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Review

UAV Communication in Space–Air–Ground Integrated Networks (SAGINs): Technologies, Applications, and Challenges

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Abstract: With the continuous advancement of 6G technology, SAGINs provide seamless coverage and efficient connectivity for future communications by integrating terrestrial, aerial, and satellite networks. Unmanned aerial vehicles (UAVs), owing to their high maneuverability and flexibility, have emerged as a critical component of the aerial layer in SAGINs. In this paper, we systematically review the key technologies, applications, and challenges of UAV-assisted SAGINs. First, the hierarchical architecture of SAGINs and their dynamic heterogeneous characteristics are elaborated on, and this is followed by an in-depth discussion of UAV communication. Subsequently, the core technologies of UAV-assisted SAGINs are comprehensively analyzed across five dimensions—routing protocols, security control, path planning, resource management, and UAV deployment—highlighting the progress and limitations of existing research. In terms of applications, UAV-assisted SAGINs demonstrate significant potential in disaster recovery, remote network coverage, smart cities, and agricultural monitoring. However, their practical deployment still faces challenges such as dynamic topology management, cross-layer protocol adaptation, energy-efficiency optimization, and security threats. Finally, we summarize the applications and challenges of UAV-assisted SAGINs and provide prospects for future research directions.

Keywords: 6G; wireless communication; Space–Air–Ground Integrated Networks; unmanned aerial vehicle

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1. Introduction

With the successful commercialization of fifth-generation mobile communication technology (5G), people have started exploring the next generation of mobile communication technology. This technology, 6G, aims to provide ubiquitous network coverage, enabling individuals to access the internet and enjoy network services through devices at any time and anywhere. However, current terrestrial networks are constrained by fixed base stations (BSs), which can lead to interruptions in network communication and challenging recovery when the distance is too great or failures occur. Furthermore, remote areas (e.g., mountain regions, oceans) are limited by infrastructure, making access to the network difficult [1].

To address these issues and achieve the grand vision of 6G networks, researchers are exploring networks with broader coverage, faster speeds, and more stable connections called Space–Air–Ground Integrated Networks (SAGINs). SAGINs are a fusion of terrestrial networks (TNs) and non-terrestrial networks (NTNs), incorporating terrestrial, aerial, and satellite networks with a layered structure and highly dynamic characteristics [2]. In recent years, SAGIN research has become a hotspot in the field of mobile communication. To promote SAGIN development, the 3rd-Generation Partnership Project (3GPP) has formulated and continuously refined key technology standards for satellite radio access networks, core NTNs, and the NTN-supported Internet of Things (IoT), among others [3]. As a crucial component of 6G technological development, SAGINs have the potential to shape future network architectures.

Currently, SAGIN development faces many challenges. Due to the end-to-end (E2E) communication between ground and space (space to ground/ground to space) being sensitive to extreme weather conditions and solar storms, the connection between satellite networks and TNs remains unstable. Furthermore, in urban areas, satellite–ground communication is easily disrupted as wireless signals are absorbed and attenuated when penetrating buildings and obstacles [2,4]. The role of aerial networks is increasingly prominent in addressing these issues, though the exploration of aerial networks remains insufficient. Aerial networks, situated in three-dimensional space between terrestrial and satellite networks, often consist of various aircraft equipped with communication devices and capabilities.

In recent years, thanks to breakthrough advancements in battery and communication technologies, the development of unmanned aerial vehicles (UAVs) has advanced rapidly and achieved large-scale commercialization. UAV communication technology has also seen significant progress, with ad hoc UAV networks solving numerous issues in sectors such as vehicular networks and transportation [5,6]. The highly dynamic and mobile characteristics of UAVs make them particularly suitable for SAGINs, positioning them as the main component of aerial networks. Figure 1a shows the hierarchical network structure of an SAGIN, where ground communication facilities can directly communicate with satellites or interact through an aerial network formed by UAVs. However, long-distance signal transmission is prone to interference, and the mobility and computational limitations of satellites hinder the long-term provision of stable services by satellite-assisted ground networks. To address this, a High-Altitude Platform (HAP, e.g., airship and balloon), with its altitude advantage and large size, can serve as an aerial base station to provide network support for remote users, as illustrated in Figure 1b, while collaborating with Low Earth Orbit (LEO) to enhance bandwidth and alleviate network load. Particularly in cases of ground facility failure or overload, a Low-Altitude Platform (LAP) can act as a communication relay, delivering stable regional network coverage to edge users, achieving full coverage, low latency, and stable connections, as depicted in Figure 1c. In the future, UAV-to-satellite communication is expected to become a key focus. Currently, the main research on UAV communication can be divided into two categories: (1) cellular-connected UAVs, where a UAV connects to mobile communication networks and performs flight tasks, and (2) UAV-assisted cellular networks, where a UAV acts as a network relay, providing network services to other devices [7]. UAV-assisted SAGINs provide a feasible solution for eliminating coverage holes. A UAV, characterized by high mobility and freedom from terrain limitations, can quickly respond and be deployed in remote areas or regions affected by natural disasters, where TNs are unavailable or interrupted, thereby restoring network communication. Therefore, the dynamic and mobile nature of UAVs makes them highly suitable for SAGINs and positions them as the primary contributors to aerial networks. The development of UAV communication and SAGINs are closely intertwined, with UAV-assisted SAGINs becoming one of the key technologies to achieve ubiquitous coverage, auxiliary relaying, and information collection in SAGINs [8].

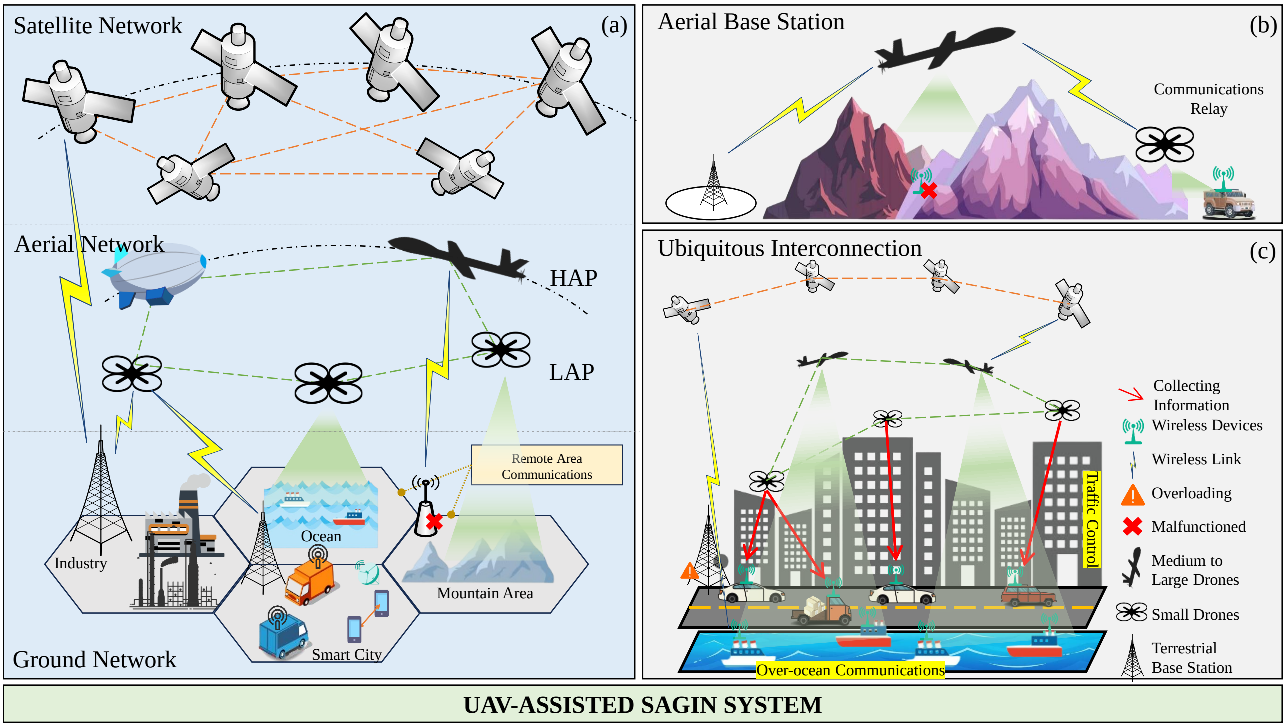

Figure 1. Architectural diagram of UAV-Assisted SAGIN. Subfigure (**a**) demonstrates the hierarchical architecture of SAGIN, where different network layers are primarily interconnected through wireless links. Subfigures (**b**,**c**) present application scenarios of SAGIN. In (**b**), a large UAV serves as an aerial base station collaborating with a small UAV communication relay to provide connectivity services for remote devices. Subfigure (**c**) highlights operational advantages of UAVs, while functioning as base stations, they can simultaneously execute other specialized missions. SAGIN integrates terrestrial and maritime environments through this architecture, enabling ubiquitous interconnection.

With the advancement of 5G, TNs have made significant progress in terms of scale and performance. However, the coverage of TNs heavily depends on well-developed infrastructure, making it difficult for remote areas and regions with underdeveloped infrastructure to access 5G networks. According to data from the Global Digital Economy Conference, as of now, the global terrestrial population coverage of 5G is about 45%. For maritime regions, due to the lack of sufficient infrastructure, relying solely on terrestrial or constellation networks is challenging for providing stable and wide-ranging network services. As shown in Figure 1, SAGINs connect terrestrial, aerial, and space networks through unified standards. Unlike traditional fixed terrestrial base stations, LAPs and HAPs act as aerial base stations and relay nodes, featuring advantages such as redeployability, high flexibility, and lower costs. Additionally, UAVs demonstrate significant application value in fields such as rescue, transportation, and military operations. In the long run, SAGINs benefit from both terrestrial and satellite networks and are expected to achieve effective cost control.

Motivation and Contributions

SAGIN-driven future network communications have three main use cases: enhanced mobile broadband (eMBB), ultra-reliable low-latency communication (URLLC), and massive machine-type communication (mMTC). These impose strict requirements on UAV-assisted SAGINs to improve quality of service (QoS) metrics in terms of (1) stability, (2) throughput, (3) latency, and (4) security. In recent years, researchers have developed numerous UAV-assisted SAGIN studies, covering areas such as (1) system architecture, (2) path planning, (3) routing and scheduling, (4) resource allocation and energy management, and (5) the deployment of drones. These research achievements are highly significant for the development of SAGINs. However, there is currently no comprehensive review of the important stage of research results on UAV-assisted SAGINs. According to the survey results in Table 1, existing surveys on UAV-assisted SAGINs have summarized key aspects such as security [9], resource allocation [10–12], routing protocols [13], path planning [14], and UAV deployment [14,15]. In addition, the review [6] analyzes routing algorithms driven by artificial intelligence (AI). Some surveys focus on specific areas while neglecting others, and although review [2] provides a comprehensive overview, it offers only general viewpoints. Therefore, a thorough review of the current research progress on these key technologies is essential and would provide valuable guidance for future studies and technological development.

Table 1. Analysis of recent survey studies on SAGINs.

Ref.	Year	RP [1]	SC [2]	PP [3]	RM [4]	EM [5]	DP [6]	Contribution
[16]	2018	✓			✓			Review of SAGIN research, covering design, resource allocation, and performance optimization, with future directions.
[13]	2019	✓						Analysis of routing protocols in UAV networks, comparing features and discussing design challenges.
[17]	2019					✓		Examination of power configurations and energy management in electric UAVs, revealing research gaps.
[9]	2021	✓	✓					Review of security in Space–Air–Ground–Sea Integrated Networks (SAGSINs), addressing threats and defense strategies.
[15]	2021						✓	Evaluation of UAV-based LoRa networks, highlighting low-bit-rate connection reliability for long-distance transmission.
[12]	2021			✓	✓	✓	✓	Survey of resource optimization in UAV-assisted wireless networks, addressing key metrics and future challenges.
[2]	2022	✓	✓	✓	✓	✓	✓	Vision for 6G technologies enhancing SAGINs and addressing ecosystem challenges.
[10]	2022		✓		✓			Summary of UAV-assisted maritime communication advancements in architecture, resource management, and trajectory optimization.
[14]	2022			✓			✓	Review of UAV deployment and trajectory planning for enhancing 5G networks and beyond in coverage, throughput, and resource management.
[6]	2024			✓			✓	Study of learning algorithms in UAV-assisted SAGINs, proposing 3D satisfaction learning model.
[11]	2024		✓		✓			Review of resource management strategies in 6G-era JCC-SAGINs.
This survey		✓	✓	✓	✓	✓	✓	Review of key technologies of UAV-assisted SAGINs, including routing, security control, path planning, resource management, and deployment. Also summarizes application challenges and future research directions.

[1] Routing protocols. [2] Security control. [3] Path planning. [4] Resource management. [5] Energy management. [6] Deployment of UAVs.

The contributions of this paper are as follows:

(1) We provide a comprehensive and detailed description of the network architecture and technical features of UAV-assisted SAGINs.

(2) We summarize the key technologies for UAV-assisted SAGINs, including routing protocols, path planning, resource allocation, security control, and aerial deployment.
(3) We summarize the advantages of UAV-assisted SAGINs and their applications in various fields. In addition, we summarize future research directions based on the above technical analysis and application results.

Figure 2 shows the overall structure of this article. The remainder of this article is divided into five sections. Section 2 introduces the background, including SAGIN and UAV communication. Section 3 reviews the significant research on UAV-assisted SAGINs, including routing protocols, security control, path planning, resource management, and UAV deployment. Building on this, we elaborate on the applications of UAV-assisted SAGINs in Section 4. In Section 5, we summarize the existing challenges and look forward to future research directions. Finally, Section 6 summarizes the work presented in this paper. The main terminology abbreviations used in this paper are listed in Abbreviations.

