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Review

UAV Ad Hoc Network Routing Algorithms in Space–Air–Ground Integrated Networks: Challenges and Directions

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Abstract: With the rapid development of 5G and 6G communications in recent years, there has been significant interest in space–air–ground integrated networks (SAGINs), which aim to achieve seamless all-area, all-time coverage. As a key component of SAGINs, flying ad hoc networks (FANETs) have been widely used in the agriculture and transportation sectors in recent years. Reliable communication in SAGINs requires efficient routing algorithms to support them. In this study, we analyze the unique communication architecture of FANETs in SAGINs. At the same time, existing routing protocols are presented and clustered. In addition, we review the latest research advances in routing algorithms over the last five years. Finally, we clarify the future research trends of FANET routing algorithms in SAGINs by discussing the algorithms and comparing the routing experiments with the characteristics of unmanned aerial vehicles.

Keywords: unmanned aerial vehicles; flying ad hoc network; routing algorithms; space–air–ground integrated

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1. Introduction

Space–air–ground integrated networks (SAGINs) are multi-domain dynamic networks that comprise satellite networks for communication, navigation, and meteorology; unmanned aerial vehicle networks; and ground-based wired and wireless network facilities. These networks can be flexibly deployed to provide wide coverage and high applicability. As such, SAGINs have the potential to enable a range of critical applications, including disaster response, search and rescue, and remote sensing, among others [1,2]. Unmanned aerial vehicle networks play a bridging role, enabling the interconnection of satellite and ground-based networks by undertaking data transmission and communication relay tasks to achieve goals such as information sharing and collaborative work [3]. The rapid development of integrated air–space networks is therefore partly due to research related to unmanned aerial vehicles (UAVs) [4]. UAVs are often referred to as drones [5], and in recent years, with the development of automation and radio technology, UAVs have been used in a wide range of applications, including but not limited to field rescue, cargo transportation, industrial monitoring, and communication relay operations. In SAGINs, flying ad hoc networks (FANETs) are formed by the collaboration of multiple UAVs, at least one of which is connected to a ground station or satellite. FANETs can perform complex and variable missions at a lower cost, with greater efficiency, and in a more hostile environment. In the context of SAGINs, FANETs find broader applications in assisting communication and improving communication efficiency. A FANET can serve as an aerial base station to provide communication services for users in cellular networks [6]. Additionally, FANETs can assist edge computing by offloading computational tasks when IoT devices exceed their computational capacity. Failure to process tasks promptly may result in significant response latency, which the FANET can alleviate by supporting local devices such as vehicular networks through computation offloading [7]. Furthermore, with the development of the sixth-generation mobile communication system (6G) in the era of ubiquitous connectivity [8], there is a demand for higher quality and more precise communication links. UAVs can integrate with intelligent computing to achieve communication awareness through resource allocation and route planning [9]. Although the participation of FANETs effectively expands the network dimensions of SAGINs and enhances network resilience, whether it is assisting ground cellular network communication, task offloading, or achieving communication awareness, a set of excellent routing strategies is essential to support these functionalities. FANETs have the following characteristics due to the unique physical characteristics of the UAVs:

- High dynamics: The stability of the routing path is greatly affected by the rapid speed of the drone's movement through the air [10].
- High loss of connection rate: Due to the flight height, terrain, and weather of the UAV, there will be situations where the UAV loses connection with ground nodes or other UAVs [11].
- Low bandwidth and high latency: Due to the long communication distance between UAVs, the communication signal is affected by factors such as atmosphere and terrain. The communication bandwidth is low, and the communication latency is high [12].
- Energy consumption limitation: The energy consumption of UAVs is limited by the fact that the batteries or fuel that sustain them and communicate with them cannot be replenished in real time in the same way as the ground network [13,14].

Efficient and reliable routing algorithms can effectively improve the efficiency and reliability of packet transmission in the FANETs and reduce network congestion and service interruptions. The routing algorithm is also the key link to ensuring proper communication in FANETs. However, due to the nature of FANETs, the FANET routing algorithms need to consider factors such as the location, speed, and direction of the UAVs to adjust the routing path in a timely manner. In addition, the rejoining of nodes and re-establishment of routes due to the loss of UAVs need to be taken into account. Finally, communication quality needs to be guaranteed within energy consumption limits while meeting the individual needs of users and operators.

We have investigated the latest reviews in FANET-related fields, and several researchers have surveyed and summarized aspects of UAV-related fields in recent years. Amila et al. [15] in 2020 proposed a graph-classification-based classification method for the UAV routing problem and summarized the latest research progress on existing UAV routing and scheduling problems, which is more complete but has a different focus from this paper. In October of the same year, Bhisham et al. [16] addressed the UAV routing problem but focused on UAV safety with extensive research on UAV collision avoidance and connectivity. Syed et al. [17] reviewed various routing protocols for wireless sensor networks and summarized the challenges facing the UAV sensor network industry. Haque et al. [18] discussed UAV communication network characteristics, design, applications, and routing protocols, focusing on the quality of service (QoS) and power aspects of the study. In addition, Chen et al.'s [19] survey was based on four communication architectures under FANET. The above studies all differed in the direction and focus of their investigations. Our main objective is to gain insight into current research trends in UAV self-assembled network routing algorithms for the application of air–space integrated networks and to outline possible future research directions. Specifically, this paper makes the following contributions:

- In this paper, we review 48 relevant articles, which were published in the past five years and represent the latest research advancements in routing algorithms. We conduct an in-depth analysis of the limitations of these routing algorithms.
- We categorize existing routing algorithms into eight major classes and discuss the optimization directions for each class. Additionally, we provide insights into the research directions for FANET routing algorithms in the context of future SAGINs.
- To provide foundational experimental ideas for future researchers, we summarize the existing research's experimental methodologies from multiple aspects, including network scale, UAV types, and simulation platforms. Moreover, we present the trends and shortcomings of the experimental designs in the form of statistical charts to provide a visual analysis of experimental methodologies.

The structure of the paper is linked to the sections as shown in Figure 1. The remainder of the paper is organized as follows: Section 2 introduces the basic architecture of FANETs under SAGINs and provides a categorical review of the routing protocols. Section 3 discusses the latest research progress in FANET routing algorithms over the last five years. Section 4 provides a comparative analysis of recent research. In addition, future research directions are foreseen at the end of Section 4 based on this analysis. Finally, Section 5 concludes the paper.

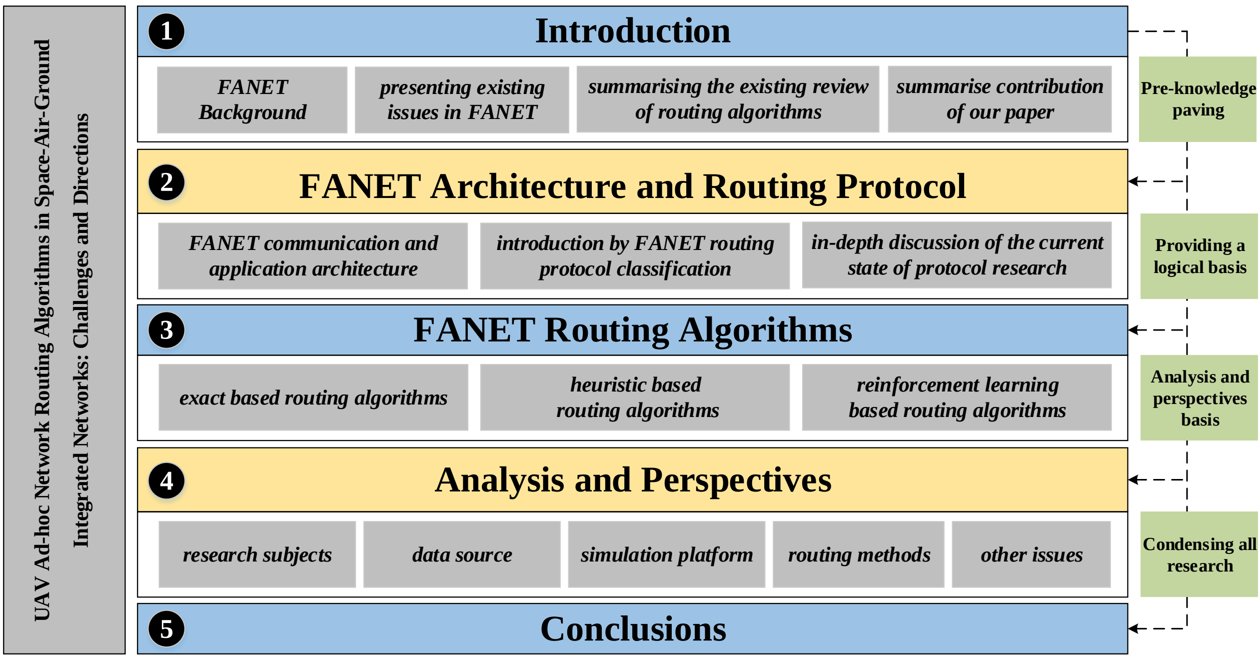

Figure 1. Paper content structure.

