drone for air hovering accounts for the drone's total energy consumption [121], it is connected to the drone's physical attributes. Furthermore, the energy harvesting control techniques affect the hovering energy consumption. As a result, the energy cost of the drone hovering remains constant and may be omitted in the objective function that seeks to reduce the average system energy cost. Fig. 8 illustrates energy harvesting from tethered drone to untethered drones and from untethered drones to smart devices in the smart environments

2) Protocols and Models for Energy Efficiency: The use of energy harvesting to charge batteries is a promising technique. Reference [119] presented a Markov energy model to examine the possibilities of an energy harvesting-assisted communication system's energy outage, shortage, and service loss. Nguyen *et al.* [120] developed an energy-harvesting-aware routing protocol for smart environment networks to extend smart devices' lifetime in the face of changing traffic loads and energy availability. In cached-enabled energy-harvesting-aided smart environment networks, the authors of [117] introduced a Stackelberg game solution to incentivize the charging station to send energy to the smart devices in the environment. The magnetic resonant coupling model was used in [117] to charge the drone batteries wirelessly. It was shown that the drone's battery life was increased from 30 to 851 minutes. Furthermore, a multi-agent Q-learning model is used for cognitive transmission power management in smart environment networks, where each smart devices learns its power control [122]. DRL has been used to improve the performance of network strategies in time-varying situations in smart environment networks [123].

3) Tethered Drones: The idea of Tethered drones comes from Tethered balloon technology, in which tethered is used for multiple purposes such as power supply, fixed balloons to the ground, and high data transmission [124], [125] [126], [127], [128], [129], [130]. One of the most significant obstacles toward using drones is their short endurance since a conventional electric drone would need to be recharged every hour. However, this issue can be solved by using tethered drone, as shown in [131], [132], [133]. Through a tether linked to a base station, a TUAV obtains continuous power and high-bandwidth communication. As a result, tethered drones outperform free-flying UAVs in this application, especially for B5G networks. The authors of [131] presented a suboptimal closed-form solution to optimize the LoS probability given the inclination angle and the tether length. The authors of [132], [134] proposed a Tethered drone connected to a ground base station through a cable in the proposed arrangement, which supplies both energy and data to the Tethered drone. Also, for drone-assisted cellular networks , in [134], the authors proposed tethered drones. The results showed that the proposed Tethered drone can fly for a long-distance flight compared to the untethered drone. The authors of [135] introduced Tethered drone coverage probability and analyzed the optimization of end to end signal-to-noise ratio. The findings showed that the tethered drones provide better performance in cellular offloading compared to the battery-operated drones. Moreover, the authors of [136] discussed the correction position of Tethered drones in weather conditions with focusing on finding the optimal position for tethered drones.

Summary: Tethered drones can play a vital role in prolonging the operation time and improving the computing capability over smart environments. Furthermore, Tethered drones with support of FL and blockchain can provide more advanced services over a large area due to their extended flight time. On the other hand, Tethered drones can serve as a minner in case of collaborating with multi untethered drones due to the energy limitation of untetherd drones. In such systems, the untethered drone can work for local processing, while the Tethered drone work for global processing and aggregation with high level of security using blockchain technology.

B. Connectivity and QoS

Drone technology integrated with machine learning has revolutionized mobile crowdsensing (MCS). MCS leverages ubiquitous smart device sensing capabilities that are an essential component of smart environments [137], [138]. Due to the limitation of MCS in QoS satisfactory, the drone becomes a possible solution to assist MCS challenges [48], [139], [140]. Drones can allow autonomous crowdsensing anywhere, anytime due to low cost, flexible mobility, and easy and fast deployment [141]. Moreover, drones equipped with smart devices can be used for many MCS applications such as monitoring the traffic environment, public safety, disaster management, and surveillance [142]. In some applications, sharing sensing data has more sensitive information and potentially private information during data gathering and training [143].

The authors of [144] extended work done by [16], [17] and discussed the use cases in 5G networks, while the authors in [145] discuss how to bring intelligence, learning closer to mobile edge networks where data is gathered. Hence, FDL can be helpful in training drone models as compared to centralized techniques. Furthermore, the drone has limited computing power and bandwidth, so it cannot support centralized techniques, and therefore, DFL is the most suitable solution for drone-based supporting smart devices environment. The authors of [57] showed how FDL was applied for drone-based wireless networks.