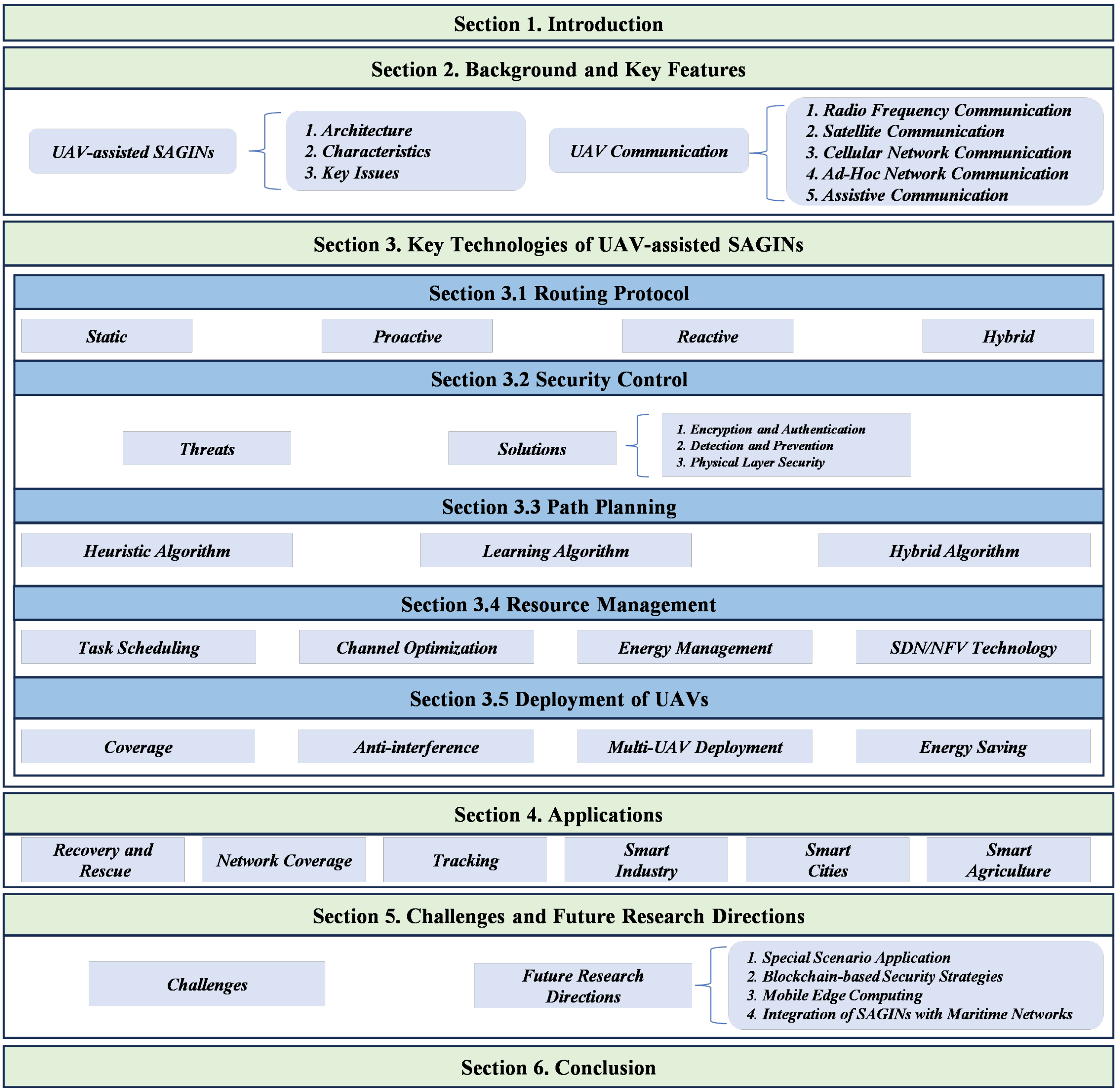

Figure 2. A preview of the overall structure of this paper.

2. Background and Key Features

2.1. UAV-Assisted SAGINs

With the development of global communication technology, the demand for seamless coverage and efficient connectivity is increasing, and SAGINs have emerged as one of the key technologies to achieve this goal.

2.1.1. Architecture of UAV-Assisted SAGINs

Overall, an SAGIN proposes a layered network architecture that integrates aerial platforms such as satellite systems and UAVs with ground networks to build a coordinated and robust network ecosystem [2]. As shown in Figure 1a, satellites are distributed at the top level, providing critical communication and data transmission services for the entire network. Drones, balloons, and airships form the middle layer of the network, which are flexibly deployed in the air to supplement the functionality of satellites and provide services closer to the ground. The ground part is the foundation of the network, including ground stations and control centers, responsible for the management and control of the network, ensuring the stable operation and efficient coordination of the entire system [18]. This precise integration aims to achieve wide coverage, strengthen network connectivity, and drive the development of a range of applications from remote sensing monitoring to providing broadband access in inaccessible areas.

(1) *Satellite Network*: The satellite network constitutes the space-based component of an SAGIN, primarily comprising satellites in diverse orbits, including LEO (e.g., Starlink and OneWeb constellations), Medium Earth Orbit (MEO), and Geostationary Earth Orbit (GEO), as well as synchronous and relay satellites. These networks enable seamless global communication, particularly in remote areas, oceans, and deserts where terrestrial base stations are unavailable. By synergizing LEO satellites (low latency, high bandwidth) with GEO satellites (wide area coverage), a multi-source data transmission system is established to meet demands for low latency and high throughput.
(2) *Aerial Network*: The aerial network consists of UAVs and HAPs, serving as a flexible and dynamically adaptive intermediate layer between space and terrestrial networks. It can be rapidly deployed for emergency scenarios to act as a temporary communication relay or backup network. While low-altitude platforms are susceptible to weather and mobility constraints, seamless handover and load balancing can be achieved through coordinated operations with satellite and terrestrial networks.
(3) *Ground Network*: The ground network forms the foundational layer of an SAGIN, encompassing cellular networks (5G/6G base stations), IoT devices, and fiber-optic infrastructure. It supports direct user access and delivers high-speed data transmission, catering to real-time requirements in the industrial IoT, vehicular networks, and other latency-sensitive applications. Ground base stations dynamically allocate satellite and aerial resources via Software-Defined Networking (SDN) and Network Function Virtualization (NFV) technologies to optimize the QoS requirements of E2E. However, remote regions remain reliant on satellite and aerial networks for connectivity, while densely deployed IoT devices are prone to interference.

Unlike traditional networks, SAGINs are expected to abandon the "best-effort" design philosophy. Instead, SAGINs aim to achieve reliable network control, provide deterministic latency, and comprehensively consider QoS requirements and network stability. SDN and NFV offer new design paradigms for the SAGIN architecture, significantly influencing the development of future networks. SDN addresses the complexity caused by the lack of transparency in traditional distributed control networks through a centralized control approach. Its core concept is to decouple the control plane from the data plane and manage the network via programmable interfaces. SDN controllers can provide detailed network state parameters and exercise precise control over the network [19]. However, relying solely on software programming is insufficient to fully resolve network complexity. Current research efforts are focused on advancing programmable hardware chips and programming languages to further enhance the capabilities of SDN. The core of NFV lies in abstracting and managing computing, storage, and network resources through Network Virtualization and Virtual Network Function (VNF) technologies. VNF detaches network functions from underlying physical networks, enabling on-demand deployment and dynamic management. Multiple VNFs can be combined into Service Function Chains (SFCs), which are dynamically orchestrated and deployed by SDN controllers. This approach has been applied to address resource orchestration and management challenges in SAGINs [20]. Furthermore, NFV leverages virtual network platforms to enable computing-capable network nodes to perform data processing tasks, thereby advancing edge computing and cloud computing.

2.1.2. Characteristics of UAV-Assisted SAGINs

The hierarchical complexity of an SAGIN primarily stems from the integration of its various network layers. For example, the SN segment, particularly GEO, has a much lower data transmission rate compared to TNs. This is determined by the characteristics of network components; currently, satellite nodes have limited data bandwidth but can provide global network access. In addition to cross-layer performance gaps, differences within the same network layer also impact overall network performance. For instance, there are significant variations in propagation delay and data transmission rates among GEO, MEO, and LEO satellites. To address these differences, researchers are optimizing network structures and functions based on the characteristics of the nodes. As described in [16], we summarize the key characteristics of SAGINs and present them in Table 2.

Table 2. Analysis of UAV-assisted SAGIN characteristics.

<table>
<tr><th>Network</th><th>Component</th><th>Altitude (km)</th><th>Full Coverage Requirement</th><th>Transmission Delay</th><th>Propagation Loss</th><th>Data Rate</th></tr>
<tr><td rowspan="3">Satellite</td><td>GEO</td><td>35,786</td><td>3</td><td>>200 ms</td><td>High</td><td>Limited</td></tr>
<tr><td>MEO</td><td>2000 to 35,786</td><td>6 to 12</td><td>100 to 150 ms</td><td>Medium</td><td rowspan="2">Reaches Gbps</td></tr>
<tr><td>LEO</td><td>300 to 2000</td><td>>100</td><td><20 ms</td><td>Low</td></tr>
<tr><td rowspan="2">Aerial</td><td>HAP</td><td>10 to 50</td><td>-</td><td rowspan="2">Medium</td><td>Low</td><td rowspan="3">Up to 10 Gbps</td></tr>
<tr><td>LAP</td><td>≤10</td><td>-</td><td>Low</td></tr>
<tr><td colspan="2">Ground</td><td>-</td><td>-</td><td>Lowest</td><td>Lowest</td></tr>
</table>

In addition, frequency band allocation is another critical issue in SAGINs and the frequency band allocation standards for wireless communications are set by the International Telecommunication Union (ITU) to promote the efficient global utilization of the spectrum and avoid signal interference. In SAGINs, the communication frequency bands for terrestrial services are widely distributed, while frequency band allocation for aerial services remains uncertain. Therefore, our focus is primarily on analyzing the frequency band information allocated for space-to-earth (StE) services, as shown in Figure 3. Moreover, the 3GPP is advancing the development of frequency band standards for 5G New Radio in NTNs, and more frequency bands applicable to SAGINs are expected to be further included.

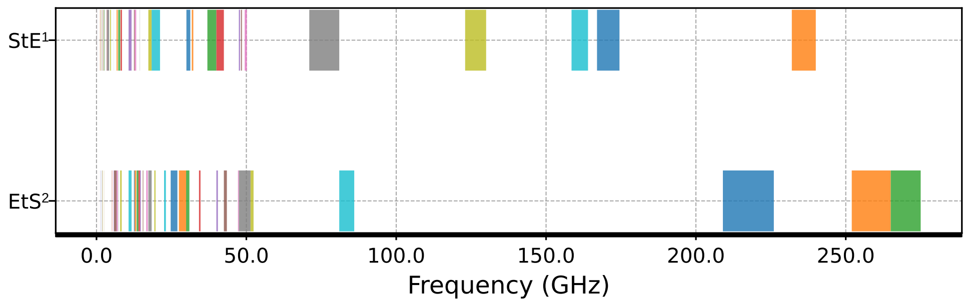

Figure 3. Analysis of frequency band allocation in SAGINs. Different colors are used to distinguish adjacent frequency bands. StE[1]: space to earth; EtS[2]: earth to space.

2.1.3. Key Issues of UAV-Assisted SAGINs

On one hand, research on 6G-SAGINs focuses on addressing protocol compatibility and seamless handover performance among heterogeneous network components within a framework integrating UAV-as-a-Service (UaaS) and computational networks. On the other hand, while advancing ultra-low latency and ultra-high reliability transmission through resource allocation optimization, challenges such as frequent access point handovers and link anti-interference issues intensify. In summary, the key challenges can be primarily categorized into three aspects, (1) hierarchical architecture, (2) dynamic characteristics, and (3) extreme environments, with current research hotspots including the following:

(1) *Cross-Layer Protocol Adaptation:* Protocol heterogeneity introduces complexity to SAGIN systems. The traditional TCP attributes packet loss to congestion, leading to performance degradation in high-bit-error-rate SAGIN scenarios. In contrast, the Licklider Transmission Protocol in Delay Tolerant Networking (DTN) employs a delay-based acknowledgment mechanism to distinguish packet loss causes and optimize transmission efficiency [21].

(2) *Network Virtualization and Service Architecture:* Virtualized service architectures are considered baseline technologies for integrating SAGINs. By abstracting UAVs' and satellites' computational, storage, and communication resources into dynamically allocatable virtual resource pools, they enable on-demand service deployment and task offloading [22]. However, virtualized SAGINs still face challenges such as dynamic topology management, cross-domain security, and additional migration costs and control overhead introduced by virtualization.

(3) *Network Resource Awareness:* Unknown topologies increase the complexity of resource discovery. Multi-source sensors collect data on location, signal strength, energy consumption, and link quality, while vision, radar, and radio frequency identification (RFID) technologies enhance environmental perception.

(4) *Topology Prediction:* Aimed at forecasting future topology changes based on historical and real-time data while dynamically sensing current states, topology prediction is a performance bottleneck for path planning and deployment tasks [5]. Common in UAV swarm ad hoc networks and constellation topology prediction, current approaches include machine learning (ML)-based and physics-based models, categorized as offline or online depending on the prediction methods.

(5) *Dynamic Traffic Load:* For traffic scheduling, SAGINs employ centralized and distributed modes. SDN-like architectures enable global traffic path optimization with controlled latency and load [23]. SDN also allows virtual network resource parti-

tioning based on service requirements, prioritizing critical services (e.g., allocating dedicated satellite bandwidth for emergency communications during disasters).

(6) *Resilient Security:* Adaptive security mechanisms enhance SAGIN availability in dynamic topologies. Dynamic defenses include Moving Target Defense, which periodically alters node IPs, ports, and encryption keys to impede attackers [24], and Zero-Trust Architecture, which enforces continuous authentication and authorization for cross-layer access requests [25]. AI-driven anomaly detection integrated with SDN controllers isolates malicious nodes. Additionally, channel attacks [26,27] on UAVs remain one of the key challenges in dynamic conditions.

(7) *Endurance and Efficiency:* The short endurance of small UAVs (commercial UAVs typically last less than 2 h) and long-term hovering requirements for HAPs are critical technical barriers. Hybrid hydrogen fuel cells and solar energy offer viable solutions [17], exemplified by Google Loon's solar-powered balloons achieving months-long flight. The joint optimization of UAV endurance and resource allocation is often modeled as NP-hard (resource–power) problems, solved via heuristic or AI-based iterative algorithms [28,29].

(8) *Latency Tolerance and Low Latency:* SAGINs must support both latency-tolerant and low-latency critical services. GEO satellites (approx. 250 ms one-way latency) struggle to meet real-time demands [16]. LEO/MEO satellite priority routing reduces latency to 20–40 ms, while inter-satellite links minimize ground relay overhead. For latency-tolerant traffic, non-real-time data are transmitted via edge channels to avoid bandwidth contention with critical services.

