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# Multi-UAV networks for disaster monitoring: challenges and opportunities from a network perspective

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## Abstract

Disasters, whether natural or man-made, demand rapid and comprehensive responses. Unmanned aerial vehicles (UAVs), or drones, have become essential in disaster scenarios, serving as crucial communication relays in areas with compromised infrastructure. They establish temporary networks, aiding coordination among emergency responders and facilitating timely assistance to survivors. Recent advancements in sensing technology have transformed emergency response by combining the collaborative power of these networks with real-time data processing. However, challenges remain to consider these networks for disaster monitoring applications, particularly in deployment strategies, data processing, routing, and security. Extensive research is crucial to refine ad hoc networking solutions, enhancing the agility and effectiveness of these systems. This article explores various aspects, including network architecture, formation strategies, communication protocols, and security concerns in multi-UAV networks for disaster monitoring. It also examines the potential of enabling technologies like edge computing and artificial intelligence to bolster network performance and security. Further, the article provides a detailed overview of the key challenges and open issues, outlining various research prospects in the evolving field of multi-UAV networks for disaster response.

**Key words:** multi-UAV network, architecture, mobility, optimization, disaster, security

## 1. Introduction

In recent decades, the world has faced a growing threat from natural disasters, with their impact on human life and infrastructure becoming increasingly pronounced. A study by the Centre for Research on the Epidemiology of Disasters (CRED) and the United Nations Office for Disaster Risk Reduction (UNDRR) reveals a concerning trend, indicating that between 2000 and 2021, natural disasters caused 1.23 million deaths and incurred a substantial economic cost of US$2.98 trillion (Cred and UNDRR Centre for Research on the Epidemiology of Disasters (CRED) 2021). Despite technological advancements improving disaster management efficiency, a slight increase in the number of deaths compared to the previous two decades is attributed to the rising frequency and severity of these events, particularly due to the effects of global warming. The COVID-19 pandemic has underscored the urgency for innovative disaster prevention and mitigation methods. Simultaneously, as disasters like the cyclone in Indonesia, the Tornado in Kentucky, landslides in China, the typhoon in the Philippines, and the flash floods in India witnessed in the years 2020–2021 continue to wreak havoc, the need for effective post-disaster communication systems becomes evident. The golden time within the first hours after a disaster is crucial for saving lives, necessitating the development of reliable and quickly deployable emergency communication networks.

Despite notable advancements in wireless communication technology, addressing communication challenges during disaster relief activities remains an ongoing concern. The literature in disaster research underscores significant limitations in executing first response operations, especially when the terrestrial communication networks are partially damaged or completely destroyed. In search-and-rescue (SAR) missions, the need for real-time and reliable communication is important, as first responders must coordinate their actions and collaborate with other teams. Micheletto et al. (2018) advocate for the use of flying ad hoc networks to offer communication support in disaster scenarios, with unmanned aerial vehicles (UAVs) serving as communication gateways among first responders across various locations in the affected area. An equally interesting topic that is often compared with UAV networks is the Internet of Things (IoT) (Aggarwal and Kumar 2020; Boursianis et al. 2022). Though both of these networks work on a similar paradigm of collaborative wireless networking, they differ in terms of fundamental principles and applications (McEnroe et al. 2022). IoT is characterized by a wide-ranging network of diverse devices, including sensors, actuators, and everyday objects, interconnected through existing communication infrastructures. Its primary goal is to facilitate data exchange for automation and improved efficiency in various domains, such as smart homes, healthcare, and industrial processes. In contrast, ad hoc UAV

Fig. 1. UAV applications in disaster management.

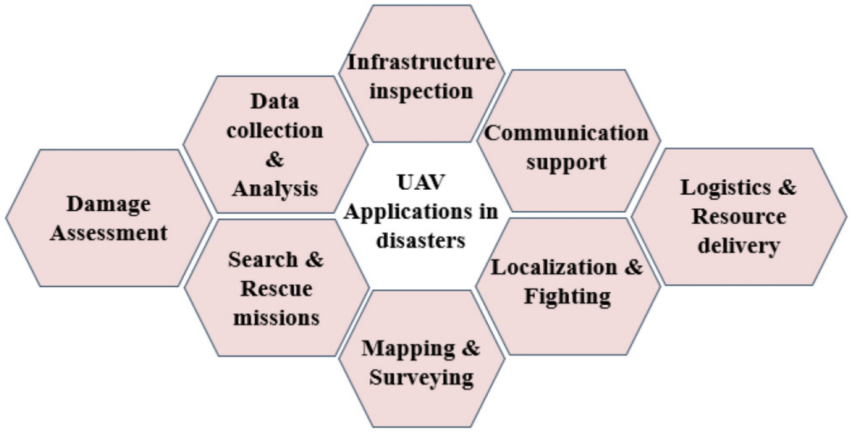



Fig. 2. Network scenario in a disaster.

networks focus on the dynamic formation of temporary communication links among UAVs, typically in scenarios where traditional infrastructure is lacking or impractical. Ad hoc UAV networks prioritize mobility, flexibility, and rapid deployment, making them suitable for applications like disaster response, surveillance, or military operations. While both technologies leverage wireless communication, their specific architectures, scalability, and intended use cases distinguish them significantly. Its applications range from surveillance, medical aid delivery, SAR, and providing relayed communications to many more (Luo et al. 2019). Figure 1 outlines various applications of UAVs during disasters. The dynamic and flexible nature of these vehicles and the non-requirement of a preexisting network infrastructure allow them to quickly adapt to changing environmental conditions. They can be deployed rapidly to areas that are difficult to reach by the responders, thus playing a key role in remote or disaster-stricken locations. This is particularly valuable for coordinating rescue and relief efforts as well as facilitating information exchange among affected communities. This integration offers a dynamic and efficient solution to bridge gaps in communication infrastructure, particularly in the aftermath of natural disasters or emergencies. Figure 2 illustrates a network scenario during disasters.

The development of collaborative UAV networks also poses challenges, necessitating advanced communication and control systems, distributed algorithms, and addressing safety concerns. The control system must adeptly manage the intricacies of multi-UAV operations, optimizing the trajectories while ensuring safe and efficient mission execution. An additional challenge lies in developing distributed algorithms that enable UAV collaboration while preserving autonomy capable of navigating diverse circumstances such as node failures, communication failures, hostile attacks, and changing environmental conditions. Thus, careful consideration of all the network aspects is required to ensure efficiency, reliability, and security. From a network perspective, the article delves into multiple facets of multi-UAV networks for disaster monitoring and surveillance, encompassing recent developments in communication protocols, network architecture, topology, path optimization, fault tolerance, routing, and security.

