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Blockchain-based Federated Learning in UAVs Beyond 5G Networks: A Solution Taxonomy and Future Directions

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ABSTRACT Recently, unmanned aerial vehicles (UAVs) have gained attention due to increased use-cases in healthcare, monitoring, surveillance, and logistics operations. UAVs mainly communicate with mobile base stations, ground stations (GS), or networked peer UAVs, known as UAV swarms. UAVs communicate with GS, or UAV swarms, over wireless channels to support mission-critical operations. Communication latency, bandwidth, and precision are of prime importance in such operations. With the rise of data-driven applications, fifth-generation (5G) networks would face bottlenecks to communicate at near-real-time, at low latency and improved coverage. Thus, researchers have shifted towards network designs that incorporate beyond 5G (B5G) networks for UAV designs. However, UAVs are resource-constrained, with limited power and battery, and thus centralized cloud-centric models are not suitable. Moreover, as exchanged data is through open channels, privacy and security issues exist. Federated learning (FL) allows data to be trained on local nodes, preserving privacy and improving network communication. However, sharing of local updates is required through a trusted consensus mechanism. Thus, blockchain (BC)-based FL schemes for UAVs allow trusted exchange of FL updates among UAV swarms and GS. To date, limited research has been carried out on the integration of BC and FL in UAV management. The proposed survey addresses the gap and presents a solution taxonomy of BC-based FL in UAVs for B5G networks due to the open problem. This paper presents a reference architecture and compares its potential benefits over traditional BC-based UAV networks. Open issues and challenges are discussed, with possible future directions. Finally, we present a logistics case study of BC-based FL-oriented UAVs in 6G networks. The survey aims to aid researchers in developing potential UAV solutions with the key integrating principles over a diverse set of application verticals.

INDEX TERMS Beyond 5G networks, 6G, Blockchain, Federated Learning, Unmanned Aerial Vehicles

I. INTRODUCTION

Unmanned aerial vehicles (UAVs), or popularly drones, are aircraft without any human pilot on board and are mainly controlled and managed remotely or via embedded autonomous computer programs. UAVs came into existence in the early 1920s and were designed for military operations. Today, UAVs are preferred in different verticals like agriculture, healthcare, Internet-of-Things (IoT), military surveil-

lance, and ubiquitous network coverage with the rise in technology. UAVs have minimized human interventions and augmented the interface between humans and logistic support in challenging environmental conditions. UAVs typically consist of three distinguished components: software, hardware, and underlying communication channel. UAV software component consists of firmware, middleware, and operating system that control UAV movements and perform dynamic

decision modeling. The hardware components consist of sensors, flight controller unit (FCU), light detection and ranging (LiDAR), and radar components. The communication channel interfaces the UAV with the ground station and group of UAVs, commonly termed as UAV swarms. UAVs are categorized under five different types depending on application requirements- unmanned ground vehicles, unmanned air operations, unmanned surface vehicles, unmanned underwater vehicles, and unmanned spacecraft. A recent report from *Markets and Markets* predicted that global UAV market is expected to reach USD 58.4 billion by 2026, at a compound annual growth rate (CAGR) of 16.4% [1].

Recently, UAVs have been heavily employed for surveillance and boundary demarcations, maps, remote sensing, search and rescue operations, disaster control, and infotainment. Specific use-case UAVs are increasingly deployed in the market to support different applications. In most applications, UAVs collaborate as swarm units, controlled through a swarm controller at the ground station. UAVs communicate and share data with each peer UAVs to perform time-sensitive and computationally expensive tasks, which requires intelligence in the communication channel. The shared data between UAVs must be trained using machine learning or deep learning models, depending on the application type and the generated data. In a traditional UAV system, local data from each UAV is sent to the centralized server and then results are sent back to each UAV for training and testing purposes. However, the centralized sharing of UAV data raises privacy and security concerns. A malicious adversary can launch an informed attack on the central server to damage the communication actively, leading to catastrophic effects.

To address the privacy of user data captured by UAVs, a decentralized notion of learning is required, where the captured data can be trained locally. Recently, federated learning (FL) has been designed as a decentralized learning mechanism. The central model is shared with local nodes, and local nodes train the model with their associated data. The updated parameters are sent then sent back to the FL server. Due to its inherent benefits, FL is increasingly employed in many generic applications like google keyboard suggestions, healthcare purposes, and cellular communications [2], [3]. Once data is locally trained, it is aggregated and the FL server is responsible for computing the updated model gradient based on the sum result. The process is iterated until the end application reaches a desired level of accuracy, and the end devices (mobile nodes) also become more accurate [4]. Collected data from end-devices continuously updates the local model instead of frequently communicating data to the server, which provides advantages like balanced workload at user end-devices, provision of computing resources, significant time reduction and enhanced accuracy compared to centralized server topology. Integration of FL in a swarm of UAVs is a feasible option to solve the security and privacy issues. FIGURE 1a shows the global FL market trend which shows an increased adaptability for a variety of applications [5].

However, FL preserves privacy as it shares the model parameters instead of training data. Still, an adversary might access unauthorized information by polluting the global model through its local data. Once the fake parameters are shared, iteratively, it might pollute the training of the global model. Thus, with small-scaled adversarial learning models, an adversary can eventually form a physical or logical attack like distributed Denial-of-Service (DDOS), replay, impersonation, message injection, spoofing, malware infection, eavesdropping link, and line-of-interference attacks [7]. The adversarial poisoning attack on the data and model and the inherent assumption on the nodes to form a membership for collaborative learning are inherent limitations in FL attack categories. To secure these attacks, a notion of reliability is required to be introduced in the FL learning process that mitigates the constructive failure of global models or the privacy leakage of UAVs.

UAVs orchestrate edge services in a mobile edge computing (MEC) network and serve as an access point for important industry verticals [9], [10]. Under such circumstances, the reliability and availability of the MEC server are of prime concern. In FL, model aggregation results under the MEC server attacks result in a single point failure that greatly affects the operations and swarm maintenance. Moreover, the scalability of modern edge computing systems is limited to managing the aggregation of updated offloaded from millions of IoT-enabled UAV devices. FIGURE 1c shows security and privacy concerns in UAV communications. Blockchain (BC) is a potential solution to curb the limitations mentioned above and induce trust in FL communication. BC assures traceability, decentralization, scalability, immutability, non-reusability, enhanced security and privacy in FL-assisted UAV communication. In BC, data (or transactions) are stored as blocks linked to an immutable chain. The ledger state is communicated to all nodes in the BC network. BC eliminates the requirement of third-party security management and thus introduces trust management in UAV open channels.

The holistic integration of BC-leveraged FL-assisted UAVs ensures the utmost level of data privacy, trusted exchange, and traceable access, under continuous local updates, due to topology change with diverse UAV mobility, models, and network constraints [10]. FL implementation via BC is simplified as the requirement of a central server is eliminated, and thus single-point failures are eliminated in the system. BC allows traceability among the network entities and chronologically monitors the channel behavior, transparent to all peer UAVs. With BC-assisted FL, easy traceability of model parameter/update origin is determined through the stored logs as ledger entries. Every client updates its local model in the form of transactions aggregated as unconfirmed transactions in the mempool address. The miners verify the transactions and form blocks, append the block header, and add the FL model data on the chain. Now each authorized user can view the verified updates, and once the global model aggregates the result, it stores the updated gradient on the BC. Thus, each download by a local node is trusted, and

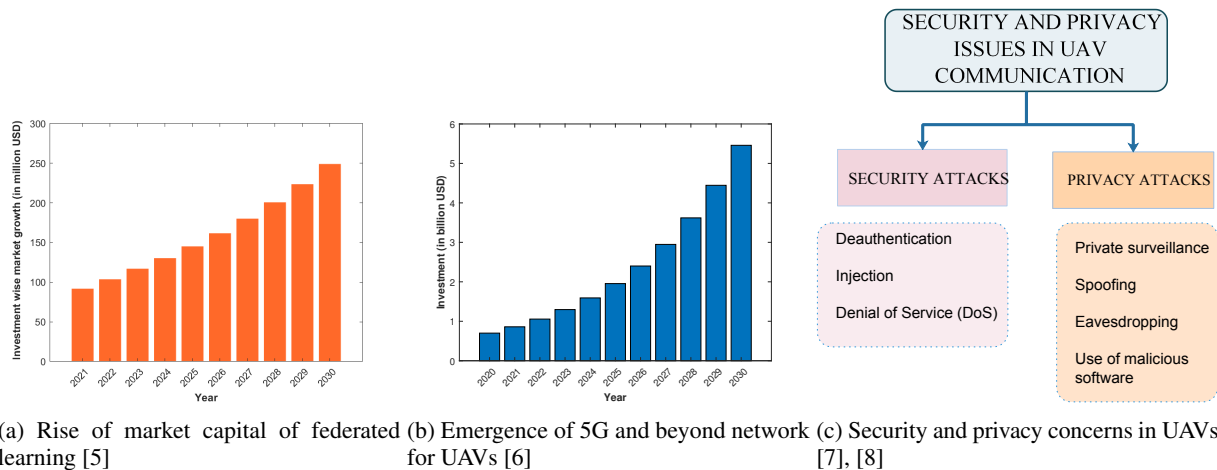


FIGURE 1: FL global market forecast, 5G/B5G emergence and UAV security and privacy issues

the user computes the new version of the global model with defined epochs. In the case of an adversary, the poisoned training updates are not verified through consensus, and thus poisoning attacks are eliminated with the help of BC.

Apart from security, another important aspect is the UAV latency. Generally, UAVs require adaptive communication at low latency to address real-time surveillance, spatial identifications, tackling war zones and critical communication to and from ground control stations (GCS). With massive connections and device-to-device communication, considerable bandwidth is required. Currently, UAVs operate over 4G-long term evolution (4G-LTE), or LTE-advanced (LTE-A) links to communicate with the GCS. For data-driven applications, the GCS-UAV communication based on 4G suffers from feed buffering and glitches, which results in higher processing and transmission delays under peak traffic conditions. Additional potential issues include inconsistent bandwidth, line-of-sight (LOS) interference, limited UAV mobility, handover management, interference between a drone user equipment and terrestrial user equipment, and intermittent disconnections, limiting UAV communication’s real-time communication network with GCS. Moreover, the geographical terrains with limited coverage from terrestrial GCS may not provide the required connectivity services to the cellular-connected UAVs.

To address the issue, researchers have shifted attention towards the fifth generation and beyond fifth-generation (5G/B5G) wireless networks, which envision higher coverage and connectivity and diverse B5G-enabled service sets. In 5G communication, to ensure real-time connectivity with GCS, tactile internet (TI) allows the capture of haptic UAV feedback at extreme low-latency ($< 1\text{ms}$). Machine type communication (mMTC) can support industrial IoT links with parallel data uploads and download setups. mMTC supports connectivity through a massive number of devices. Finally, for bandwidth and throughput support, enhanced mobile broadband (eMBB) service is present ($\approx 10\text{ Gbps}$), that allows bulk data transfers, at ultra-high relia-

bility (99.99999%) [11], [12]. Moreover, 5G offers flexible in-network services, virtualization of resources, better and swift adaptation to the difficult terrains to support UAV requirements. 5G antennas are built over massive multiple-in-multiple-out (m-MIMO) channels that allow parallel carrier aggregation, which reduces the noise outage probability of non-5G channels. However, with the rise of services like augmented reality, virtual reality, massive-IoT, space-air-underground communication, in the near future, 5G networks would be non-adaptive in terms of communication requirements. Researchers have shifted towards expanding 5G services and the B5G phase, with a shift towards sixth-generation (6G) communication networks.

6G is envisioned to support terahertz channels, AI-enabled radio communication, and intelligent wave-coding. 6G is expected to support optical wireless communication, where the desired information can be transferred over low sending and receiver antennas. This is specifically useful for underwater and space communications [13]. Moreover, the overall backhaul network is expected to support photonic communication, to support high bandwidth requirements [14]. Thus, with 6G, UAV communication would be near real-time, even in ultra-dense connection setups. It would allow flexible support to UAV swarms for accurate flight control and route information, even in intermittent connection setups. 6G enabled UAVs exploits MEC to realize optimization of the energy resource by offloading tasks at the edge of the flight control system’s network. FIGURE 1b shows the emergence of 5G and beyond the market for UAVs to assist a variety of applications like defense, aircraft, and civilian applications [6].

A. POTENTIAL BENEFITS OF B5G-ASSISTED UAVS

The major advantages of the B5G-assisted UAV system are as follows.

- 5G/B5G communication networks are supported through a higher mobile spectrum which provides wide accessibility beyond visual line of sight (BVLoS). Due

TABLE 1: Abbreviations and their meanings

Abbreviation	Meaning	Abbreviation	Meaning
1G	First Generation	IoV	Internet-of-Vehicles
3D	Three Dimensional	LDHMC	Long-Distance and High Mobility Communications
4G	Fourth Generation	LiDaR	Light Detection and Ranging
5G	Fifth Generation	LoS	Line-of-Sight
6G	Sixth Generation	LTE	Long-Term Evolution
AI	Artificial Intelligence	LTE-A	LTE-Advanced
ANN	Artificial Neural Networks	MBRLLC	Mobile Broadband Reliable Low-Latency Communications
AQI	Air Quality Index	MEC	Mobile Edge Computing
B5G	Beyond 5G networks	ML	Machine Learning
BC	Blockchain	m-MIMO	massive Multiple-In-Multiple-Out
BFL	Blockchain-based Federated Learning	mMTC	massive Machine Type Communications
BVLoS	Beyond Visual Line-of-Sight	MR	Mixed Reality
CAGR	Compounded Annual Growth Rate	mURLLC	massive Ultra-Reliable Low-Latency Communications
CNN	Convolutional Neural Networks	NFV	Network Function Virtualization
DaaS	Drone-as-a-Service	NIR	Near Infrared Measurements
DDL	Digital Distributed Ledger	PoS	Proof-of-Stake
DDoS	Distributed Denial-of-Service	PoW	Proof-of-Work
DL	Deep Learning	QoS	Quality-of-Service
DRL	Deep Reinforcement Learning	QoE	Quality-of-Experience
eMBB	enhanced Mobile Broadband	QoS	Quality-of-Service
eRLLC	enhanced Reliable Low-Latency Communications	RGB	Red Green Blue
FAA	Federal Aviation Administration	RL-ACO	Reinforcement Learning-Ant Colony Optimization
FCU	Flight Controller Unit	SC	Smart Contracts
FeMBB	Further enhanced Mobile Broadband	SDN	Software-Defined Networking
FL	Federated Learning	SGD	Stochastic Gradient Descent
GCS	Ground Control Stations	SGX	Software Guard Extension
GS	Ground Stations	TEE	Trusted Execution Environments
HCSs	Human-Centric Services	TI	Tactile Internet
IIoT	Industrial IIoT	U2X	UAV-to-Everything
IoMT	Internet-of-Military Things	UAVs	Unmanned Aerial Vehicles
IoT	Internet-of-Things	UGVs	Unmanned Ground Vehicles
		UHD/SHD	Ultra/Super High Definition

to the wide spectrum range, the 5G/B5G network improves the UAV bandwidth requirements for high data transfer from IoT sensors. Further, the physical radio is artificial intelligence (AI)-enabled, allowing channel estimation, equalization, coding, error corrections, and signal constructions based on observed data. Machine learning (ML) and deep learning (DL), based architectures are designed to be trained over-collected network data, forming an intelligent cohesion to support various applications like IoT, vehicular networks, Industry healthcare and others. With AI-driven radio, secure and reliable connectivity is enabled that provides cost-effective UAV operations for a variety of use cases [15], [16], [17]

- 5G/B5G allows greater control and management through software-defined networking (SDN) and network function virtualization (NFV) that greatly improves UAV performance in heterogeneous, dynamic, and complex networks. It decouples the data and control plane operations of UAVs and GCS, which simplifies the UAV flying control route management and the ground operations over heterogeneous links. SDN provides UAV software implementation, while NFV provides mathematical functions to serve path trajectory, UAV dynamic decision and monitoring, and scalable deployment.