2.2. UAV Communication

The communication system of a UAV mainly consists of three parts: the ground control station, the UAV platform, and the communication link [30]. The ground control station is responsible for sending control commands to the UAV and receiving transmitted data. The UAV platform is equipped with various sensors, flight control systems, and communication devices, responsible for data collection, processing, and transmission. The communication link is used for information transfer between the ground station and the UAV. The stability, anti-interference, and transmission speed of the communication link have a direct impact on the success of UAV missions; hence, wireless communication technology plays a significant role in UAV systems.

2.2.1. Radio Frequency Communication

Radio frequency (RF) communication is the most traditional and widely used method for UAV communication. RF communication has strong penetration and anti-interference capabilities over short distances, making it suitable for the local control of small UAVs. With the widespread application of UAVs, spectrum resources are becoming increasingly scarce, making the optimization of channel selection and the improvement of spectrum efficiency crucial. Challita et al. [31] proposed a deep reinforcement learning (DRL)-based interference management scheme for RF communication in UAVs connected to cellular networks, aiming to reduce interference in multi-UAV scenarios and enhance spectrum efficiency. In [32], the authors established an RF communication path loss model between UAVs and ground stations and analyzed the impact of signal propagation from different heights and distances. They proposed the optimal flight altitude suitable for RF communication, thereby maximizing ground coverage and enhancing communication reliability. With the increase in communication needs, optical communication and millimeter wave communication have become important directions for future high-speed communications. For example, free-space optical communication is being widely studied in short-distance, high-bandwidth-demand scenarios.

2.2.2. Satellite Communication

Satellite communication (SATCOM) is primarily used for remotely controlling and monitoring large-scale UAV activities, such as military or rescue drones. SATCOM provides global communication coverage and can meet the demands for long distance and high bandwidth, but the high-speed mobility of UAVs poses challenges for data transmission with satellites. In [33], the authors analyze the issue of rapidly changing channel characteristics due to the mobility of UAVs and propose a new three-dimensional channel modeling and tracking method to achieve a stable connection between UAVs and satellites. In [34], the authors explore the advantages of applying optical communication technology to the data transmission between UAVs and satellites and propose several solutions aimed at achieving a more efficient and stable drone–satellite optical communication link.

2.2.3. Cellular Network Communication

With the popularity of 4G and 5G cellular networks, the application of cellular communication technology in UAVs has gradually increased. The advantage of cellular network communication is that it can utilize existing infrastructure, reducing construction costs while providing stable communication support. In [35], the authors studied the optimization of cellular network architectures that support high data transmission rates and wide area coverage for UAVs and proposed application scenarios and technical challenges for UAVs in diversified services (such as spectrum sharing and interference management). In [36], the authors looked forward to the development trend of cellular communication from 5G to 6G, introduced the key communication requirements of aerial platforms, including the latest progress in the 3GPP standards, and discussed emerging needs in industrial and military applications. We expect that 6G will integrate future wireless access technologies, including OFDM–microwave, OFDM–millimeter wave, terahertz communication, URLLC, and seamless communication technology based on integrated space–air–ground networks. Unlike earlier generations that relied on narrowband, 6G will support ground broadband coverage and will also enhance regular broadband, ultra-broadband, and wireless internet technologies [37].

2.2.4. Ad Hoc Network Communication

Ad hoc networking is a network model without the need for fixed infrastructure, allowing UAVs to establish communication links through multi-hop transmission between nodes. This technology is suitable for scenarios where multiple UAVs work collaboratively, such as post-disaster search and rescue, group reconnaissance, and other missions. In [38], to improve the performance of UAV networks in dynamic tasks, the authors introduced a cluster-based fault-tolerant routing technique. This technique divides UAVs into multiple communication clusters, allowing other nodes to quickly take over when some nodes fail, preventing link interruptions. In [39], the authors proposed a large-scale, decentralized, full-duplex ad hoc network for UAV communication, enabling each UAV node to have independent routing and forwarding capabilities and allowing each node to transmit and receive data simultaneously, enhancing system resilience and data transmission efficiency. The authors also proposed a cluster-based hierarchical architecture and distributed access technology, effectively improving the network's robustness and bandwidth utilization, suitable for complex flight missions and dynamic environments.

2.2.5. Assistive Communication

In the future, UAV communications will mainly develop in the direction of high efficiency, intelligence, low cost, and large coverage and will be integrated with popular technologies such as artificial intelligence and blockchain. For example, intelligent communication based on artificial intelligence can dynamically select the optimal communication path, adjust the transmission rate, and adapt to the communication needs in complex environments. In [40], the authors proposed an AI-driven algorithm for the dynamic resource allocation problem. Through real-time learning and optimization, communication resources are allocated to UAVs in different flight missions, thereby achieving more efficient data transmission and low-latency communication. In [41], the authors proposed an energy optimization method based on deep learning and reinforcement learning. It can optimize the flight path and data transmission strategy of a UAV in real time according to factors such as the remaining energy, signal strength, and transmission delay of the sensor node, thereby reducing energy consumption and transmission delay. At the same time, the introduction of blockchain is expected to solve data security and privacy issues in UAV communications. The decentralized and highly secure distributed mechanism provided by blockchain technology eliminates the dependence of UAV networks on a central server, effectively preventing data tampering and information leakage.

3. Key Technologies of UAV-Assisted SAGINs

3.1. Routing Protocols

In UAV-assisted SAGINs, routing protocols play a crucial role. Due to SAGINs' integration of multi-dimensional communication networks in the air, ground, and space, the design of their routing protocols must take into account the high dynamism of drones, frequent changes in network topology, and unique challenges in multi-dimensional environments. Effective routing protocols can ensure the efficient and reliable transmission of data packets in complex and ever-changing network environments. This section will provide an overview of several key routing protocols used in unmanned aerial vehicle-assisted SAGINs, including their working principles, advantages, limitations, and challenges in practical applications. Table 3 shows the analysis of common routing protocols.

3.1.1. Static Routing Protocols

A static routing protocol is an automatic route discovery mechanism preconfigured by network administrators, which does not rely on dynamic routing protocols [42]. In SAGINs, this means that network administrators need to manually set up routing tables and specify the path of data packets from the source node to the destination node based on the predetermined flight path and mission requirements of the UAV. In UAV-assisted SAGINs, the implementation of a static routing protocol begins with network administrators preconfiguring routing tables, including setting fixed routing paths as communication links between UAVs and ground stations, satellites, or other network nodes [43]. Huang et al. [44] proposed a communication topology-preserving motion planning method to enable static routing in UAV networks. When a packet arrives at a router or drone node, the device forwards the packet to the next designated node based on the preset routing table entry. This process does not involve complex algorithm calculations but is directly carried out based on the administrator's configuration. In addition, static routing protocols provide a high degree of stability and predictability, which is particularly important for the control instructions and critical data transmission of UAVs. In situations where the network topology is relatively fixed, static routing protocols can ensure the reliability of data transmission.

Table 3. Analysis of routing protocols.

Ref.	Routing Protocol	Protocol Type	Working Principle	Advantages	Limitations
[45]	OSPF	Proactive Routing Protocol	Link state algorithm	Fast convergence, suitable for large networks	Not suitable for frequently changing network environments
[46]	DSDV	Proactive Routing Protocol	Distance vector algorithm	Quickly responds to topology changes	Not suitable for frequently changing network environments
[47]	WRP	Proactive Routing Protocol	Routing algorithm based on distance vector	Supports reliable transmission over wireless networks	The update cost is high when the topology changes
[48]	IS-IS	Proactive Routing Protocol	Link state routing protocol	Quickly converges and adapts to complex network topologies	Configuration and management are relatively complex
[49]	AODV	Reactive Routing Protocol	On-demand distance vector algorithm	Saves bandwidth, suitable for dynamic networks	Route discovery delay
[50]	DSR	Reactive Routing Protocol	Source routing algorithm	No need to maintain a global routing table	The cost of path discovery is high, and the response speed to link errors is slow
[51]	ABR	Reactive Routing Protocol	Adaptive bit rate algorithm	Improves the adaptability and user experience of video streaming	The algorithm is complex and requires accurate network state estimation
[52]	ZRP	Hybrid Routing Protocol	Combining active and reactive algorithms	Balances the advantages of active and reactive methods	Realizing complexity
[53]	TORA	Hybrid Routing Protocol	Suitable for highly dynamic mobile environments, controlling message propagation range to be small and reducing network overhead	Balances the advantages of active and reactive methods	The possible use of suboptimal routing to reduce the overhead of discovering routes
[54]	EIGRP	Hybrid Routing Protocol	Distance vector routing selection technology based on DUAL algorithm	Fast convergence, reduced bandwidth usage, and support for multiple network layer protocols	There is a regional concept, which is suitable for networks with relatively small scales

3.1.2. Proactive Routing Protocols

In the construction of SAGINs, proactive routing protocols maintain routing tables at each network node to achieve the real-time tracking of network topology and optimize packet transmission paths. A proactive routing protocol is a routing protocol based on global network information. In this protocol, each node periodically broadcasts routing information and maintains a routing table containing routing information for all other network nodes. These routing tables enable each node to have the global topology information of the network and thus know the optimal transmission path before data transmission. In proactive routing protocols, common routing protocols include OSPF [45], DSDV [46], WRP [47], IS-IS [48], etc.

In proactive routing protocols, each node updates its routing table by periodically broadcasting routing information. This information includes the presence of neighboring nodes, link status, and the optimal path to reach each network node. Recent research has integrated machine learning techniques to enhance these protocols, particularly in the context of SAGIN IoT Networks. In Yuan et al. [55], an extended Extreme Learning Machine (ELM) model was proposed to predict communication blockage and improve satellite routing efficiency. When the network topology changes, such as by adding or removing links, the affected nodes generate new routing update information and broadcast it to other nodes so that all nodes can update their routing tables to reflect the new network topology. Due to each node having the latest routing table, when a data packet needs to be sent, the node can immediately determine the optimal path to reach the destination node, thereby reducing routing latency. The extended ELM model has shown to be effective in processing large-scale data with high accuracy and fast calculation speed, which is crucial for the dynamic and real-time communication needs of UAVs and other components in SAGINs.

Proactive routing protocols provide fast routing decisions, which are of significance for the dynamic and real-time communication needs of drones. However, in highly dynamic network environments, these protocols face challenges such as frequent topology changes and the high mobility of nodes. To address these challenges, researchers have proposed various optimization strategies Eiza et al. [19] proposed a hybrid SDN-based architecture to implement secure and QoS-aware routing in SAGINs, utilizing multiple SDN controllers at different levels to find multiple routes that meet security and QoS requirements. Liu et al. [56] developed deep learning-assisted routing algorithms to utilize quasi-predictable network topologies and operate in a distributed manner, improving coverage quality by reducing end-to-end latency and increasing end-to-end throughput. In addition, in order to achieve the global optimization of resources in large-scale networks and collaboration between heterogeneous networks, Liao et al. [57] proposed a multi-controller deployment strategy based on a simulated annealing algorithm for 6G SAGINs supporting SDN, aiming to balance controller load and improve network performance. These strategies emphasize the integration of advanced technologies such as SDN and deep learning to improve the efficiency and adaptability of active routing protocols in SAGINs' complex dynamic environment.

3.1.3. Reactive Routing Protocols

A reactive routing protocol is a routing protocol designed specifically for mobile ad hoc networks (MANETs). This type of protocol does not preset routes but dynamically discovers and maintains routes when data transmission needs arise. Reactive routing protocols typically consist of two main stages: route discovery and route maintenance. In reactive routing protocols, common routing protocols include AODV [49], DSR [50], ABR [51], etc.

In the route discovery phase, when the source node needs to send data to the destination node but lacks an effective route, it initiates the route discovery process by broadcasting a route request to explore the path to the destination node. After the routing request reaches the destination node, the destination node sends a routing response (RREP) to the source node to establish the route. In our previous research [38], we discussed in detail the special requirements of flying ad hoc networks in SAGINs, including the mobility of drone nodes themselves, vulnerability to interference, and limited channel capacity. At the same time, we also need to consider interaction and integration with other networks such as ground stations and satellite networks to achieve better network performance.

In the routing maintenance phase, in order to reduce future routing discovery overhead, nodes can store discovered routes in the routing cache for subsequent transmission. When the network topology changes, only the routing paths that affect data transmission need to be updated. This on-demand update mechanism reduces unnecessary control messages and adapts to the dynamic characteristics of drone networks.

In UAV-assisted SAGINs, reactive routing protocols can quickly respond to changes in drone location and dynamic adjustments in network topology, providing flexible routing solutions for communication between drones and data transmission between drones and ground stations. Quy et al. [58] proposed many routing algorithms in their research, including their performance, efficiency, and applicability, particularly in the SAGIN environment.

3.1.4. Hybrid Routing Protocols

A hybrid routing protocol combines the advantages of active routing protocols and reactive routing protocols, aiming to adapt to the complexity and dynamics of drone communication in SAGINs. This protocol uses an active routing protocol locally to maintain accurate routing information and can narrow the propagation range of routing control messages. When the target node is far away, it uses a reactive routing protocol to search and discover routes. In addition, hybrid routing protocols such as Zone Routing Protocols (ZRPs) [52] use multi-range technology and propose a hybrid routing protocol framework called a Regional Routing Framework. Active routing protocols are used within a region to maintain routing information at all times, while on-demand routing protocols are used outside a region for on-demand routing selection. The size of the region can be adjusted to adapt to changes in local or temporary networks, in order to achieve optimal overall network performance. The temporarily Ordered Routing Algorithm (TORA) [53] is a reactive routing protocol that uses a link-reversal distributed algorithm to limit the transmission of routing information to a small number of nodes closest to topology changes, and nodes only store routing information from neighboring nodes. This mechanism enables the TORA to respond quickly to topological changes in the network while maintaining low overhead. The Enhanced Interior Gateway Routing Protocol (EIGRP) [54] is an advanced distance vector routing protocol that combines the advantages of link state and distance vector routing selection protocols. By using the DUAL algorithm, it can achieve network convergence as quickly as possible. The EIGRP uses bandwidth, latency, reliability, and other metrics to evaluate the quality of routing paths. It supports variable length subnet mask, routing aggregation, and fast convergence and is suitable for complex network environments. It has high scalability and flexibility in routing selection.