In [146], the authors proposed a blockchain-based solution to establish drone terminal data security in which edge computing is used to support computing and storage for drones. The authors of [147] introduced blockchain for drone and IoT management with providing security and trust in agriculture scenarios. The results showed significant decrease in time operations with providing security and trust during drone management in a decentralized and autonomous way. The authors of [32] introduced blockchain and FL techniques for drones in B5G networks for disaster management and response. The study focused on blockchain for maintaining low latency and improving the energy efficiency of drone networks. One of the weak points of the drone is the lifetime of the battery. Therefore, the mission of drones needs to be very short. The authors of [148] introduced FL to minimize drone traveling time with a guarantee to satisfy connectivity in smart environment. The finding showed effectiveness in connectivity and traveling time of drone networks.

Summary: Blockchain technology can be employed to build a decentralized drone edge intelligence learning network via securely connecting drones to collaboratively perform tasks in smart environments. Fig. 9 shows that the drones only require to send the updated local model of training their local sensing data to the base station instead of sharing raw data. The training process is continuing until the global model approaches the desired level.

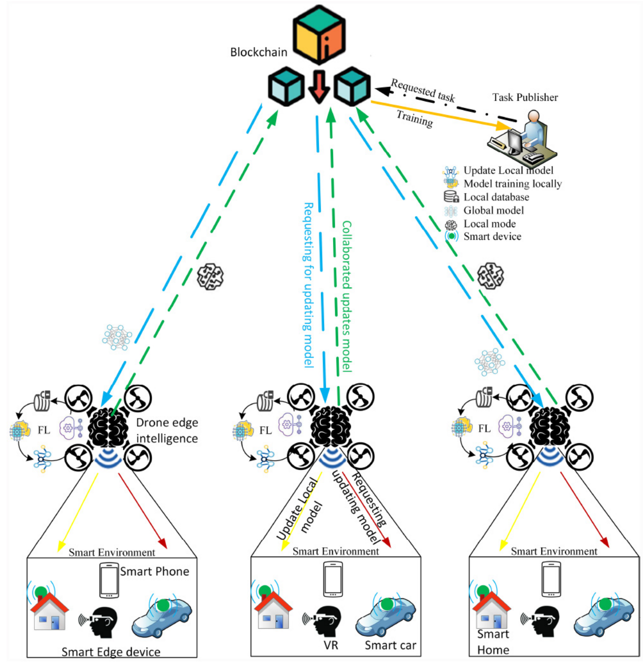

Fig. 9. Blockchain and FL enabling connectivity of drones edge intelligence.

C. Data Collection

Autonomous automobiles are used to assist drone battery recharging. The authors of [49] presented a drone cruise path control protocol for high priority data sensing. Then, under velocity and uplink rate limits, Zhang *et al.* [50] introduced an energy-efficient technique for cellular drone systems to maximize drone sensing and data transfer. Moreover, the authors of [51] established a novel sequential model for drones based on proximal policy optimization and LSTM to maximize the data collection ratio and decrease energy consumption when performing sensing tasks. Furthermore, the authors of [71] proposed a blockchain-based decentralized architecture for data exchange in a drone-to-smart environment, using a Cournot model to maximize advantages for drones and smart devices of smart environments. In addition, a secure blockchain-based system for data management in drones networks can improve security while reducing communication and compute overheads [149].

To limit the drone's energy consumption while meeting the QoS requirement, the authors in [150] introduced power regulation in drone networks for the data gathering service. Moreover, [151] introduced DRL to optimise each drone's transmission power, route, and cell association in drone swarm assisted networks to reduce interference and wireless transmission latency by improving data collection from smart environments.

Furthermore, the authors of [152] introduced time-varying cache-enabled smart environment networks to reduce data transmission delays caused by cache storage capacity and the freshness of smart environment data. To establish a dependable and safe smart environment, the authors of [153] discussed a data collecting and secure sharing strategy that combined Ethereum blockchain with DRL.