With responsive communication, trusted operations is equally important. Moreover, a large amount of data is collected at local UAV nodes, and thus FL is a viable choice to induce privacy in model learning. The amalgamation of BC, FL, and B5G in UAV networks drive a responsive,

secured, and decentralized learning paradigm, satisfying end-user quality-of-service (QoS) requirements. Recently, many proposed surveys have discussed UAVs, their coalition with BC, and communication networks. In the near future, AI will predominate UAVs and communication networks. Moreover, FL has shifted researchers to exploit low-powered learning models with local data that allows user customization. Thus, in the future, it is envisioned that a holistic integration of BC, FL, and B5G/6G communication networks would play a pivotal role in driving UAV operations. To date, limited research has been carried out in a similar direction. Thus, the proposed survey addresses the gap and presents a solution taxonomy of BC-based FL in UAVs for B5G networks. We present a reference architecture and compare its potential benefits over traditional BC-based UAV networks. Table 1 shows the list of abbreviations and the associated meaning used throughout the article.

B. AMALGAMATION OF BC, FL, AND B5G IN UAVS

The motivation behind the survey is presented as follows.

- UAVs are already engaged in providing real-time applications such as healthcare, military, IoT, healthcare, etc. In these applications, the privacy of user data is of utmost concern. Thus, the inclusion of FL plays the prime motive, where we train a model locally without sharing the data from local nodes. FL thus ensures the security and privacy aspects of shared data among UAV networks or swarms.
- BC technology, on the other hand, guarantees trust between nodes through cryptography mechanisms and consensus protocols in distributed, open, and au-

TABLE 2: Potential benefits of FL integration in Industry UAV projects

Project	Year	Application scenario	Objective	Potential benefits of FL
Aerial Metrics [18]	2020	Crash Investigation	Development of collision reconstruction scenarios using UAVs	Inclusion of FL enables fast reconstruction of image without depending on third party software
Urban Drones [19]	2020	Safety of Life	Development of life-saving drones for search and rescue, supply of life-saving materials	Inclusion of FL helps in real-time decision capability to handle the exchange of information among a swarm of UAVs using reinforcement techniques
qAIRa [20]	2020	Pollution monitoring	Development of UAVs for air quality measurement and environmental monitoring	Combination of sensor and vision-based methods achieve fine-grained 3D mapping of air quality index (AQI) with low energy consumption by using UAV. Convolutional neural networks (CNN) techniques enable different agencies to collaboratively monitor AQI without sharing raw data
IdeaForge [21]	2021	Agriculture	Development of UAVs for land surveying, crop production enhancement and monitoring	FL enables fast surveying through model aggregation between two extreme hops where generated data is offloaded to local edge network built on agriculture land
Zipline [22]	2021	Healthcare delivery	Development of UAVs for medical supply delivery shipments to health facilities in various countries	FL-enabled artificial neural network models the routing and provide predictions regarding related to next hope node and provides extracts of optimal routing path between source and destination nodes

onomous environments. Thus, BC assists FL-driven UAVs to share the learning results in transactional ledgers so that model gradients, weights, and other parameters are not affected. Moreover, the global server can store the global model meta-information on BC, which subsequently can be downloaded by local nodes.

- Since UAV networks generates massive data in real-time scenarios. Therefore, there is a requirement for near-real-time communication at extremely low latency. Thus, B5G networks (or 6G) can orchestrate massive UAV communication's latency and bandwidth requirements. Moreover, it supports dense UAV connectivity, mobility, and stringent end-latency requirements. With B5G NFV, the networking functions are managed as black-boxes, which simplifies control of UAV trajectory and in-flight swarm operations. 6G network architecture is envisioned to support deep sea-air-ground communication and massive information-centric IoT networks, with customized links to cater to specific requirements.

Table 2 presents real-world industry deployments of UAV for variety of applications. The table also highlights the potential benefits of FL integration in UAV projects. With FL, UAV applications are expected to provide optimal performance, enhanced security, robust performance against link failures. Local UAV data is not required to be shared, with high connectivity among nodes at low latency.

C. KEY TAKEAWAYS

The key takeaways of the survey are highlighted as follows.

- We propose a reference architecture that fuses BC, FL, and B5G in UAV communications to support a diverse set of application endpoints like edge services, traffic prediction, vehicle parking occupancy, healthcare, remote sensing, surveillance, package delivery, virtual reality applications, and industry 4.0 production and manufacturing. BC-assisted FL-UAVs assure data privacy and adaptive service provisioning, with continuous monitoring of mobility models. B5G networks ensure upper bounds on latency constraints and enhance QoS

in UAV-UAV and UAV-GCS communications.

- A solution taxonomy of BC-assisted FL-enabled UAV networks for B5G networks is proposed based on proposed research questions we address through the survey. We connect the security, communication, and analytics at end-point UAV application perspective through assisted use-cases as examples.
- Open challenges and potential research directions of the integration are discussed, and a case-study *Mil-Drone* is presented that integrates BC-assisted FL-UAV analytics for Internet-of-Military-Things (IoMT) application. We present the case study in the backdrop of B5G communication links and discuss the reference architecture and components.

D. ORGANIZATION AND READING MAP

FIGURE 2 presents the organization and survey reading map. Section II presents an overview of various key technologies and their integration with UAV scenarios. Then, we present a systematic overview of existing UAV surveys in terms of security, communication, and AI perspective. Section III presents the review methodology adopted for the survey. Based on the research questions of the study, section IV presents an existing BC-driven UAV network and the potential limitations. Next, we present a proposed architecture of BC and FL-assisted UAVs for B5G communication networks to support secure information sharing and local learning that assures privacy in UAV application scenarios. Section V discusses the proposed solution taxonomy of FL, BC and B5G in UAV applications. Section VI presents the open issues and challenges, with potential research directions for BC-assisted FL for UAV applications in B5G networks. Section VII presents a proposed case study *Mil-Drone* to secure UAV-access scheme for IoMT operations. Finally, section VIII concludes the article.

II. BACKGROUND AND STATE-OF-THE-ART

In this section, we present the details of the evaluation timeline, basics of FL training, B5G networks, BC-assisted UAV communication, and benefits of FL-UAV communication.

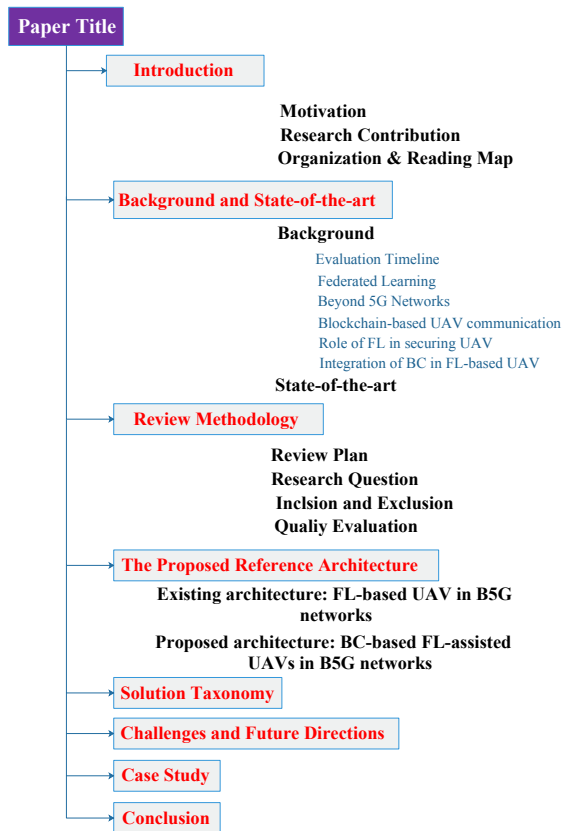


FIGURE 2: Survey and Reading Map

The details are presented as follows.

A. BACKGROUND

This section presents the background of various technologies adopted for our research. The section is divided into four subsections. The first subsection discusses the timeline of important events related to the early stages of UAV technology and subsequent adoption of wireless network generation, from first-generation (1G) towards B5G/6G deployments. The second and third subsection discuss the basics of FL, features of B5G/6G and its potential vision to support a variety of UAV applications. The fourth and fifth subsection discuss the applicability of BC and FL respectively to support UAV communications in terms of privacy and security aspects. Finally, the sixth subsection explores the integration of UAV applications. The section, therefore, addresses RQ 1 and RQ 2 put ahead in the review methodology. We address research question RQ 1 through introduction and applicability of FL to address security aspects for various UAV user-centric applications and research question RQ 2 through detailed discussion of the integration of BC in FL-enabled UAV in beyond 5G networks.

1) Evaluation Timeline

FIGURE 3 presents the timeline of important events related to the early stages of UAV to subsequent interface with FL and BC. The timeline also depicts the shift from 5G wireless networks towards 6G deployments by 2030.

Historically, UAV applications started as early as 1917 during World War I as pilot-less vehicles called *Aerial Target*. In 1918, America flew the first air torpedo called as *Kettering Bug*. Since then, a flock of drones has been developed for various military applications like war, surveillance and reconnaissance [23]. In 2006, the federal aviation administration (FAA) deployed the fleet of commercial UAVs in the air for search, rescue, and disaster relief operations. In early 2000, 3G networks were proposed to support a line transfer rate of 144 Kbps. The later version of the 3G release, often depicted as 3.5G, and 3.75 G, shifted from Kbps to Mbps to support broadband access in smartphones. Standards like internet access, video calling, and mobile TV were developed. At the same time, cryptocurrencies gained attention, and in 2008, Satoshi Nakamoto proposed Bitcoin cryptocurrency as a decentralized ledger often denoted as Blockchain 1.0 specification. Later, in Blockchain 2.0, smart contracts (SCs) were designed to automate payment flows among ledgers between transacting peers through defined rules and specifications of contract setups. SCs were unalterable and are Turing complete.

In 2016, Google coined the term FL as a DL framework for integration that allowed effective model designs over local data, assured enhanced security, and provided impetus over centralized counterparts, like cloud analytics. Blockchain 3.0 emerged with the design of various decentralized applications and the adoption of BC to different sectors like healthcare, finance, Internet-of-Drones, and many others. At this time, the shift towards Industry 4.0 enabled sensor-driven communication, and thus big-data applications gained attention. With massive data generation and ingestion, security and privacy requirements became paramount. In 2019, FL use-cases were designed for UAV communication, and with the release of 5G new-radio (NR) standards, the vision of massive IoT became a reality. 5G drove a range of verticals ranging from smart health, vehicular networks, and industry. With MEC support, edge-based communication services are designed, with SDN/NFV to support the networking management. 5G also witnessed the rise of responsive internet, with haptic enabled feedback through tactile internet (TI). Recently, non-orthogonal multiple access (NOMA) schemes for 5G networks were proposed, owing to their ability to serve many users simultaneously and frequency division. Two primary techniques in 5G-NOMA were discussed, power-domain (PD-NOMA) and code-domain (CD-NOMA). NOMA exploited the superposition coding at the sender transmitter, with successive interference cancellation at the receiver-transmitter to support multiplexing in the power domain.

In the future, edge-AI adaption to UAV communication is

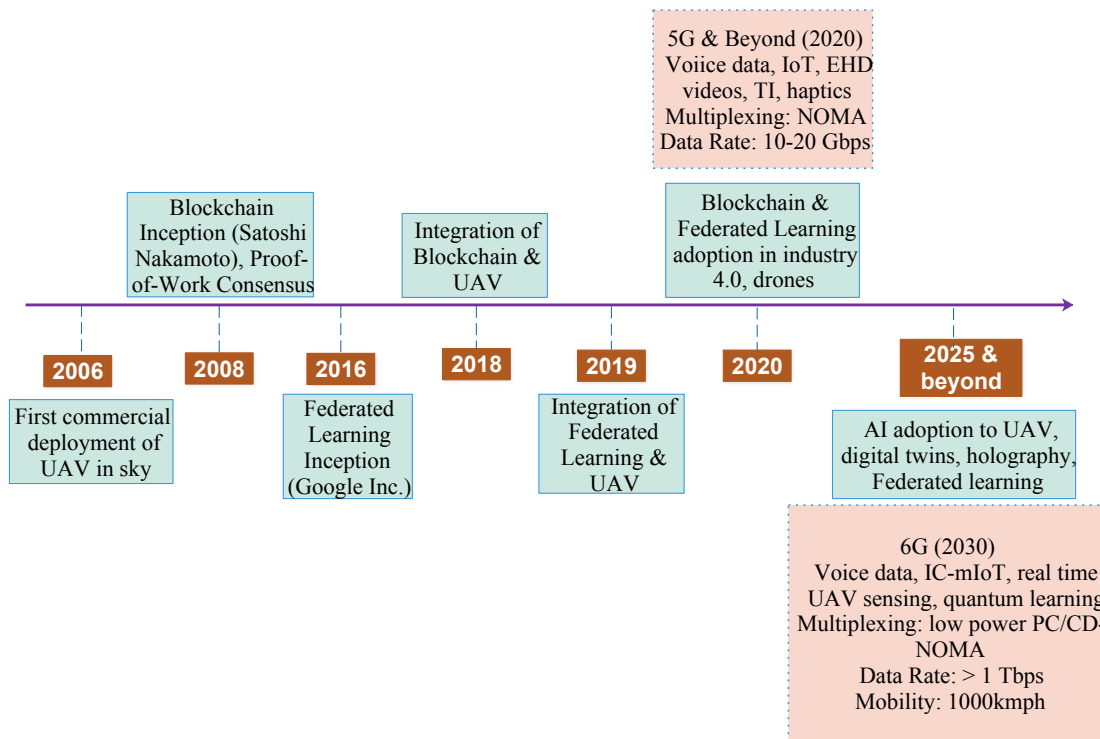


FIGURE 3: A holistic timeline of key technical drivers

expected [24]. Also, with rising developments in augmented reality (AR), and virtual reality (VR) applications, interesting use-cases are infused that combines BC and B5G networks for AR/VR [25]. By 2030, 6G networks are expected to support massive information-centric IoT (IC-mIoT) applications, with high UAV mobility of 1000 kmph. Also, industry 4.0 would shift towards massive personalization and hyper customization, which would pave the way towards Industry 5.0. Industry 5.0 is expected to support B5G network communication, massive data transfer, cohesive robots, digital twins, and FL for local data analytics.