2. FANET Architecture and Routing Protocol

We briefly review the FANET communication and application architecture for discussion and discuss in detail the FANET routing protocols and their development in recent years.

2.1. Communication and Application Architecture

We show the communication architecture of the FANETs in Figure 2. We have divided the UAVs into an upper layer of large fixed-wing UAVs and a lower layer of small rotary-wing UAVs according to their wing type and operational altitude. Large fixed-wing UAVs typically have high mobility, higher altitude, and longer battery life, as well as wider signal coverage, allowing them to act as a communications relay between space-based and air-based networks. Smaller rotary-wing UAVs are lighter in weight, cheaper to produce, can remain stationary and take off and land vertically, and are suitable for covering ground users, vehicles, and IoT nodes for close monitoring and short-term emergency communications [20,21].

The high mobility of the lower layer of small rotary-wing UAVs leads to frequent changes in the topology of the FANETs, and the speed difference between the upper layer of large UAVs and the lower layer of small UAVs leads to the possibility of each node joining or leaving the network at any time. This requires the network to be able to react quickly to topology changes when nodes join, exit, or are abnormally destroyed. The use of traditional routing increases the routing overhead, which in turn reduces network performance and ultimately has a negative impact on user quality of service (QoS) and operator operating costs [22,23]. At the same time, this poses the challenge of high time-variability and complexity for SAGINs.

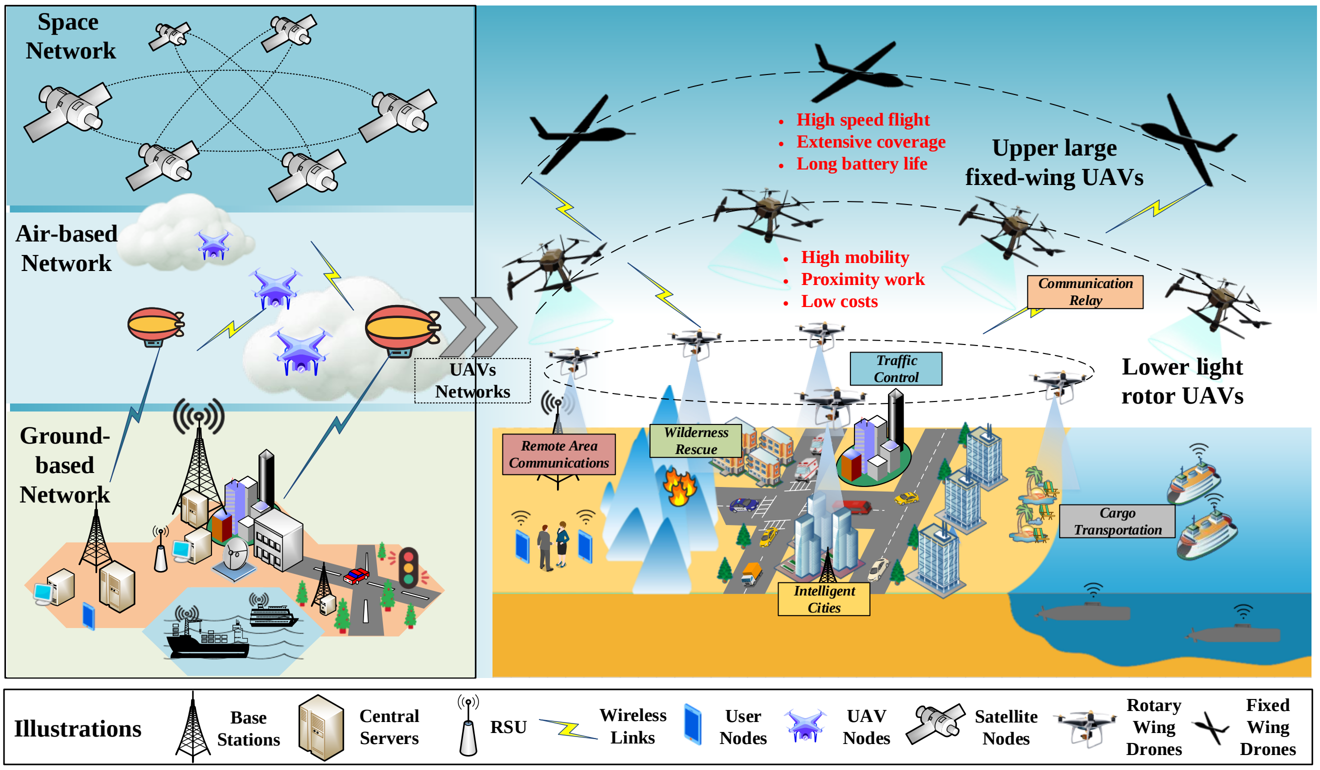

Figure 2. Schematic diagram of the layered architecture of FANETs under SAGINs.

As shown in Figure 3, unlike a traditional FANET, the FANET network in SAGINs needs to consider not only the UAV nodes' own mobility, vulnerability to interference, and limited channel capacity, but also the interaction and integration with other networks, such as ground-based base stations and satellite networks, to achieve better network performance.

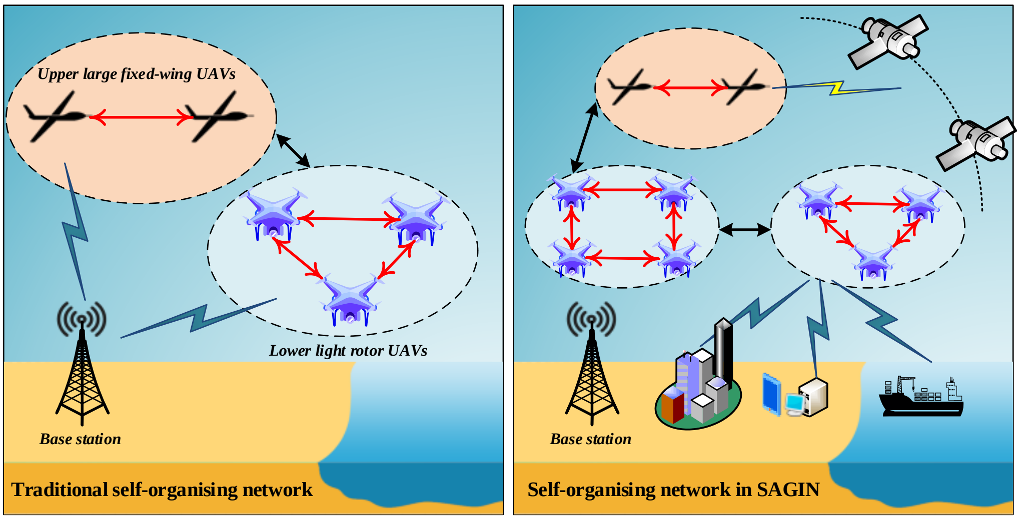

Figure 3. The difference between traditional self-organizing networks and self-organizing networks in SAGIN.

2.2. Routing Protocols

The routing protocol in FANET refers to the mechanism and rules for data transmission between UAV nodes by establishing routing paths [24,25]. As shown in Figure 4, we have divided the routing protocols into eight categories based on the routing methods.

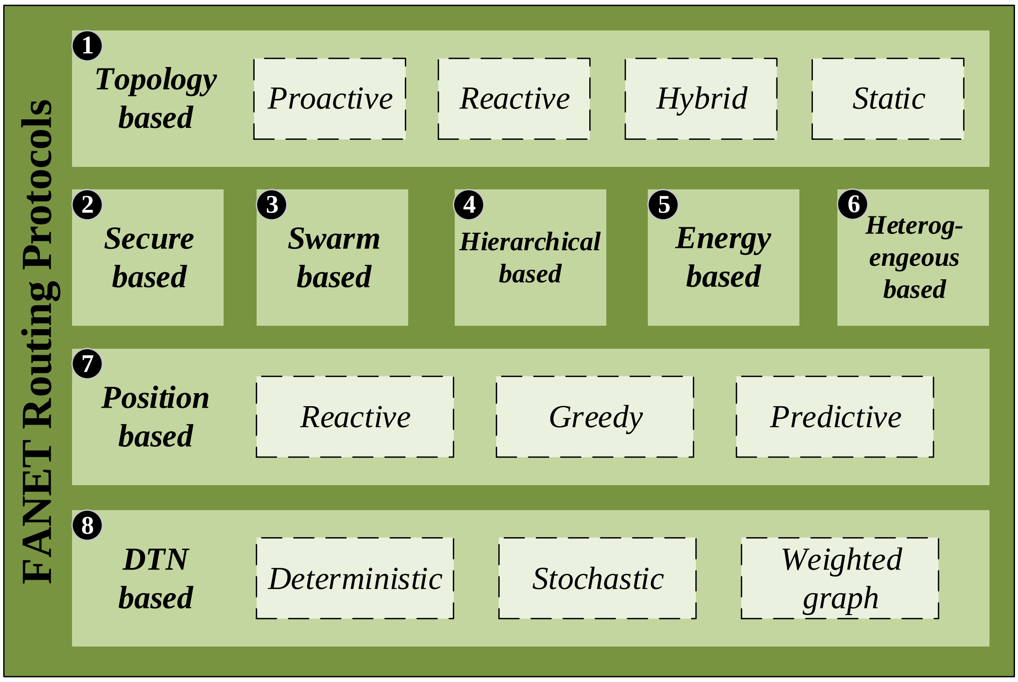

Figure 4. FANET routing protocols classification.