## 1.1. State-of-the-art surveys and our contributions

In recent years, there has been a surge in interest in development of multi-UAV networks, particularly focusing on

Table 1. A comparison chart of existing surveys.

| Reference | Deployment/ architecture | Mobility model | Communication protocols | Channel modelling | Routing | Coverage and connectivity | Security |
|---|---|---|---|---|---|---|---|
| Deepak et al. (2019) | ✓ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ |
| Shakhatreh et al. (2019) | ✗ | ✗ | ✓ | ✗ | ✗ | ✗ | ✓ |
| Jahir et al. (2019) | ✓ | ✗ | ✓ | ✗ | ✓ | ✗ | ✗ |
| Luo et al. (2019) | ✓ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ |
| Hentati and Fourati (2020) | ✓ | ✓ | ✓ | ✗ | ✓ | ✗ | ✗ |
| Garnica-Peña and Alcántara-Ayala (2021) | ✓ | ✓ | ✗ | ✗ | ✓ | ✗ | ✗ |
| Matracia et al. (2022) | ✗ | ✗ | ✓ | ✓ | ✓ | ✓ | ✗ |
| Javaid et al. (2023) | ✗ | ✗ | ✓ | ✗ | ✗ | ✗ | ✗ |
| Our survey | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |



cutting-edge technologies like UAV swarm-based edge computing and machine learning (ML) techniques. While it is true that there exist several survey papers on UAV networks, it is essential to recognize that the landscape of UAV applications is constantly evolving, and emerging technologies demand a fresh perspective and in-depth analysis. The uniqueness of the article lies in its comprehensive exploration of network-centric aspects related to multi-UAV systems, particularly in the context of disaster monitoring. To the best of our knowledge, there is no survey that has extensively covered all the network aspects from a disaster perspective. Table 1 outlines the available surveys and evaluates each of them across various network aspects.

The major contributions of this work are as follows:

- Provides valuable insights into network-centric aspects associated with multi-UAV systems. By exploring different communication protocols, formation control techniques, network architectures, trajectory optimization schemes, data management and routing, and security aspects, the work presents an overview of the conventional methodologies that have evolved to help mitigate disasters, thereby ensuring speedy recovery efforts to save human lives.
- Emphasizes the paramount importance of security in the context of multi-UAV networks used for disaster monitoring. The paper delves into the potential vulnerabilities that these networks may face and explores solutions to overcome the threats that can compromise their reliability and functionality.
- Makes a significant contribution by identifying and analyzing the challenges inherent in deploying multi-UAV networks to pave the way for unlocking the full potential of multi-UAV networks in disaster applications.

## 2. System architecture

Disaster surveillance requires an efficient network architecture that can facilitate the coordination of UAVs with other agents in the network. A well-designed network architecture can enable effective communication and information sharing, which are critical for situational awareness and decision-making in disaster scenarios. In this article, we will discuss the different aspects of network architecture for disaster surveillance, including topology, communication architecture, and formation strategies.

### 2.1. Topology

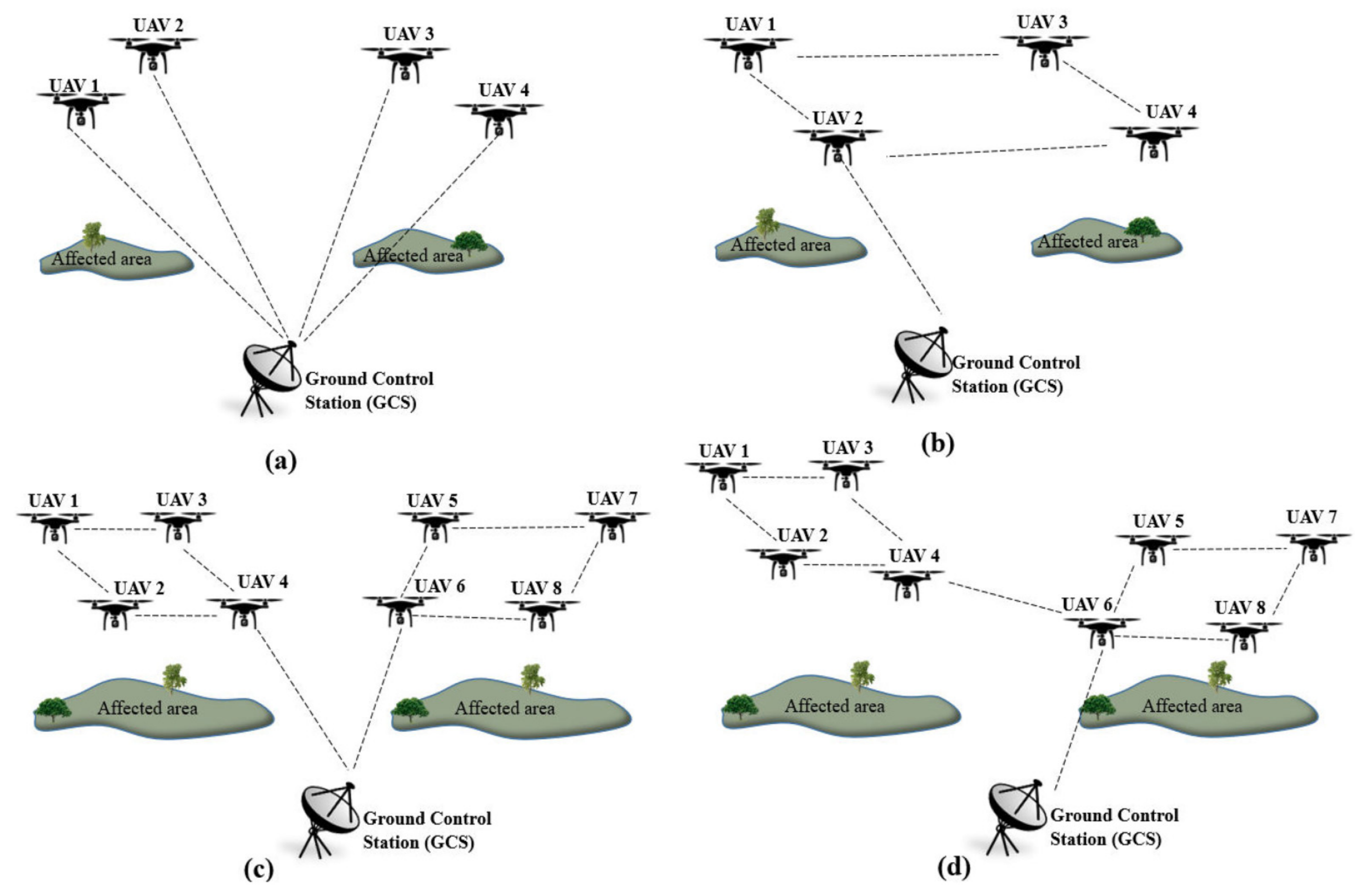
The topology of a network can have a significant impact on its performance, efficiency, scalability, and reliability (Bekmezci et al. 2013). There are various types of network topologies related to single UAV and multi-UAV systems that well suit various applications, each with its own advantages and drawbacks.