2) Federated Learning

The concept of FL was introduced by Google [26], [27] as a decentralized approach against traditional ML/DL-based cloud models. FL has distributed ML that assists model training on massively distributed decentralized data. In FL, mobile and wireless nodes train the local DL/ML models collaboratively. The local parameter updates, i.e., weights, neurons, and gradients, are aggregated and communicated to a global cloud-assisted server in a secured and encrypted manner. The aggregation step assures the privacy of the original data at the source and improves latency bottlenecks at the central server. Thus, FL is an optimal choice for resource-

constrained networks as huge data requirements and bulky DL models are not required. Rather, tiny models at edge nodes design their models on local data. This assures that sensitive data attributes are preserved and fine-tuning of model parameters is customized according to local requirements. The end-to-end FL process is interpreted via the stochastic gradient descent (SGD) algorithm, whose expression is presented as follows.

$$W_{i+1} = W_i - \alpha \frac{\partial F(z)}{\partial W} \quad (1)$$

where α is the learning rate, or step size of gradient descent at iteration i and $\partial F(z)/\partial W$ is the partial derivative of loss function $F(z)$ with respect to weight W .

In addition to the above, FL improves the network overhead by avoiding data transmission to a central authority, thereby minimizing energy and bandwidth consumption. FL also enables wireless devices to collaboratively and parallelly learn the shared prediction model while restoring device privacy. The above aspect makes FL an enabling technology for the next UAVs-based wireless networks to train learning models compared to centralized cloud-centric approaches. There are different types of FL-enabled architecture for UAV, viz. collaborative FL, multi-hop FL, fog learning and scheduling-based FL.

3) Beyond 5G networks

Emerging applications such as telemedicine, mixed and extended reality (MR/XR), real-time haptic communication, vehicle-to-everything (V2X) mobility, platooning, cooperative control, and UAV surveillance are readily deployed in smart cities. To assure QoS to diverse requirements of these links requires massive data uplink rate, massive dense connection setups, extremely high data rates, extreme precision, and ultra-high reliability to support mission-critical cyberspace applications. Current 5G networks are limited in coverage/mobility and uplink performance during Non-Line-of-Sight (NLoS) conditions and thus fail to provide real-time quality of experience (QoE) to end-users.

Beyond fifth-generation (5G) networks, with a shift towards 6G, is the successor to 5G cellular communication systems. 6G network promises a shift to a higher frequency range (millimeter or terahertz) and provides substantially higher capacity at low latency. 6G networks are human-centric and integrate users, processes, mobile devices and networks, service management for several applications. 6G technology enables edge intelligence through ML, DL, and FL models. 6G supports 1 Tbps user data rate, round-trip latency of < 0.1 ms, and introduces new services like extremely reliable low latency communications (eRLLC), with a reliability rate of 99.9999999%, mobile broadband reliable low-latency communication (MBRLLC), massive ultra-reliable low-latency communication (mURLLC) and human-centric services (HCSs) [9], [28].

6G communication supports dense connectivity, AI-enabled massive coverage, high device-to-connectivity ratio [29], at low power networking nodes. 6G networks are expected to support massive traffic through decentralized solutions and advanced networking mechanisms [30]. 6G-based SDN/NFV functionality automates the optimization process by operating services in the virtualized container. 6G finds a variety of UAV-enabled applications such as surveillance, military, agriculture and farming systems, medical services, surveying, and many others.

4) Blockchain-based UAV communication

Blockchain (BC), or decentralized ledger, stores records timestamped, chronological, and immutable. BC is a key enabler for secured and trusted UAV communication in 5G networks. BC provides various advantages to the UAV networks such as adaptability, scalability, immutability, transparency, fast and efficiency, and delivery services with privacy and security [31], [32]. 5G-enabled UAV-UAV communication via GCS satellites is secured against potential adversarial attacks, as shared ledgers are non-alterable. The digital distributed ledger (DDL) characteristics assure the truthfulness of stored information and provide secure one-to-one and broadcast facilities in the UAV network. The other BC characteristics, such as chronology, consensus and auditability, enable control, coordination, integrity, trust in UAV swarm formation, as well as the exchange of cryptographically cached secured data from air to ground sensor networks

[33]. By creating a common communication channel, BC enables UAVs to request other UAVs in emergency cases, extreme cases of low battery, system faults, and other sensor malfunctions. BC also enables storage of complex computations UAV synchronization, where ledger information can be downloaded by UAV in an offline manner to optimize processing time and optimize the power management functionalities [34].

5) Role of FL in securing UAVs

UAVs have limited resources and power to communicate and share data. Traditional DL-based approaches require high storage power to exchange UAV data to centralized servers, which are not feasible for low-powered environments. At centralized servers, UAV communication requires high consumption of network bandwidth energy. Thus UAVs have a shorter network lifetime. Additionally, data sent to central cloud servers are susceptible to leakage attacks, impersonation, and identity exchange of UAVs. Thus the users' sensitive data is at high risk once they are trained on central servers.

FL enables distributed ML mechanism for UAV swarms without sending any raw data to the centralized servers, or GCS, where the global models are designed to train on collective data. Inclusion of FL-UAV learning thus assures privacy and supports operations such as air quality index (AQI) monitoring, target recognition, joint power allocation, and others efficiently and responsively. FL-UAVs follow the training process in three steps: initialization, models training, and global model aggregation. Due to its privacy-preserving nature, low communication overheads, and low latency. Applications of FL in UAV networks include altitude and mobility information optimization for air-to-ground communication, determination of energy consumption during UAV path prediction, intelligent deployment as base stations, assignment of resource blocks to UAVs as per user requirements, minimization of power requirements in cooperative flying ad-hoc networks, customization of edge enabled massive UAV-IoT networks, and intelligent caching at edge networks [35].

6) Integration of BC-based FL in UAVs

Once data from local models are trained, the parameter updates, weights, and model information is communicated back to central servers. In such cases, continuous iterations are required to update and minimize the losses at the global model. However, the global models are based on a centralized approach. They rely on central cloud servers for continuous updates from aggregators to finalize the parameters for the global model. The scheme has an inherent limitation, as the centralized global model is susceptible to single-point failure, unreliable links, eavesdropping, and leakage of sensitive data. In terms of resources, central models require high power to accumulate all the updates, and thus power management is a critical concern at the global server. There are high possibilities of failures of heterogeneous radio links between UAV-UAV and UAV-GCS communication on the networking

front. The gradient updates might reveal information about the training data of any particular participant, and thus a malicious attacker might identify the model weights from the uploaded gradients. This is possible due to the closed-loop exchanges (locally trained model update followed by a globally aggregated model update), and the communication delay is significantly large to complete the entire global FL training. This poses a critical limitation in real-time communication during emergencies and essential operations of warfare. In UAV scenarios, various algorithms such as secure multiparty communication, differential privacy, and homomorphic encryption have been applied; however, they are limited in providing concrete convergence to the FL model due to scattered geographical locations of UAV and become prone to malicious attacks [36]. Also, with the increase in the number of UAVs, collaborative learning for authentication across multiple domains becomes stringent.

To address the limitations, BC-based FL-UAV communication works without any central global server and stores data in the form of a list of linked blocks using the cryptographic hash of the previous block. BC enabled FL leverages secure model exchange in the presence of malicious UAVs. Participating miners share and validate all their local updates based on the consensus and miner updates. Via SCs, peer UAVs are identified and only authorized UAVs can participate in the FL communication process. Only authenticated UAVs identified through ledgers communicate and accept gradient updates for further aggregation based on authorized UAVs. Every peer UAV that participates in the FL process trains an initial model using its local dataset and provides the local updates to its associated committee node for validation. Once the committee nodes reach a consensus, the global model is stored in the current distributed ledger of the BC and synchronized with the ledger. During the latest round of training conduction, the participating UAVs obtain the latest global update from their associated committee nodes. The process is iterated until the final convergence is attained.

B. STATE-OF-THE-ART

This subsection presents the discussion on the existing surveys that have discussed the key principles of integration of 5G/B5G networks and BC as a potential benefit to FL-enabled communication to address latency, privacy, security, and trust issues in the wireless UAV ecosystem. Table 3 presents the comparison of existing state-of-the-art surveys with the proposed solution. Qu *et al.* [43] proposes *DFL-UN*, a novel decentralized architecture that enables FL within UAV networks without involving central entity. They have conducted a simulation study and validated the end-to-end performance through parameters like cross-entropy loss and overall training latency, which significantly improve the proposed architecture. Finally, they discussed the potential issues and research directions of the proposed scheme *DFL-UN*. Li *et al.* [44] proposes a systematic study on the discussion of privacy and security in the field of BC-based FL methodologies. The authors have discussed the integration of

BC with FL in various human-centric applications about IoT and smart environments. The experimental results address the gaps and new challenges to evaluate lightweight BC methodologies. The research bifurcates BC and FL-enabled applications into horizontal and vertical FL mechanisms. Authors in [45] propose blockchain-based federated learning (BFL) design for autonomous vehicular networking. The method implements a private and efficient setup for on-vehicle local updates exchange decentralized fashion through a mathematical model for end-to-end delay analysis at the system level through a joint consideration of communication latency and consensus delay. Authors in [46] present a systematic survey for BC application in FL for distributed ML paradigms. They discuss *BCFL* and its integration for existing FL-enabled applications and its feasibility in various industry verticals, including Internet-of-Vehicles (IoV), 5G/6G communication, computing mechanisms, and provides a survey of BC for training nodes in various incentive mechanism. Authors in [35] discussed FL in UAV communication networks to improve communication overhead, data privacy, and data security aspects in UAV-based wireless networks. The authors have mentioned various use cases of FL like 5G and beyond, IoT, edge computing, and discussed open issues and future research direction of FL. Authors in [47] propose a collaborative ML approach for UAV-based service providers such as Drone-as-a-Service (DaaS) that assists in several UAV-oriented applications. They propose a multi-dimensional contract-matching-based incentive mechanism and derive an optimal UAV placement in specified sub-region considering aspects like sensing, computation, and transmission modeling in the IoV paradigm. Pham *et al.* [42] proposes an efficient algorithm *UAV-SFL* for wireless power transfer for sustainable FL-enabled UAV networks based on transmission time, bandwidth allocation, power, and UAV placement. The model successfully implements green revolution for transmission power reduction by approximately 78% compared to existing benchmarks. Mehta *et al.* [38] presents a survey on the architecture, requirements, and use cases for BC-envisioned security solutions and 6G-enabled wireless connectivity in UAV communication. The authors also present a solution taxonomy for various UAV-enabled applications in 6G wireless communication infrastructure and finally present a use case involving blockchain and 6G for Industry 4.0 application. Li *et al.* [15] presents comprehensive survey on UAV communication toward 5G/B5G networks. The authors restrict various 5G techniques on UAV networks based on different physical domains and finally discuss open issues and possible future trends in UAV communication based on the latest development.