2.2.1. Topology-Based

Topology-based routing protocols do not require consideration of complex traffic types and load-balancing issues [26], and the algorithm is relatively simple. It relies only on the connectivity of the UAV nodes in the FANET (i.e., the topology) to plan routing paths, regardless of factors such as the type of network. Proactive, reactive, static, and hybrid topology-based routing protocols are categorized. The basic principles, advantages, and disadvantages of these protocols are shown in Figure 5.

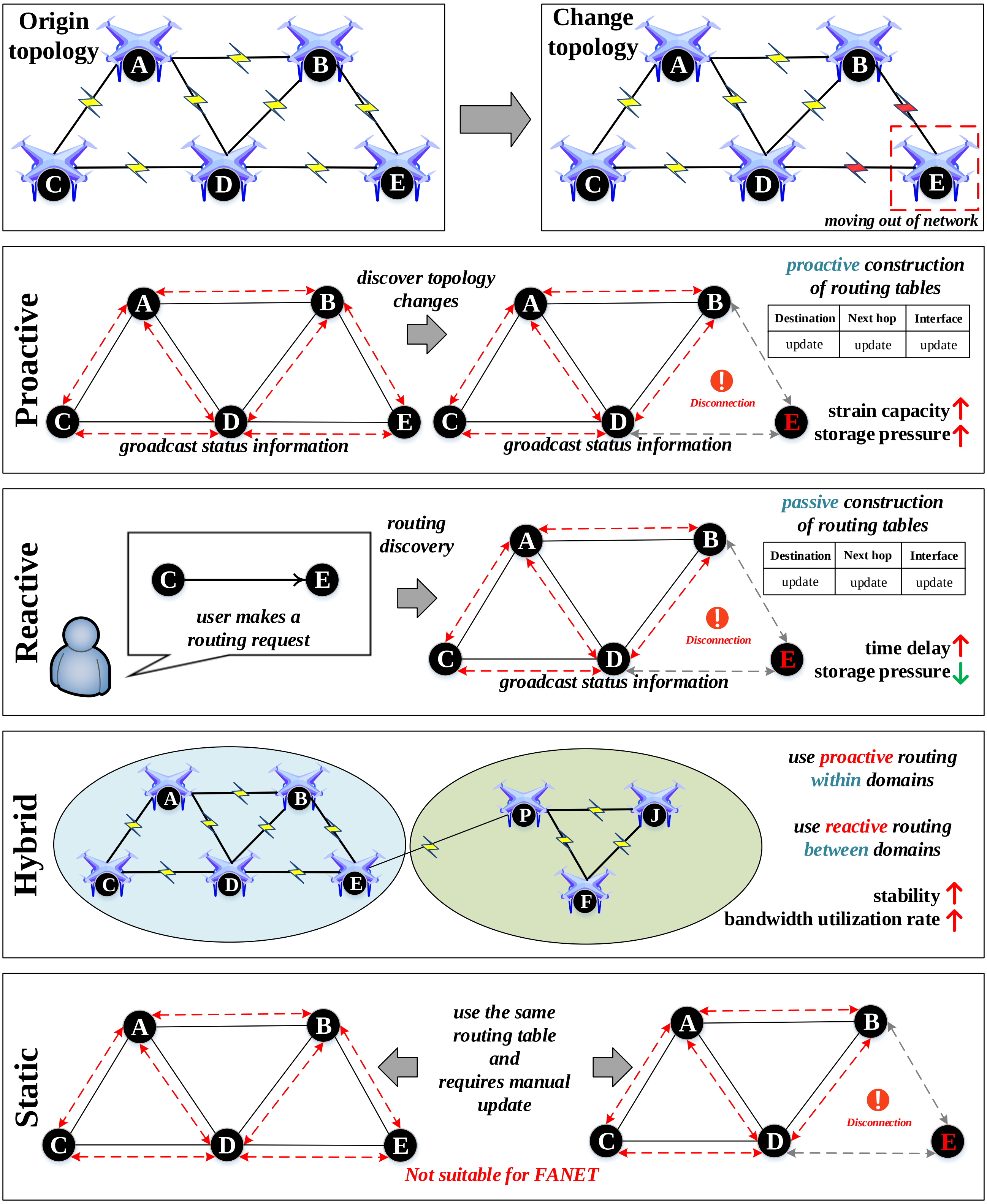

Figure 5. Topology-based routing protocols.

In proactive routing protocols, UAV nodes actively send route requests, thus finding reachable destination nodes and establishing routes. In other words, the routing table is updated as routes are changed and maintained at all communicating nodes. This type of routing is suitable for scenarios where the node density is low and the network topology changes slowly [27,28]. Similarly, static routing requires the routing table to be manually configured so that routing paths between nodes are specified, and the routing paths do not change as the network topology and node state change. This routing method is also only suitable for scenarios where the network topology is stable and the communication pattern between nodes is relatively fixed. In contrast to proactive routing and static routing, reactive routing means that when a node needs to send data to a destination node, it will only find a reachable destination node and establish a route by sending a route request [29]. For example, Dynamic Source Routing (DSR) [30] is a reactive routing protocol that uses a request-response mechanism to establish routing paths and carries routing information in the packet. When a packet reaches its destination, the destination sends a reply packet to the source node, which contains the routing path used to reach the destination. This type of routing is more suitable for scenarios like FANETs, where the node density is high and the network topology changes quickly. However, as reactive routing networks broadcast to find reachable nodes, they can put a strain on computing and storage resources. Hybrid routing uses both static and reactive or proactive routing to select the appropriate route for different UAV usage scenarios.

The rapid movement of the UAV nodes in a FANET leads to frequent changes in the network topology, and the traditional routing algorithm takes into account a single factor in route selection, making it difficult to fully consider other performance parameters of the entire network. In addition, when the nodes undergo violent movements, traditional topology-based algorithms cannot respond to such changes promptly, which can easily lead to link disruptions. Therefore, traditional routing algorithms have been difficult to apply directly to highly dynamic FANET scenarios. However, many researchers have made targeted improvements to traditional routing protocols based on FANET characteristics. For example, the DSDV protocol needs to consider the effects of factors such as the limited energy of UAV nodes and link quality, and Khan et al. [31] introduced the Bellman–Ford algorithm to improve it based on DSDV. Zhang et al. [32] proposed SAP-DSDV, which automatically adjusts the routing update period through the link stability between UAV nodes. Kaur et al. [33] implemented a random waypoint and Gaussian–Markov model integration to achieve improved QoS performance parameters for AODV, DSR, and DSDV protocols in FANETs.

In general, operations such as calculating shortest paths and maintaining routing tables in topology-based routing protocols require significant computational and storage resources, which puts an overhead strain on resource-limited UAVs. In addition, it is often necessary to expose network topology and node state information, which can lead to some security issues such as route forgery. In the next subsection, we will introduce security-based routing.

2.2.2. Security-Based

UAVs in FANETs use multiple hops to forward data and information in order to efficiently and collaboratively complete their missions, which increases the risk of malicious attacks on the network [34]. Moreover, FANET networks are often used in mission-critical applications such as security for large events, making the security of the network particularly important. Security-based routing protocols focus on enhancing the security of the network to ensure that packets are effectively protected during transmission. The following describes the security-based routing protocols that have been highly cited in recent years.

The SUANET routing strategy proposed by Maxa et al. [35] uses keys to authenticate UAV nodes and place them to be tampered with. Multiple encrypted security parameters are also used to prevent malicious attacks on the communication link. Similarly, the PASER routing protocol proposed by Mohamad et al. [36] secures the routing messages through a cryptographic function. Danielle et al. [37] propose a routing protocol that uses digital signatures to encrypt routing information, and the protocol considers both FANET and ground-based networks. Similar to SUANET, a key management mechanism is also proposed to provide public and private keys to each new UAV node joining the network.

Furthermore, the VRU routing protocol proposed by Hamideh et al. [38] considers both FANET and VANET, using a trust-based scheme to detect malicious nodes.