#### 2.1.1. Single UAV systems

Single UAV systems refer to the deployment and operation of UAVs as independent entities, distinct from collaborative or multi-UAV systems. It is important to note that while the system is not limited to a single UAV node, there could be multiple UAV nodes working concurrently to deliver services. In this configuration, each UAV operates as an individual unit under the direct control of a ground station (GCS), as denoted in Fig. 3*a*. The range of flight for each UAV depends upon the communication range of the GCS, which serves as a central command hub for vehicle navigation and operation. This individualized approach allows for precise control and management of each UAV, making it particularly suitable for tasks where autonomy and simplicity take precedence over collaborative efforts.

From the perspective of a disaster recovery network, single UAV systems play a role in tracking victims and vehicle movements. However, a notable challenge remains in the limited capability of a single UAV node to execute tasks effectively. Some researchers are addressing this concern by optimizing sensor functionality, hardware, and software to enhance the capabilities of single-UAV nodes. A single UAV system proves advantageous in observing multiple objects, facilitating rapid object localization (Bekmezci et al. 2013). Furthermore, it aids in investigating the precise extent of an operational area that has been disrupted post-disaster. Tasks such as navigation, monitoring, and control can be efficiently performed using a single UAV system, eliminating the need for additional resources to accomplish these tasks.

**Fig. 3.** UAV communication architectures: (*a*) single UAV system, (*b*) multi-UAV ad hoc network, (*c*) multi-group ad hoc network, and (*d*) multi-layer ad hoc network.




Nasr et al. (2019) suggested using UAVs for wireless communication in areas without terrestrial infrastructure, with a focus on public safety, especially for rescuing shipwrecked individuals. Drones detect and locate victims through emergency signals from safety jackets, employing Received Signal Strength Indicator (RSSI) measurements for localization. The mobility of UAVs is utilized to create virtual anchors, enhancing victim localization. The proposed method involves launching UAVs from a naval base to patrol the disaster area and scanning for emergency signals from safety jackets equipped with transmitters. A strategy to track ground-moving targets in complex indoor and outdoor environments with UAVs based on computer vision is presented in Chen et al. (2017). An embedded camera is provided on the UAV platform to provide a real-time video stream to the onboard computer, where the target recognition and tracking algorithms are implemented. A probabilistic estimate for the monitored area by a single UAV tracking multiple objects is calculated in Albert and Imsland (2017). A constant velocity model is considered to establish a performance bound for position estimate errors, determining the period of visit when monitoring multiple objects. Li et al. (2016) introduced a fast target localization method for a single UAV, addressing issues such as accuracy, real-time requirements, and cost constraints in existing methods. The proposed approach involves multi-point observation of the target along an expected trajectory, generating multiple rays intersecting with a horizontal plane to form a specific region. The steepest descent method with the Armijo searching algorithm is used to estimate the target height, with the criterion of minimizing the area. The method does not require prior target height information, making it versatile across different conditions.

### 2.1.2. Multi-UAV systems

During disasters, the limitations of single UAV systems become apparent. The challenges of maintaining consistent communication links with the ground station can arise due to the dynamic and unpredictable nature of disaster environments. Additionally, scalability poses a significant concern, as a single UAV may be insufficient to cover large and complex disaster areas effectively. To address these challenges, researchers have turned to the concept of multi-UAV systems (Micheletto et al. 2018). A comprehensive review of various applications involving multiple UAV systems that have been developed in recent years is presented in Skorobogatov et al. (2020). In a multi-UAV architecture, UAVs operate collaboratively, forming a network where they can communicate and coordinate with the other members of the network. This shift from a centralized approach to a distributed and interconnected network allows UAVs to share information, make collective decisions, and adapt their strategies based on real-time data. The advantage of multi-UAV systems lies in their ability to enhance redundancy, reliability, and scalability during disaster response efforts (Micheletto et al. 2018). By distributing tasks among multiple UAVs, the system becomes more resilient to individual failures and disruptions. Furthermore, the coordination and communication capabilities among peer UAVs within the network empower these vehicles to make informed decisions collectively. This collaborative decision-making process enhances situational awareness, enabling a more efficient and adaptive response to the dynamic conditions prevalent in disaster-stricken regions.

In the context of multi-UAV systems, various network topologies are considered to facilitate communication and coordination among the UAVs, as shown in Figs. 3*b*, 3*c*, and 3*d*. Three prominent topologies that are often explored in the literature are multi-star, mesh, and hierarchical mesh (Esrafilian et al. 2020). In a multi-star architecture, each UAV forms a local star connection, and one node from each star extends its connection to the ground station. This architecture has extended scalability when compared to single UAV systems; however, scalability is limited by the number of connections that the ground station can handle. If any of these central nodes fail, it can disrupt the communication and coordination within that particular group of UAVs. With multiple star connections, the communication overhead also increases, as each UAV needs to maintain connections not only with its local central node but also with the ground station. This architecture is not generally preferred in disaster missions as the fixed structure of star connections may limit the flexibility to adapt to changing mission requirements or dynamic environmental conditions.

In a mesh topology, every node is interconnected, allowing information to hop through intermediate nodes to reach its destination. The self-forming and self-healing nature of this network allows for the automatic establishment of connections between neighbouring UAVs, contributing to a system that is both scalable and capable of reconfiguring itself as UAVs enter or leave the network. In Portmann and Pirzada (2011), the applicability of wireless mesh network (WMN) is assessed in the realms of public safety, disaster recovery, and crisis management communication. The analysis aims to determine the extent to which WMN technology aligns with the unique communication needs in scenarios related to public safety, disaster recovery, and crisis management. Dey and Ray (2017) built an ad hoc mesh network of UAVs tailored for disaster management and remote sensing applications. The network established connections among multiple UAVs, enhancing the coverage of the observable area. The approach is based on process patterns, which define context-dependent behaviours of UAVs in various situations. Ganesh et al. (2021) introduced the ubiquity network (UbiQNet) architecture, which leverages drones to establish a mesh network for communication during emergency situations. It was primarily aimed at allowing victims to relay their situation and location to responders efficiently.

The mesh topology can be broadly classified as hierarchical and clustered (Ueyama et al. 2014). Hierarchical mesh networks organize UAVs in a layered structure, facilitating efficient communication and coordination. The network is divided into tiers, each with specific functionalities. The higher tiers typically consist of UAVs with advanced computational capabilities, acting as coordinators and relaying information to the lower tiers. This hierarchical arrangement enhances scalability and adaptability in dynamic environments. At the top tier, command-and-control UAVs oversee the entire network, managing task distribution and communication protocols. Intermediate tiers may include relay UAVs responsible for data transmission and coordination within their respective clusters. The lower tiers consist of task-specific UAVs, ensuring a distributed approach to mission execution. The study presented by Celtek et al. (2019) introduced a solution to the limited communication range in drone applications by proposing a hierarchical tree topology-based wireless drone network. The network comprises three main components: control center, master drone, and slave drones. The tree model emphasizes the effectiveness of a well-organized drone swarm in completing applications in a shorter timeframe. A similar approach is addressed in Chen et al. (2021) on the formation control problem in fixed-wing UAV swarms through the establishment of a group-based hierarchical architecture. The UAVs are organized into non-overlapping groups, each with a selected group leader. The group leaders coordinate path coverage to manage the mission process among different groups, while followers track their direct leaders for inner-group coordination.