On similar lines, authors in [48] discuss UAV placement in 5G and beyond networks. They have presented three use cases and corresponding state-of-the-art UAVs in wireless communication. Research also focuses on UAV 3D placement and resource allocation problems in the 5G/B5G wireless network and its state-of-art work. Authors in [49] propose UAV-assisted FL where owners utilize UAV for

TABLE 3: Comparative analysis of the proposed survey with existing state-of-the-art surveys

Author	Year	Objective	1	2	3	4	Pros	Cons
Zeng <i>et al.</i> [37]	2019	The survey presents an overview of recent advances in UAV communications using UAVs and 5G and beyond networks	Y	Y	N	N	Emphasis is on the integration of UAV with 5G through applications in UAV-assisted wireless communication, and cellular-connected UAVs	Different aspects of UAV applications are discussed, but their challenges and issues are not presented
Mehta <i>et al.</i> [38]	2020	The paper presents a broad overview of the architecture of BC enabled UAV communication using 6G network and its use cases	Y	Y	N	Y	Precise outlook on the usage of 6G and UAV integration for space, air, and ground-based networks along with a discussion of solution taxonomy	Implementation and empirical analysis of the presented case study is not provided
Zeng <i>et al.</i> [39]	2020	The paper implements FL based technique for joint power allocation and scheduling in UAV networks	Y	N	Y	N	Proposes novel framework to enable FL within a swarm of wireless-connected UAVs using convergence analysis	The framework assumes trusted UAVs in the network
Gupta <i>et al.</i> [40]	2021	The paper presents a systematic survey on BC-envisioned software-defined UAV for efficient network management	Y	N	N	Y	Describes the proposed BC-based architecture for UAV using various software technologies as well as future challenges	Implementation and analysis of UAV under multi-hop collaboration is not explored
Wu <i>et al.</i> [41]	2021	The paper presents a comprehensive overview of the latest research on 5G and beyond cellular network integration with UAVs to enable the cost-effective solution to ground users	Y	Y	N	N	Explores solution to UAV and cellular verticals by exploiting high altitude and three dimensional (3D) movement of UAV along with advanced wireless technologies	Does not explore security aspects and latency for mobile edge computing for offloading heavy tasks
Li <i>et al.</i> [15]	2021	The paper provides a comprehensive survey on UAV communication toward 5G/B5G wireless networks	Y	Y	N	N	Discusses next generation space-air-ground UAV enabled communication exploring 5G techniques along with possible identification of future trends for UAV communications	Security and latency perspective for UAV-GCS communication is not explored
Pham <i>et al.</i> [42]	2021	The paper discusses the concepts of sustainable FL for wireless power transfer in UAV networks	Y	N	Y	N	Jointly optimizes time, power and bandwidth for increased UAV transmit power efficiency	Variety of UAV applications are discussed for energy-efficient FL scheme but their challenges and issues are not presented
Aloqaily <i>et al.</i> [10]	2021	The paper proposed FL and BC-enabled solution for UAVs and unmanned ground vehicles (UGVs)	Y	N	Y	Y	Proposed solution cooperatively ensures power availability to UAVs for efficient end-to-end device connectivity	Does not explore 5G/6G communication at edge of the network
Proposed	2022	The paper proposed integration of blockchain and B5G in FL-enabled wireless UAV networks	Y	Y	Y	Y	Reference architecture of the possible integration is presented, along with a discussion of open issues and future directions. The integration of BC in FL-assisted B5G/6G is supported through a proposed case study	-

1-UAVs, 2-5G/6G, 3-FL, 4-BC, Y-shows parameter is considered, N-shows parameter is not considered.

intermediate model aggregation and relay the parameters to the data owners. They also propose a contract-based incentive approach for UAV authentication and improve the overall communication efficiency. Zhang *et al.* [50] studies key techniques of UAV-to-Everything (U2X) and propose a network that enables UAVs to jointly optimize the communication modes with full dimension as per sensing requirement. The authors also discussed the reinforcement learning model for performance estimation of the proposed framework and finally discussed a potential solution to the open problems of U2X communication. Authors in [51] provide state-of-the-art applications of FL in B5G/6G wireless technologies based on performance metrics, highlight the FL operational challenges, and provide solutions to important networking areas such as cellular, IoV, UAV, re-configurable intelligent surfaces, and IoT, etc.

C. SURVEY GAP

Existing surveys to date have underlined key technologies, protocols, and implementations related to 5G/B5G & federated learning in massive UAV communication developed for healthcare, military and other industry verticals. However, holistic integration of B5G and BC in FL-enabled UAV wireless networks is not unitedly visioned. Thus, a protocol

reference architecture is required to inscribe the end-to-end solution from communication and security-based architecture layers. The proposed survey fills the open research gap by integrating B5G and BC in FL-based UAV ecosystems to serve massive UAVs for healthcare, industry 4.0, render real-time analytics, responsive communication, and connection bandwidth through a secure and private network in open channels. In the survey, we accord key principles, reference layered architecture, and a possible discussion of an integrated solution supported and validated through a case study.

III. REVIEW METHODOLOGY

This section discusses the systematic review methodology and the same is formulated as per the review regulations proposed by Kitchenham *et al.* [52], [53]. The review is bifurcated into five logical steps as explained below.

A. REVIEW PLAN

The review paper explores and outlines the survey systematically. The key contents of the literature are (i) identification of the research questions, (ii) identification of probable source of data, publications and studies (iii) search criteria on

TABLE 4: Research questions to support the proposed study

Q. No.	Research Question	Objective
RQ 1	What is the importance of FL and how it helps in enhancing security aspects for UAVs?	To explore the key features of FL to improve security and privacy in UAVs.
RQ 2	What are the decentralized characteristics of BC that would help in its integration with FL-assisted UAVs in B5G networks?	To explore BC and its features in UAVs to improve security and privacy.
RQ 3	What are the visions and applications of B5G/6G to provide network orchestration in UAV?	To discuss B5G key principles, features, and underlying protocols in employing highly reliable and fast end-to-end application for UAVs.
RQ 4	What are the challenges for BC adoption in FL-assisted UAV applications in B5G/6G networks?	To get the insight of FL and BC technologies and major challenges associated with adopting for various UAV applications.
RQ 5	What are the challenges of FL and BC for end-to-end delivery of UAV-based applications in B5G networks?	To help in understanding various open research questions and challenges in adopting FL and BC and the impact of the efficiency of the communication network in employing UAVs for data/traffic management, detection, and intelligence scenarios with required reliability.
RQ 6	What are the key benefits of BC and FL in the UAV B5G scenario?	To present a use-case scenario that conceptualizes the integration of BC and FL in B5G networks.

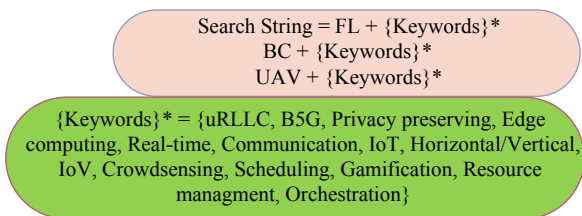


FIGURE 4: Search Strings

collected data, (iv) applicability of inclusion and exclusion criteria, and (v) quality assessment.

B. RESEARCH QUESTIONS

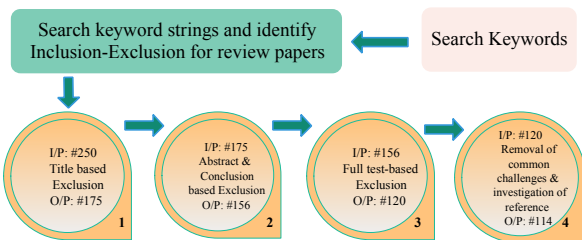


FIGURE 5: Inclusion and exclusion criteria

We provide an overview of BC and FL applications in UAV networks. We also highlighted the potential benefits of B5G/6G communication in UAVs to ensure seamless interaction and quality of experience. Table 4 identifies and sets down a few research questions along with their objectives to support the survey carried out.

C. DATA SOURCES

We have identified digital data sources like IEEEExplore, Springer, Wiley, ACM, Science Direct, Elsevier, SPIE Digital Library, and many more. They provide vast and diversified literature that helps to carry out a proposed survey. The work explained by Kitchenham *et al.* [52], [53] also strongly recommends utilization of various electronic sources such as

articles, technical reports, blogs, books, patent contributions to implement the exhaustive survey in the field of interest.

D. SEARCH CRITERIA

We have searched and considered various papers related to BC, FL and its use case in UAV applications and integration of the above technologies in UAV for B5G/6G networks. FIGURE 4 defines the keywords and search strings utilized for a search of relevant topics and papers. The search is progressed through the inclusion of online articles as well as references cited in the collected papers.

E. INCLUSION AND EXCLUSION

The process is initiated by filtering the papers according to the topic's relevance. Initially, we examined the academic repositories for the papers concerning the search strings that combined FL and UAVs. Afterward, we searched the papers with keywords FL in B5G networks, FL and UAVs in B5G networks. Finally, we searched the papers with keywords BC with FL networks BC with UAV-FL in B5G. We also utilized OR keywords to enhance our academic database. We also gathered papers centering keywords like edge intelligence in FL, BC, and FL in UAV, UAV for B5G/6G, and B5G service names like uRLLC in UAV, eMBB in B5G, and others. Then, we excluded the papers that were not of potential interest for our survey article. FIGURE 5 depicts the inclusion and exclusion criteria for proposed survey.

F. QUALITY EVALUATION

We have evaluated on the reference literature quality as per standard guidelines issued by Database of Abstracts of Reviews of Effects (DARE) and Center for Reviews and Dissemination (CRD) [52]. The reference literature surfaces the required quality assessments.

IV. EXISTING AND PROPOSED REFERENCE ARCHITECTURE OF B5G-ASSISTED UAVS

This section initially presents the existing architecture that presents a centralized cloud-based model learning for UAVs underlying B5G networks. We highlight the potential limitations of cloud-based central learning and justify the shift towards FL learning. We present a holistic UAV coverage over

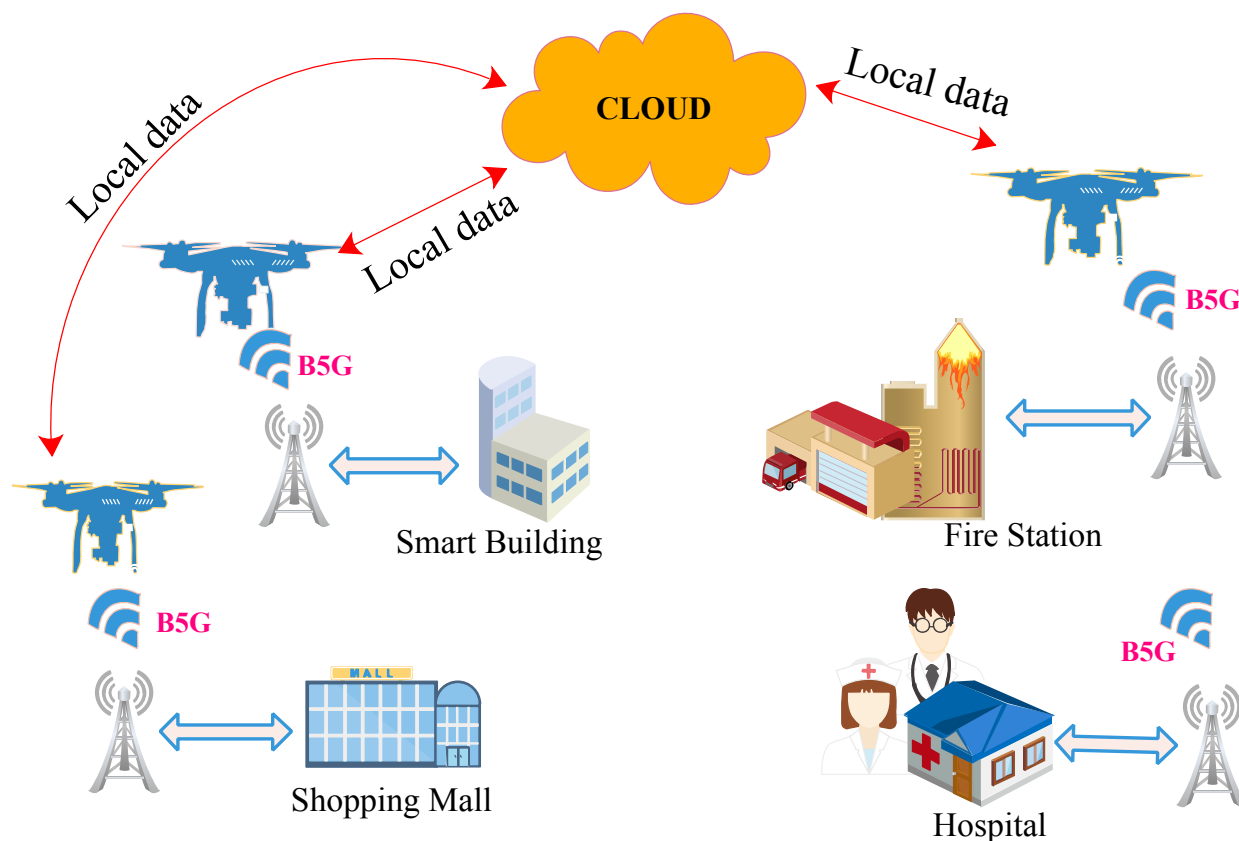


FIGURE 6: Existing MEC-enabled centralized cloud architecture of UAV underlying B5G networks

different smart city use-cases like smart hospitals, buildings, shopping centers, emergency control, and many others in both the architectures. Finally, we discuss the role of B5G/6G communication to support end-to-end network management issues in these applications. Thus, the section addresses RQ 3 and RQ 4, presenting the potential benefits of B5G and BC integration through an architectural overview in the UAV ecosystem.

A. EXISTING ARCHITECTURE: CENTRALIZED MEC-ASSISTED UAV IN B5G NETWORKS

A UAV swarm network is deployed to provide various services such as smart sensor-based networks, autonomous vehicles, emergency services, healthcare. These applications are served by peer UAV or IoT-assisted UAV architecture. UAV swarms communicate to GCS and exchange a large amount of data. To allow for real-time communication and support, the B5G network is utilized between UAV and GCS to allow flexibility, high precision, accurate LOS, flexible in-network services, and virtualization of resources. In some techniques, the UAV swarm controller communicates with peer UAVs in its range and is supported through edge-offloading to

satisfy massive user requests. Due to computation ability and battery capacity limitation, UAV swarms cannot perform resource-intensive tasks and have limited memory to carry out operations. Thus, we require a cloud-based centralized GCS server to store the humongous data. GCS server allows computationally intensive tasks but is limited with high-end user latency of processing data. To avoid this limitation, MEC platforms are designed that computationally offloads tasks are closer to the UAV node, so latency constraints are achieved. Moreover, MEC nodes support content caching and control, and requests are forwarded to cloud servers only if the data is not present at MEC servers. MEC servers support the UAV task offloading process, where large task sets are broken into smaller segments for processing at MEC. The results are scheduled and sent back to UAVs.