D. Security and Privacy

The studies in [65], [80], [154] used FL to facilitate drones applications, including quality sensing with drone swarms [154], secure drone crowdsensing with blockchain [80], and huge drone communications [65]. By avoiding sending experienced data to a central node, FDL protects the privacy of drone data and lowers network cost and latency. Although the major goal of the FDL idea is to protect privacy, sharing some local models may nevertheless disclose private information. As a result, the authors developed a safe aggregation technique in [155], allowing clients to encrypt their local models while enabling the FL server to aggregate them without decrypting them. Analyzing the global aggregated model, on the other hand, can assist in revealing the participation of some learners. As a result, creating algorithms to ensure privacy at the participant level is critical rather than safeguarding acquired data.

For supporting IoT networks, the authors of [156] introduced FL-based drone authentication. DNN was proposed for drone authentications. Experiments indicated that the proposed model provided a higher true positive rate and improved the performance of drone authentication. For smart cities, the authors of [157] provided a low-latency safe authentication technique for drones' networks using blockchain technology. Therefore, each drone that wants to join the network could register to become authenticated on the blockchain. Furthermore, in [158], the authors discussed the convergence of AI and blockchain for the sustainable smart city, and highlighting the security challenges in smart city applications. For IoT systems, the authors of [159] proposed closed loop and open loop RFID systems as decentralized mutual authentication algorithms for smart environments. Reference [160] proposed FL-IIoT for android malware identification. They applied two methods, i.e., Generative adversarial network (GAN) and Federated GAN. The finding showed that FL-IIoT provided high-level security for participating in IIoT while interacting without compromising privacy. Moreover, [161] presented a novel authentication method that used blockchain and SDN methods to eliminate the required for re-authentication during frequent handover between heterogeneous cells. The proposed method is intended to ensure low latency, suitable for a 5G network in which devices/users are replaced with the least latency among heterogeneous cells using their public and private keys given by the developed blockchain component while maintaining their privacy.

Using a single server to handle all sensed data is inefficient, especially when data is often dispersed across a wide network. FL and blockchain integration allows highly scalable intelligent edge data crowdsensing solutions and delivers high levels of privacy and security.The integration of FL and blockchain is investigated in [80] to create a mobile crowdsensing system based on drones. With blockchain supporting, drones' data training and model exchange are monitored and traceable for attack detection and data alteration prevention.

Although FL can protect users' privacy during training, data characteristics encoded in model updates can be exposed, revealing personal information [162]. A differential privacy approach is used to address this issue, which involves inserting artificial noise into each communication round's local gradient training. Then, an incentive system is added to recruit additional drones in the training to increase the overall FL performance. The evaluation results show that drones have a high utility and low aggregation error while lowering convergence delay. In addition, [163] proposes an incentive-based crowdsensing/crowdsourcing architecture for IoT in edge computing, based on FL. To encourage additional users to contribute computational resources for running FL models, each client can earn an incentive after successfully uploading their computed parameter to the MEC server. Finally, in [81], an integrated FL-blockchain architecture in IoT settings is used to examine another edge crowdsourcing technique.

Summary: A crowdsourcing-powered FL system is designed to enable distributed ML training at the network edge. The ultimate objective is to improve appliance manufacturer service quality while protecting consumer privacy using various privacy methods. Blockchain is linked with FL training to identify and prevent malicious attacks from altering gradient updates and audit the parameter update of FL clients like IoT smart devices in smart environments. The suggested FLchain's viability with high training accuracy, security protection, and low system latency has been demonstrated through implementation results.

E. Sustainable Smart Environments

Drones have offered a number of advantages to the environment sustainability. Drones with video cameras are extremely beneficial for swiftly obtaining photos of huge expanses of land, such as agricultural crops, forest regions, and fire management. In this way, drones can reduce pollutant emissions resulting from ground or air control and get to a critical point sooner before an incident occurs. Furthermore, drones are commonly utilized for parcel deliveries and other uses in civic and commercial spheres [164]. Even though drone is still in its infancy in terms of commercial applications, its current and anticipated commercial applications have already demonstrated the potential to drastically alter several industries in terms of reducing workload and overall production costs, saving time, increasing work efficiency and productivity, and bridging the urban-rural divide.