FANETs have different characteristics from ground-based networks, so most of the routing protocols proposed for ground-based networks are not applicable to them. The emphasis on data security by network users and operators has recently been increasing year by year, and the introduction of emerging technologies such as federation learning has placed greater demands on existing research into security-based routing protocols. Furthermore, a great deal of existing research still focuses on the efficiency of routing protocols and does not pay much attention to the security of routing. There is a need to focus more on the security of routing transmissions to prevent contamination and tampering with UAV nodes and communication links.

2.2.3. Swarm-Based

A routing protocol based on swarm draws heavily on the collective behavior, collaboration, and self-organization mechanisms found in swarm intelligence [39]. It treats the nodes in a UAV network as a group and implements routing decisions by means of collective intelligence. In recent years, many scholars have studied and improved routing protocols based on swarm intelligence.

Zheng et al. [40] proposed a dynamic UAV network routing protocol based on the ant colony algorithm, which improved the convergence speed and stability of the routing protocol by optimizing the pheromone update mechanism in the ant colony algorithm. Similarly, Yu et al. [41] proposed a dynamic source routing protocol based on ACO to address the problems of low data transfer rate and high routing overhead in FANETs with conventional routing. In contrast to the studies by Zheng and Yu et al., Alexey [42] abstracts the routing process of the FANET as the colony behavior of bees. The routing process is divided into two parts: bees exploring the pistil (available nodes) and bees carrying food (transmitting data packets). The special point of this protocol is that the relay drone node is not involved in the decision-making process, and all decisions are given by the source node.

Despite the achievements of swarm-intelligence-based routing protocols in FANETs, there are still some problems and challenges. Firstly, many swarm-intelligence-based routing protocols may face slow convergence and high computational complexity [43] when dealing with large-scale FANETs. Secondly, most of the swarm intelligence algorithms used in current research are based on heuristic strategies and do not fully consider the special characteristics of the FANET and practical application scenarios. Meanwhile, there is complementarity between swarm intelligence algorithms that can be fused with each other to optimize routing protocols.

2.2.4. Hierarchical-Based

The development of network clustering methods and mobile edge computing has led to the development of hierarchical-based routing protocols. Hierarchical routing algorithms rely to a certain extent on the formation of clusters. Since each layer has different configuration requirements, routing incompatibilities may arise [44,45]. Combining the characteristics of hierarchical routing, some researchers have improved the protocol for FANETs.

MPCA is a classical hierarchical routing protocol proposed by Zang et al. [46]. MPCA is essentially a predictive clustering algorithm. Because of the time-varying nature of the FANET, UAV networks can be joined or lost at every moment. This study, therefore, predicts the movement of UAVs by the relative position between every pair of UAV nodes, their speed, and the probability of this node staying in this self-assembled network, and uses this to select the node for the next hop of the packet. The advantages of MPCA in terms of reliability and stability are also demonstrated through simulations. Zhao et al. [47] investigated the problem of optimizing the placement of drone relay nodes for SDN-FANET and proposed an SD-UAVNet architecture. This architecture includes a FANET controller that considers global drone context information, preventing drone collisions, optimizing UAV movement, and establishing routing paths to determine relay node deployment to provide QoE-enabled video transmission. Based on this research, Pedro et al. [48] considered the impact of control information on the network and proposed a cluster-based control plane management protocol, CAPONE. This protocol reduces network overhead while ensuring drone management and control message delivery in SDN-FANET.

Hierarchical-based routing protocols can better overcome the uncertainty of topology and movement in FANETs. However, they may make the SDN central controller or cluster head nodes so crucial that their failure may cause the entire network to go down or become inefficient. Currently, FANETs face highly variable task topologies, unstable network link connections, weak network security protection, and application heterogeneity. Therefore, further improvements to the SDN-FANET architecture are necessary to address issues such as limited user computing resources, high network latency, and fragile security protection in harsh environments.

2.2.5. Energy-Based

Energy-efficient routing protocols are crucial for ensuring reliable communication and extended network lifetime in FANETs. These protocols are designed based on the principle of minimizing energy consumption to reduce network energy usage [49] and extend network lifetime while maintaining communication quality [50,51].

In recent years, many researchers have optimized and improved energy-based routing protocols. For example, Fekher et al. [52] used fuzzy logic that minimizes the network's energy consumption by locating the UAV and then electing the next cluster head, which increases the network's lifetime. Additionally, Zhu et al. [49] proposed an energy-efficient routing protocol based on RPL that supports two transmission modes to meet the needs of UAVs in IoT applications.

Despite the improvements made to energy-based routing protocols, FANETs still face several challenges and problems. Firstly, most existing routing protocols rely on simplified energy consumption models that may not accurately predict actual energy consumption, leading to reduced routing performance. Secondly, most routing protocols ignore the problem of simultaneously considering multiple objectives (e.g., delay, reliability) in practical applications. Finally, as FANETs continue to grow, existing routing protocols may face issues related to low scalability and high complexity. To address these challenges, future research can focus on exploring more accurate energy consumption models to improve routing performance.

2.2.6. Heterogeneous-Based

FANETs serve as relay networks in SAGINs and must connect with a variety of platforms, including ground stations, satellites, manned aircraft, and near-space platforms, in the practical use of UAVs [53]. Typically, FANETs communicate with a variety of networks, particularly those that are fixed nodes or those that are positioned on the ground. Researchers have therefore developed the idea of heterogeneous routing protocols.

Omar et al. [54] propose a new routing protocol for UAV-assisted vehicle self-assembly networks. The UAV improves the overall connectivity between vehicles by collecting information about ground traffic density and vehicle connectivity status in order to relay data when the only vehicles on the ground cannot be connected to each other, thus effectively improving the routing process. By adding a routing component to the UAV, Omar et al. [55] has further extended UVAR. The extended version consists of two protocols: UVAR-G for ground-to-air communication and UVAR-S for air-to-air communication. however, this protocol still suffers from high latency and energy failures. Visha et al. [56] propose a routing protocol using distributed priority that provides a solution to the sparsity of FANETs and ground-based networks by using the characteristics of red-black trees.

Existing heterogeneous-based routing protocols generally focus more attention on other networks cooperating with the FANET and can cause higher latency and energy consumption. In addition, most of these protocols only consider static networks and do not take into account the mobility of network nodes. The next step still requires continued research on heterogeneous-based routing protocols if the efficient collaboration of individual self-organizing networks under SAGINs is to be achieved.

2.2.7. Position-Based

FANETs frequently modify their network structure as a result of the high mobility of drones, which has led to the widespread adoption of position-based routing protocols in these networks. Reactive, greedy, and predictive are the broad categories used to describe these protocols.

The reactive routing protocol RGR [57] utilizes location information in routing. Upon packet transmission, the protocol initiates a broadcast of a route request message to nodes within communication range. Upon receiving the message, the UAV node selects the node in the routing table that is closest to its own location as the next hop. If the node is not found, then the protocol selects the node that is the next furthest away as the next hop. In the 2000s, GPSR [58] was a classical greedy routing protocol that relied on location information to make forwarding decisions. For example, if a packet cannot reach the destination node in the next hop, the protocol selects the node closest to the destination node's location as the next-hop address in a greedy manner. Kim [59], Silva [60], and Yang et al. [61] later proposed further improved protocols based on GPSR. Li et al. [62] proposed a routing protocol that dynamically adjusts the frequency of beacons sent by predicting the location of UAVs. The prediction-based location routing protocol can reduce communication delays and overheads by anticipating UAV locations.

Despite the results of research into position-based routing protocols, there are still a number of pressing issues that need to be addressed. For example, existing protocols struggle to support large-scale UAV networks with high mobility in order to guarantee delays or delivery rates. Secondly, GPSR does not consider display cases such as link failures and collisions in order to reduce the number of hops. We believe that future research on position-based routing protocols can be developed in the following directions: developing more stable routing protocols to improve the communication stability of UAV networks through methods such as multi-path or redundant paths; designing high-performance routing protocols for large-scale FANETs to meet the growing demand for UAV applications; and combining technologies such as deep learning to investigate intelligent routing decision methods so that routing protocols can cope with dynamic topological networks.

2.2.8. DTN-Based

The delay-tolerant network (DTN) is a network architecture for communication in the absence of stable end-to-end connections, mainly for sparse networks. It is characterized by unstable connections between nodes, frequent link disruptions, high transmission delays, and low communication bandwidth. Existing DTN-based routing protocols can be divided into three main types: deterministic, stochastic, and weighted graph.

For sparse networks where the behavior of communicating nodes can be easily predicted, Yin et al. [63] propose fountain-code-based greedy queueing and a location-assisted routing protocol to reduce transmission delay. For unpredictable topological network changes, Li et al. [64] designed a routing protocol that can adapt to stochastic dynamic networks using a fuzzy-inference-system-assisted swarm intelligence algorithm based on the DTN architecture. For scenarios where UAVs conduct urban patrols with similarly defined routes, it is easy to predict the location of each communication node because the movement route is predetermined. In this case, a weighted graph is designed, where the closer the two UAVs are, the greater the weight. The nodes for each hop are then selected using the probabilities estimated in the previous step. TENSR [65] is a typical case.