Clustered mesh networks organize UAVs into tightly knit groups or clusters, promoting collaboration within each cluster and efficient inter-cluster communication (Uddin et al. 2018). Each cluster operates semi-autonomously, with a designated cluster head coordinating the activity. This approach minimizes the need for direct communication between all UAVs, reducing complexity and resource consumption. Within a cluster, UAVs can share information rapidly, facilitating real-time decision-making. The cluster head manages intra-cluster communication, ensuring that tasks are distributed effectively among its members. Inter-cluster communication is achieved through designated gateway UAVs that relay information between clusters, optimizing the use of available bandwidth.

Clustered mesh networks are well-suited for applications requiring localized coordination, such as search and rescue missions or monitoring specific geographic areas. They offer a balance between decentralized decision-making within clusters and coordinated efforts across the entire network. A fully autonomous and adaptive disaster recovery network based on a traditional cell network structure is presented in Bupe et al. (2015) with 7-cell clusters arranged hexagonally, utilizing MAVLink for communication. The algorithm establishes a hierarchical structure by designating higher-ranked UAVs as super nodes, and centrally managing UAV cells. Zobel et al. (2019) introduced strategies to enhance the efficiency of inter-cluster flights for data ferry UAVs, seamlessly integrating various optimization functions to accommodate scenarios with multiple objectives. A comprehensive framework for leveraging mini-UAVs in disaster monitoring, emphasizing the benefits of a distributed network structure, is

**Table 2.** A brief analysis of the literature on UAV deployment.

| Reference | Description |
|---|---|
| Zhao et al. (2018) | Presented two UAV deployment algorithms: a centralized one for known ground user positions and a distributed motion control algorithm for on-demand coverage without global information |
| Zhang and Duan (2017) | Developed an optimal deployment algorithm for emergency UAV deployment, minimizing delay in covering a target area by dispatching diverse UAVs from a central location |
| Malandrino et al. (2019) | Investigated using UAVs for wireless coverage in emergencies, and solved an optimization problem to maximize user throughput and ensure fairness across disaster-affected areas |
| Busnel et al. (2019) | Proposed a distribution algorithm for autonomous target discovery and self-organization of UAVs, ensuring connectivity within a multi-hop aerial wireless network |
| Wang et al. (2019) | Developed an adaptive UAV scheme using the majority rule for sector selection without real-time user tracking. Optimizes UAV displacement to enhance throughput and transmission probability, accounting for user density |
| Panda et al. (2019) | Aimed to create and deploy a cost-effective, user-friendly emergency communication network, supporting on-site surveillance to ensure robustness, with connection management |
| Hydher et al. (2020) | Investigated optimal placement of UAVs as aerial base stations for enhanced network connectivity, spectral efficiency, and maximum quality of service (QoS) requirements |
| Jin et al. (2020) | Examined emergency response needs and utilized regional disaster susceptibility, traffic inconvenience, and terrain complexity for recommendations on UAV and payload deployment in different regions |
| Masroor et al. (2021) | Addressed UAV deployment for disaster management in wireless networks, optimizing UAV placement for minimum distance, cost, and quantity through an integer linear optimization problem (ILP) |
| Lin et al. (2022) | Proposed an adaptive UAV deployment scheme aiming to optimize the deployment location of UAVs for enhanced coverage of ground nodes while minimizing energy consumption |

presented in Joshi et al. (2020). The architecture facilitates exploration of large and disjoint terrains through the formation of multiple clusters. To ensure isolation between clusters and optimize network energy, UAVs employ adaptive power communication techniques (Ramesh 2014).

## 2.2. Deployment

While UAVs offer various benefits in emergency scenarios, the challenging task of deploying them effectively for optimal coverage remains a significant issue. Al-Hourani et al. (2014) introduced an analytical approach for optimizing the UAV altitude, aiming to maximize radio coverage for ground nodes (GNs). Building upon this, Mozaffari et al. (2016) proposed an efficient deployment strategy utilizing circle packing theory to ascertain the optimal UAV locations based on the number of UAVs. Delving into the coverage problem, Alzenad et al. (2017) broke down UAV deployment into horizontal and vertical dimensions. The horizontal deployment was modelled as the smallest enclosing circle problem and a circle placement problem. In Dong et al. (2018), a thorough examination of UAV communication characteristics and collaborative coverage led to the derivation of an optimal deployment density function to achieve maximum coverage of GNs. The approach predominantly relied on average path loss for UAV location determination, aiming for maximum wireless coverage range or node count. In Zhao et al. (2018), a centralized deployment algorithm and a distributed motion control algorithm for node coverage are presented. Lyu et al. (2017) introduced a novel placement algorithm, deploying the mobile base station of the UAV in a spiral manner until all GNs were covered. However, these methods either used probability functions or neglected communication conditions in deployment.

Liu et al. (2020) utilized deep reinforcement learning (RL) for UAV deployment, emphasizing long-term communication coverage. Nevertheless, this approach assumed a fixed UAV altitude and communication range, overlooking the impact of obstacles in actual communication scenarios. Existing work often generates line of sight (LoS) and non-line of sight between UAVs and GNs randomly based on probability functions, neglecting real-world scenarios where specific information about the entire area, such as GN distribution and building characteristics, is not directly accessible to the UAV. In Lin et al. (2022), the objectives and constraints are redefined to consider real-world complexities. The approach optimized information collection for energy-efficient communication at GNs by determining ideal UAV hovering locations. To conserve energy given the limited computing power, the strategy minimizes broadcasts to the GNs. The UAVs are guided to optimal positions through an adaptive deployment scheme, considering environmental factors. Metaheuristic-based multi-objective optimization algorithms like MOPSO, NSGA-II, SPEA2, and PESA-II are employed in Gupta and Varma (2021) to find optimal UAV placements, balancing conflicting network objectives such as target coverage, Quality of Service, and energy consumption in the post-disaster scenario. Hydher et al. (2020) introduced a simplified approach for optimizing UAV positions and assigning user equipment (UE) in an aerial base station (ABS) network with the objective of maximizing total spectral efficiency while ensuring minimal quality of service (QoS). Table 2 lists all the recent studies on UAV deployment.

## 2.3. Mobility model

The performance of protocols in ad hoc networks is significantly influenced by node mobility (Bekmezci et al. 2013). The node movements are depicted using mobility models, which can closely reflect real-life scenarios in the designated context. Analysis of mobility models for UAV networks in disaster scenarios can be approached by considering two subclasses: those based on UAV mobility and those based on survivor mobility.