3.2. Security Control

The heterogeneity and dynamic nature of SAGINs make the networks vulnerable to various attacks, mainly involving three levels: data security, network security, and physical-layer security. In data security, data protection should be strengthened to ensure the confidentiality of data during communication transmission, and encryption technology should be used to prevent data eavesdropping, tampering, and forgery. In terms of network security, the main security threats include denial of service (DoS) attacks, man-in-the-middle attacks, malware propagation, etc. It is necessary to strengthen the monitoring and defense of malicious traffic and adjust the intrusion detection algorithm to adapt to the limited computing power in SAGINs. In terms of the physical layer, drones and satellite channels are susceptible to frequency band interference, which affects the communication quality or navigation ability of drones. The anti-interference ability and reliability of communication links should be improved through technologies such as frequency hopping, beam-forming, and waveform encryption. In this section, we review in detail the research on the safety control of UAV-assisted SAGINs and present the results in Table 4.

Table 4. Significant research on safety control.

Key Technologies	Ref.	Method	Attack	Contribution
Encryption and authentication technology	[59]	PUF	FA	A lightweight authentication and key agreement protocol based on physically unclonable functions.
	[60]	DWT-CT	EA	Developed an encryption scheme based on discrete wavelet transform (DWT) and chaos theory, specifically for data protection in real-time applications in UAVs.
	[61]	HF	ZDA	A platform that allows developers to develop private and permitted blockchains with the Hyperledger Fabric framework.
	[62]	BTS	ZDA	Proposed a trust management framework based on blockchain timestamp sequences (BTSs), which reflects the performance of UAVs.
	[27]	SST	JA	Proposed a blockchain-based drone-assisted cellular network–secure spectrum trading framework.
Intrusion detection and prevention	[63]	DRL	JA	An intrusion detection system designed using DRL methods.
	[64]	ML	EA	Designed a feature extraction method based on autoencoders, combined with machine learning models for intrusion detection in UAV communications.
	[65]	DCNN	EA	Proposed an intrusion detection system based on deep convolutional neural networks.
	[66]	CIDS	ZDA	Proposed a collaborative intrusion detection network architecture (CIDS) based on Hyperledger Fabric and Snort IDS.
	[67]	ADS	DDoS	A smart-grid DDoS attack tracking scheme using UAV mobility and an adaptive beam search (ADS) algorithm to reconstruct attack paths and accurately locate attack sources is proposed.
Physical-layer security	[26]	FSO-RF	EA/JA	A method to achieve secure communication using a hybrid FSO/RF link in two-stage uplink transmission.
	[68]	TD3	JA	A double-delayed deep deterministic policy gradient (TD3) algorithm based on DRL.
	[69]	DRT	FA	A GPS spoofing detection and mitigation scheme based on distributed radar tracking (DRT) and data fusion.
	[28,70]	RIS	EA/JA	(1) A joint beam-forming design for an RIS-assisted satellite–terrestrial hybrid relay network. (2) A scheme for enhancing the security of satellite downlink communications using a novel absorbing RIS.

3.2.1. Security Attacks

Cybersecurity attacks can be categorized into two types based on their objectives: obtaining sensitive data and disrupting network systems. Network attackers exploit system vulnerabilities to illegally infiltrate systems and gain access to critical system data and sensitive user information or employ attack methods to damage systems, potentially extorting financial benefits from system operators. Such cyberattacks span various fields, including government, IT, and finance, often leading to service outages and significant financial losses. In UAV-assisted SAGINs, attack methods are more diverse and complex. In addition to traditional cyberattacks faced by communication networks, such as DoS attacks and zero-day exploits, SAGINs encounter new challenges. Low-altitude UAVs primarily rely on radio communication and they are vulnerable to channel jamming and GPS spoofing. Furthermore, control commands exchanged between UAVs and ground or space control stations may be intercepted and altered, potentially allowing attackers to hijack UAVs. The primary security attacks on UAV-assisted SAGINs are as follows:

(1) *Jamming Attacks (JAs)*: These involve maliciously injecting high-power signals into communication channels to disrupt communication and interrupt services [27]. Such attacks are common in wireless and military communications. For instance, UAVs in signal-blocked areas may lose access to control signals and data. Anti-jamming technologies are essential for SAGINs, and current methods and research advancements addressing frequency band jamming are discussed under physical-layer security.

(2) *Fraudulent Attacks (FAs)*: Attackers disguise themselves as legitimate users or systems to gain illegal benefits or damage the system [69]. These attacks exploit system permission vulnerabilities or weaknesses in communication protocols. A common example is attackers manipulating BGP routing protocol rules by forging IP prefixes and injecting short paths to hijack traffic. Comprehensive encryption and authentication mechanisms are necessary to mitigate such threats.

(3) *Zero-Day Attacks (ZDAs)*: These attacks are widespread and target undisclosed or unpatched vulnerabilities, posing high risks and being difficult to prevent. Regular vulnerability assessments and anomaly detection are essential for defense. Agnew et al. [71] proposed a novel predictive queuing analysis method to accurately forecast network performance metrics in the LEO management layer, detecting zero-day network attacks with over a 94% accuracy, precision, recall, and F1-score.

(4) *Eavesdropping Attacks (EAs)*: Attackers intercept and listen to communication content to illegally acquire sensitive information. Eavesdropping attacks can be classified into active and passive modes based on the attack method [72]: (1) Active: attackers forge or tamper with communication data. (2) Passive: attackers secretly listen without being detected. In active eavesdropping, attackers not only steal data but may also engage in further fraudulent activities. To counter this threat, data encryption prevents direct data misuse, and intrusion detection systems can promptly identify attack behaviors.

(5) *Flood Attacks and DoS*: A common internet attack method that floods target servers with large volumes of junk requests, depleting system resources. Distributed denial of service (DDoS) is a variant involving attacks launched simultaneously from multiple distributed devices [73]. DDoS is simple, swift, and highly scalable. For example, in 2023, cloud service provider Akamai suffered a DDoS attack with the peak request traffic reaching 900.1 Gbps.

3.2.2. Safety Control Technologies

The current methods for addressing the five major attack strategies mentioned above are summarized into the following three categories: encryption and authentication, intrusion detection and prevention, and physical-layer security. The relationships among these categories are illustrated in Figure 4.

(1) *Encryption and Authentication*: Encryption algorithms can protect data from being eavesdropped or tampered with during transmission, but due to the limited computing resources of UAVs, encryption algorithms should be lightweight and low-energy. In [59], the authors proposed a lightweight authentication and key agreement protocol based on physically unclonable functions (PUFs), which generates a unique identifier for the UAV through PUFs, achieving identity authentication, access control, and intrusion detection. While ensuring security, it reduces computational and communication overheads. In [60], the authors developed an encryption scheme

based on discrete wavelet transform (DWT) and chaos theory, specifically for data protection in real-time applications in UAVs. This approach optimizes computational efficiency by decomposing the frequency components of the data while improving data security by using random noise diffusion. This scheme can effectively balance encryption strength and computational cost and is suitable for UAVs with limited battery capacity. Blockchain has developed into a general technology that provides higher security and transparency for UAV communications with its decentralized distributed storage, smart contracts, and tamper-proof features. According to our investigation, blockchain and UAV communication technologies can be effectively combined. In the reference [61], Jensen et al. focused on the blockchain framework Hyperledger Fabric, which is a platform that allows developers to develop private and permitted blockchains. The authors showed how to use different features of Hyperledger Fabric to protect drone swarm networks, including using digital certificates for identity management and using chain codes to define assets and transaction rules. In the reference [62], Mahsa Keshavarz et al. proposed a trust management framework based on blockchain timestamp sequences, which reflects the performance of UAVs through the observation of distributed observers. It can also detect damaged distributed observers and reduce their impact on drone evaluation. In [27], the authors proposed a blockchain-based drone-assisted cellular network–secure spectrum trading framework, which uses consortium blockchain technology to achieve distributed secure spectrum trading through the assistance of mobile edge computing. And, they designed a low-complexity non-uniform pricing algorithm and a distributed uniform pricing negotiation algorithm to maximize the profits of network operators and drone operators.

(2) *Intrusion Detection and Prevention*: Intrusion detection and defense in UAV communications are crucial. Under conditions such as highly dynamic network environments, multi-node collaboration, and resource constraints, a balance between real-time and lightweight processes must be achieved. The collaborative mechanism under a distributed architecture is particularly critical to ensuring the overall security of the network. At the same time, it is necessary to use artificial intelligence and edge computing technologies to achieve efficient threat detection and rapid response to effectively respond to various security threats such as data eavesdropping, navigation deception, and denial-of-service attacks. Traditional intrusion detection methods rely on static rules and feature matching, which find it difficult to cope with complex and changing network environments and new attacks. The introduction of machine learning and deep learning technologies has enabled intrusion detection to shift from a static mode to a dynamic mode, greatly improving the accuracy and efficiency of detection. In [63], the authors discussed in detail an intrusion detection system designed using DRL methods, which showed high efficiency and robustness in detecting unknown threats in dynamic aerial computing networks. In [64], Vuong et al. designed a feature extraction method based on autoencoders, combined with machine learning models for intrusion detection in drone communications. Experiments on actual data sets showed that this method was superior to traditional methods in both binary and multi-classification tasks. In [65], Abu et al. proposed an intrusion detection system based on deep convolutional neural networks, focusing on solving the problem of malicious behavior identification in the case of limited computing power in drone networks. Its implementation proved that the system can process large amounts of traffic data in complex network environments and maintain a low false alarm rate. Distributed intrusion detection systems (DIDSs) can defend against potential malicious attacks through the collaboration of multiple drones. By combining DIDSs

with deep learning, potential threats can be detected and classified in real time during drone communications. Hadi et al. [74] proposed a real-time collaborative intrusion detection system that uses deep learning technology to detect complex threats such as zero-day attacks through the collaborative operation of multiple drone nodes. Experiments showed that the system significantly improves detection efficiency and reduces the risk of single point failures. In [66], the authors proposed a collaborative intrusion detection system (CIDS) based on Hyperledger Fabric and Snort IDS and studied how blockchain technology can enhance the robustness and efficiency of the CIDS through trust management. In addition, for DDoS attack detection, Guo et al. [67] proposed a smart-grid DDoS attack tracking scheme that uses UAV mobility and an adaptive beam search algorithm to reconstruct attack paths and accurately locate attack sources.

(3) *Physical-Layer Security*: In physical-layer security, attackers often use frequency band interference or GPS spoofing. To protect UAV communications from interference, the anti-interference ability of communication links can be improved through frequency hopping, beam-forming, and waveform encryption. In [26], Zhang et al. proposed a method to achieve secure communication using a hybrid free space optical (FSO)/wireless RF link in two-stage uplink transmission. By using different communication links in two stages, attacks from RF eavesdroppers can be effectively defended against to maximize confidentiality. In [68], the authors proposed a double-delayed deep deterministic policy gradient (TD3) algorithm based on DRL, which solves the dual goals of energy efficiency and communication fairness in UAV-assisted air–ground integrated networks under interference attacks. In particular, it solves how to optimize system performance through intelligent resource scheduling when channel characteristics change randomly and easily cause channel capacity imbalance. In addition, reconfigurable intelligent surfaces (RISs) are able to precisely control the propagation direction, phase, and amplitude of electromagnetic waves, maximizing the signal-to-noise ratio and mitigating the impact of interference signals. Additionally, by adjusting the reflection paths to optimize signal transmission, it makes the signals difficult to track. Zhi et al. [28] proposed a RIS-assisted satellite–terrestrial hybrid relay network with a joint beam-forming design to address the blockage of satellite-to-user links. Using an alternating optimization algorithm, the design reduces the transmission power of both satellites and base stations while meeting user rate requirements. Subsequently, based on these results, Zhi et al. further optimized the beam-forming weights and reflection coefficient matrix using a penalty function and double-decomposition algorithm to maximize the achievable secrecy rate of the ground station [70]. For GPS fraud, Pardhasaradhi et al. [69] proposed a GPS spoofing detection and mitigation scheme based on distributed radar tracking and data fusion. The system can detect GPS signal anomalies in real time, identify potential spoofing attacks, and mitigate them, thereby enhancing the robustness of UAV navigation.

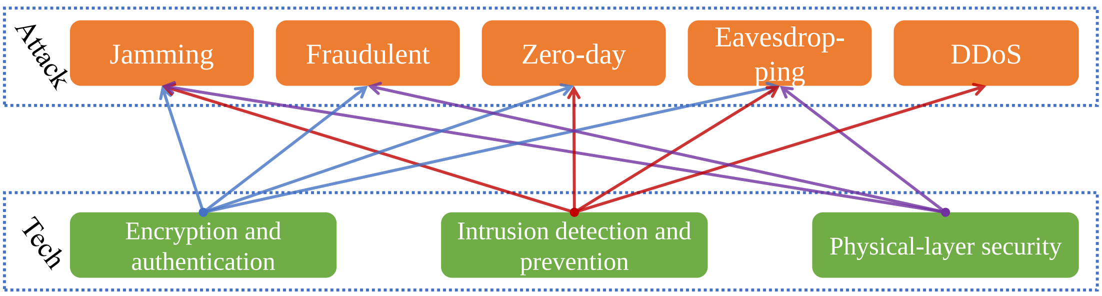

Figure 4. Correspondence between attacks and technologies.

3.3. Path Planning

Path planning is a critical component of UAV-assisted SAGINs [75], aiming to determine the optimal 3D path for UAVs from an initial point to a target destination while satisfying various complex constraints, such as kinematic constraints, energy limitations [76], and collision avoidance. From an optimization perspective, this task is essentially an NP-hard multi-objective optimization problem [77] and finds it hard to figure out polynomial-time exact solutions. With continuous advancements in science and technology, heuristic algorithms, machine learning algorithms, and hybrid approaches combining both have been proposed, offering an increasing number of viable solutions for the path planning problem in SAGIN environments. This section will comprehensively review the latest research progress of UAV path planning algorithms, and the review's results are presented in Table 5.

3.3.1. Heuristic Algorithm-Based Path Planning

The commonly used heuristic algorithms include traditional search methods such as the A* algorithm [78] and Dijkstra algorithm [79], as well as bio-inspired intelligent algorithms like ant colony optimization (ACO) [80] and genetic algorithms (GAs) [81]. These methods aim to efficiently find optimal or near-optimal solutions through intelligent search techniques, making them particularly suitable for real-time UAV path planning applications with limited computational resources.