Improving message delivery rates and decreasing network cost ratios often come at the expense of increased transmission delays in existing schemes. Therefore, it is crucial to explore ways to enhance the performance of UAVs in DTNs by integrating the deployment, trajectory optimization, energy usage, and storage allocation of UAV nodes.

3. FANET Routing Algorithms

Since FANETs are characterized by high dynamics, high loss of connectivity, low bandwidth, high latency, low node density, and energy constraints, they pose a serious challenge to designing a reliable SAGIN communication architecture, where the requirements for routing algorithms are even more stringent [66–68]. Not only that, but different FANET applications have differentiated requirements for QoS. For example, applications such as forest fire rescue require real-time traffic, while applications such as information gathering and mapping can tolerate delays. Different types of applications also have different requirements for resources such as bandwidth. Thus, the differentiated QoS requirements of users can also add to the complexity of routing in a FANET [69,70]. For this reason, we discuss FANET routing algorithms in this section, divided according to the type of routing algorithm method.

3.1. Exact-Based Routing Algorithms

Exact algorithms are a class of algorithms that can find the optimal solution to a problem [71]. The algorithm exhausts the space of all possible solutions according to a set of constraints. When the size of the problem is small, exact algorithms are able to find the optimal solution in an acceptable time [72,73]. Some routing algorithm researchers are interested in exact algorithms because they can discover exact solutions and confirm the solutions' accuracy.

Niloofar et al. [74] proposed a group routing algorithm implemented using a distributed dynamic planning algorithm in 2021. This study uses dynamic planning for routing paths to achieve high throughput and load-balanced data forwarding. While the experiments proved that this approach could provide reliable and stable routing for UAVs, this study only discussed one performance metric. Furthermore, due to the high complexity of the algorithm, more time and computational resources are consumed when facing large-scale FANETs. In the same year, an adaptive routing algorithm based on linear programming (LP) was proposed by Gharib et al. [75] for the optimization of routing path lifetime and path length. This study applied the RWP and G-M migration models to evaluate network performance and achieved good results in terms of success rate and throughput. In addition, Lee et al. [76] proposed the use of staged fuzzy logic, where a threshold is set and then the node is scored according to the state of the UAV node (e.g., its energy consumption). If a node scores above the threshold, this node is given the opportunity to participate in the next routing node. Such methods can be used in the routing process to select routes with high fitness, low latency, and low hop count for data transmission. The focus of the study by Cheng et al. [77] is also on UAV energy consumption. They effectively solved the UAV multi-trip routing problem by modeling the problem as a non-linear function of payload and flight distance. The researchers added a dual indicator formulation to the solution process and devised a branch-and-cut algorithm (B&C). Although the algorithm achieved good results, the effect of factors such as UAV speed and wind speed on the algorithm was not considered when optimizing for routing.

3.2. Heuristic-Based Routing Algorithms

The heuristic algorithms are search algorithms based on experience and illuminating knowledge [78]. Heuristic algorithms can be used to find optimal or sub-optimal solutions in large-scale, complex environments such as SAGINs. Unlike exact algorithms, heuristics can be used in converting NP-hard problems into problems where a solution is found close enough to the optimal solution in an acceptable amount of time [79,80]. Moreover, as the exact algorithm sets more constraints, it is limited by the size of the network. The trend will be toward large-scale UAV clustering efforts in the future. Routing algorithms for UAVs can be abstracted as a path search problem. Heuristic algorithms are usually based on a search strategy that continuously approaches the optimal routing path through iterative optimization based on the characteristics and constraints of the problem, without searching the entire solution space. As a result, researchers in recent years have used heuristic algorithms as a means of routing optimization.

The time and difficulty of solving routing for UAVs with navigation, steering, and uncertain constraints spikes. Shang et al. [81] used a modal algorithm to minimize UAV routing algorithms for three-dimensional flight distances. The algorithm uses a hierarchical architecture combining a meta-heuristic algorithm and a genetic algorithm (GA). Experimental results show that the algorithm proposed by Shang et al. has good stability, but the algorithm is poorly optimized. Muhammad et al. [82] proposed a routing optimization algorithm combining GA with a simulated annealing algorithm (SA), where GA is used to search for the global optimal position of nodes and SA uses local search operators to avoid trapped local optimal solutions. Zhang et al. [83] proposed an improved artificial bee colony algorithm that introduces a cooperative strategy based on the traditional artificial bee colony algorithm (ABC), determines a multi-UAV routing path that satisfies the cooperative requirements by calculating the routing spacing, and uses the routing penalty degree for evaluation. In addition, to avoid the algorithm falling into local optimality, the algorithm uses a slow communication method and replaces the fully connected topology with a ring topology. The algorithm is optimized mainly for energy utilization and routing efficiency. However, the algorithm is limited in terms of the size of the UAV and the number of missions.

Particle swarm optimization (PSO) [84] is a widely researched optimization algorithm due to its simplicity, ease of use, global search capability, fast convergence, and parallelizability. These advantages make PSO a relatively mature algorithm with a well-established research base, which is why it continues to attract the interest of many researchers.

Sun et al. [85] improve the traditional particle swarm algorithm by introducing an adaptive weight factor and an inertial weight factor to implement a clustered routing algorithm. The study addresses the problem that traditional PSO tends to fall into local optimum solutions by using variable neighborhood search. The algorithm first determines the best clustering head node by using an improved PSO. Other UAVs are then selected to connect to the best clustering head node by comparing distance and energy parameters. Ultimately, data transmission is carried out via the path with the lowest number of hops. This study used energy consumption and network lifetime as optimization objectives, but the study did not explore the performance of this algorithm under large-scale FANET. Similarly, Ma et al. [86] designed a contingent FANET task-driven routing algorithm using a binary particle swarm algorithm and used a weighted time-expansion graph to accommodate dynamic network changes. This study focused the optimization objectives on latency performance and network resource utilization and achieved good results. These researchers' studies also demonstrate the effectiveness of particle swarm algorithms for optimizing FANET routing algorithms.

While the exact algorithm can provide a globally optimal solution, its high time complexity makes it unsuitable for real-time applications, especially with larger problems. In contrast, heuristic algorithms are faster and can deliver better solutions in a shorter time frame, although they may not guarantee a globally optimal result. In order to address these issues, the researchers reviewed below have explored combining both algorithms for routing optimization.

Ozkan [87] is the first study to combine heuristic and exact algorithms for solving a multi-UAV routing problem under distance constraints. The authors establish constraint mechanisms to design ILP models and use SA and local search algorithms to assist in the search for routing solutions. Finally, the researchers demonstrate the effectiveness of this study by comparing it with a GA-only routing strategy. In contrast to Ozkan et al., Kaya et al. [88] focus their optimization objective on minimizing the number of UAVs in the FANET, retaining only the minimum number of UAVs that can support the service within the self-assembled network. Kaya et al. propose a formula for minimizing the number of UAVs, which is solved with the aid of a GA. This algorithm uses the idea of greed to continually compress the number of drones so that when the number of drones does not satisfy the services in the network, the number of drones before this compression is the minimum number of drones. Sudipta et al. [89] similarly combine the exact algorithm with a heuristic algorithm to minimize the total flight communication cost by formulating cost constraints on the cost of charging, acceleration, and hovering of the drones. In this, two heuristic search algorithms were used to help the model solve for the communication cost minimization in an acceptable time.

3.3. Reinforcement-Learning-Based Routing Algorithms

Reinforcement learning (RL) [90] is a machine learning method that learns optimal action strategies by interacting with the environment to maximize cumulative rewards. It is a method that does not require manually labeled training data and learns through autonomous experimentation and feedback. Reinforcement learning is adaptive and can adapt to different network topologies and channel states to learn the optimal routing policy. RL is also real-time, allowing learning to take place through real-time interaction with the environment [91,92], enabling real-time adjustment of routing policies in dynamic environments. In addition, the learning process does not depend on specific data distributions and statistical models, enabling it to handle complex environments that are non-linear, non-stationary, and non-Gaussian [93,94], and is suitable for handling large-scale dynamic problems such as FANET under SAGIN. In the process of flying UAVs, the current state includes information about the position, speed, and remaining power of the UAV, while the future state depends only on the current state, independent of the historical flight of the UAVs, so the UAV flight process has Markovian properties (MDP). The MDP process can be represented by a triple $< S, A, R >$, where state denotes the finite set of states of the agent, action denotes the set of actions available to the agent, and reward denotes the reward value of the environment. By continuously trying to take different actions in this process, the intelligent body can find the optimal policy in the state space. The Markov decision process is illustrated in Figure 6. It is because of the adaptive, efficient, robust, and real-time nature of reinforcement learning that research on the use of reinforcement learning for FANET routing algorithms has been favored by many researchers in recent years.