### 2.3.1. Mobility model based on UAV mobility

While various mobility models, such as the random mobility model, random waypoint (RWP) model, random walk model, and random direction model, have been proposed for mobile ad hoc networks (MANETs), their suitability for aerial networks is limited for several reasons (Bani and Alhuda 2016). In the case of the random mobility models, the distribution and movement patterns of nodes throughout the entire simulation area do not correspond to the characteristics of aerial networks. This discrepancy is particularly evident in scenarios involving aerial networks deployed for disaster response, where the unique dynamics and spatial constraints of such situations are not accurately captured by these conventional models. Therefore, alternative mobility models tailored to the specific challenges of aerial networks in disaster scenarios are required.

A semi-random circular movement (SRCM) model was designed in Wang et al. (2010) for UAVs to gather information while hovering at specific locations. The model is formulated for curved movement scenarios, with preliminary results demonstrating uniform node distributions and robust performance. The pheromone repel model (Kuiper and Nadjm-Tehrani 2006), derived from the three-way random mobility model (Xie et al. 2018), guides UAV movements based on a fixed turn radius and a probability distribution influenced by a map of recently visited positions. This model provides good coverage, but has connectivity issues (Kuiper and Nadjm-Tehrani 2006). Sanchez-Garcia et al. (2016) introduced a self-deployment algorithm for aerial ad hoc networks in disaster scenarios, utilizing the Jaccard dissimilarity metric to guide UAV movements. The mobility model aimed to establish a flexible communication infrastructure for disaster victims. Though the above models proved effective in certain aspects, they had certain flaws as they were available in two dimensions. In response to this, a 3D extension of the SRCM mobility model, termed 3DSRCM, is introduced in Mi and Dai (2021). The model incorporates a novel pheromone track selection mechanism to enhance scanning coverage and employs an orbit switch method for smoother trajectory transitions. Additional features include a track lock mechanism and highly uniform randomness to prevent potential UAV collisions. A novel distributed mobility model for autonomous UAV fleets engaged in area exploration missions is presented in Messous et al. (2016). Unlike existing models, it uniquely integrates the remaining energy level as a decision criterion alongside area coverage and network connectivity, contributing to efficient energy management and mission success based on neighbour-informed movements. Azmi et al. (2021) explored existing research on UAV mobility models, network technologies, and performance, with the primary goal of identifying the most effective mobility model for search and rescue missions.

### 2.3.2. Mobility model based on survivor/rescuer mobility

Many existing mobility models, such as the random mobility model, RWP model, random walk model, and random direction model, exhibit unrealistic patterns in the context of disaster operations (Sahingoz 2014). In SAR scenarios, rescue teams do not move randomly; their movements are influenced by obstacles like walls, debris, trees, and various other environmental factors. So, the existing mobility models based on randomness do not hold good. In Aschenbruck et al. (2007), a disaster area (DA) mobility model for disaster scenarios is discussed, which divides simulation areas into sub-regions (e.g., incident site, hospital zone) with manual node assignments. Despite efforts to mimic real scenarios, the model relies on the RWP mobility model for rescue agent movement, especially in the disaster site sub-area. Pomportes et al. (2011) proposed a composite mobility (CoM) model for disasters, combining RPGM and Levy-walk models for group mobility, with obstacle avoidance based on a geographic map and the Dijkstra algorithm. However, the CoM model relies on an accurate map and may pose challenges in disaster scenarios with modified or non-existent infrastructures (Conceição and Curado 2013). A human behaviour for disaster areas (HBDA) mobility model is discussed in Conceição and Curado (2013), designed to emulate realistic node movements in search operations for evaluating mobile wireless network performance in disaster scenarios. The HBDA prioritizes area coverage and minimizes search time, utilizing a force vector system to balance proximity and distance to neighbour nodes. A three-dimensional mobility model designed for dynamic, uncertain environments is discussed in Wang et al. (2018*b*) to enhance emergency rescue missions by addressing challenges posed by dynamic, distributed, dense, and irregular obstacles in rescue areas. Mahiddin et al. (2021) present a review of existing mobility models for studying rescue entity movements in disaster scenarios. The primary goal of this work is to identify an ideal mobility model that realistically captures the movements of rescue entities in disaster scenarios.

## 2.4. Network requirements

### 2.4.1. Rapid response

In disaster recovery networks, the foremost requirement is a rapid response. The ability to swiftly deploy and establish communication channels while considering the mobility of nodes is critical during emergencies. A quick response ensures that timely and efficient coordination among emergency responders can take place, minimizing the impact of the disaster and potentially saving lives.

### 2.4.2. Network lifetime

In the aftermath of a disaster, when conventional communication infrastructures may be compromised, the disaster recovery network becomes a lifeline for emergency response operations. During the rescue mission, the network's ability to deliver uninterrupted services is critical for coordinating efforts, disseminating information, and ensuring effective communication among response teams. Beyond the completion of the rescue mission, the network remains instrumental in supporting ongoing recovery operations, providing a vital communication backbone until the restoration of regular infrastructure.

### 2.4.3. Interoperability

Interoperability among UAVs is a crucial aspect in disaster recovery and emergency response operations. It refers to the ability of different UAVs, often from diverse manufacturers or models, to communicate, collaborate, and share information seamlessly. In disaster scenarios, various UAVs may be deployed for tasks such as aerial reconnaissance, surveillance, or search and rescue. Ensuring interoperability among UAVs is essential for effective coordination and resource optimization. It allows different UAVs to share real-time data, coordinate their movements, and collectively contribute to a comprehensive understanding of the disaster area.

### 2.4.4. Network coverage

When a disaster occurs, the communication infrastructure may be partitioned into a number of disjoint areas. In this case, a disaster recovery system should be such that it can be quickly used to interconnect the different regions of disaster. If no part of the pre-existing infrastructure is available after the disaster, then it should be possible to deploy a solution that can cover the disaster area with one network or a cluster of networks that can be interconnected to permit communication across the affected area.

### 2.4.5. Support for heterogeneous traffic types

The ability of the ad hoc network to support voice, data, and video applications is a major concern. Some proposed solutions are voice-only solutions, while others are data and/or video-only solutions. A desirable feature of the disaster-resilient ad hoc network is its ability to support different traffic types.

### 2.4.6. Network capacity

Consider a situation where some or all the victims in a disaster area have devices with which they can communicate with the outside world, but the infrastructure is damaged by the disaster. The ad hoc network must have sufficient capacity to handle the sessions generated by both the victims and the disaster relief crew members. Thus, the multi-UAV network solution should have the capacity to support this traffic scenario.

### 2.4.7. Ease of use and equipment cost

In the context of disaster recovery networks, two critical factors are ease of use and equipment cost. User-friendly features contribute to the ease of use, enabling response teams to quickly and effectively establish communication infrastructure. Affordable network equipment allows for scalability and broader accessibility, ensuring that even organizations with limited budgets can deploy effective communication systems during crises. Balancing cost-effectiveness with performance is essential to making disaster recovery networks accessible, sustainable, and impactful in their support for emergency response efforts.