Healthcare: Drones play a vital role for supporting medical services in distant locations, for instance, in cases where normally take a long time to reach and respond a patient suffering from cardiac arrest or other life-threatening illnesses [165]. Drone technology has many benefits for supporting healthcare such as delivering medical supplies, vaccine delivery, faster lab tests. Drones are already used for medical blood supplied while the short delivery time can contribute to saving people lives. Drones can support vaccines delivery to the hardest area due to unconnected transportation keeping vaccines cool and viable during transport. drones can also quickly fly blood from disease and illness people in remote or rural areas to central laboratories and hospitals for testing.

Disaster Management: The natural catastrophes, such as mudslides, earthquakes, floods, explosions, and wildfires, necessitate rapid and prompt medical treatment since the lives of some survivors are at stake [166]. Drones intelligence can thus be used to swiftly scan the region and detect victims using onboard cameras that provide real-time data [167]. Drones with gas sensors and cameras may be flown over volcanic areas, oceans, and forests, to monitor the condition. Drones can identify natural catastrophes before they happen, informing residents and allowing them to escape [168].

Pollution Management: Drones also have the significant benefit of being a safe and environmentally friendly technology. For example, when drones are used for last-mile delivery, it decreases the amount of carbon dioxide emissions that would have been created if the products were delivered by other means [169].

Economics: Drones are now available can fill a delivery service niche in sparsely inhabited locations with low consumer density. The regulatory landscape and last-yard delivery limits are likewise more loosened in rural regions. The economic benefit of decreasing the expense of a driver to visit remote consumers is clear in rural locations, but drone range is a crucial factor in this context.

Environmental: The impact on the environment is likewise enormous. Drones are more ecologically friendly than delivery vans since batteries power them. Many firms' dependence on autos would be reduced if delivery drones became widely used. This would be good for the environment, as it would help many countries decrease emissions and reach emission objectives established by numerous international accords. Furthermore, drone delivery can complete deliveries that cars can not or can only do at significantly higher costs, and it can always efficiently save money and reduce CO2 emissions. Safety considerations and last-yard limits, on the other hand, are likely to limit the gains that economies of scale may provide. Drone delivery as a shopping system is one of the most ecologically beneficial modes of transportation in a variety of circumstances [170].Furthermore, Blockchain technology empowered drone to deliver goods and medicine to quarantine area with high-level security during COVID-19 [171], [42], [172], [173].

IV. Challenges and Future Directions

The main focus of this paper is to investigate the potential of an integrated blockchain and federated learning solution in drone networks to enhance energy efficiency and connectivity among drones and also smart devices while improving QoS. The implementation of FL for drones edge intelligence is still in its early stages and the impact of combination of blockchain and FL for drone edge intelligence is not fully investigated yet. Therefore, many new opportunities can be offered, and many challenges exist in using FL to enable drone edge intelligence networks. Here, we discuss some of the challenges in future research.

Channel Quality and Signal Strength: FL techniques may enable drones' edge intelligence prediction in decentralized ways. Therefore, drones can dynamically and efficiently adjust their location, trajectory and autonomously to optimize the signal strength and connectivity [171]. The authors of [174] proposed that an artificial neural network to determine the drones' location to better serve smart devices according to the predicted channel quality of dynamic environments.

Trajectory Planning at Drones Edge Intelligence: The trajectory of drones may impact their energy efficiency and the signal strength between smart devices in smart environments. FL can enable drone edge intelligence to identify suitable trajectories based on predicting the energy consumption for each trajectory. FL techniques such as deep learning may predict the energy consumption for drone edge intelligence and effectively deal with heterogeneous data [175]. In this case, blockchain technology can be used for efficient energy sharing; if the battery of one drone edge intelligence is almost depleted, the nearest one may replace it and gather data from smart environments. Furthermore, if one sensor's data is not received due to the presence of a malicious device (dirty sensor), the drone can borrow the missing data from the nearest drone using the decentralized blockchain.

Drone Edge Intelligence Deployment: In order to improve connectivity and coverage of the network, the optimal drone deployment depends on the position of smart environments devices, channel quality, signal strength, path loss, distance, etc. FL is an efficient solution to deal with heterogeneous smart devices. Then combining of multi-drone edge intelligence model can help in generating the global model. Here, blockchain can be used to verify and authenticate the generated models and distribute them to all drone edge intelligence in a decentralized way. Furthermore, in the case of drone edge intelligence used as a station above a smart device in a smart environment, hybrid deep learning techniques can help solve the collaboration between smart devices and drone edge intelligence [176].