Traditional algorithms like the A* and Dijkstra algorithms are widely used in UAV path planning due to their simplicity and effectiveness. However, they exhibit long computational times in large-scale search spaces. To improve the efficiency of these algorithms, some studies have proposed enhancements. For instance, Chen et al. [82] proposed an improvement to the A* algorithm by calculating the cosine values between the initial node and target node, as well as between the current node and target node, to filter out expansion nodes with large angular deviations. This reduces the search space and accelerates the algorithm's execution speed.

Bio-inspired intelligent algorithms, such as GAs and ACO, have gained increasing attention due to their adaptability and efficiency. Fu et al. [83] proposed a heuristic evolutionary algorithm, drawing inspiration from GAs, and designed replacement, crossover, mutation, length, and smoothness operations to enhance the path construction process. Liu et al. [84] further extended this field by introducing a modified sparrow search algorithm. This algorithm incorporates a chaotic strategy to enhance population diversity, uses adaptive inertia weights to balance convergence speed and exploration ability, and combines the Cauchy–Gaussian mutation strategy to avoid stagnation. These improvements enable the algorithm to exhibit faster convergence and a broader search space in dynamic and complex path planning scenarios.

Moreover, hybrid algorithms that combine multiple strategies have shown promising results in enhancing both global and local search capabilities. Lin et al. [85] proposed a hybrid particle swarm optimization (PSO) algorithm that integrates simulated annealing (SA) to improve the global search strategy. By introducing a dimension-based learning strategy for each particle, the algorithm reduces oscillation and accelerates convergence, making it more effective in complex path planning tasks. Zhang et al. [86] proposed a heuristic intersection search and rescue optimization algorithm. By combining crossover strategies with the basic SAR algorithm, this method improves convergence speed while maintaining population diversity. The authors also introduced a real-time path adjustment mechanism to address UAV path constraints, such as the minimum turning radius, thus improving the feasibility and safety of path planning. Ait et al. [87] proposed a hybrid algorithm combining chaotic eagle optimization and SA, termed CEO-SA. By using Singer mapping, this algorithm enhances population diversity and effectively explores the search space. SA is used as a local search mechanism to optimize the current best solution, thus improving both global and local search capabilities.

Table 5. Significant research on UAV path planning algorithms.

Method	Ref.	Specific Algorithm	Contribution
Heuristic Algorithm	[82]	An improved A* algorithm	Simplifies the search space of the A* algorithm and improves path search efficiency.
	[83]	A novel heuristic algorithm inspired by genetic algorithms	Enhances path diversity, aiding in escaping local optima.
	[84]	A modified sparrow search algorithm	Improves path diversity, balances convergence speed and exploration ability, and effectively avoids stagnation.
	[85]	A hybrid particle swarm optimization algorithm combined with simulated annealing	Reduces oscillation and accelerates convergence.
	[86]	A heuristic crossing search and rescue optimization algorithm (HC-SAR)	Enhances convergence speed while maintaining path diversity and introduces a path smoothing mechanism.
	[87]	A hybrid algorithm combining chaotic eagle optimization and simulated annealing (CEO-SA)	Uses Singer mapping to enhance path diversity and simulated annealing for local search, balancing global and local search.
Machine Learning	[88]	A lightweight 3D path planning algorithm based on YOLO	Enables rapid obstacle detection in complex environments, reduces computational burden, and improves path planning efficiency.
	[89]	A multi-layer path planning algorithm based on reinforcement learning	Balances global and local optimization, enhancing path planning performance.
	[90]	A DRL method for UAV path planning using global situational information	Establishes a rapid evaluation model, improving the generalization and real-time capabilities in obstacle avoidance.
	[91]	A lightweight real-time path planning algorithm based on reinforcement learning	Integrates global training with local adaptability, dynamically adjusts exploration probability, and enhances robustness.
	[92]	A path planner based on explainable deep neural networks	Incorporates a feature attribution model for generating intuitive textual and visual explanations.
Hybrid Algorithm	[93]	A global–local hybrid UAV path planning algorithm based on A* and Q-learning	Simplifies the OPEN set, improves path planning efficiency, and addresses the exploration–exploitation dilemma.
	[94]	A deep learning method trained via genetic algorithms for multi-UAV path planning efficiency	Uses genetic algorithms as a "coach" to provide training "experience" for deep learning without convergence processes, balancing efficiency and effectiveness.
	[95]	A gray wolf optimization algorithm based on reinforcement learning	Employs reinforcement learning to enable independent operations by each wolf, avoiding local optima and smoothing issues through geometric and optimal adjustments.
	[96]	A multi-strategy cuckoo search algorithm based on reinforcement learning	Dynamically invokes large-scale saltation and single-dimension shift strategies during iterations using deep learning, balancing exploration and convergence.
	[97]	A multi-modal cooperative multi-objective particle swarm optimization algorithm based on reinforcement learning	Utilizes reinforcement learning to guide particle update selection and develops multi-modal cooperative strategies, improving efficiency and robustness.

In summary, heuristic algorithms, ranging from traditional methods like the A* and Dijkstra algorithms to bio-inspired approaches such as GAs and ACO, offer diverse and efficient solutions for UAV path planning. While traditional algorithms provide simplicity and reliability, bio-inspired methods and hybrid algorithms enhance adaptability, search efficiency, and convergence speed, making them suitable for real-time applications in dynamic and complex environments. As UAV path planning continues to evolve, the integration of multiple strategies holds great potential for further improving performance and robustness in practical scenarios.

3.3.2. Machine Learning-Based Path Planning

With the increasing complexity of UAV application scenarios and the growing uncertainty of environments, traditional path planning methods face significant limitations in real-time adaptability and global optimization capabilities. ML, particularly reinforcement learning (RL) and deep learning (DL), offers innovative approaches to UAV path planning in dynamic environments like SAGINs [98]. ML-driven algorithms can adapt to real-time changes and make intelligent decisions, enhancing both global optimization and local adaptability.

In UAV path planning, obstacle avoidance is an essential issue that must be addressed. With the increasing application of machine learning in UAV path planning, deep learning-based object detection methods have begun to be integrated with path planning algorithms to solve real-time obstacle avoidance problems. Tullu et al. [88] proposed a lightweight 3D path planning algorithm based on the YOLO (You Only Look Once) object detection algorithm. This algorithm uses YOLO to quickly detect obstacles in the environment and generates collision-free paths based on the relative positions of these obstacles. This approach avoids the high computational burden of storing frontier nodes and constructing complete environmental maps, as required by traditional path planning techniques, enabling UAVs to efficiently plan paths and avoid obstacles in complex environments in real time.

RL has been widely applied in UAV path planning in recent years due to its ability to learn optimal strategies through interaction with the environment, especially when dealing with dynamic and uncertain environments. Cui et al. [89] proposed a multi-layer path planning algorithm based on reinforcement learning. This method uses a composite Q-value mechanism to select the optimal action in each time step, significantly improving the efficiency and performance of UAV path planning by combining global and local optimization, particularly in environments that require balancing exploration and exploitation. Yan et al. [90] proposed a UAV path planning method based on DRL with global situational awareness. This approach uses the STAGE Scenario software for simulation, allowing UAVs to plan paths in dynamic environments in real time and adapt to environmental changes. The method demonstrated the potential of DRL in managing global optimization and immediate responses. Xi et al. [91] developed a lightweight real-time path planning algorithm based on reinforcement learning, named adaptive soft actor-critic (ASAC). By integrating global training with local adaptability, the algorithm enhances its generalization ability. Through the introduction of cross-layer connections to prevent feature loss and an adaptive temperature coefficient that dynamically adjusts exploration probability, ASAC significantly improves the robustness and practicality of UAV path planning in complex urban environments.

As UAV applications continue to expand, explainable artificial intelligence is becoming increasingly important in path planning because it provides insights into the algorithmic decision-making process, which is crucial in applications requiring transparency and interpretability. To address this issue, He et al. [92] proposed an explainable deep neural network-based path planner by modeling the navigation problem as a Markov Decision Process (MDP) and using DRL methods to train the network in a simulation environment. They introduced feature attribution models to generate intuitive textual and visual explanations, enabling robust and interpretable path planning for quadcopter UAVs to autonomously fly in unknown environments.

In summary, machine learning, particularly reinforcement learning and deep learning, has shown great promise in addressing the challenges of UAV path planning in dynamic and uncertain environments. By integrating real-time adaptability, obstacle avoidance, and global optimization, ML-driven approaches offer a significant advancement over traditional methods. As technology advances, the synergy between ML and UAV path planning is likely to play a crucial role in enhancing the autonomy and performance of UAVs in real-world settings.

3.3.3. Hybrid Algorithm-Based Path Planning

In UAV path planning, a single algorithm often struggles to balance global optimization and real-time responsiveness. As a result, hybrid algorithms have gradually gained widespread attention as an effective solution to complex path planning problems [99]. By integrating heuristic algorithms with machine learning techniques, hybrid algorithms achieve a better balance between global optimality and real-time performance. They exhibit enhanced adaptability and efficiency, particularly when addressing challenges such as dynamic constraints and multi-objective optimization. Consequently, hybrid algorithms have become a critical research direction in UAV path planning.

Specifically, some studies focus on combining heuristic search and reinforcement learning techniques to achieve superior path planning in complex flight environments. For example, Li et al. [93] proposed a global–local hybrid UAV path planning algorithm based on the A* algorithm and Q-learning. The algorithm improves the A* algorithm's search strategy, step size, and cost function and simplifies the OPEN set to enhance planning efficiency. Meanwhile, by incorporating a dynamic exploration factor into Q-learning, it addresses the exploration–exploitation trade-off, effectively adapting to local dynamic path adjustments and significantly improving path quality, execution efficiency, and safety.

Another category of hybrid algorithms integrates bio-inspired intelligent algorithms with deep learning techniques to tackle complex path planning problems. For instance, Pan et al. [94] proposed the DL-GA algorithm, which uses a GA to collect state and path data from diverse scenarios, generating high-quality samples for training deep neural networks. This integration enables the network to quickly produce optimized paths meeting stringent real-time requirements, improving both planning efficiency and adaptability to complex environments.

Additionally, Qu et al. [95] proposed an RL-based gray wolf optimization algorithm. By incorporating RL mechanisms, individual agents can adaptively select four operations (exploration, exploitation, geometric adjustment, and optimal adjustment) based on accumulated performance. The algorithm also employs cubic B-spline curves to smooth the generated paths, effectively addressing path planning in complex three-dimensional flight environments. Yu et al. [96] developed a reinforcement learning-based multi-strategy cuckoo search algorithm. This algorithm combines large-scale jumps and one-dimensional movements as search strategies, dynamically adjusting parameters during the search process. These enhancements improve the original cuckoo search algorithm's search capability and convergence, significantly boosting performance in solving complex path planning problems. Zhang et al. [97] proposed a multi-modal cooperative multi-objective particle swarm optimization algorithm based on RL. This algorithm incorporates three particle update modes—exploration, exploitation, and hybrid—and leverages RL to guide the selection of update strategies. By achieving a balance between global search and local search in complex three-dimensional environments, the algorithm significantly enhances the efficiency and effectiveness of UAV path planning solutions.

In summary, hybrid algorithms offer greater adaptability and optimization capabilities for UAV path planning by flexibly integrating heuristic algorithms and ML techniques. With ongoing technological advancements, hybrid algorithm-based path planning methods are expected to enable more efficient and safer navigation in increasingly complex flight environments.

3.4. Resource Management

In SAGINs, UAVs serve as aerial base stations to provide stable network services. Resource management and allocation methods typically involve multiple aspects such as UAV deployment, path planning, data transmission, and spectrum allocation. This section will provide a detailed review of resource management research in UAV-assisted SAGINs, focusing on key areas such as task scheduling, channel allocation, energy management. The survey results are presented in Table 6.

3.4.1. Task Scheduling

The aerial network formed by UAVs has the following characteristics: (1) highly dynamic nodes and (2) highly dynamic network topologies. UAVs are often in motion, causing the network topology to change continuously due to the joining or leaving of nodes. Besides serving as communication relays, UAVs can also carry sensors and data collection equipment to obtain environmental parameters, optimizing user scheduling and network structure. Furthermore, the deep integration of SAGINs and edge computing has given rise to new edge cloud computing visions. In the following subsections, we will summarize task scheduling methods in UAV-assisted SAGINs from the perspectives of task types and application scenarios.

(1) *Computation Offloading*: UAVs provide computational resources for terminal devices with low computational power (e.g., IoT devices) or offload tasks to ground base stations, edge servers, or satellite nodes, alleviating local computational loads and enhancing network computing performance. The flexible deployment of UAVs showcases their advantages in extending computational capacity. For instance, Nguyen et al. [100] studied the UAV placement optimization problem, combining user association, partial offloading control, computational resources, and bandwidth allocation to reduce the weighted energy consumption of ground users (GUs) during computation offloading with UAVs. Since computation offloading optimization problems are typically difficult to solve and highly complex, many AI-based methods have been employed in recent years to jointly optimize computation offloading and resource allocation. For example, Gao et al. [101] proposed a dynamic policy-based online optimization method using DRL and perception assistance to address uncertainties in UAV deployment and task arrivals, optimizing computational loads in SAGINs.

(2) *Time Consumption*: Time complexity is a crucial metric for task scheduling, reflecting the efficiency of scheduling algorithms. Industries such as the industrial IoT and smart healthcare, which are highly latency-sensitive, often demand ultra-low latency. For latency-sensitive applications in the IoT, Chen et al. [102] proposed a robust task scheduling algorithm with risk aversion, addressing a two-stage stochastic optimization problem to minimize latency. In a computation offloading scenario, Zhou et al. [103] designed an online offloading decision method based on UAVs flying along predetermined trajectories to collect IoT device tasks within their coverage. However, in reality, UAV flight trajectories are often not entirely fixed. Therefore, Kang et al. [104] designed a task scheduling algorithm allowing UAVs to fly within a certain coverage area, employing a joint-optimization DRL method. Additionally, Zhou et al. [105] designed a task scheduling strategy that minimizes offloading and

computation latency for all tasks under UAV energy constraints using a risk-aware reinforcement learning algorithm, identifying optimal parameters to balance latency and risk minimization.