### 2.4.8. Outdoor and indoor scenarios

A disaster-resilient network necessitates the capability to operate seamlessly in both indoor and outdoor environments. Disasters can strike in various settings, ranging from urban areas and buildings to remote outdoor locations. The adaptability of the network to function effectively in indoor spaces, such as shelters, facilities, or structures, is essential for maintaining communication during evacuations or within emergency response centres. Simultaneously, the ability to operate in outdoor environments is critical for addressing disasters that occur in open spaces or areas with limited infrastructure. Outdoor functionality is particularly crucial for search and rescue missions, surveillance, and the coordination of response efforts in the affected regions.

### 2.4.9. High precision for localization and search operation

Effective subject or survivor localization enhances the overall efficiency of response teams by enabling them to navigate complex and dynamic disaster environments. It allows for targeted and expedited deployment of resources to specific locations, minimizing response time and increasing the likelihood of successful outcomes.

### 2.4.10. Scalability

In disaster missions, scenarios may arise where the network experiences fluctuations in the number of UAVs, either with the addition of more UAVs to the network or the departure of UAVs from the network. These dynamic changes can be influenced by evolving mission requirements, the need for additional surveillance or rescue capabilities, or the completion of specific tasks by individual UAVs. Network adaptability is crucial to accommodate these variations, ensuring seamless integration and disengagement of UAVs without compromising overall communication and operational efficiency.

### 2.5. Critical insights and gaps in existing studies

In disaster scenarios, robust system architectures are essential for UAV networks to enable efficient coordination and rapid decision-making. Relevant UAV architectures to match the scale, type, and specific challenges of each disaster are crucial. Factors like flexibility, adaptability, robustness, and operation in resource-limited environments must be considered when designing UAV architectures for disaster response and monitoring. For localized incidents or smaller-scale disasters, simpler UAV architectures may suffice, with single UAV systems or small groups performing tasks such as damage assessment, search and rescue, or supply delivery to isolated areas. However, for widespread disasters covering large or multiple areas, more complex architectures are typically needed. Multi-UAV systems, swarm-based approaches, or networked UAV fleets operating in coordination with ground-based and satellite systems can be explored to provide comprehensive coverage and efficient aid delivery. Despite their theoretical efficiency, practical design challenges and environmental limitations require further investigation. A major challenge is the heterogeneity of UAVs, where theoretical analysis often assumes homogeneous sets of UAVs, but in practice, differences in batteries, payload capacity, and endurance impact architecture selection. While heterogeneous network studies are recently gaining attention, their practicality remains largely unexplored. Terrain also plays a crucial role in communication coverage, with obstacles such as mountains or buildings potentially blocking signals between ground bases and UAVs, particularly in urban areas. Node failures can disrupt network topology, necessitating topology updates when a UAV fails or is introduced. While UAV coordination enhances system reliability by accommodating topology updates, it also places additional workload on active UAVs due to missions previously assigned to failed agents. To maintain system efficiency without overloading network agents, controlled redundancy is crucial. Task offloading to peer UAVs or high-altitude platforms (HAPs) is considered for complex computations. In disjoint missions, clustering is considered beneficial, where one UAV acts as the cluster head and others as cluster members. However, all these mechanisms involve developing robust localization algorithms resilient to environmental uncertainties. Localization and mapping methods such as SLAM, GNSS, and computer vision face difficulties in disaster environments due to factors like debris, smoke, and low visibility. Challenges such as poor lighting and occlusions complicate feature extraction and localization accuracy (LA) in computer-vision methods. The effectiveness of these systems in disaster scenarios remains underexplored.

Another critical aspect of architectural design is resource allocation. While path planning and trajectory optimization have been extensively studied in the literature, research focusing on maximizing the utilization of available resources by deploying UAVs in optimal numbers is still limited. Additionally, efficient 3D placement of UAVs to ensure maximum coverage of the area and the victims is in its early stages of exploration. The altitude of the UAV operation also impacts the payload it can carry. Although heuristic-based optimizations assuming uniform user distribution have been discussed, an efficient deployment strategy tailored for disasters is lacking in the literature. Existing studies often treat UAVs as independent entities without considering backhaul connectivity. Moreover, they often assume fixed user locations, which is not the case in disasters, where rescue teams and victims may relocate to safer areas. Therefore, object detection and tracking have become vital. While various mobility models based on randomness have been explored, ground mobility during disasters cannot be approximated as random. Furthermore, existing deployment models overlook victims stuck inside buildings, necessitating the incorporation of non-line-of-sight communication paths into the optimization problem. A generalized mobility model adaptive to all types of disasters is lacking in current studies, necessitating further exploration. While the studies by Aschenbruck et al. (2007) and Pomportes et al. (2011) consider adaptive mobility schemes for rescue teams and users, there is a need to incorporate obstacle avoidance without relying on accurate maps, as such maps may not be available in disaster scenarios. Models based on human behaviour have also been explored, but predicting real-time human behaviour is not practically feasible as it depends on the type of disaster as well.

## 3. Communication aspects

In the aftermath of a disaster, establishing swift and reliable communication networks is paramount for effective coordination in relief efforts. UAVs play a crucial role by forming ad hoc networks through various wireless technologies.

### 3.1. Wireless technologies

While the literature explored multiple wireless links such as Bluetooth (Khan et al. 2019) and zigBee (Acosta-Coll et al. 2021) to provide resilience in wireless sensor networks, the choice narrows down to considerations of cost, communication range, compatibility, and regulatory compliance for a UAV network. Cellular communication solutions such as 2G, 3G, 4G, and others offer expanded coverage, yet their effectiveness hinges on the presence of base stations (BSs), making them unsuitable for emergency communication systems in scenarios lacking infrastructure (Avanzato and Beritelli 2019). Furthermore, they entail a substantial drain on device energy, contributing to escalated operational costs (Mekki et al. 2019). Technologies such as Wi-Fi and WiMAX stand out, with Wi-Fi (IEEE 802.11) gaining prominence due to its ubiquity, cost-effectiveness, and the widespread use of smartphones equipped with Wi-Fi capabilities among survivors. Although WiMAX is superior in coverage, its dependence on specific infrastructure and receiver requirements can limit its utility in the dynamic and often unpredictable context of disaster response. Harrington et al. (2020) outline the development of a multiple drone network within a Wi-Fi environment, highlighting the ability to coordinate and control the drones autonomously through the exchange of flight commands. However, latency in transmitting commands could potentially disrupt the coordination and synchronization of flight plans within a network of multiple drones. Hayat et al. (2015) investigated the application of IEEE 802.11n and

802.11ac standards in aerial WiFi networks. Indoor and outdoor performance tests, including multi-sender networks in infrastructure and ad hoc modes, are conducted to simulate real-world UAV scenarios. Though implementation in small UAVs showed promising data rates and throughput indoors, it faced challenges outdoors due to low signal strength, resulting in decreased throughput as the UAV moved away from the base station. For it to be considered for disaster applications, additional research is required to enhance reliability and throughput, particularly considering the high mobility of UAVs. Gu et al. (2015) focused on the integration of WiFi signals into airborne networks for the swift deployment of WiFi infrastructures, particularly in scenarios lacking existing communication infrastructure, such as disasters. A notable aspect of the study involves the utilization of directional antennae for long-range WiFi signal transmission, aiming to boost signal strength and minimize interference with other WiFi channels. The research conducted field tests to assess how distance impacts WiFi signal throughput, shedding light on the practical considerations of employing directional antennae in UAV-based communication systems.