Resource Allocation: Drone edge intelligence faces the challenge of resource allocation due to the limited frequency spectrum. The heterogeneous data gathered from the smart environment and data rate are depending on applications. ANN reinforcement learning is suitable for enabling drone edge intelligence to generate predicted models [174]. In contrast, ANN reinforcement learning helps optimize the relationship between drone edge intelligence and smart device data rates in smart environments.

Obstacles: Collaboration of multi-drone edge intelligence to perform common goals is crucial. Data routing via drone edge intelligence is required to satisfy QoS parameters (end delay and network capacity) and guarantee energy efficiency. Transmission data between the drones edge and server needs to be performed with a high-level accuracy. FL techniques can play a vital role in data transmission routing models (based on speed, direction, energy etc.) among multi-drone edge intelligence. ANN can be implemented to predict the routine performance regarding optimal routing path for each drone edge intelligence [177]. The local model is aggregated to generate a global model to control multi-drone edge intelligence with the help of a decentralized ledger.

Traffic Load: To deal with IoT device connectivity and battery lifetime challenges, the traffic load between smart IoT devices and drone edge intelligence must be considered. High traffic load of all smart devices in a smart environment leads to consuming energy and an overhead to the network. Therefore, using distributed FL can be a suitable solution for such an issue. Smart devices can make their local model by using FL techniques. At the same time, blockchain can be used to provide the decentralized network with high privacy between drone edge intelligence and smart devices in smart environments. These solutions may help reduce network overload and with a lower transmit power.

Connectivity and Accuracy: There are particular issues related to drone edge intelligence networks such as heterogeneous resource capacity, which includes data size, computing, energy, channels and etc. Therefore, new studies must be focused on efficient FL techniques that consider connectivity maintenance with ensuring high accuracy learning. For example, the trade-off between communication delays, computation, and learning accuracy.

Collaboration Among Drones Edge Intelligence Network: A single drone may not be able to offer the service adequately enough. In reality, the collaboration of numerous drones edge intelligence over smart environments is required to meet the enormous demand of a range of terrestrial consumers. Furthermore, to provide a service as a whole, numerous drone edge intelligence should be intelligently controlled. The use of multiple-agent RL for intelligent control of numerous drones is both intriguing and challenging [15].

FL Drone in B5G: B5G provides a unique communication architecture for autonomous vehicle systems to execute complex smart applications. Drones may be used as relay devices to convey communications and assist edge servers because they fly near the smart devices or the end-users. Furthermore, using FL techniques, drones may assist in processing the acquired data and sending the learned model to ground station, where all of the received models are pooled and compared for decision making. However, adopting FL integrated drone technology places additional constraints on computation, necessitating optimising drone resources based on efficient task allocation, scheduling, and various other mechanisms to reduce energy consumption and extend operation lifetime.

Storage Off-Chain: Drones trade a variety of data. Some of the data may be too huge to fit into the blockchain properly, or it may need to be modified or deleted often. To solve this issue and improve speed, off-chain blockchain storage should be made available.

Designing Framework for Energy Efficiency Analysis: The combination of FL and blockchain to design an efficient framework for energy efficiency analysis is needed to be addressed and discussed more with highlighting the benefits of the combination. Furthermore, efficient protocols are also needed for improving energy efficiency, maintaining QoS and enhancing tasks computation.

V. Conclusion

There is an increasing interest to utilize drones in various civilian applications such as disaster management, and smart cities and environment However, there still remain several challenges related to drone operations including privacy, security, energy consumption, and loss of connectivity to reach the desired energy efficiency and high QoS since the current implementation of this technology often rely on centralized data processing at the ground station. FL is known as a key technology to enable local data processing and decision making at edge devices where only the information of the local trained model is shared among the agents rather than transferring the raw data. Therefore, FL can facilitate distributed model training among multi-drone edge intelligence with the help of B5G to share updated models to obtain a global model of task performance in smart environments. However, latency, energy consumption, security, network partitioning, learning quality, and security are amongst the challenges of using FL approaches. Blockchain technology has the potential to overcome some of these issues including the risk of single point failure and other security threats that promote edge intelligence in a decentralized way. This paper provides a framework for how blockchain and FL convergence enables drone-edge intelligence for green and sustainable smart environments.

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