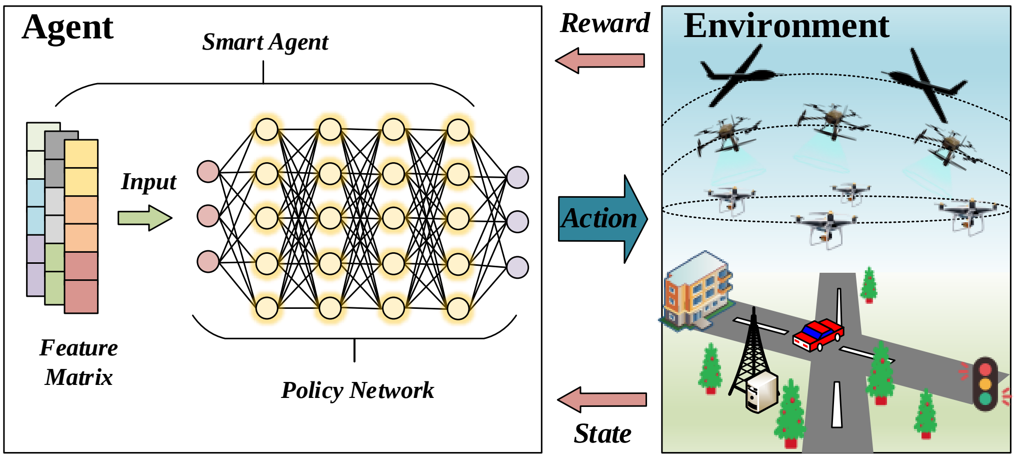

Figure 6. Markov decision processes.

Some researchers have focused their attention on using the classical-value-function-based reinforcement learning algorithm Q-learning, and we analyze the latest research developments below.

Stefania et al. [95] propose a Q-learning approach to improve the QoE of video users in a cellular area by introducing rewards related to quality of experience (QoE) metrics that address the distribution of drone swarms. The algorithm defines the state space as three types of information (i.e., drone location, flight time, and residual energy). By designing a global reward associated with the QoE, the algorithm can determine the optimal location for drone signal coverage. Experimental results show that the algorithm is able to match video users' requests to drones with sufficient remaining bandwidth. As the complexity of the algorithm increases with too many constraints, this method sets constraints only for users and routing paths in order to control the complexity of the algorithm, but a real FANET environment requires a comprehensive consideration of constraints. Similarly, a method that can adaptively adjust the capability of Q-learning parameters was proposed by Liu et al. [96]. This method can automatically adjust the learning rate and discount factor according to the delay of each hop during packet transmission. Liu et al. also proposed discovering potentially optimal routing paths using existing knowledge. Since UAVs are highly dynamic, there is a higher probability of link breakage and topology changes occurring. The difference between this method and the traditional method is that this method does not use past topological relationships but re-estimates the UAV neighborhood relationship each time to select a reliable next hop. In addition, Arnau et al. [97] propose a Q-learning-based routing algorithm aimed at reducing connectivity loss and energy constraints in UAV networks, and this algorithm enables dynamic routing. The study proposes a trajectory generation method that uses a segmented linear movement model to generate node movement trajectories. In addition, the researchers propose a full-echo Q-routing algorithm with optimized control of the adaptive learning rate in order to select unstable links, minimize the total energy consumption of the network, and minimize packet loss. Experimental results show that the algorithm is able to adapt to dynamic changes in the network and does not require manual re-initialization after network topology changes. Muhammad et al. [98] propose a UAV self-organizing network algorithm, called FAN-RL, for 5G using reinforcement learning. This algorithm feeds UAVs with higher residual energy and stability as environmental states into a policy network to determine optimal routing, extend network lifetime, and reduce energy consumption and the number of broken links. To reduce energy consumption, extend network lifetime, and minimize the number of broken links, this algorithm utilizes a policy network that considers higher residual energy and stability of UAVs as environmental states for optimal routing. FAN-RL uses a modified Q-routing model embedded in a central controller to select the best possible routes based on the UAV self-organizing network's higher remaining charge and stability, resulting in improved QoS and network lifetime. Although effective in reducing energy consumption and extending network lifetime, FAN-RL only considers the impact of network density and stability on the time the network provides service, the amount of UAV power, and the number of failed links, and does not consider other factors such as link jitter. Kumar et al. [99] proposed an algorithm for delay-sensitive FANETs called XiA that utilizes Q-learning and considers the SAGIN's FANET characteristics, designing a bonus function that factors in channel conditions and equipment configurations to minimize the time required to forward data to the access point via multiple relay UAVs, including those in restricted or affected communication areas. If the UAVs are unable to reach the access point, they send the data to the LEO satellite, which then forwards the data to the access point. This algorithm improves the latency by 82% compared to the traditional Dijkstra shortest-circuit algorithm and the FAN-RL method proposed by Muhammad et al. [98] in 2020. Although consideration of satellite networks is added in the paper, attention to ground nodes in SAGIN is still missing. Jiang et al. [100] proposed a Q-learning-based adaptive UAV-assisted geographic routing algorithm with concerns about path selection errors in the routing mechanism, reduced convergence speed due to routing table maintenance, and the inability to use it for a long time after convergence. The algorithm adds consideration of ground network nodes.

As the research progresses, more researchers are thinking beyond Q-learning based on value functions, and some of them have innovatively proposed the use of multi-intelligent reinforcement learning to solve the routing problem in complex FANETs. In contrast, multi-intelligent reinforcement learning can improve the efficiency and performance of system routing through techniques such as parallelization.

Wang et al. [101] proposed a training routing strategy using an actor-critic neural network. This algorithm state space includes FANET local information and global information based on the mean field. The complexity is greatly reduced compared to the high complexity of centralized routing algorithms facing large-scale networks. Similarly, Qiu et al. [102] continue to adapt multi-intelligent reinforcement learning to the complex and variable FANET environment by using LSTMs instead of the fully connected layers of actor-critic networks. The algorithm starts with an LSTM-based behavioral network that performs an output operation based on the current state, followed by an intelligent body that operates, receives a reward and evolves to a new state, and finally updates the parameters of the judging network using a loss function and updates the parameters of the behavioral network using a gradient ascent algorithm. The algorithm has advantages in terms of transmission delay and transmission rate. Unfortunately, the method was only tested against traditional routing algorithms and not against other reinforcement-learning-based routing algorithms. Wang et al. [103] also proposed a hybrid PG-based routing control algorithm. This algorithm uses a centralized training platform to guide each UAV node through policy updates, enabling the UAV nodes to collaboratively learn. In addition, the algorithm innovatively introduces a counterfactual baseline scheme to improve the convergence speed of the algorithm. In the training phase, joint values are generated by feeding the environment state and joint behavior into the neural network, after which each decentralized intelligence is trained based on the joint values, and in the execution phase, each intelligence will make behavioral choices based on its local observations. The algorithm greatly improves the collaboration between UAV nodes and effectively balances network congestion and group distribution while maintaining high throughput capabilities. Multi-intelligent reinforcement learning is also employed by Qiu et al. [104] for routing optimization. However, their algorithm is distinct in that it uses the packet loss rate and routing overhead of the routing protocol as the optimization objective. Each node is considered an intelligent agent, and its neighboring nodes are evaluated based on local information. The value function takes into account link quality, residual energy, and queue length, among other factors, to minimize the probability of routing vulnerabilities. Additionally, the protocol utilizes global rewards for collaborative data transmission.

Researchers have abstracted UAVs as nodes and FANETs as topological networks, converted the FANET routing problem into a graph problem, and then used graph neural networks (GNNs) in deep learning to optimize it. For example, Wang et al. [105] proposed a GNN-based joint optimization framework for solving the joint flight relay localization and routing optimization problem in UAV and IoT networks. The approach uses reinforcement learning algorithms to optimize the locations of all UAVs via relay GNNs and location GNNs and select optimal relay paths to improve network throughput, reduce latency, and increase energy efficiency. Experimental results show that the method has significant advantages over existing methods in solving joint optimization problems. FANET routing problems often involve large-scale nodes and edges, and the combination of GNNks and RL can handle these large-scale problems quickly and efficiently. This study provides an innovative combination of GNN and reinforcement learning, which also provides a new way of thinking about joint routing optimization under SAGIN.