Various research studies have explored the potential adoption of LoRa-based protocols, such as LoRaWAN, for UAV communications, showcasing diverse applications, implementations, and use cases with long-range capabilities. In Stellin et al. (2020), LoRaWAN is utilized where multiple UAVs function as aerial LoRaWAN gateways. This configuration provides network coverage for ground-based LoRaWAN end nodes, leveraging LoRaWAN solely for ground-to-UAV applications in emergency scenarios, while the primary network relies on Wi-Fi, assuming LOS links. A similar methodology is outlined in Sharma et al. (2018), where multiple UAVs collaborate to establish a sophisticated LoRaWAN-centric urban surveillance system, ensuring efficient and targeted network coverage. However, across these referenced works, LoRa-based communications predominantly serve ground-to-UAV interactions, connecting on-field nodes with the LoRaWAN network. This approach significantly extends network coverage for specific use cases in designated operational regions but is not suitable for critical missions in remote areas. Another approach to UAV-enabled flying LoRaWAN networking is detailed in Saraereh et al. (2020), with a specific focus on disaster management applications. This strategy combines flying LoRaWAN GWs with Wi-Fi communications from a UAV-to-ground access point (AP) and LoRaWAN end nodes. The objective is to accompany emergency operators, collecting data and positions. Even in this context, LoRa-based communications play a vital role in gathering data from ground-end nodes, ensuring a reliable network for emergency applications while tracking the movement of ground devices. An alternative scenario involving UAV-to-ground LoRaWAN communications is outlined in Rahmadhani et al. (2018). The authors detailed the utilization of LoRaWAN for communication between flying UAVs and the existing LoRaWAN ground network. This application focuses on transmitting crucial telemetry data, including GNSS coordinates (latitude, longitude, and altitude), drone speed, and heading direction. However, the work has not explored the use of LoRa for communication among multiple flying UAVs. This oversight limits the potential use cases and effective operational ranges of the system, particularly in scenarios where distant UAVs could utilize nearby flying UAVs as relays to broadcast their telemetry data to the LoRaWAN ground network. Utilizing IEEE 802.11s-based mesh networking within UAV swarms, as proposed in Morgenthaler et al. (2012), offers direct visibility between nodes, particularly at high altitudes, enabling Wi-Fi signals to propagate freely without physical obstacles. However, elevated flight altitudes mitigate interference from urban Wi-Fi networks, potentially expanding operational ranges.

To harness the advantages of communication protocols and mitigate their respective limitations for the implementation of UAV swarms, a mesh strategy is proposed in Davoli et al. (2021). This involves integrating LoRa- and IEEE 802.11s-based communication patterns through opportunistic switching, handling, and management mechanisms. This approach aims to address various use cases involving UAV swarms while striking a balance between operational range and available bandwidth. By combining different wireless communication networks—utilizing a LoRa-based layer for long-distance and payload-constrained communications, and an IEEE 802.11s-based layer for mid-range and unconstrained payload applications—a coexistence framework is established. Operating on separate layers, a smart switching mechanism is essential for selecting the most appropriate network based on real-time considerations such as task requirements and network quality conditions. This proposed switching mechanism is designed to optimize performance in diverse application scenarios by considering the capabilities and constraints of each available communication protocol in terms of operational range and admitted payload.

## 3.2. Communication link design

Unmanned aerial systems employ two distinct wireless communication links (Li et al. 2020). The first is the air-to-ground (A2G) and ground-to-air (G2A) link, establishing connectivity between the UAV and a GN. The second is the air-to-air (A2A) link, facilitating communication between multiple UAVs engaged in collaborative flight tasks. Design considerations for both links involve tailored specifications to accommodate particular communication scenarios, incorporating factors such as communication connectivity, flight trajectories, and the probability of successful completion of flight tasks.

A mobility-aware multi-UAV placement strategy for establishing a disaster-resilient communication network is discussed in Peer et al. (2020). The strategy formulates an optimization problem aiming to maximize the coverage of ground users by UAVs while adhering to the constraint of UAV flight time. Notably, the study focuses on emergency first responders as the ground users, modelling their mobility within the disaster-affected region. The connectivity restoration strategy outlined in Kurt et al. (2021) involves moving specific nodes based on a connected dominating set heuristic, designed to optimize connectivity in dynamic and challenging environments. The strategy focused on maintaining a core for the wireless ad hoc network, ensuring that every node remains reachable to every other node. By identifying and moving specific nodes strategically, the approach aims to minimize movement while maximizing the restoration of connectivity, a critical factor in disaster response where time and resources are often constrained. Li et al. (2020) proposed an optimized UAV-aided data collection design for emergency scenarios, prioritizing mission completion time. It strategically addresses trajectory, altitude, velocity, and data link optimization challenges with ground users, employing algorithms tailored to minimize mission time effectively. However, addressing the optimization problem involving continuous trajectory variables may present a challenge due to potential computational complexity and scalability issues. Moreover, discretizing the trajectory for optimization could potentially lead to errors and reliance on the number of discretized points, which may influence the overall quality of the solution. Do-Duy et al. (2021) addressed the joint optimization of real-time deployment and resource allocation for UAV-aided relay systems in emergency scenarios such as disaster relief. It introduced a rapid K-means-based user clustering model and optimal power and time allocation, utilizing UAVs as flying base stations for immediate network recovery and ongoing connectivity maintenance during and after disasters. The work has only analyzed a straightforward network configuration consisting of a source node and a single UAV-assisted relay node. This simplification limits the complexity of the network model in practical, harsh environments.

In contrast to the exploration of A2G/G2A links, studies focusing on A2A links concentrate on facilitating collaborative flight tasks involving multiple UAVs. Given that A2A can be modelled as line-of-sight propagation, its link quality is influenced by the mobility of multiple UAVs. Consequently, the research direction shifts from enhancing A2A link quality to coordinating the positions of multiple UAVs for collaboration. Due to the dynamic mobility of UAVs, these collaborative positions constantly change, necessitating the development of routing protocols, a specific aspect covered in Section 5.