MEC servers employ edge-intelligence models to monitor data and task requests and offload similar content from cloud servers, to maximize the servicing of UAV requests. MEC addresses the backhaul latency issues, as it minimizes the transmission latency [54]. FIGURE 6 shows the centralized MEC-enabled architecture for existing UAV application scenario. A local controller collects information about the states

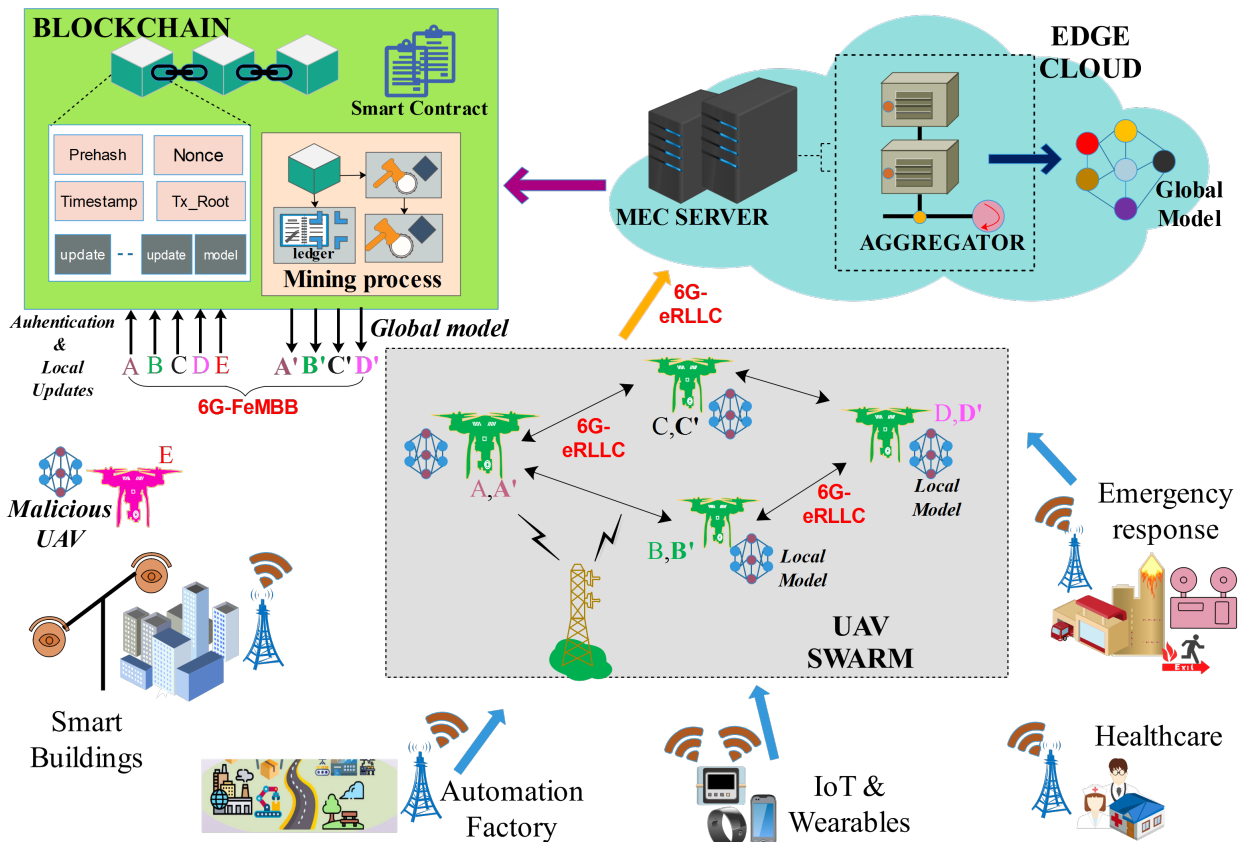


FIGURE 7: Proposed reference architecture of BC-based FL-assisted UAVs underlying 6G networks

of existing entities (smart users, UAV, server) and offloads various activities such as task computation, energy management, path planning, UAV coordinates, current ephemeris, resource management, and other related data to the MEC-enabled cloud server. The accumulated data at the MEC server is analyzed, processed, and trained through various AI techniques such as deep reinforcement learning (DRL), supervised/unsupervised ML, artificial neural network (ANN), genetic algorithm, and reinforcement learning-ant colony optimization (RL-ACO) for efficient decision making, and results are offloaded back to users upon fulfillment of the task's execution. Thus, edge-AI-enabled MEC allows joint optimization and constraint satisfaction regarding delays, energy consumption, and traffic prediction of UAV swarms.

B. THE PROPOSED REFERENCE ARCHITECTURE: BC-BASED FL-ASSISTED UAVS IN 6G NETWORKS

In this subsection, we present a BC-based proposed reference architecture supported via an FL-assisted UAV ecosystem at the backdrop of 6G communications. the proposed architecture caters for the requirements of diverse applications like smart vehicles, emergency disaster management and security,

massive IoT and industrial IoT, healthcare, building, automation and many more. FIGURE 7 presents the schematics of the proposed architecture design.

In the proposed architecture, we envision two types of UAVs, normal UAVs and malicious UAVs. The malicious UAVs exhibit byzantine behavior where they propose false updates to peer UAVs to sabotage the entire swarm operation. We consider that the global server is MEC-assisted to address the computational constraints of UAVs. The global server powers 6G-driven FeMBB links to address the bandwidth requirements of massive data. It also features a powerful centralized server structure for exchange and offload processing and collected trained data from remote UAV nodes. We apply ML/DL algorithms for analytics at the global server, and trained model parameters are communicated to local UAV nodes. However, this communication raises a security concern where a malicious UAV can launch an informed attack, and data leakage and impersonation attacks are possible. Further, central MEC-global servers can be flooded with many bogus synchronized (SYN) requests by bot servers, which results in DDoS attacks. This is critical as healthcare and military operation data is highly confidential, and thus

sharing and storage of data on central servers involve high risk.

Thus, in the proposed scheme, we deploy an FL-based solution where all local participants jointly build a global mathematical model iteratively without revealing the underlying data or encryption algorithms. However, FL-based learning has inherent limitations, such as a lack of reward mechanism for participating entities in the FL network, data/model poisoning attacks, and trust among heterogeneous nodes. Thus, BC-based ledger management augments and builds a secured and trusted FL learning paradigm and protects the global model's integrity against single-point failures.

In the proposed architecture, we envision a massive framework where a large amount of data is exchanged between users through a swarm of UAVs controlled by GCS and mobilized through an array of a 6G-based network of land, airspace and massive wireless TI networks. 6G employs edge intelligence and ML/DL algorithms over the UAV traffic and forms the radio communication parameters. To leverage the supportive performance of a cellular-connected UAV network in a 6G environment, it is critical to provide low latency, trusted content-caching and supportive softwarization. As earlier stated, ML/DL algorithms require high resources and are not effective for UAV networks. In our proposed scheme, we envision MEC-assisted FL-UAVs, SDN-controlled for network management and orchestrate computing resources through the SDN control plane. This improves the link quality, UAV swarm topology formation, and joint task allocation to MEC servers. Through assisted edge-AI, multiple users send the task requests to MEC servers. The servers employ task classification models, and FL-networks form task prediction and send the learning parameters back to local UAV nodes.

To exploit the same, MEC selects a set of worker UAV M and delivers the global model to selected UAV m . FL process enables iterative training of global model \mathbf{w}_g with local data $D_{m \in M}$ and sends the model updates \mathbf{w}_m to the aggregator. The process is repeated until the trained model/learning result is delivered to the user in a specific UAV-enabled application. Equation (2) and equation (3) shows the relation between local and global model optimized through a loss function \mathcal{F} . FL reduces the computation complexity and transmission overhead in 6G networks and enhances privacy and security.

$$\mathbf{w}_m^* = \arg \min \mathcal{F}(\mathbf{w}_m), \quad m \in M \quad (2)$$

$$\mathbf{w}_g = \frac{1}{\sum_{m \in M} |D_m|} \sum_{m=1}^M |D_m| \mathbf{w}_m \quad (3)$$

To assure trust in FL-model learning and MEC operations during the model aggregation phase, we propose BC-ledgers to store the global parameters and local updates from participants. A possible real-world use-case scenario is presented to highlight the requirement of BC-assisted FL-learning. Consider a compromised local participant (malicious UAV) that sends forged or incorrect learning parameters to nearby UAVs in the swarm network. Trust in the FL ecosystem is

considered two-way; the local participants trust the global MEC server model for training. The global model trusts the local UAV participants to update its global model based on local inputs collaboratively. However, in real-world scenarios, any party might be malicious and may send fake model parameters/training results to each other. Thus, BC-based FL-aggregation and model update is a viable choice to assure a trusted and reliable ecosystem. We have considered that local updates are captured, aggregated, and verified through a BC-assisted transactional ledger in the proposed system. This allows immutability and traceability in operation sets and mitigate the false attack vectors. Similarly, the global model computes the pre-trained model results and stores them in BC as the transactional ledger. As miner nodes verify and broadcast the on-chain ledger to all UAV nodes, malicious UAV nodes or malicious FL-server fake updates are easily captured and eliminated from participating in the data sharing process. The user/device that receives the block containing the verified updates iteratively computes the updated learning rate for the global model, and eventually, the desired accuracy is achieved. SC transactions enable end-to-end implementation of cross-domain authentication as well as updation of model aggregation. To maintain the integrity and confidentiality of captured data, permissioned BC is preferred for secured and trusted UAV communication, owing to its customized consensus that fits the application requirements. Moreover, to address the scalability issue of BC-storage overheads, the data can be stored in off-chain ledgers like interplanetary file systems (IPFS). The content meta hash is stored only in the on-chain BC storage. This maximizes the overall throughput and latency of the ecosystem.

To enhance the effective utilization of computing resources, UAV incorporates optimal caching to store local models from different users/devices and develop own learning through collaboration in a UAV swarm and provide recommendations. The underlying 6G network significantly increases UAV-to-UAV network transmission speed BC transaction processing speed and ensures decentralization. It enables edge content caching, as whenever the content is present, the 6G-eRLLC service enables transmission of model parameters for user/device and UAVs. Moreover, the former handles UAVs' dynamic behavior and high mobility through adaptive learning of handover decisions using deep reinforcement learning (DRL) models.

V. SOLUTION TAXONOMY

Conventional machine learning approaches rely on the central entity where received data for training and testing, query processing is not always feasible to be shared over open wireless communication channels. Due to the security and privacy concerns and large communication overheads, the data exchange to the central server is not an optimal choice. FL is a decentralized ML approach that allows us to keep the data from where it is generated and maintain the privacy of the data by only sharing the gradient update to the global central node that aggregate such updates from all local node.

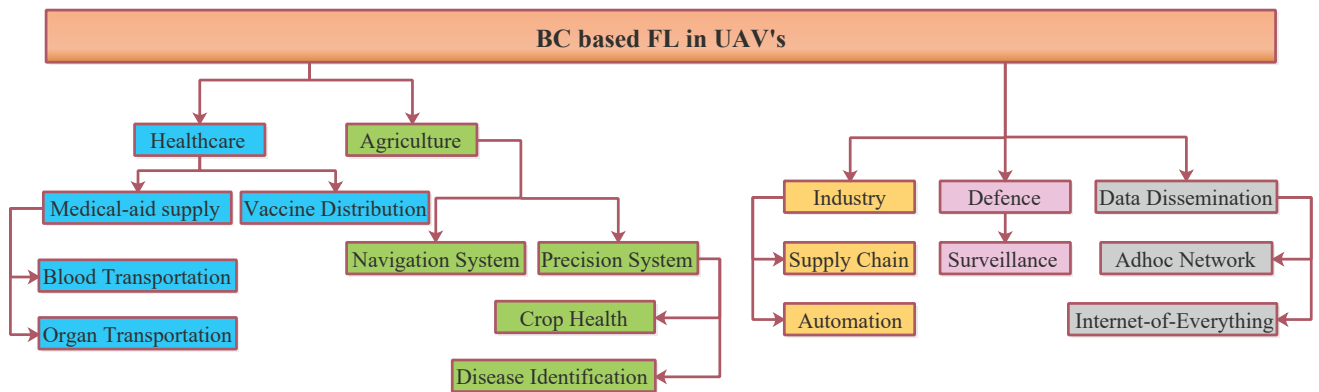


FIGURE 8: The proposed Solution Taxonomy

It utilizes the processing power of devices where data is generated and allows them to train the model based on data that preserves privacy. 6G will enable better live content popularity prediction, extremely high capacity, and high-speed communication, with data rates up to 1 Tbps. The spectrum band capacity of 6G is ≈ 100 times the capacity of 5G, and it helps the local nodes download the model update quickly and propagate the local gradients to the global model at near-real-time. It can provide communication with < 1 ms latency. In the application of FL, where data is sent and captured through moving entities such as UAVs, we need a communication network that provides a larger coverage area and massive connectivity with high precision positioning and high sensing capability. This technology provides better communication, making UAVs more reliable and secure in any allied field, with increased geographical areas. Some application requires a group of UAVs to communicate with other UAVs and create an intelligent swarm that makes use of AI and ML techniques to take decisions to any obstacles and uncertain situation, immediately sense the data and sends it back to the GCS nodes for quick response and respond to the situation based on the global learning available at each local nodes. Moreover, to assure the privacy and location parameter of each UAV, the BC network is preferred. BC allows them to communicate securely over the network and enables them to assist in an emergency. Through BC, fake parameter updates are easily prevented by providing each entity in the system with a digital wallet and SC allowing only registered entities to send a local update in the blockchain. FIGURE 8 describe the amalgamation of BC-based FL for UAVs in B5G networks for different application scenarios such as healthcare, defense system, data dissemination, agriculture and Industry. In such applications, UAVs collect data, convert them to sampling signals, and forward them to ground stations for further processing. The data received from UAVs are used to train the local model and updates are propagated to the central node for aggregation via BC to ensure only genuine local updates are considered to develop global updates. The details of the solution taxonomy are presented as follows.

A. HEALTHCARE

With the rapid development of hardware and software, medical devices, Internet-of-Medical-Things, sensor devices and body area networks have become more frequent in clinical health response monitoring systems. The data is sent via responsive communication networks like 5G/B5G to remote nodes in such setups. Local ML models are designed to detect, analyze, and predict patient health conditions. However, patient health data contains sensitive attributes, and thus the public release of health datasets is often anonymized with privacy-preservation techniques like k -anonymity, I -diversity, differential privacy, and other models. Thus, the released public datasets are often generic, and designed ML models are not fully exploited to their potential. FL is an optimal choice to address the trade-off between privacy and data availability, as data is trained at local mobile nodes. To form trusted FL, BC is integrated with such environments where the collected data from different stakeholders are stored on ledgers. To assure security, proper encryption techniques are coupled with BC to provide confidentiality of health records [55].

- **Disease Analysis:** Authors in [56] highlighted the potential of clinical data and its processing at clustered FL on edge devices which can leverage the potential of remote healthcare centers, how FL can use for better analysis of Ultrasound and X-ray reports. Architectures that use BC in their framework, such as ethereum, to provide security to the clinical data [57]. To impose extra security on patients' health records, FL is used to send only the updated gradients of your local ML model and to prevent your model updates from privacy attacks; we use differential privacy mechanism [58].
- **Vaccine Distribution:** In edge intelligent emergence technology, UAVs are used as relay stations that capture the environment information, and FL strengthens UAV to perform decentralised learning by updating the local model and send the update to the global model, and BC is incorporated in the framework to provide trusted ecosystem [59]. UAVs are used to transport the

vaccines in remote areas and based on the population of the area, a k number of vaccines are transported from the main center to the nodal center where each person is registered in the BC. After giving vaccines, the ledgers are updated to prevent fraudulent entries in the vaccine distribution [60]. To add an extra layer of security in BC, nodes aggregate local updates via Intel software guard extension (SGX) in trusted execution environments (TEE), and the hash value is stored in the blockchain [61].