In SAGIN, the satellite, aerial, and ground-based networks each possess distinct network characteristics, requiring different routing algorithms to accommodate them [106]. To address the frequent changes in network topology, it is advantageous to integrate reinforcement learning, which offers a long-term vision for sequential problems. Additionally, it is essential to consider the utilization of Markov decision processes to model the comprehensive network routing problem in SAGIN. In addition, the proposed routing algorithm should provide guarantees across multiple metrics, such as transmission delay and packet loss rate. While addressing the challenges of topology changes and frequent link switching, it is important to reduce the demands on node storage and computational capabilities (considering that UAV and satellite nodes have significantly lower computational and storage capacities compared to ground-based nodes). Therefore, novel routing algorithms should integrate the characteristics of the integrated network scenario while ensuring the adaptability of the routing process. In the study of SAGIN routing, the complexity of the protocol framework also serves as a significant hindrance to the development of routing algorithms [107], as SAGIN employs separate protocol frameworks for satellite–ground, aerial–ground, and aerial–satellite connections. Among them, there are numerous base stations, drones, or satellites with specialized purposes that adopt independent protocol frameworks for security reasons. This is also one of the most challenging issues in current research on SAGIN routing algorithms. To address this challenge, we can draw on the layered control approach proposed by Qu et al. [108] and the idea of designing a software-defined network based on a layered hybrid architecture proposed by Eiza et al. [109]. By introducing the concept of separating control and transmission in a software-defined network into the heterogeneous SAGIN context [110], we can attempt to add a controller to each layer of the existing network structure, ensuring unified protocols and programming interfaces between layers.

4. Analysis and Perspectives

4.1. Analysis of Experiments

With the development of 5G and 6G communication technologies in recent years, the development of SAGINs has been greatly driven by the development of FANETs as an important relay linking ground-based and space-based networks, and UAV-related research in this field is favored by an increasing number of researchers. Routing algorithms transport packets from source nodes to destination nodes quickly and reliably. The design of routing algorithms for FANETs plays a fundamental role in improving the reliability and network performance of FANETs and SAGINs. We queried the number of UAV routing algorithms researched over 10 years in the Web of Science core database using a side-by-side query with keywords (UAV routing, FANET routing, and drone routing), and the results are shown in Figure 7. The figure clearly shows that research on routing algorithms for UAVs has been increasing year by year in recent years. It also shows that users and operators are demanding more and more operational efficiency, security, and reliability from UAVs, and existing routing techniques cannot meet the increasing number and scale of FANETs. In Table 1, we focus on comparing 48 experimental approaches that have been researched on routing algorithms for UAVs since 2018.

Table 1. Analysis of routing algorithms in published FANETs.

Ref.	Network Scale (Sorties)	UAV Type	Method	Dataset Type	Simulation Platform
[82]	76	Small drones	GA+SA	Real dataset	Win10+Python
[102]	20–70	Small drones	MADDGP+LSTM	Self-generated	NS-3
[103]	10	Small drones	MARL	Self-generated	Ubuntu16.04
[81]	100	Small drones	MA+GA	Real dataset	Win10+Python
[111]	15	Small drones	Fuzzy Logic+Q-learning	Self-generated	MATLAB
[112]	30	Small drones	FSR+Dijkstra	Self-generated	NS-2
[88]	12	Medium to large drones	GA+BM	Real dataset	MATLAB
[99]	50	N/A	Q-learning	Self-generated	NS-3
[101]	12	N/A	MARL+CNN	Self-generated	MATLAB
[77]	10–30	Small drones	B&C	Self-generated	Python+Gurobi
[113]	5–10	Medium to large drones	Fuzzy Logic+RL	Self-generated	MATLAB
[100]	25	Medium to large drones	Fuzzy Logic+Q-learning+DFS	Self-generated	NS-3

Table 1. *Cont.*

Ref.	Network Scale (Sorties)	UAV Type	Method	Dataset Type	Simulation Platform
[114]	14–18	Medium to large drones	Minimize network power+K-means	Self-generated	MATLAB
[95]	3	Medium to large drones	Q-learning	Self-generated	MATLAB
[98]	100–1000	Medium to large drones	RL	Self-generated	MATLAB
[96]	25	Small drones	Q-learning	Self-generated	WSNet
[104]	20, 40	Small drones	Q-learning	Self-generated	NS-3
[87]	1–7	Medium to large drones	SA+MILP	Real dataset	MATLAB+ILOG
[115]	150	Small drones	KF+Shortest-circuit algorithm	Self-generated	MATLAB
[75]	50–100	Medium to large drones	OPAR	Self-generated	NS-3
[116]	10–100	Small drones	Greedy algorithm+HA+RL	Self-generated	OPNET
[117]	5–100	Medium to large drones	MILP+HA	Self-generated	Python+AWS c5n.4xlarge
[97]	10–20	Different types of drones	SA+Q-learning	Self-generated	N/A
[118]	100	Small drones	ACO	Real dataset	Raspberry Pi+Python
[119]	25	Different types of drones	GA	Real dataset	MATLAB
[120]	200	Small drones	DNN+Greedy algorithm	Self-generated	NS3
[121]	10-100	Small drones	HA+Fuzzy clustering	Self-generated	MATLAB
[122]	10–40	Small drones	Multicast routing protocol algorithm	Self-generated	NS-2
[123]	40–100	Small drones	DDQN	Self-generated	Python
[124]	100	Small drones	SA	Self-generated	Python+F-SDN
[85]	20–200	Small drones	PSO	Self-generated	MATLAB
[125]	1–4	Medium to large drones	LS+HA	Real dataset	MATLAB
[83]	30	N/A	ABC	Self-generated	N/A
[74]	137	Small drones	Online learning algorithm	Real dataset	MATLAB
[86]	15	Small drones	PSO	Real dataset	N/A
[126]	25	Small drones	Q-learning	Self-generated	WSNet
[127]	1–6	Small drones	Agent-based algorithms	Self-generated	Python+Windows
[89]	5–30	Small drones	ALNS+MBATA	Real dataset	Python+Gurobi
[128]	10–100	N/A	Routing conversion+Shortest path algorithms	Self-generated	Python+Gurobi +Windows
[129]	20–40	Small drones	L&F (HA)	Self-generated	Java+Python +CLPEX+ILOG
[130]	>100	N/A	Hybrid algorithms	Self-generated	MATLAB+C++
[131]	10–40	Small drones	Multicast routing algorithms	Self-generated	NS-2

Table 1. *Cont.*

Ref.	Network Scale (Sorties)	UAV Type	Method	Dataset Type	Simulation Platform
[76]	100	Small drones	Fuzzy logic	Self-generated	NS-2
[108]	N/A	Small drones	Load-balancing dynamic routing algorithm	Self-generated	Windows+OPNET +C++
[105]	2–35	Medium to large drones	GNN+RL	Self-generated	N/A
[132]	10–200	Medium to large drones	DPSO	Self-generated	N/A
[133]	50	Small drones	Digital signature algorithms	Self-generated	NS-2
[134]	60–100	Small drones	RL	Self-generated	Python

* N/A indicates that this item is not mentioned in the paper.

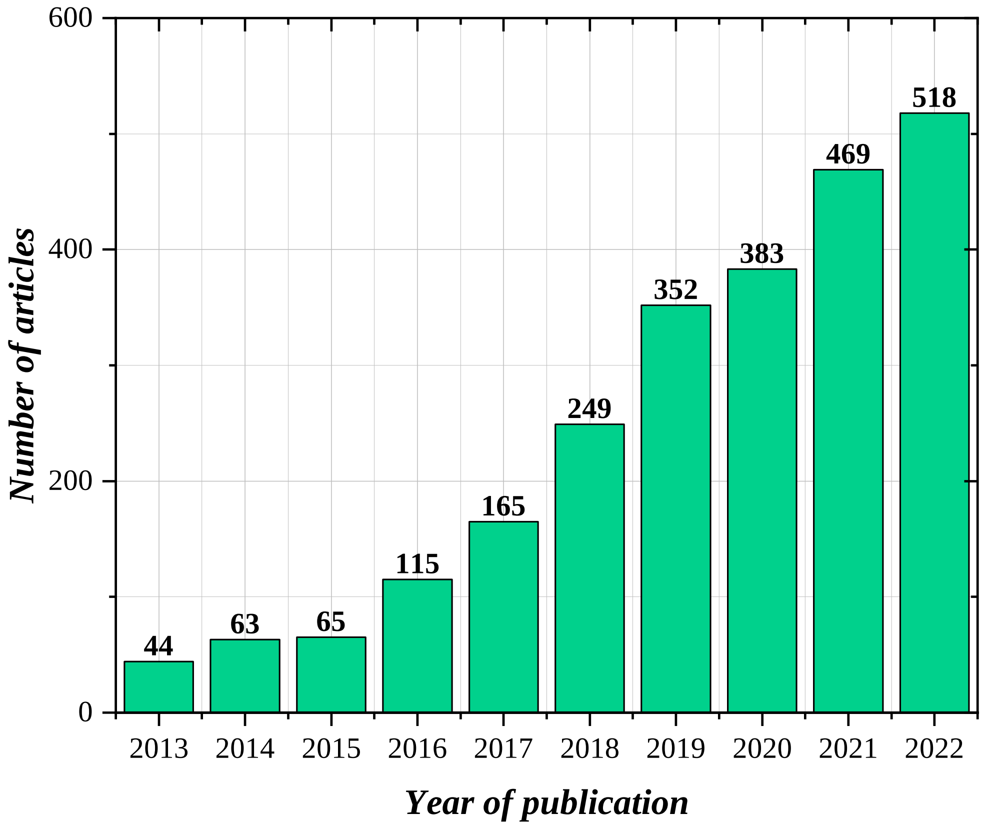

Figure 7. Trends in the publication of papers related to UAV routing algorithms from 2013 to 2022.