(3) *Environment-Oriented Algorithms* : UAVs are known to be susceptible to environmental interference and impacts. For instance, network stability is poorer in disaster-affected areas compared to normal regions. Some studies focus on the environmental effects on task scheduling, such as how interference significantly affects the reliability of communication links among UAVs, BSs, and GUs. Regarding the joint optimization of energy saving and fair resource scheduling, Chen et al. [68] proposed a DRL-based TD3 algorithm to optimize UAV trajectories, enhancing fairness between GUs and ground elements to resist interference. In emergency communication scenarios, Zhang et al. [106] studied the balance between task latency and energy consumption, proposing a method to minimize multi-UAV deployment costs. Niu et al. [29] formulated the task scheduling problem in disaster scenarios as a two-stage Lyapunov optimization problem. Through the joint optimization of task sizes transmitted from the control center to UAVs, local computation tasks, and tasks offloaded by UAVs and mobile devices, they minimized energy consumption in distributed computing systems while ensuring computational queue stability. Additionally, some studies address QoS by proposing task scheduling methods based on fairness and communication security. For example, He et al. [107] designed a task scheduling algorithm considering both fairness and security. Tian et al. [108] proposed a satisfaction model based on user task delay requirements and residual energy states to jointly optimize task offloading decisions and UAV scheduling strategies. Similarly, Fan et al. [109] constructed a general task scheduling framework considering diverse task types and requirements in SAGINs, integrating intelligent learning algorithms to jointly optimize task scheduling and resource allocation strategies.

3.4.2. Channel Optimization

Channel resources are critical yet highly susceptible to interference. Unlike traditional static channel estimation methods, the high mobility of UAVs and satellites continuously alters the line-of-sight (LoS) conditions for UAV-to-ground and UAV-to-satellite links. LoS communication refers to direct E2E communication under unobstructed conditions, and changes in these conditions significantly impact channel impulse response, channel transfer function, path loss, shadow fading, and root mean square delay spread, among other characteristics. Huang et al. [110] considered the impact of the LoS on communication in the joint optimization of offloading and resource allocation in a hybrid cloud and multi-access mobile edge computing (MEC) scenario within an SAGIN. Ismail et al. [111] proposed a probability-based service allocation strategy for LoS links. When the LoS probability is high, services are provided by UAVs; otherwise, they are provided by RSUs. Additionally, a mechanism based on the signal-to-interference-plus-noise ratio threshold is employed to reduce interference and improve communication reliability. Moreover, the vibration and pitch angle changes in UAVs during hovering can cause Doppler effects, leading to signal shifts and intensified channel state variations. Therefore, monitoring and sensing channel congestion is crucial for effective channel allocation. Channel tracking refers to the process of the real-time monitoring and updating of the dynamic characteristics of channel state information as it changes over time in a wireless communication system. This is essential for adapting to the time-varying nature of wireless channels and improving the performance of communication systems. In [33], a dynamic channel model and a three-dimensional dynamic turbo approximate message-passing (3D-DTAMP) algorithm are proposed. These are designed to track dynamic channels in Ka-band UAV–satellite communication systems, achieving better channel tracking performance while reducing pilot overhead and maintaining comparable complexity. In addition, UAV communication faces the challenge of backhaul link attenuation [112]. Research by Cui et al. [113] investigated the clustering and tracking of multi-path components in time-varying air-to-ground (A2G) channels and proposed a cluster-based tracking (CBT) method. By jointly considering the coupled effects of UAV vertical mobility, A2G communication, and dynamic computational requirements, Zhou et al. [114] formulated a non-convex constrained optimal control problem to optimize the overall energy efficiency of UAVs.

3.4.3. Energy Management

UAV energy management is a multifaceted issue involving energy harvesting, storage, distribution, and usage. As communication relays in SAGINs, UAVs not only need to sustain flight and basic communication functions but also handle additional energy-intensive tasks such as network communication, traffic scheduling, and computation offloading. Effectively managing UAV energy has therefore become a key research focus. This section summarizes recent research efforts in UAV energy management, covering critical areas such as energy harvesting, power control, data transmission, and deployment optimization.

(1) *Energy Harvesting*: UAV energy harvesting techniques aim to support operations by replenishing power through methods like solar energy conversion, wireless energy transfer, and hybrid energy recycling. Solar-powered UAVs convert sunlight into electricity, offering an environmentally friendly advantage. UAVs from HAPs benefit from superior solar exposure, enhancing their energy harvesting efficiency. However, for low-altitude UAVs, environmental obstructions significantly hinder efficiency. To address this, wireless energy transfer has emerged as a crucial solution. Ramzan et al. [115] explored RF energy harvesting in a cooperative communication scenario, where a UAV relay collected energy from RF signals transmitted by a satellite using power-splitting relay protocols. Based on this, they proposed a UAV relay-assisted network optimization framework with cooperative energy harvesting. Additionally, Fu et al. [116] introduced a power control strategy for joint communication, efficiently utilizing harvested energy while reducing channel interference over limited time periods. Dang et al. [117] further optimized network throughput under security constraints with energy harvesting.

(2) *Energy-Saving Data Transmission*: The high backhaul link load caused by massive data flow and limited cache capacity often degrades system communication and energy efficiency. To address this, Gu et al. [118] proposed an energy-aware coded caching strategy. This method optimizes UAV transmission power through content placement and coded transmission (CT) techniques. To reduce energy consumption in link data transmission, Nelson et al. [119] developed an RL-based hybrid data scheduling approach. This method uses energy consumption as the optimization reward during iterative processes and outperforms traditional shortest-path routing algorithms in terms of network energy usage and average latency.

(3) *Energy-Saving Task scheduling*: Real-time computation offloading tasks increase network burdens, such as distributing incoming computation tasks to cloud nodes. Imbalanced task scheduling can lead to resource waste or even node failures. For power-intensive tasks, optimizing energy consumption is necessary and justified. Zhang et al. [120] proposed a heuristic algorithm to minimize the maximum energy consumption among multiple UAVs while meeting delay constraints. With the exponential growth of IoT devices and user requests, Srivastava et al. [121] introduced a hierarchical offloading strategy. Terminal devices initially offload requests to UAV-based edge computing resource pools, and when a node's resources are exhausted,

tasks are further offloaded to other idle nodes. This study used the Nash equilibrium to determine the optimal offloading strategy.

3.4.4. SDN/NFV Technology

The collaboration of SDN and NFV enables efficient network management, including managing core functionalities such as traffic scheduling and computational task offloading, offering innovative design concepts for the complex structure of SAGINs. Currently, the integration of SDN and NFV with SAGINs and edge computing, especially in AI-driven network management, VNF deployment, and IoT device support, has garnered significant interest in research.

Applying SDN to SAGINs first requires addressing the structural complexity introduced by heterogeneous layered networks. Figure 5 illustrates the design of an NFV/SDN-supported SAGIN framework. As the control center of the whole network, SDN controllers must monitor global network resources in real time to achieve deterministic task scheduling. However, in traditional deployment schemes, SDN controllers are typically placed in satellite networks, which struggle to overcome hierarchical network limitations. During cross-layer transmissions, intermittent link disruptions and signal fluctuations can severely impact the delivery of critical instructions. To address this, Chen et al. [122] proposed a hierarchical multi-controller deployment scheme, with the primary controller located in the TN and secondary controllers placed in satellite nodes. This architecture not only enhances resource awareness but also effectively alleviates the load on a single controller.

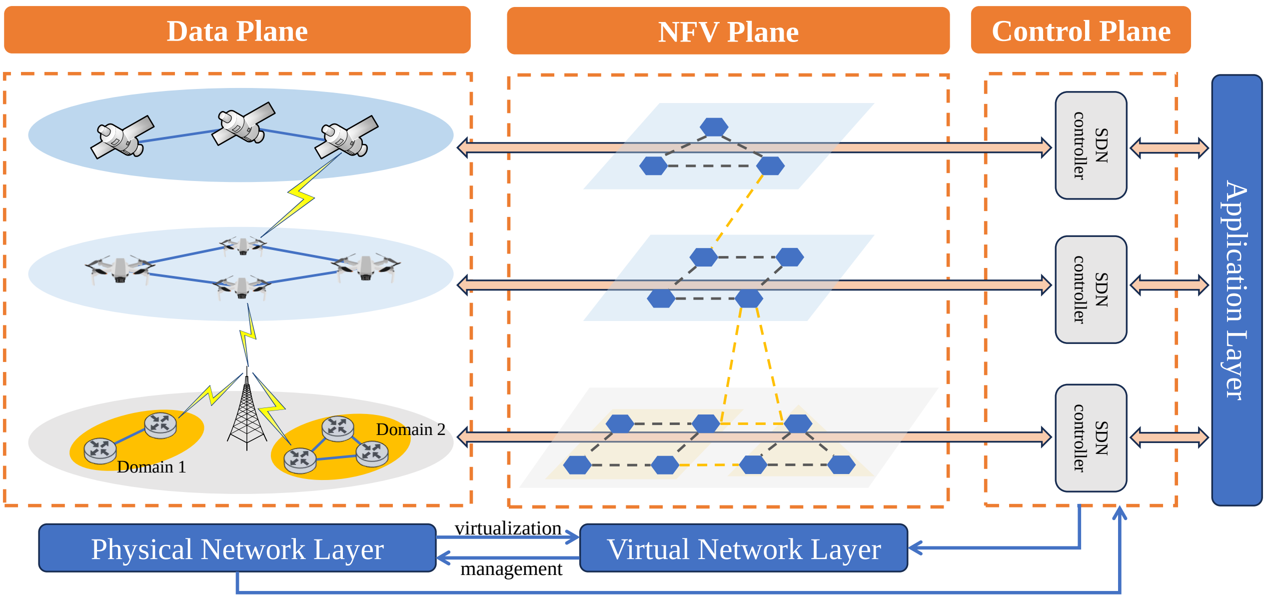

Figure 5. An NFV/SDN framework design integrating a UAV-assisted SAGIN.

Table 6. Significant research on resource management.

Key Technologies		Ref.	Method	Contribution
Task scheduling	Computation offloading	[100]	SCA	The research solves non-convex optimization problems using the successive convex approximation (SCA) method in multi-hop satellite communication and computing offloading, minimizing energy consumption and optimizing UAV control and user scheduling.
		[101]	DDPG PA	The study integrates a framework that optimizes task offloading and control in SAGINs using deep reinforcement learning and perception-aided (PA) methods, enhancing decision quality and network stability.

Table 6. *Cont.*

Key Technologies		Ref.	Method	Contribution
Task scheduling	Time consumption	[102]	RTS-RA	The work introduces an access and transmission control scheme with a robust task scheduling with risk aversion (RTS-RA) algorithm for offloading tasks, outperforming others in delay, data transmission, and energy consumption.
		[103]	RS-DRL	The study proposes a delay-oriented task scheduling (DOTS) scheme for SAGINs, using risk-sensitive (RS) DRL to minimize UAV processing delays under energy constraints.
		[104]	DDPG	The study minimizes IoT device processing delays in SAGINs by optimizing task scheduling and UAV trajectories.
		[105]	CMDP	UAVs are deployed as "flying gateways" to collect tasks, using a constrained MDP (CMDP) model to minimize system delay while considering task drop rates and energy consumption.
	Tasks in different scenarios	[68]	TD3	A DRL-based twin-delayed deep deterministic policy gradient (TD3) algorithm optimizes UAV trajectories in SAGINs under jamming attacks, maximizing energy efficiency and user fairness.
		[106]	Swap Matching SCA	The study solves the system cost minimization problem for task scheduling and multi-UAV deployment with exchange matching and convex approximation algorithms.
		[29]	DQN	A decentralized computing network task scheduling model is proposed, minimizing computing and transmission costs while ensuring queue stability through a two-stage optimization algorithm.
		[107]	MADDPG	A three-dimensional multi-UAV-assisted MEC system is proposed, considering fairness and security, using the Nash equilibrium and multi-agent deep deterministic policy gradient (MADDPG) algorithms for optimization.
		[108]	GA	A task priority model is proposed, developing a computation offloading framework that includes user grouping and joint task offloading and UAV scheduling, solved with a genetic algorithm (GA).
		[109]	DRL	A general task scheduling framework is constructed for diverse task types and requirements in SAGINs.
Channel optimization		[110]	SAC DRL	The study proposes a hybrid multi-agent soft actor-critic (SAC) algorithm for joint task offloading and resource allocation in MEC.
		[111]	RSU-UAV collaboration	A proposed strategy for drone and roadside unit (RSU) resource allocation uses probabilistic access, dual-base station control, and load balancing to enhance vehicular network performance, enabling dynamic power management and efficient service delivery.
		[33]	3D-2D-MM 3D-DTAMP	A 3D-2D Markov Model (3D-2D-MM) for UAV satellite communication is proposed, with a 3D dynamic turbo approximate message-passing (3D-DTAMP) algorithm for tracking dynamic channels.
		[113]	SAGE	A Space-Alternating Generalized Expectation–Maximization (SAGE) and K-Power-Means (KPM) method combined with a clustering-based tracking (CBT) approach models time-varying A2G channels, enhancing UAV wireless communication system modeling.
		[114]	Primal decomposition	Primal decomposition with a gradient projection iterative algorithm optimizes energy efficiency in UAV computation offloading, addressing UAV mobility, A2G communication, and computation dynamics.