- **Medical aid Supply:** UAVs use the intelligent network and interact with swarm and GCS to deliver medical aid to remote places. The scheme takes advantage of FL for quick response to uncertain situations and obstacles. UAV allows supplies to difficult terrains and zones, where human intervention is not possible [62]. Gupta et al. [63] proposed a BC-based medical aid delivery ecosystem using UAVs in healthcare 4.0, providing end-to-end security by capturing communications of UAVs with GCS and updating the transactional state on global BC ledgers. UAV delivers the blood and organs in a critical situation by maintaining the required temperature to the destination way faster than other communication [64], [65], [66]. To utilize UAVs in different environmental conditions and avoid congestion, a path planning architecture is required for effective emergency response from UAVs. UAV path planning algorithm can be improved with a genetic algorithm, particle swarm optimization, and ant colony optimization techniques [67].

B. AGRICULTURE

Traditionally, red-green-blue (RGB) and near-infrared measurement (NIR) sensors were used in agricultural sites which lack hyperspectral range and precision. The inspection was earlier performed via satellite and manned air-crafts to sense areal data through digital imaging. Such coupled technology is expensive and restricted only to certain geographical areas due to complex logistics or environmental conditions. The hyperspectral technology allows us to use small and lightweight sensors in UAVs that support hundreds of bands [68]. UAVs can be used in a variety of applications related to crop management by capturing high-resolution images and sending the data to ML models for further analysis, such as detection of crop health crop insects so that timely action can be taken to increase the overall productivity.

- **Navigation System:** To provide improved navigation and remote sensing, UAVs are installed with hyperspectral sensors that have the capabilities to capture minute details in high resolution. With the inclusion of Kalman filters (KF), the spectral algorithms are further modified to predict future UAV positions with higher accuracy. Thus, the base GCS employs KF algorithms to form effective GCS-UAV navigation links that allow real-time monitoring and control instructions to manage mission-critical applications [69]. Through effective

computer vision training algorithms like masked region-based CNN (Mask R-CNN), Faster R-CNN, and you look only once (YOLO v3), UAV-based object tracking and detection algorithms are improved [70].

- **Precision System:** The actual proliferation of UAVs in smart farming is not yet fully utilized, the technology is selected and deployed to capture and sense the data and further processing of those images. Authors in [71] discussed the general method of data acquisition and image processing for precision agriculture. Conclusion: There are so many precision agriculture applications that calculate the vegetation index that helps optimize the crop's effectiveness. Researchers have identified the open challenges and future directions for precision agriculture with the use of computer vision, ML, and AI algorithms [72], [73], [74].
 - **Crop Health:** UAVs are used to monitor crop's health regularly by assessing the condition such as the color texture of the images received from the sensors in different lighting conditions and timings throughout the day. With the help of ML techniques, we detect crop health of different crop types with different parametric conditions. FL enables the global model to be downloaded and used at local nodes in such cases. The author in [75] discussed the benefits of UAVs in agriculture and their limitations, mainly how they assist farmers to maximize their profit by detecting the health of the crop on time.
 - **Disease Identification:** With the help of better image processing units and sensors available in UAVs, high-resolution images are sent for detection and categorization of disease and classification according to its severity, colour and texture. Authors in [76] divided the dataset into bare ground and radish fields and employed DL algorithms to detect yellow rust disease from the captured hyperspectral images received from UAVs. Similarly, authors in [77] applied DL models to detect and classify Fusarium wilt of radish field through captured UAV images.

C. INDUSTRY

With the advent of Industry 4.0 and the shift towards Industry 5.0, industrial processes and pipelines are automated. The processes are data-driven and employ sensors, people, processes, and manufacturing units to integrate the components, operations, and control systems cohesively. Thus, the shift towards cyber-physical driven industrial process has interesting UAV-driven use-cases. One particular use case of industrial deployment in the oil and gas industry requires effective UAV surveillance of gas pipelines to detect gas leakage, and real-time inspection, with effective alarm systems to notify in case of leakages. A large amount of data is generated due to continuous UAV monitoring, and the data is highly sensitive and shared over public channels. Thus, UAVs employ proper

authentication and security processes to carry out operations like oil spills, leakage-related accidents, and pressure maintenance. The data is shared over wireless channels over long-distance IoT networks through networking protocol stacks. Another industry use case involves logistic operations, where goods are shipped, and ML algorithms are used to assure the validity of shipped articles. In the food industry, food items must maintain a fresh state from the production cycle until they reach the markets. It involves a lot of intermediate points in the supply chain, and every point is monitored to assure freshness of the product [78]. Supply-chain-based UAVs employ a greedy algorithm that offloads the computing task of sensor nodes within smart factories. UAVs collect the data and handover it to edge nodes which are responsible for distributing the task to other peer nodes for faster processing [79]. Some industrial use-cases are mentioned as follows.

- **Supply Chain and Automation:** In industry 4.0 evolution, the latest technologies are employed to make automated operations. Products are tagged with smart radio frequency identification (RFID) barcodes, and the supply goods are then mounted on delivery UAVs that deliver the goods to the recipient. UAVs are required to maintain inventory control, and the local data can be analyzed through FL algorithms. Finally, the captured data are maintained as transaction ledgers and added to BC. It preserves the item traceability, especially when the goods come from third-party vendors, and ensure origin traceability. Tight upper-bounds on round trip latency are maintained to manage resilient control for in-flight UAV modules. B5G network services like muRLLC are a viable fit to assure the same. To support UAV operations, inventory transactions are managed on edge servers that deploy FL models to detect swarm movement irregularity and store the information on BC ledgers [80], [81].

D. DEFENCE

UAVs capture high-resolution images that can be used in defense and military setups. Recent incidents from Israel and Iraq where UAVs are used to intercept the encrypted video feeds allowed space for a systematic cyber attack, such as navigation spoofing and link interception. This allows a large group of UAVs equipped with military-grade electronic defense and counter operations standards. Recently, small interceptions in military data are also considered a serious concern, owing to the high sensitivity of military operations. Thus our traditional defense systems are not mature enough to detect and analyze such threats. Unconventional flight patterns at low altitude with terrain masking effect make it invisible and lead to high false alarm generation rates. Thus, a short defense radar system base UAVs is set up. It senses and warns the perimeter surveillance radar system that makes a strong defense system against low and slow unidentified threats [82].

- **Surveillance:** UAV-based positioning system is developed which provides positioning service from its current location and with advanced IoT-based aerial UAV that has on-board image-based demarcation of land technique that sense the illegal trace-passing of an unidentified object and immediately initiates the alarm systems, by sending the signal to local ML model. The communication is carried over a secure communication channel, and UAVs are equipped with path planning and module capable of recalculating paths when an obstacle comes [83].

E. DATA DISSEMINATION:

UAVs are used to improve the quality and efficiency of data dissemination in different applications. UAVs collect aerial data with the help of sensors and store the information in the local buffer. The data is immediately sent to the GCS or other peer UAVs from the local buffer for fast transmission. The data is further used to train the local model and the updates are sent to the global model entity for further aggregation.

- **Adhoc Network:** UAVs help the ground vehicle to send data from one entity node to another by increasing the network connectivity. Authors in [84] represented the new architecture model to send data in vehicular Adhoc network and explored different cyber and false attacks on data dissemination. The authors compared the different false attacks patterns on data dissemination and performed the security analysis to identify the security goals. To provide secure data dissemination in UAV scenarios, architecture is defined using BC, which identifies the forger node using game theory and used proof-of-stake (PoS) consensus protocol for block validation [85]. Jacob *et. al* [86] proposed a method that enhances the transmission efficiency and coverage capacity of the UAV swarm and also analyses the interference generated due to inter-drone communication.
- **Internet of Everything:** UAV-based data dissemination frameworks are designed for internet of everything (I2X) ecosystems. Almasoud *et. al* [87] proposed an algorithm to maximize the minimum bit received from the IoT devices and increase cooperation between IoT and UAVs in sensing the spectrum, with these UAVs making the decision when it comes under the range of spectrum availability. For efficient and flexible data dissemination among especially distributed IoT devices, a joint optimization on the resource assignment strategy is designed [88]. To disseminate the data over low powered devices to a long-distance, a closed-loop transmission diversity approach is used to enhance the transmission [89]. To maximize the minimum amount of data received from base stations, scheduling, bandwidth allocation, and mobility of UAV is required along with constraints such as power and mobility [90].

VI. CHALLENGES AND FUTURE DIRECTIONS

This section discusses the open issues challenges in integrating the key drivers, namely BC, FL, and B5G networks in UAV communication. We highlight the challenges and present the future directions. This section addresses the RQ 5 question as it culminates the challenges of BC and FL in security and update handling in B5G-envisioned UAV ecosystems. Table 5 highlights the key research directions, possible limitations, and proposed future directions of integrating BC in FL-UAVs. The challenges are presented in two aspects: the security and communication front.

BC suffers from bandwidth limitations, throughput, attack vectors, and scalability. The problems are severe while executing SCs in public BC ledger domains. The former faces limitations like lack of formal contract verification, storage constraints, unsustainable consensus mechanisms, and contract-based attacks. Thus, it is paramount to design an effective BC network that seamlessly integrates the local FL model training. Such integration would ease the high overhead dependency on transaction ledgers, with the amount of data generated by the UAV swarms during handshake and control operations. Moreover, the availability aspect of the B5G communication network plays an important role in catering latency parameter update rates in critical scenarios such as healthcare. B5G networks are in the experimental phase and require an effective implementation to assure industry-ready solutions, with unified protocol and implementation rules. FIGURE 9 depicts the overall picture of challenges and prospects of the holistic integration of the key technical drivers.

A. SECURITY:

Although BC provides trust, traceability and decentralization for training edge devices, it still has its security flaws, such as 51% attack, which is a critical problem of proof-of-work (PoW) consensus algorithm. In PoW, miners try to validate a block full of transactions. Thus a miner with high computational resource, power, and storage can control the network by contributing more than 50% of the mining power in the network with its added resources. In such a case, the miner group would easily create a side chain that would be legitimate, and thus miners would add transactions to the sidechain [91]. Apart from 51% attack, BC is susceptible to the double-spending attack, where a user spends an amount twice for the same set of transactions. SCs are flawed with reentrancy flaws, code injection, out-of-bound logic exception, and gas-based attacks in close association with BC. Thus, permissioned BC, where SCs are executed as chaincodes in docker containers, assures privacy and integrity of data operations. A validation protocol is required to be developed for BC and SCs, that assures the transactions are secured against possible attack vectors. The issues of BC-based attacks should be handled before the FL learning models are designed. Possible research directions to the same are presented as follows.

- A hybrid consensus design that combines PoW and

Proof-of-Stack(PoS) together. Firstly, PoW identifies the elected miner node that presents the solution to the difficult problem and presents a hash smaller than the target hash. In the second phase, the PoW winner miner selects another miner that proposes the block's combined hash, which is lower than the bet (or assured stake) of the network. As the value is lower than the stake value, there is a high probability that the elected PoS miner would add the block. The elected PoS miner should have a high reputation of adding valid transactions in the BC, and thus it would assure a fair mining ecosystem. However, the hybrid consensus scheme would fail if the PoW winner colludes with a dishonest PoS miner. Thus future research work could be directed towards the design of a fair mining and incentive ecosystem [92], [93].

- The encoder and decoder-based DL models detect the anomalies in the UAV ecosystem, which is achieved by identifying the characteristics of BC with specific timestamps which describe the state of the network, and then identify the incorrect changes in the chain with the help of neural network model [94].
- Another method to mitigate 51% attack on blockchain by using weighted history information. This approach is often termed Proof-of-History (PoH), and it presents only specific timestamps of the mining process, which are the important and essential steps. The approach is followed in the Solana Chain ecosystem, and in the approach, we compute the frequency of the miner to add a block through the PoH history. Based on the history, miner nodes are assigned weights. More weighted miner has a higher chance of election in the next round [95].

B. FAKE PARAMETER UPDATE:

Fake parameter updates from the local model can impersonate a genuine local model client which broadcasts incorrect parameters by training the model on malicious or inaccurate data, which may affect the accuracy of the global model aggregation. The adversary node broadcasts the fake parameters, and miners are not able to recognize the fault during mining which indirectly affects the learning rate of the local model that has downloaded the updated global model from the on-chain repository [96]. The solution to this problem is to integrate BC into the system. Every local learning model is first published in the BC via a registered digital wallet through SC execution. SC allows only registered entities to execute the contract. Finally, the global model is updated by aggregating all the local updates, and the updated global model is published again in the chain with version and timestamps.