We have focused mainly on the experimental methods, the objects, and the settings. The studies listed in Table 1 will be analyzed below.

Research subjects: As shown in Figure 8, 60.4% of the routing algorithms we discuss are focused on small rotorcraft UAVs. The reason for this in our analysis is that because of their low manufacturing and development costs and their wider user-base orientation, the relevant UAV companies invest more in the development of small UAVs, which ultimately leads to smaller UAVs having an advantage in terms of maturity. However, in FANET construction, cooperative communication of UAV nodes at all levels is required. In future research, reliable routing algorithms for large UAVs should continue to be designed for their large payloads, long endurance, and high-speed flight characteristics. Secondly, the algorithms should be designed in a way that multiple types and levels of UAVs are studied simultaneously, as in [97,119]. For example, faster UAVs should be deployed around nodes that are latency-sensitive, and UAVs with higher load capacity should be deployed around nodes with high storage resource requirements.

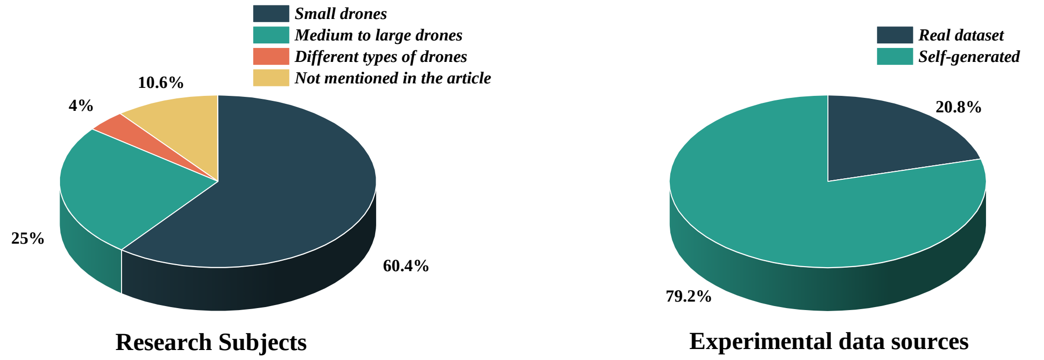

Figure 8. Proportion of UAV routing algorithm research subjects and research data sources in the last 5 years.

Data source: Similarly, as shown in Figure 8, 79.2% of the studies used data generated by a simulation tool for their experiments, and only 20.8% used UAV data from a real environment for their experiments. The use of simulated data allows for easier control of the routing experimental environment and more flexibility in setting parameters and conditions while saving time and economic overhead; however, experimentation in real environments or with real datasets can reflect the adaptability of UAVs in complex, dynamic environments. We believe that future experiments investigating the design of routing algorithms for UAVs could include real datasets for validation or multiple sets of experiments using simulated and real datasets, respectively.

Simulation platform: Many researchers used the more developed Network Simulator 2 (NS-2) and Network Simulator 3 (NS-3) as their simulation platforms of choice. Because NS-2 and NS-3 were partially developed in C++, it is challenging for researchers to implement protocols and debug the code. Additionally, they employ a time-driven simulation method, which is less effective for large-scale simulations. In the future, we ought to think about creating a simulation platform for SAGIN that can model networks at various scales or granularities.

Routing methods: Most routing algorithms reflect an effort to optimize the employment of RL-related algorithms in recent years as RL research has gained in popularity. The application field of UAVs expands as the network size increases as businesses raise their investment in UAV research. Since it is nearly impossible to meet all constraints at once, future research should focus on the use of reinforcement learning algorithms in conjunction with the integration of other algorithms to create a routing algorithm that can be adaptive for the different QoS requirements of users. Additionally, UAVs might be utilized for tasks such as medical rescue and event security, which would include a lot of sensitive data and put significant pressure on the drone routing algorithms' security. Therefore, exploration of a more secure routing algorithm will also become a hot topic. Researchers can use federated learning techniques to encrypt and train data inside the drone nodes to protect private data, and finally submit the trained sub-models to a central server for aggregation and federated learning.

4.2. Analysis of Other Issues

FANET routing algorithms should not be limited to data transmission problems. Other issues, such as communication resource scheduling and collaborative scheduling, can also be modeled as routing problems. For example, for the resource scheduling problem, we need to specify the objectives and constraints of the scheduling problem first. Next, the tasks to be allocated and the types and amounts of resources available are identified. The nodes to be allocated resources are abstracted as communication nodes in the routing algorithm, the minimum resource requirements are used as attributes, and the communication and collaboration relationships between resources are modeled as edges of the network. The routing algorithm is then used to select the path that is closest to the target value (or has the highest evaluation metric). Similarly, the dynamic deployment of service function chains based on the virtualization of network functions can be modeled as a routing problem. The two problems are situated in very similar contexts (e.g., the situation where a drone joins or leaves the network due to battery capacity or dynamic flight is similar to the situation where a node in the physical network fails and cannot continue to serve the virtual network function). We can try to abstract the physical network nodes as drone nodes and the communication links between the physical nodes as wireless communication links between the drones in the routing problem. For the deployment of service function chains, we can abstract them as path selection processes. In addition, the routing algorithm proposed for the FANET environment can be applied to satellite self-assembly networks or vehicle self-assembly networks, which also have highly dynamic characteristics. Specifically, the original routing algorithm for FANET can be replaced with constraints on flight speed, bandwidth limits, and so on, that are consistent with the characteristics of satellite and vehicular self-assembly networks. In general, the application of routing algorithms is very promising, and future researchers can try to model dynamic graph problems with a large number of constraints as FANET routing problems and use improved routing algorithms to solve them.

In addition to the applications mentioned above, a large number of challenges remain with the FANET routing algorithm in the context of SAGIN. UAV collisions and signal loss are frequent problems in FANETs, so more complex network situations also need to be included in researchers' focus. The ability of routing algorithms to handle dynamic problems and uncertainty is also a critical aspect of measuring algorithm reliability and performance. Algorithms that can predict the behavior of drones should also be proposed for such problems. When algorithms have the ability to predict the actions and states of UAVs in advance, they can prepare UAVs to react accordingly in a targeted manner. SAGIN construction requires a large number of UAVs as relay nodes for air-based and ground-based networks, and an increasing number of applications rely on UAVs. However, a large number of studies have involved small-scale UAVs due to limitations in algorithms and experimental conditions; this does not match the trend of an increasing number of UAVs in future networks. Furthermore, because of its unique heterogeneity, self-organization, and time-variability, SAGIN has limited and unbalanced network resources in all three network segments compared to traditional terrestrial or satellite networks; in particular, FANET computational and storage resources have a large gap compared to terrestrial networks. This poses a challenge for protocol optimization, resource management, and allocation. Based on the previous analysis and discussion, it is easy to see that the development of machine learning offers new development opportunities for FANET algorithms. UAVs are limited by computational and storage resources, which requires us to pay more attention to the time complexity and algorithmic space complexity when designing them, and it is important to develop machine learning solutions with rapid learning capabilities. Furthermore, although one of the most important features of SAGIN is air–ground convergence and multidimensional communication, existing routing algorithms are more focused on interoperability within FANETs or are only studied for routing algorithms between two self-assembled networks (e.g., satellite and ground or UAV and ground). In the future, joint optimization should be carried out in conjunction with nodes at each level, in each autonomous domain. Therefore, we should not only focus on hierarchical routing within UAVs; we should also propose a reasonable modeling scheme for multi-source heterogeneous SAGINs in the next step, considering the key metric parameters affecting network performance and proposing integrated routing algorithms that can cope with users' differentiated quality of service.

5. Conclusions

Networks are expanding in scale as a result of the development of SAGINs and UAV technology, and user requirements are diversifying. It is vital to develop a routing algorithm that is safe, dependable, and effective and can be used on large-scale networks. In this paper, we present the latest communication architecture for UAV networks under SAGINs and introduce the applicable routing protocols for FANETs. In addition, we review the latest routing algorithms for FANETs and analyze the limitations of existing routing algorithms, discussing and analyzing the optimization directions for each type of approach. In addition, we summarize the experimental scenarios of existing research in terms of network size, routing algorithm research targets, and simulation platforms, and we visualize the trends and shortcomings of the designed experimental scenarios in the form of statistical charts. Finally, we make plans for future research on routing algorithms for FANETs under SAGINs. We propose a routing algorithm that is based on the current state of research on routing algorithms and takes into account the highly dynamic and other network characteristics of FANETs while incorporating space-based and ground-based networks in SAGINs.

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