Table 6. *Cont.*

Key Technologies		Ref.	Method	Contribution
Energy management	Energy harvesting	[115]	OAA	A multi-criteria framework for energy-efficient RRM in IoT networks is developed, proposing an outer approximation algorithm (OAA) to solve the joint optimization problem for device selection, drone relay allocation, and power allocation.
		[116]	Convex optimization	The article proposes an offline convex optimization method and an online convex-assisted reinforcement learning approach to jointly design UAV flight trajectories, user association, and power control for solar-powered WNs.
		[117]	PSO CGA	The study examines primary network interruption probability, secondary network throughput, and EAV leakage probability, proposing a hybrid particle swarm optimization and continuous genetic algorithm (PSO-CGA) approach to optimize UAV relay (UR) configuration and NOMA power allocation.
	Energy-saving data transmission	[118]	Encoding cache	An encoding caching strategy is proposed to reduce GEO and UAV backhaul traffic, saving transmission energy by considering user heterogeneity and channel models.
		[119]	Q-Learning DQN	The study presents Q-learning and DQN algorithms to enhance energy efficiency in hybrid UAV-assisted networks, choosing optimal comms tech for UAV-GS links, surpassing standard routing and hybrid schemes in energy use and latency.
	Energy-saving task scheduling	[120]	SCA	The study minimizes maximum UAV energy consumption, solving the non-convex mixed-integer nonlinear programming problem with successive convex approximation-based algorithms.
		[121]	Game theory	A two-tier offloading strategy reduces UAV-mounted edge device energy consumption through UAV mesh topology connections, using game-theoretic mechanisms for optimal offloading decisions.
SDN and NFV Technology		[123]	Heuristic method	This study enhances SAGIN slicing resource allocation with the Slice-Soft-SAGIN framework, jointly optimizing wireless and wired resources for efficient service orchestration through detailed module design and evaluation.
		[122]	GA	A k-means-based network partitioning strategy minimizes latency between switches and controllers, dynamically adjusting subnet management using controller load factors and GA-based allocation.
		[124]	DRL	The resource scheduling problem is modeled as a multi-domain VNE problem, optimized with DRL by constructing feature matrices and training agents to derive node embedding probabilities.
		[125]	Gale–Shapley	Using a reconfigurable time-expanded graph (RTEG), a multi-slot matching game algorithm combined with Dijkstra's algorithm efficiently identifies the shortest paths.
		[23]	DSAC	A heterogeneous federated learning framework with UAV edge servers and LEO satellite cloud servers addresses task fairness within limited satellite service time, leveraging UAV trajectory planning, DSAC algorithms, and dynamic reward adjustment.
		[126]	Heuristic and RL hybrid method	The VNE problem incorporates link availability, processing time, and data rate demands, solved via a linear relaxation-based heuristic algorithm and an RL-VNE solution adaptable to network changes.

The dynamic structural characteristics of SAGINs make resource sharing challenging, and NFV is leveraged for agile resource allocation. For instance, Cao et al. [125] modeled the SFC deployment problem as a many-to-one bilateral matching game and proposed a heuristic approach based on the Gale–Shapley algorithm to maximize the number of successfully deployed SFCs.

Stable low latency facilitates efficient resource allocation. Network slicing technology has been introduced to provide differentiated and customized network services by dynamically adjusting the bandwidth and computing resources of each slice, thereby improving resource utilization. Cao et al. [123] proposed a framework called Slice-Soft-SAGIN, which ensures service integrity through sequential deployment while optimizing spectrum and computing resources jointly to enhance orchestration efficiency.

In addition to heuristic methods, ML techniques have also made significant advancements in network resource management. DRL algorithms, in particular, are driving the intelligence of controllers. In this context, resource allocation problems are often modeled as joint optimization problems to meet QoS requirements. Zhang et al. [124] proposed a DRL-based multi-domain network resource orchestration algorithm, which improves the accuracy and efficiency of cross-domain VNE through the segmental modeling of the network. However, the dynamic topology of SAGINs complicates the weight allocation strategy in joint optimization problems, significantly affecting model performance and convergence speed. One solution is to incorporate fairness in task and resource competition during optimization. For example, Huang et al. [23] introduced a DRL method optimized with a distributed soft actor-critic (DSAC) algorithm for resource allocation in SAGINs and aggregation weight optimization in federated learning. Although this method improves performance, its increased complexity makes scalability challenging. Furthermore, to address the limitations of static VNE algorithms in dynamic environments, Maity et al. [126] proposed a heuristic VNE scheme combined with RL-based optimization. The RL agent selects the appropriate VNE algorithms based on topology changes and service demands.

In summary, the integration of SDN and NFV offers innovative solutions for resource management in UAV-assisted SAGINs, showcasing vast potential for research and practical applications.

3.5. Deployment of UAVs

The deployment and placement of UAV is a critical research topic in UAV-assisted communication networks. It involves the planning of UAV positions and altitudes in 3D space. Unlike path planning, which focuses on finding efficient routes from start to finish, UAV deployment aims to devise a comprehensive task implementation scheme, including task allocation, take-off point selection, and network support. UAV deployment must meet constraints such as airspace regulations, UAV quantity, battery endurance, and task priority, enabling single or multiple UAV deployment orchestration. These problems are often highly complex and challenging to solve directly. This section reviews recent research on UAV deployment, and a list of relevant reviews is displayed in Table 7.

3.5.1. Coverage

UAV deployment can be divided into two types: aerial base station and communication relay deployment. The first type provides stable connections over large areas, offering services to regions without network access. The second type enhances end-to-end connection quality, enabling long-distance communication, and is commonly used in scenarios requiring low-latency end-to-end communication, such as military operations or emergency rescue missions. In SAGINs, UAVs serve as aerial base stations to enhance ground user coverage and provide high-probability LoS transmission, which has lower signal attenuation and noise, significantly improving communication quality.

In addition, the number of UAVs directly affects coverage. A smaller number may fail to provide large-scale stable coverage, while excessive numbers increase collaboration complexity and resource waste. Liu et al. [127] proposed a method to remove redundant UAVs, achieving comprehensive network coverage with minimal UAV usage while ensuring QoS and network stability.

Table 7. Significant research on the deployment of UAVs.

Core Objectives	Ref.	Method	Contribution
Coverage	[127]	UDA-DD UDA-DS	This work proposes UAV-BS algorithms that simplify 3D positioning for minimal UAV-BS placement, enhancing service connections based on user demand and QoS with UDA-DD and UDA-DS algorithms.
	[128]	EC	This work optimizes UAV coverage by adjusting antenna parameters to minimize path loss for cell-edge users using an elliptical clustering (EC) algorithm.
	[129]	Lloyd-like algorithm	This work achieves reliable wireless uplink for users by optimizing the 3D deployment of drones as base stations, while minimizing user transmission power consumption.
	[130]	ADPM	This work introduces an alternating-direction penalty method (ADPM)-based iterative algorithm to optimize UAV deployment and antenna orientations in multi-UAV systems for improved sensing accuracy.
	[131]	Joint optimization	This work proposes a dynamic model and offloading scheme for UAV-BS systems to reduce resource waste and interference by optimizing the serving radius (SR), UAV deployment, and coverage.
Anti-interference	[132]	Joint optimization	This work presents an energy-efficient deployment algorithm for UAVs as flying roadside units (RSUs) in vehicular networks, considering power consumption, latency, and backhaul link capacity for smart city V2X applications.
	[133]	Altitude optimization	This work develops a 3D multi-UAV deployment algorithm to maximize ground user system throughput under co-channel interference, using a two-stage approach for QoS-driven UAV network deployment.
	[134]	K-means clustering	This work proposes a clustering-based algorithm for UAV deployment in 6G networks, addressing UAV mobility-induced interference and QoS issues, with optimized 3D placement and re-clustering for load balancing.
	[135]	DRL	This work introduces a QoE-driven, energy-efficient adaptive deployment strategy for multi-UAV networks using hybrid DRL, optimizing UAV mobility, energy consumption, and throughput.
Multi-UAV deployment	[136]	AAP placement	This work presents an energy-efficient 3D placement algorithm for aerial access points (AAPs) to optimize uplink communication, addressing inter-cell interference and energy consumption.
	[137]	DLA	This work introduces a decentralized learning algorithm (DLA) for optimizing the 3D deployment of UAV swarms in MIMO systems to maximize channel capacity.
	[138]	WVP	This work proposes a decentralized deployment algorithm based on Weighted Voronoi Partition (WVP) for UAV-based flying base stations to minimize UAV–user distance while maintaining connectivity with stationary base stations.
Energy-saving deployment	[139]	K-CUT	A heuristic algorithm optimizes the AAP position and remodels the channel allocation problem as an interference minimization problem, using a K-CUT-based algorithm for A2G networks.
	[140]	GS	Energy-efficiency and task completion time are enhanced by optimizing the transmission power and flight trajectory, using a user grouping strategy (GS) based on the traveling salesman problem (TSP).
	[141]	Joint optimization	This study addresses the energy-saving issue of deploying UAV swarms to fully cover target areas under cooperation and no-fly zone constraints.

Moreover, coverage is influenced by multiple factors such as UAV position and altitude, antenna power, and beam configurations. UAV antennas generally fall into three types: omnidirectional, directional, and adjustable. Omnidirectional antennas offer broad coverage but experience significant signal attenuation with distance. To improve their communication range, UAVs can employ directional antennas with more focused signals. However, the radiation pattern of directional antennas is irregular. Noh et al. [128] proposed an elliptical clustering (EC) algorithm based on analyzing actual beam direction patterns to maximize user coverage probability for UAV base stations. Guo et al. [129] devised a deployment method for UAVs equipped with directional antennas, and Zhou et al. [130] designed a joint optimization approach for multi-UAV deployment and directional antenna orientation. Furthermore, the service radius (SR) of UAVs is not fixed during the tracking process. Liu et al. [131] proposed a dynamically adjustable model to optimize UAV deployment.

3.5.2. Anti-Interference

In interference scenarios, UAV communication channels are prone to degradation, increasing network latency and reducing throughput. Demir et al. [132] considered real-time latency and backhaul attenuation issues during UAV deployment. Additionally, co-channel interference diminishes communication quality between UAVs and ground base stations. Valiulahi et al. [133] employed mean-shift techniques and GPS-provided user location data to determine the Cartesian coordinates of UAVs and optimized their altitude and transmission power using block coordinate descent techniques. Consul et al. [134] optimized 3D UAV deployment to continuously mitigate interference rather than addressing it in a one-off manner. To enhance UAVs' autonomous anti-interference capabilities, Zhou et al. [135] proposed an adaptive deployment strategy based on reinforcement learning (RL) and used QoE optimization to enhance user experience in UAV deployment.

3.5.3. Multi-UAV Deployment

Most deployment methods are designed for multi-UAV scenarios. Compared to single-UAV deployment, multi-UAV deployment is more complex. Theoretically, there is an upper limit to the number of UAVs that can be deployed in a specific area, beyond which communication quality degrades. Babu et al. [136] used a novel AAP layout algorithm based on regular polygons to determine the horizontal positions of AAPs and calculated the exact upper limit for deployable AAPs within a given circular area. When multiple UAVs collaborate, more channel capacity is consumed. Gao et al. [137] designed a decentralized learning algorithm to maximize the optimal Nash equilibrium of multiple-input–multiple-output (MIMO) systems, achieving higher UAV channel capacity. Huang et al. [138] optimized UAV deployment by reducing the average distance between heterogeneous UAV swarms and users, validating the approach's effectiveness in non-line-of-sight scenarios.

3.5.4. Energy-Saving Deployment

Frequent UAV deployments incur significant costs, making deployment cost reduction a critical aspect of SAGIN energy optimization. UAV deployment involves identifying optimal aerial access point (AAP) locations. For single-UAV deployment, Zhai et al. [139] designed a comprehensive optimization model integrating AAP location, channel allocation, and power, proposing a heuristic algorithm based on the maximum weighted independent set to optimize AAP locations. Zhang et al. [140] studied UAV broadcast coverage strategies to maximize energy efficiency by optimizing AAP locations through user grouping strategies derived from the traveling salesman problem (TSP). For multi-UAV deployments, Zhang et al. [141] proposed an energy-driven optimal deployment strategy, achieving a balance between ground flight distance and flight altitude.

4. Applications

UAV-assisted SAGINs form a comprehensive information transmission platform that effectively enhances network communication capabilities, response efficiency, and coverage [38]. Drones, as a crucial component of the aerial network, due to their unique mobility and flexibility, play a vital role in various practical scenarios, such as post-disaster reconnaissance and emergency rescue [142], broadband access and network coverage in remote areas [143], security inspection and target tracking [144], low-altitude traffic and logistics distribution [145], IoT task collection and offloading [103], static resource caching and distribution [146], and crop health monitoring and pesticide and fertilizer spraying [147].

4.1. Post-Disaster Recovery and Emergency Rescue

In the aftermath of natural disasters or sudden emergencies, certain affected areas may become inaccessible due to complex geographical conditions, restricted transportation, or the threat of secondary hazards, significantly impeding the execution of rescue operations. UAVs, with their flexible deployment, high mobility, and remote operation capabilities, can play a critical role in such scenarios. As aerial platforms, UAVs can swiftly conduct reconnaissance missions over disaster-stricken regions, capturing high-resolution images, videos, and environmental data to construct 3D [148,149] models of the affected areas. This enables rescue teams to make informed decisions and formulate effective action plans. Additionally, UAVs can be equipped with emergency communication devices (e.g., LTE/5G BS) or payload delivery systems to provide communication support or deliver essential supplies to stranded individuals. The literature [150] refers to several examples of UAV applications in disaster responses in Japan, including those in Hiroshima (2018 landslide), Okayama (2018 flooding), and Kanagawa Prefecture (2019 flooding and landslide).

4.2. Broadband Access and Network Coverage

In remote and extreme environments, such as mountainous regions, deep valleys, or isolated islands, conventional communication infrastructure often struggles to provide adequate coverage [151]. This results in weak network signals and low data transmission efficiency, which significantly restricts both production operations and everyday communications. In scenarios involving field activities like mining, forestry monitoring, or scientific research in these areas, drones can serve as temporary airborne base stations or communication relay nodes, supported by SAGINs. This arrangement enables broadband access and network coverage, effectively filling the coverage gaps of ground networks. Compared to the high costs and long construction timelines associated with setting up terrestrial base stations, drones offer a more flexible deployment option, swiftly covering designated areas and ensuring stable communication services, thereby greatly enhancing operational efficiency in fieldwork settings. The literature [152] discusses extending cell tower coverage using UAVs, with encouraging results.

4.3. Security Inspection and Target Tracking

In fields such as the military, border protection, and public safety, drones can carry out tasks such as border surveillance, reconnaissance, patrolling, and target tracking with the support of an integrated space–air–ground network. They collect and transmit real-time image data, sensor data, and GPS information, feeding the situation back to the command center. This enables commanders to stay updated on frontline developments and respond swiftly to emergencies. Furthermore, drones can cooperate with ground forces and satellite imagery for multi-layered collaborative monitoring, providing comprehensive coverage of borderlines or high-risk areas and establishing a dynamic three-dimensional defense network. This efficient inspection and tracking system significantly enhances emergency response capabilities, thereby safeguarding national and public security. The literature [153] refers to the use of UAVs for surveillance and reconnaissance in military areas, and by analyzing the case of the Ecuadorian armed forces, it is concluded that the use of UAVs in terms of national security has a positive impact.