C. COMMUNICATION DELAY:

Communication delay of FL training is heavily dependent on up-link and down-link rates, which highly affect the global model updates and its redistribution among all the local models. Every local client model has its unique training data,

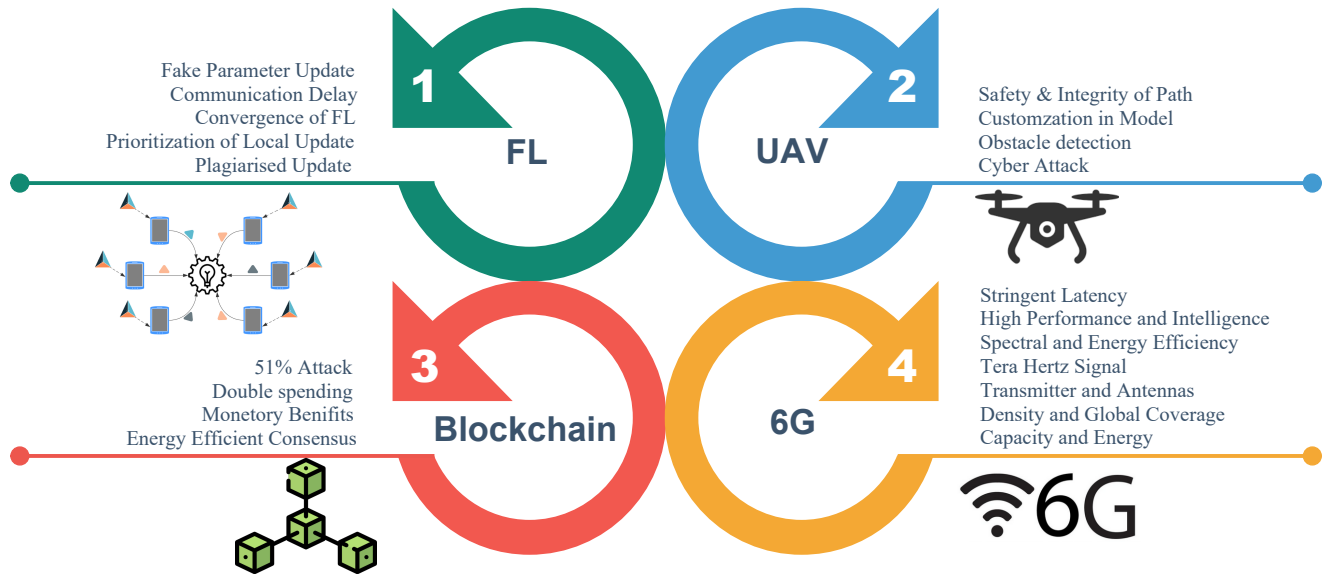


FIGURE 9: Open issues and challenges of BC-assisted FL solutions in B5G-enabled UAVs

different network conditions, and different initial parameters for the model training. If the number of FL participants grows exponentially, the sending and receiving of model updates will create a bottleneck on the network. Its variable end bandwidth supports each local FL participant, and thus it induces variable delays in communicating updates back to the global model. This results in inconsistent model updates at the server, as aggregation is not synchronized. One possible solution is to apply model compression to minimize the network delays and streamline a consistent delay at the aggregator while conforming the updates to the global server [97].

D. CONVERGENCE OF FL:

Due to the heterogeneity of different edge or IoT devices, the convergence of FL algorithms is not assured. As the edge behaviors depend on local conditions, the edge models apply different mechanisms to interpret and process the data. Edge systems are characterized by CPU usage, hardware, and I/O usability, and thus networking stacks are not mature enough to handle the discrepancy. Furthermore, the base networks operate over heterogeneous constraints of UAV battery and power management, and therefore FL model training convergence is not smooth. To cite an example, IoT devices are restricted with limited computing capability, and weak and intermittent disconnections at local nodes would require high time to train the data and propagate the training results back to the aggregator nodes [98].

E. PRIORITIZATION OF LOCAL UPDATE:

The local model updates can be prioritized based on the frequency of the update sent to the server, which allows the global system to consider the most recent update first to

increase the block validation. Furthermore, this consensus allows the reputed IoT or edge device to propagate the changes quickly for faster aggregation. In this way, we allow the client or IoT device with frequent updates to be given more priority for block verification, which sets up a biased system of updates on the global model, as the local node with higher update frequency affects the global model schematics [99].

F. MONETARY BENEFIT:

Encouraging edge devices to participate in the mining process is a key challenge. FL nodes would require all the available resources and share their fair share of computing power to the mining pool to increase the mining throughput. The FL nodes would require an incentive mechanism that inspires them to participate in resource-sharing. Thus, proper incentive mechanisms for resource sharing FL nodes are an open issue that would benefit the miner nodes to carry out computational intensive tasks. Thus, FL-as-a-Service (FLaaS) is a future research problem [100], [101]. However, the incentive distribution has to be fair for all participating FL nodes. Therefore, the fair incentive FL mechanisms in the open mining system is a critical problem of study.

G. PLAGIARIZED MODEL UPDATE:

To maximize the economic benefits, the FL nodes allocate a major portion of CPU resources to the mining pool, and fewer resources are utilized for sending local updates is a recently proposed solution. The model update is often copied to next-hop local nodes or IoT edge gateways in such cases. However, in such a scenario, the neighboring node should be trusted to carry out the operations fairly so that incorrect and plagiarized updates are not sent to the global server. To

asset, the fair ecosystem and verify the edge node forwards the correct update to the global model is a challenging and open problem of study [102].

H. VARIABLE LATENCY CONSTRAINTS:

FL trains its data at the local level and uses it for applications such as live healthcare analytics or an autonomous vehicle, where the application predict the results at little or no delay, i.e., FL can reduce latency by optimizing the model that eliminates the requirements of edge, or MEC-offloading models for accurate diagnosis and prediction. However, with variable networking delays, the latency at different nodes is different, and thus the final FL convergence is difficult to achieve. Moreover, with the inclusion of BC-based update validations, the miners require more time to verify the transactions and add them into blocks. As local models would update at a variable rate, a unified choice of consensus protocol is difficult to apply for the entire problem [103].

I. SAFETY AND INTEGRITY OF UAVS TRAFFIC MANAGEMENT:

As the number of UAVs increases in a swarm network, effective failure management and alert system is required to be designed in case of emergency and contingent situations. A timely response mechanism should be designed to prevent UAV-based calamities during in-flight swarm operations. Effective UAV path planning algorithms are required to be set up for an incident response. The design of alert and management systems for UAV swarm networks for managed path planning and alert control is an open study problem.

J. CUSTOMISED MODEL FOR SPECIFIC SCENARIOS:

Multiple UAVs communicate with each other and share information about their surroundings to visualize the target location better. Effective AI training models are designed to monitor the traffic and weather conditions for different locations and sensing environments to exploit the same. The design of AI models for monitoring traffic and weather conditions and UAV swarm scheduling would require different AI models for different collected data. Moreover, as geographical landscapes are different, a single unified model design to cater to all requirements is impossible. Thus, scenario-specific AI models are designed, and it requires an effective switching of AI models over the collected data. Managing AI-schedulers in real-time to support swarm operations requires a huge amount of bandwidth and computing power. As UAVs are resource-constrained, they have to offload the tasks to the nearby edge, or cloud servers, which induces variable communication delays. Moreover, as tasks are delegated, it induces the risk of data confidentiality, and thus modern B5G networks that envisions space-air-ground communication require an effective network manager. Researchers have proposed the NFV function to manage the scheduling of AI models. However, an all-effective model is still far from reality that can cater to the requirements of the right blend

of load balancing, routing, and traffic association of the collected model data.

K. OBSTACLE DETECTION:

It is very hard for UAVs to detect an object or other UAV and avoid them instantly. Thus, object detection algorithms are designed to allow UAVs to detect near objects or blockages that can prevent crashes or UAV collisions. At the same time, it is required to broadcast the obstacle signal to all peer UAVs in the network. Thus, modern UAV swarm networks are required to have automatic object avoidance and detection algorithms that are in-built and hard-coded in the UAV memory, rather than building detection algorithms on the local sensor units.

L. ATTACKS ON UAVS:

In UAV swarms, a group of autonomous UAVs moves from source to destination and exchange route information and other details with their peer nodes. There is always a possibility of exploiting vulnerabilities in communication and traffic management systems and chances of a cyber attack by an intruder, which makes UAVs malfunction and change their routes or even crash in populated areas. Other possible threats include denial-of-service (DoS) attacks, where the UAV nodes are flooded with many SYN requests that potentially block the resources and exhaust the UAV bandwidth. In addition, it might cause UAV congestion collisions and drain the UAV energy. Another possible attack is the setting up of jammers, which would disrupt the communication signals between UAVs and GCS. Spoofing is another common attack where an attacker intercepts sensitive information by eavesdropping on the communication link through address resolution protocol packets. Following are the possible solutions against such attacks:

- Ensure a high level of security to stop denial of service by installing firewall and intrusion detection system between UAVs and GCS. Segment the network and encrypt the sensitive information during the communication. Integrating the identification method with encryption of transmitted data prevents MAC address and service set identifier of UAVs and ground station.
- Using continuous monitoring to analyze the real traffic pattern and a strong sense of typical network activity, and real-time monitoring assures the mitigation of DoS attacks before the full control by the adversary. Also, the UAV networks are required to monitor soft signals like slow performance, unusual packet drops, poor connectivity, or increased traffic along a particular path.
- Security team that analyses such activities are required to be ready with the disaster management system and access the risks to restore the network. The security analysts are required to be assigned definite roles and responsibilities, with a checklist for necessary tools and the know-how to continue essential mission-critical operations.

TABLE 5: Key research directions and possible solutions in UAV based FL and BC Ecosystem

TP	Area	Ref. No.	Year	Objective	Limitations				Solution with FL and BC
					1	2	3	4	
Security Front	Healthcare and Agriculture	[57]	2019	Ethereum based framework to provide security to clinical data.	✓	✓	X	✓	Incorporating FL and BC will allow the different stakeholders to contribute in clinical research and findings with trust.
		[58]	2019	Proposed a differential privacy preservation scheme for sensitive healthcare data.	X	✓	X	✓	Introducing BC along with differential privacy makes it more secure, trust-able and reliable ecosystem.
		[59]	2021	BC-based framework to provide trust in the healthcare ecosystem.	✓	✓	✓	✓	Integration of BC and FL with UAV mobility strengthen the trust and improve the medication.
		[60]	2021	BC-based framework that uses UAV for vaccine distribution using underline network.	✓	✓	✓	X	Integration of FL will improve the expected number of vaccination doses in an territory.
		[63]	2020	Proposed BC-based medical aid delivery using UAV's in healthcare 4.0	✓	X	✓	X	Integrating FL to know the average requirement of medical aids will enhance the system.
		[69]	2011	Low cost framework for agricultural remote sensing via UAVs.	X	X	✓	X	FL will help to identify the probable area for sensing the land.
		[71]	2019	Precision based smart farming using UAVs	X	X	✓	X	BC and FL will provide trust and immutability which allows the smart farming to incorporate data form different parts of the world.
		[76]	2020	Framework for UAV-crop monitoring for crop diseases through convolutional neural network	X	X	✓	X	FL helps to provide more insights of wilt from different parts of the world with same climate conditions.
[104]	2018	Identification of yellow rust in crop via multi-spectral aerial imagery using UAVs.	X	X	X	X	FL will help the model to be trained on variety different samples from the glob.		
Communication Front	Defence and Industries	[78]	2015	Framework to ensure safety and security with UAVs in Oil and Gas industries.	X	X	✓	✓	BC and FL will provide the immutability and different hazardous situations to act on from all over the world.
		[79]	2018	Monitoring and optimization of UAV assisted fog computing for smart factories.	X	X	✓	X	Based on FL global model updates will increase the accuracy of monitoring smart factories via UAVs
		[80]	2019	Framework for inventory traceability in supply chain using BC based UAVs	✓	X	✓	X	Integrating FL will allow to consider the global trends to increase the productivity in supply-chain.
		[81]	2018	BC based framework to ensure trust in the supply chain ecosystem	✓	X	X	X	FL allows updated model which face challenges of supply-chain in smart industries.
		[82]	2018	BC and UAV based surveillance radar system makes strong defence system	✓	✓	✓	X	To increase the efficiency of the radar base surveillance system we need global training data which FL can provide.
		[83]	2018	UAVs with path planning module for path tracking and surveillance	X	✓	✓	X	FL and BC can improve the demarcation, path planning and immutability to the data.
		[84]	2018	Security analysis of false data dissemination attack on UAVs	✓	✓	✓	X	To detect the false data we need strong model trained on global data, which makes it essential to introduce FL and BC.
		[85]	2019	A framework for secure data dissemination of internet of drones	✓	✓	✓	X	To improve the data dissemination FL can be introduced to identify the malicious node to improve the security.

TP: Taxonomy Parameter, 1-Trust, 2-Security, 3-Mobility, 4-Global Updates, ✓-shows parameter is considered, X-shows parameter is not considered.

M. HIGH PRIVACY AND INTELLIGENCE:

In 6G, AI interacts with private data and refine them to improve the network functionality to deliver better services. To achieve this, we need to balance intelligence and privacy in a humanoid network by anonymizing sensitive information through third-party decentralized agents. The balance in AI comes at the increased cost of network complexity and the high production cost of gadgets. Thus, to handle the tradeoff, proper innovations in device structure are required to provide better security and anonymized data at lower prices that maintain the balance between intelligence and privacy of the data [35], [105]. Differential privacy is another mathematically proven technique part of 6G that prevents the data from linkage-attacks through added noise from neighboring nodes. It allows generating signals that are non-traceable to a particular UAV or edge nodes [106].

N. SECURITY, SPECTRAL AND ENERGY EFFICIENCY:

Complex computation is required to design solutions to provide security with spectral efficiency in 6G, and possible solutions apply encryption algorithm, or design physical layer security, or intelligent AI models that identify

the network state and design input parameters [107]. In a similar direction, current research is focused on establishing a relationship between spectral and energy efficiency. One possible solution is energy harvesting, where radio and solar energy is harvested from the local ambiance. Further, spectral efficiency can be improved by proper resource management such as dynamic link adaptation protocol, which comprises modulation, adaptive coding and power control to enhance the quality of the radio channel, bit rate and robustness of transmission, dynamic channel allocation and diversity scheme, which improve the reliability of the signal by using more than two communication channel with different characteristics this helps to combat fading, and co-channel interference [108].

O. TERA-HERTZ SIGNALS:

6G works on terahertz frequency signals and requires antennas to generate continuous terahertz frequency. Currently, it is complex to generate frequency signals with a 300-micrometer wavelength. Thus, complex circuits design is required to increase the production cost of antennas. Another problem with the terahertz signal is it attenuates to 0 after traveling to a certain distance in the air, which incurs energy

loss due to molecular spreading and absorption due to conversion of the tera-hertz signal to the internal kinetic energy of the molecule. The loss increases when the environment contains moisture, so amplifying the signal at every 1 meter distance is very hard. Much innovation is required to bring down high propagation delay in terahertz frequency. Other parameters such as low noise and high sensitivity should be considered while designing transceivers. Complementary metal-oxide-semiconductor and graphene material can be used to design transceivers and further to enhance the performance in terms of transmission power. Silicon germanium, gallium arsenide/nitride, and indium phosphide-based material are required to be used in the design of the signal detector and generator units [109], [110].

P. TRANSMITTER AND ANTENNAS:

To meet the 6G requirements in the FL ecosystem, we require a highly efficient transmitter and receiver system because of the high integration of radiofrequency. As explained above, it involves the integration of high silicon nodes. Furthermore, the material used to construct antennas highly affects the transmission speed of radiofrequency. Thus, to achieve higher data rates, we need efficient radio frequency, which depends on the intrinsic and extrinsic composition property of the material used. So researchers need to focus on fabricating the material design to meet the 6G vision. In the case of satellite connectivity, UAVs would require power and antenna capability to send the data over large distances, and thus it adds up to the communication overheads. Moreover, the communication costs increase, and therefore research has shifted towards the design of powerful aggregator nodes that collect the data from UAVs or IoT from considerable distances and forward the same to the satellite for operations[111].

Q. CAPACITY AND ENERGY:

6G-enabled UAVs need significant processing units to process data, and thus to model the huge data influx, high energy and resource consumption is required. In such cases, advanced modulation techniques are employed to maintain peak to average power ratio. Moreover, enhancement in spectral bandwidth is maintained through encoding techniques that improve the number of signals levels per data bit. Another technique employs the reuse of spectral frequencies in case of high node density [112].

R. DENSITY GLOBAL COVERAGE:

6G uses a lower earth orbit satellite with low path loss and fewer transmission delays. 6G enabled satellites rotates at high speed around the earth, and it induces an unusual Doppler effect which causes signal detection and synchronization issues. To offer a seamless and better quality of communication among devices, 6G ecosystems need high-density nodes per area, resulting from higher communication costs. As 6G consist of both terrestrial and non-terrestrial

nodes, which are economically on the higher side and require more maintenance.

VII. MIL-DRONE: A PROPOSED CASE-STUDY OF BC-ASSISTED FL-UAV FOR IOMT ENVIRONMENTS UNDERLYING B5G NETWORKS

This section addresses RQ 6 by proposing a BC-leveraged and FL-assisted UAV-enabled military surveillance and regional demarcation application in the Internet-of-Military-Things (IoMT) ecosystem underlying B5G networks. The proposed case-study reference architecture provides a rich QoS and enhanced security and trusted data exchange due to the amalgamation of FL and BC technologies. UAVs are widely employed in surveillance. military demarcations, search and rescue operations, and emergency disaster response networks. In military surveillance, UAV monitors the boundaries on a 24×7 bases to prevent illegal activities like trespassing by neighboring country militants smuggling and trafficking of illegal goods across national and international demarcated boundaries. UAV enables categorization of country or region boundary based on land, stream and coastlines. UAV military operations are limited by various factors such as diversified geographical terrain, the accuracy of sensors onboard UAV, spatial data mapping accuracy, high resolution, consistent bandwidth, diffraction, LoS interference, limited mobility, and intermittent disconnections. Strong communication infrastructure is required to address the above issues in continuous UAV region surveillance and accurate spatial demarcations.

B5G-based tactile internet (B5G-TI) allows near-responsive decision making, high data transmission efficiency, extremely low latency ($< 0.1\text{ms}$), accurate LoS, extremely high reliability (99.99999%), virtualization of resources, flexible network services, and integration of edge computing with AI algorithms. B5G networks support a higher spatial resolution which is useful for accurate geometrical analysis and precise mapping of regional boundaries in surveillance operations and enables the significant increase in data upload to the edge cloud via a wireless network and increased implementation of AI-based DL algorithms. B5G-driven edge computing environment promises uRLLC, mMTC, which leverages enhanced cloud-assisted MEC offloading and improves the processing capability of nodes. It enables collaborative data storage, computational analysis, and network transmission procedures to improve network transmission efficiency. Thus, integration of B5G and AI will form a new network ecosystem that will support m-IoT networks at a close synergy with UAV-based applications.

However, the incorporation of AI in UAVs poses serious computational and privacy challenges. Data collaboration is an important event utilized in autonomous devices to serve various applications. Applications rely on ML algorithms to train data from data centers, which often refuses to provide these sensitive data, thus hindering the ML process. During UAV-UAV and UAV-GCS communication, the exchanged data contains sensitive military information about UAV

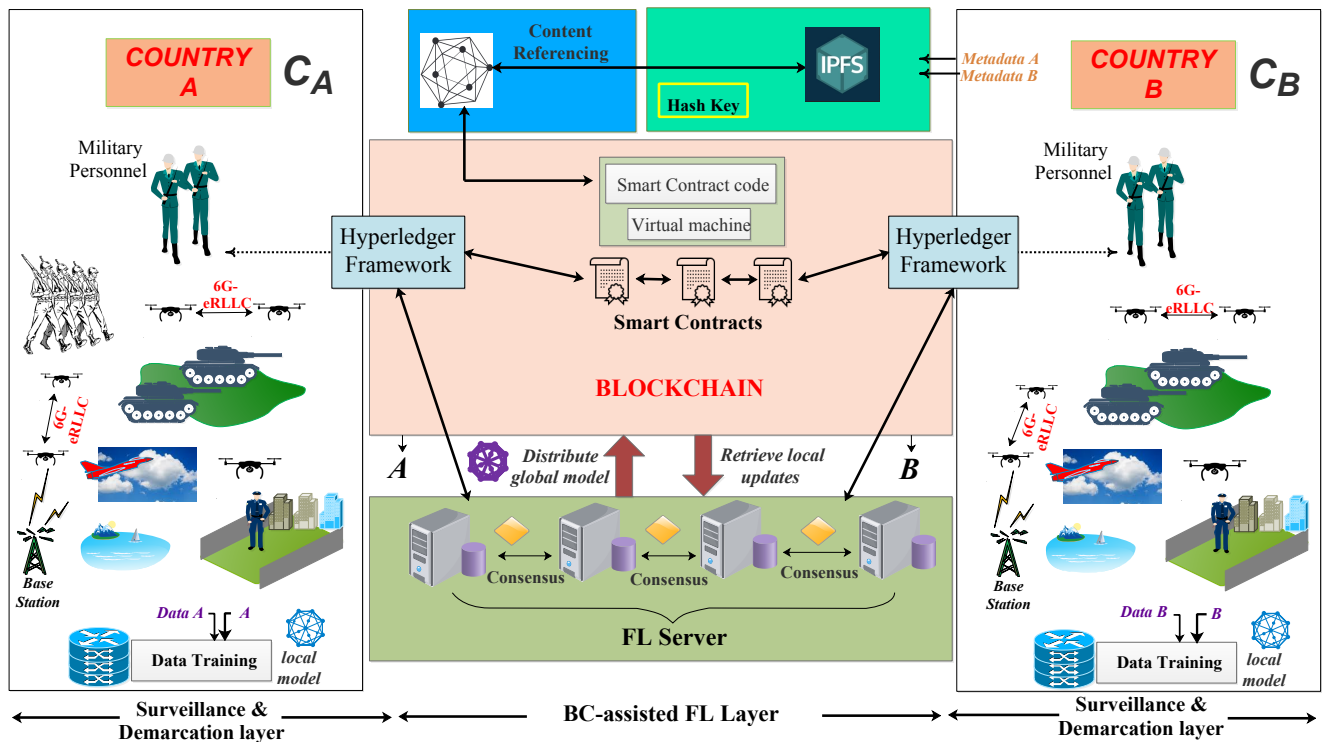


FIGURE 10: Mil-Drone: A BC and FL based UAV enabled scheme for region surveillance and region demarcation for IoMT operations

trajectory (ephemeris), path planning, updates, etc., which malicious intruders might attack to inject false propagation updates to malicious UAV. This compromises the communication link, incorrect paths, battery draining, accidents, and other incidents. Moreover, the cloud-based decision process at GCS could reveal identification about a particular UAV. The FL-based decentralized approach is utilized where actual data is not shared, and all data owners share only the local updates with a central server. The approach maintains confidentiality, enables UAVs to collaboratively train a global model based on captured data and saves network bandwidth. However, with an increase in data content sharing, the complexity of effective ML modeling is limited, which makes the central server prone to failure. The overall authentication of UAVs becomes difficult as geographical locations are scattered, which makes former prone to malicious attacks. BC technology allows authenticated UAVs to provide updates for further aggregation. Using consensus mechanisms like PoW, PoS, and IOTA enables UAVs to mine the authenticated transactions into a block which ensures transparency. BC ledgers suppress various attacks such as malicious UAV interference, UAV impersonation, DDoS, blackhole routing attacks in UAV network infrastructure. BC infrastructure controls the UAV swarm operation with improved energy-efficiency, enhanced security and low latency in the B5G network [113].

Owing to high data rate, low latency and very high-security requirements, it is necessary to ensure end-to-end application

requirements of end-user (military diplomats) by enabling trust at ground level (GCS, MEC node) and sky (UAV swarm). A case study is presented to amortize the overall requirements where we integrate BC and decentralized FL framework in B5G-TI scenario for authentication and continuous model aggregation in IoBT ecosystems. We discuss the regional demarcation and surveillance application between two countries assisted through UAV swarms and analyze the opportunities of B5G in edge computing applications like data sharing content caching to improve efficiency, quality of service (QoS) and security. FIGURE 10 shows the three-tier architecture which is explained in subsequent sections.

A. SURVEILLANCE & DEMARCATION LAYER

IoMT encloses sensor-driven warfare that provides real-time connectivity with battleships, UAVs, battle-tanks, soldiers (equipped with health-assisted sensors to recognize various characteristics) into a connected and ubiquitous network. This layer provides IoMT operation between two countries in land, air and water through a swarm of UAVs. There are two countries A and B named as C_A and C_B . A swarm of UAV U_A and U_B are responsible for military surveillance and regional demarcation operation. Each country consists of military personnel e_{mp} serving the defense forces. The swarm U_A & U_B captures and stores the surveillance and boundary data d_S and d_{RD} consisting of surveillance area latitude and longitude information, ultra/super high definition (UHD/SHD) video meta-information, video content, video

timestamp, demarcation meta-data (land, air, or underwater), demarcation boundary latitude and longitude information, and demarcation length (in km^2). Using BC-based IPFS technology, e_{mp} access the above data using private keys stored in the IPFS ledger.

B5G-TI enables real-time responsive communication for video data to prevent unidentified intruders from entering the surveillance and demarcated regions. B5G-TI network supports real-time communication between UAV swarms to assist in IoMT operations. It also assures extremely-low latency communication between UAV swarm, GCS, and TI-controller through assisted edge-offloading-based mobility models that handle many requests in UAV swarm. B5G services like FeMBB, eRLLC support high data rates, extremely low latency and ultra-high resolution/4K video transmission. B5G/6G also incorporates intelligent estimation via ML/DRL-based solutions to handle cache/edge offloading phenomenon to reduce overall network traffic and congestion, improve QoS, decision-making, and resource management (battery power, frequency band, interference), and aggregation. The captured data from the UAV is trained using the AI-based DRL technique to generate a local model from global updates received from the BC layer. The UAV swarm broadcasts the updated local model to the subsequent layer for further processing.

B. BC-ASSISTED FL LAYER

This layer incorporates a network of edge/fog servers that receives the secured local models from the BC plane and performs computing and update aggregation. They are controlled using NFV controlled network entities coupled with intelligent decision learning resource allocation. We consider a distributed AI-enabled edge architecture to provide various functionalities like very large data storage, close to user processing, optimization, UAV data (update) management, and supports FeMBB (high data upload/download) with extremely low response time.

The FL sublayer consists of a group of MEC servers (with the higher computational capability) that performs specified learning tasks at the network edge. They provide the resources for mining (e.g., PoW) at the BC network to the connected UAVs to verify the newly created block and integrate it through a consensus mechanism. MEC server initializes the FL process based on aggregation of local model updates L_{uA} and L_{uB} and sends the initial global updates G_{uAB} to UAV swarm via BC network based on weighted average process [114]. Each UAV in U_A and U_B trains its model utilizing the captured metadata as well as a global model through SGD algorithm and calculates a new local update. The computed local model is transmitted to the MEC server via BC by creating a transaction. MEC server forms a Merkle Tree structure of received transactions and creates a new block identified by a hash value, timestamp and nonce. Once mining is completed, the verified block is added to the BC network, which can be accessed by U_A and U_B utilizing a private key. MEC server node finally updates the

current global model through aggregation process retrieved from BC network. The training process is repeated until the convergence of the global loss function converges, or predefined accuracy is achieved. We prefer a consortium BC setup where C_A and C_B set up the demarcation rules through an assertive hyperledger contract. To instantiate the contract, a chaincode transaction is set up between C_A and C_B . A fabric channel and docker composer is instantiated, where an ordering service O_S is set up to execute the contract. Once the contract is executed, the results are verified, endorsed, and forwarded to the fabric service, and the contract state is finalized as *COMMIT*.

Once the contract is executed, the resulting FL model is stored in off-chain IPFS, which is accessed through two sets of keys, namely, the private key of the user, and the IPFS content key. In IPFS, we issue a resource identification tag (RIT) that forms a hashmap to the actual resource address. It is similar to indexed record storage, where the RIT points to the stored model record. The RIT is then hashed, and the hash is stored as a transaction in the mempool address. From the mempool, the miners collect the unconfirmed transactions and pack them to the on-chain global BC ledger. Any user who wants to access the latest updated global model must search the global BC ledger for the hashed RIT address. A linear search from the genesis block is required to search the hash address. It also assures that only authorized users with the hash RIT address can view the content of the global chain, and successively access the IPFS ledger. The hashed RIT value points externally to the stored IPFS record. However, to access the record, the user's private key and the IPFS content key are required. Thus, it eliminates unauthorized access to IPFS ledgers and eliminates security attacks like fake certificate generation, DDoS, and man-in-the-middle attacks.

VIII. CONCLUSION AND FUTURE SCOPE

This survey discussed BC-assisted FL for UAV networks underlying B5G communications. We presented the technical advancements and covered details about architectures, protocols, and concepts to make the readers understand the importance of FL, which assists a local learning UAV setup that assures user data privacy. Coupled with BC, it assures a trusted FL ecosystem. We also presented the key visions and fundamentals of B5G, or emerging 6G networks, and its capacity to support massive UAV networks. The integration can drive different verticals of smart cities viz Industry 4.0/5.0, Healthcare, Vehicular Networks, IoT networks, and many others. Specifically, the survey covered the state-of-the-art discussions, solution taxonomy of BC-assisted FL-enabled UAVs, a proposed reference architecture, open issues and challenges, and a unique case study. Finally, we concluded that the integration of FL and BC would serve as a secured and trusted solution for UAV networks.

As part of the future scope, the authors would like to investigate the requirements of consensus protocols that would support the FL-based algorithms for UAVs. As UAVs are

resource-constrained, effective and low-powered FL models are required for global and local training purposes. Lightweight consensus schemes would ensure synergy with FL learning. Moreover, 6G communication channels are required to be energy-efficient to support the vision of a holistic integration for UAV-enabled applications.

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