4.4. Smart Industry

With the development of the IoT, an increasing number of devices are being interconnected, including wearable devices, smart home appliances, industrial sensors, and autonomous vehicles [154]. However, these IoT devices are often constrained by limited computational power or battery life, making it challenging to meet the real-time computing requirements under the paradigm of ubiquitous connectivity. In this context, UAVs can serve as "flying gateways" to collect tasks from IoT devices and make appropriate decisions based on their offloading algorithms. UAVs can either process the collected IoT tasks using their own computational power or offload the tasks to nearby high-performance computing nodes. Once the computational tasks are completed, the results can be sent back to the IoT devices. With the support of efficient offloading algorithms, this strategy can minimize the average latency and fulfill the service requirements of various IoT devices.

4.5. Smart Cities

With the support of SAGINs, drones can function as mobile cache nodes, executing caching and distribution tasks for static resources to alleviate network load and enhance resource access efficiency. For instance, during large-scale sporting events, concerts, or other outdoor gatherings, the surge in network demand caused by crowd concentration may exceed the capacity of ground-based communication infrastructure, resulting in degraded service quality. UAVs can pre-cache popular content or essential data resources [155], providing temporary rapid distribution services during these events. This approach helps to reduce the burden on terrestrial base stations and improves user experience. While in flight, drones can exchange data with ground-based stations or satellites to dynamically update cached content, adapting to real-time changes in user demand and ensuring the timely delivery of popular content. In the context of smart city development, this caching and distribution method, supported by integrated space–air–ground networks, can effectively improve the quality and responsiveness of public services. It provides a flexible solution for managing network peak loads and enhances urban infrastructure's adaptability in response to surges in network traffic. In modern urban logistics distribution, traditional ground transportation methods often face uncertainties such as traffic congestion and accidents, especially during peak commuting hours or when delivering goods to specific areas, significantly impacting logistical efficiency. By leveraging an integrated space–air–ground network, drones can operate within low-altitude airspace as critical tools for delivering small cargo, providing rapid transport services. The literature [156] has discussed the use of UAVs to load drugs, avoid ground traffic congestion through air routes, and quickly deliver drugs to target locations. In this scenario, SAGINs enable seamless communication, ensuring that drones maintain data connectivity with command centers throughout their flight. This facilitates the comprehensive monitoring and dynamic adjustment of the delivery process, enhancing the flexibility and emergency response capability of the logistics network, thus offering essential support for the development of smart cities in the future.

4.6. Smart Agriculture

In modern agriculture, crop health monitoring and the application of pesticides and fertilizers are pivotal for increasing yields and reducing environmental pollution. Supported by SAGINs, drones equipped with sensors and imaging devices can capture high-resolution images of farmland. Advanced data analysis methods are employed to assess soil nutrient composition and moisture levels, enabling the real-time monitoring of soil conditions, crop growth, and climate changes. These data underpin precision fertilization and pesticide application, while coordinating with ground control centers and satellites to ensure real-time information sharing and accurate task execution [157]. Such an approach minimizes the environmental impact of fertilization and pesticide application, while enhancing crop productivity and quality.

5. Challenges and Future Research Directions

The flexibility and mobility of UAVs significantly enhance the capabilities of integrated networks. Future technological breakthroughs and cross-domain collaborations will create more opportunities for this field. In this section, we will analyze the main challenges and future development directions in UAV-assisted SAGINs.

5.1. Existing Challenges

Compared to traditional TNs, SAGINs integrate air-, space-, and ground-based networks and are gradually incorporating maritime communication, which makes the communication environment more dynamic and complex. Currently, UAV-assisted SAGINs face the following challenges:

(1) *Mobility and Dynamic Topology*: UAVs have high mobility and can access networks at any time and anywhere, causing the network nodes and link states in SAGINs to constantly change. Therefore, more effective routing algorithms and communication protocols are needed to fully cope with the effects of dynamic topologies. For instance, existing SAGIN routing protocols can be extended to dynamically adjust routing rules based on environmental conditions. Ricardo et al. [158] extended the CAIN, a post-disaster 6G routing protocol, to adapt to SAGIN scenarios by utilizing UAV relays to connect to satellites, thereby further expanding network coverage. Guo et al. [159] proposed a DRL routing strategy based on GANs to enable dynamic routing and ensure network load balancing. Additionally, simulation methods addressing the dynamic topology of SAGINs are noteworthy for advancing research in this field. For example, Wang et al. [160] introduced the SAGINHTE-Stack simulation framework to model the complex dynamics of SAGINs. However, the network's dynamic nature also introduces additional risks for large-scale UAV deployment and trajectory planning.

(2) *Intelligent Resource Allocation*: Dynamic nodes such as UAVs and satellites have limited resources, restricting the communication and computational capabilities of NTNs. Thus, more intelligent resource management and allocation algorithms need to be designed, considering joint optimization issues, especially in dynamic environments. Currently, while NFV and SDN have each achieved significant research progress, their integration with SAGINs remains an area requiring further exploration. By combining AI-driven VNE algorithms and SDN scheduling strategies, SAGINs can achieve efficient resource allocation and scheduling for load balancing under limited-resource conditions. For example, Cao et al. [161] proposed a novel framework to study resource orchestration and allocation for UAV-assisted E2E slicing services in software-defined 6G terrestrial networks. Additionally, AL-based resource allocation methods need further development, and multi-objective approaches specific to SAGINs should incorporate more aspects than those currently discussed. For instance, An et al. [162] proposed a joint optimization method for task offloading and UAV trajectory planning. In the future, optimization objectives are expected to encompass even broader directions.

(3) *Data and Communication Security*: UAV-assisted SAGINs create a more open network communication environment, leading to more severe security challenges. Malicious signal interference may result in data loss or communication disruption. Open wireless communication channels are vulnerable to eavesdropping from attackers, and security attacks on NTNs have a huge impact on the security and reliability of networks. This requires close collaboration with advanced data encryption technologies. For cross-layer communication, more general and reliable communication protocols will be essential core issues to address in the future. Moreover, emerging technolo-

gies for data encryption, such as blockchain and quantum communication, will offer new solutions for secure communication. For instance, Xie et al. [163] proposed a blockchain-based crowdsensing framework that integrates a reputation incentive mechanism for UAV-assisted mobile crowdsensing, which enhances the security of data sharing. Similarly, Zhou et al. [164] proposed a blockchain-assisted data-sharing scheme for Internet of Drones networks, incorporating accountability and privacy protection to improve data privacy and traceability.

(4) *Intelligent Energy Management*: UAVs are limited by their size, weight, and power, which influence flight performance, task execution capabilities, and application scenarios. Such issues are similar to resource management but equally important. In energy management, the objective of joint optimization is often to minimize the energy consumption ratio [120]. To address challenges of limited energy, more efficient energy harvesting methods need to be proposed, and energy-saving management strategies should be explored to optimize UAV deployment, power distribution, flight path planning, and other issues.

As future network architectures, SAGINs not only impose more requirements on scalability, stability, security, sustainability, and QoS but also need to address the challenges posed by emerging fields such as edge computing, the IoT, blockchain, quantum communication, and cloud computing, while collaborating closely with these domains to develop integrated solutions.

5.2. Future Research Directions

With the advancement and integration of technology, UAV-assisted SAGINs will drive innovation across many industries. In this subsection, we will analyze their future research directions from the perspectives of future applications, security, scale, and more.

5.2.1. Special Scenario Applications

In Section 4, we summarized the current application fields of UAV-assisted SAGINs. In the future, the networks will have even more widespread application scenarios, particularly in terms of optimization and application in special scenarios.

(1) *Near-zero-infrastructure Self-organizing Networks*: Zero-infrastructure self-organizing networks refer to dynamic network structures that do not require pre-deployed communication infrastructure. They rely on the self-organizing capabilities of nodes for neighbor discovery, routing maintenance, and resource scheduling, making them suitable for scenarios such as disaster recovery, battlefield communication, and remote area coverage. Their advantages include rapid deployment and flexible topology, but they face technical challenges like high energy consumption and poor routing stability.

(2) *Multi-domain Collaboration and Cross-network Integration*: Due to environmental and resource constraints, HAPs often take on more computational tasks but higher latency than LAPs [165]. Different communication protocols and differentiated resource scheduling methods need to be designed for different networks to improve the communication efficiency of integrated networks.

5.2.2. Blockchain-Based Security Strategies

Blockchain technology offers a decentralized data management platform, enabling data sharing and synchronization between nodes in SAGINs. Through encryption technology and consensus mechanisms, blockchain ensures security and privacy during data transmission [166].

(1) *IoT Security Communication*: In SAGINs, blockchain can ensure secure communication between IoT devices by preventing unauthorized access or tampering with device data through its immutability.
(2) *Traffic Offloading and Management*: Traffic in SAGINs can be offloaded and managed using blockchain technology, optimizing traffic distribution and improving network performance through blockchain's transparency and immutability. Enhanced Practical Byzantine Fault Tolerance algorithms can be used to evaluate node security, ensuring the safety of traffic offloading [167].
(3) *Digital Identity Authentication*: Blockchain can provide a secure, immutable identity authentication mechanism, enhancing the security and privacy of digital identities. For example, Liu et al. [168] introduced a blockchain-based collaborative credential management scheme for anonymous authentication in vehicular SAGINs. This scheme ensures efficient and secure credential issuance and management while reducing on-chain overhead.

5.2.3. Mobile Edge Computing

Mobile edge computing is one of the key technologies for 5G and future networks. By performing computation and processing at edge nodes near users, it avoids transmitting all data to the cloud, thus reducing latency, improving efficiency, and saving bandwidth resources [11]. The flexible self-organizing capabilities of UAVs allow edge computing nodes to be deployed in remote or disaster areas, providing stable computing services to underserved regions. The current research status and trends in the integration of MEC and SAGINs focus primarily on the following: (1) resource allocation and scheduling [101,105,124], (2) network performance optimization (e.g., latency [68,132,134] and throughput [117]), (3) energy efficiency [115,119,139], (4) security control [107], and (5) joint optimization [120,169]. Some of these studies target specific scenarios and design localized parameter optimization strategies. However, such approaches may face adaptability and efficiency challenges as the network scale expands or the state dynamically changes. Future research directions will emphasize standardization and unification, aiming to construct a standardized MEC-SAGIN integrated network architecture to enhance interoperability and deployment efficiency. With the application of artificial intelligence, dynamic optimization methods based on online learning and intelligent inference are expected to become mainstream, driving the development of stable and efficient joint optimization strategies. Transitioning from local optimization to system-level global collaborative optimization will be key to meeting the demands of complex scenarios, thereby improving network performance and scalability.

5.2.4. Integration of SAGINs with Maritime Networks

Underwater networks consist of underwater sensors, autonomous underwater vehicles, and buoy stations, connected through acoustic, radio, and optical communication methods. However, maritime communication faces challenges such as high transmission loss, strong channel variability, and limited coverage. To address these issues, technologies such as maritime collaborative positioning, UAV-based networks, and efficient data enhancement methods need to be adopted. Maritime SAGINs, through the cooperation of satellite-, UAV-, and sea-based nodes, can achieve seamless communication across land, sea, air, and space, overcoming communication obstacles in underwater environments, thereby providing more efficient network support for marine exploration and maritime safety. In addition, the integration of maritime communication also introduces additional security challenges that need to be addressed [9].

6. Conclusions

In this paper, we present a systematic survey of core technologies in UAV-assisted SAGINs. Following an exposition of the architectural principles and distinctive features of SAGINs, we analyze the functional significance and inherent challenges of UAV communications within this paradigm. The hierarchical network structure introduces complexities in real-time global network governance, particularly impacting the realization of 6G objectives including network stability, controllability, and ultra-low latency. Potential solutions such as SDN and NFV are discussed as enablers for cross-domain integration. In addition, we methodically examine critical technical dimensions: (1) routing protocol design, (2) security assurance mechanisms, (3) trajectory optimization methodologies, (4) resource management frameworks, and (5) UAV deployment strategies. Practical implementations are examined across multiple domains including disaster relief, smart city applications, and precision agriculture. Finally, we present the identification of critical challenges that require immediate attention and propose future research trajectories in three key dimensions: application-specific optimization, security enhancement, and large-scale network coordination.

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Abbreviations

The main abbreviations used throughout the paper are shown as below:

3GPP	the 3rd Generation Partnership Project
5G	5th generation mobile communication
6G	6th generation mobile communication
A2G	Air-to-Ground
AAP	Aerial Access Point
ACO	Ant Colony Optimization
AI	Artificial Intelligence
BS	Base Station
CIDS	Collaborative Intrusion Detection System
DDoS	Distributed Denial of Service
DIDS	Distributed Intrusion Detection System
DRL	Deep Reinforcement Learning
DTN	Delay Tolerant Networking
DWT	Discrete Wavelet Transform
E2E	End-to-End
EA	Eavesdropping Attack
EIGRP	Enhanced Interior Gateway Routing Protocol
ELM	Extreme Learning Machine
LEO	Low Earth Orbit
LoS	Line-of-Sight
MANET	Mobile Ad-Hoc networks
MEC	Mobile Edge Computing
MEO	Medium Earth Orbit
ML	Machine Learning
mMTC	massive Machine-Type Communication
NFV	Network Function Virtualization
NTN	Non-Terrestrial Network
PSO	Particle Swarm Optimization
PUF	Physically Unclonable Function
QoS	Quality of Service
RF	Radio Frequency
RFID	Radio Frequency Identification
RIS	Reconfigurable Intelligent Surface
SA	Simulated Annealing
SAGIN	Space-Air-Ground Integrated Network
SATCOM	Satellite Communication

eMBB	Enhanced Mobile Broadband	SDN	Software-Defined Networking
EtS	Earth-to-Space	SFC	Service Function Chain
FA	Fraudulent Attack	StE	Space-to-Earth
FSO	Free Space Optical	TORA	Temporarily Ordered Routing Algorithm
GA	Genetic Algorithm	UaaS	UAV-as-a-Service
GEO	Geostationary Earth Orbit	UAV	Unmanned Aerial Vehicle
GU	Ground User	URLLC	Ultra-Reliable Low-Latency Communication
HAP	High-Altitude Platform	VNF	Virtual Network Function
ITU	International Telecommunication Union	ZDA	Zero-Day Attack
JA	Jamming Attack	ZRP	Zone Routing Protocol

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