## 3.3. Channel modelling

In UAV-to-ground communications, the wireless environment is marked by high mobility and LoS propagation conditions (Matolak and Sun 2015; Li et al. 2019). However, the assumption of LoS is often not met due to the presence of substantial obstacles (Khuwaja et al. 2018), leading to shadowing or large-scale fading. This phenomenon results in unpredictable variations in mean envelope levels. Another distinct aspect observed in mobile communication environments is double-scattering (DSc) propagation. This type of fading occurs when either the transmitter, the receiver, or significant scatterers in their vicinity are in motion (Salo et al. 2000; Andersen and Kovacs 2002). A new channel model that considers both mobility and shadowing effects is presented in Bithas et al. (2020). The study analyzed a UAV-based communication system operating in a shadowed DSc channel. The model is versatile, representing various fading/shadowing conditions through easily evaluated mathematical functions. Additionally, a low-complexity UAV selection policy is proposed, reducing signal processing complexity without significant performance degradation compared to alternative approaches.

Matolak and Fiebig (2019) offer an overview of the wireless channel for UAVs. A comparative analysis with various other channel types is conducted, and existing measurements and models are examined. Cui et al. (2020) conducted A2G channel measurements at various frequencies (1, 4, 12, and 24 GHz) for UAV-based wireless communications. Utilizing the 3rd Generation Partnership Project channel model, it extracted crucial path loss coefficients and introduced a novel autocorrelation model for shadow fading. Statistical analysis reveals the log-logistic distribution as the best fit for small-scale fading. Second-order statistical characteristics, such as level crossing rate (LCR) and average fade duration (AFD), are employed for a comprehensive understanding of the fading behaviour. A detailed survey on UAV communication channel modelling is presented in Yan et al. (2019). The paper addressed the research gaps by conducting a comprehensive analysis of A2G, and A2A channel measurements and modelling in the context of UAV and aeronautical communications across diverse scenarios. It offers design guidelines for UAV communication link budget management, considering link losses and channel fading effects. Additionally, the work analyzed the benefits of receive/transmit diversity gain and spatial multiplexing gain achieved through multiple-antenna-assisted UAV communications. Jiang et al. (2020) proposed a 3D MIMO channel model for A2G communications in UAV environments, considering the dynamic motion of both the UAV transmitter and ground receiver. They introduced an angular estimation algorithm for real-time departure and arrival angles and also explored time-varying spatial cross-correlation functions and temporal auto-correlation functions based on different moving directions and velocities. The effect of Doppler power spectral densities and power delay profiles on the channel model is also studied.

## 3.4. Trajectory planning and localization

In a disaster scenario where time is of the essence, efficient trajectory planning and localization can provide real-time mapping of the disaster area, thereby helping responders to act swiftly. By planning trajectories, responders can cover a larger area and increase the chances of locating survivors or assessing the extent of damage in a more organized manner. This information is vital for decision-making, allowing responders to adapt their strategies based on the current situation and ensuring a coordinated and effective disaster response.

An intriguing facet of employing UAVs as network infrastructure involves crafting optimal trajectories, considering factors such as collision avoidance, meeting terrestrial user demand, addressing energy constraints, and managing flight duration. This has spurred researchers to explore optimal path planning within UAV-assisted wireless networks (Jiang and Swindlehurst 2012; Di Franco and Buttazzo 2015; Fadlullah et al. 2016; Wang et al. 2018*a*). In Wang et al. (2018*a*), the authors delved into the joint optimization of a UAV path and transmit power, aiming to maximize the least average throughput within a specified time frame. They proposed a suboptimal algorithm for the associated non-convex optimization, incorporating trajectory and power budget constraints. Meanwhile, Jiang and Swindlehurst (2012) focused on a multi-antenna UAV base station, examining optimal trajectories to maximize the sum rate of uplink communications. Di Franco and Buttazzo (2015) introduced an energy-aware UAV trajectory planning strategy for photogrammetric sensing of a designated area.

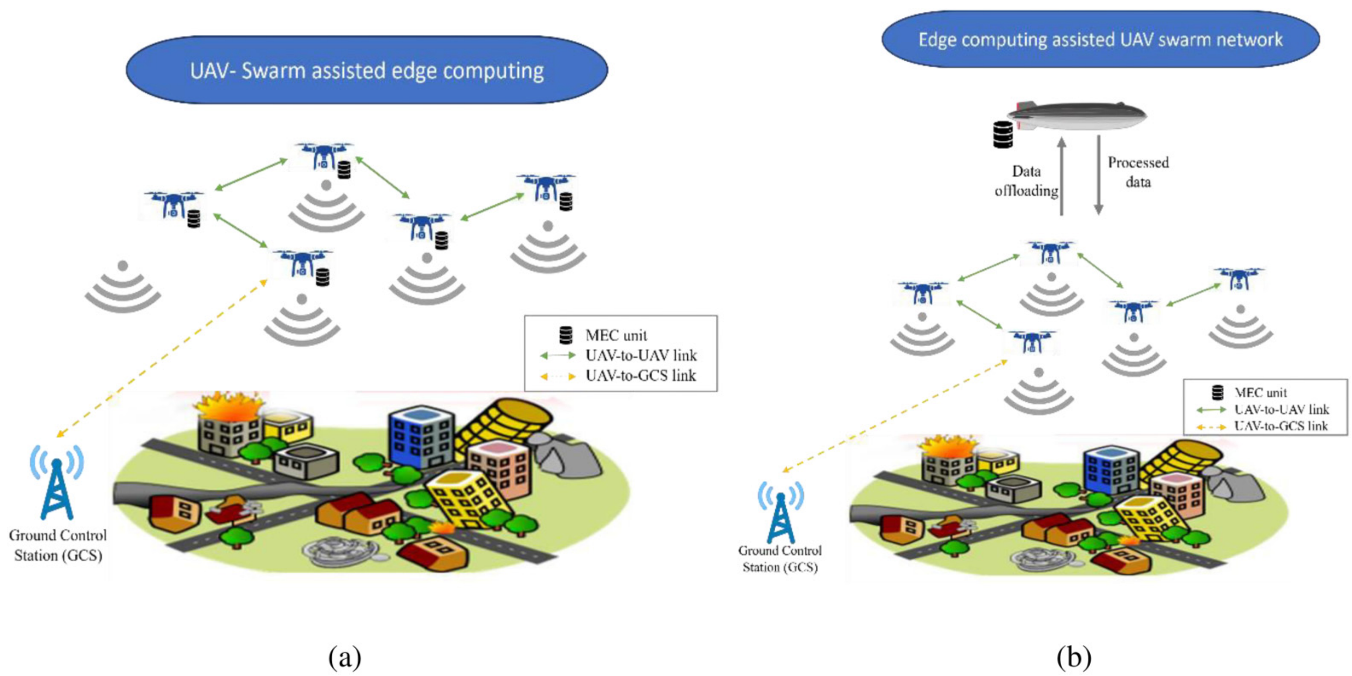
While Jiang and Swindlehurst (2012), Di Franco and Buttazzo (2015), and Wang et al. (2018*a*) concentrated on a solitary UAV, Fadlullah et al. (2016) considered a swarm of UAVs to ensure maximum network coverage and connect disconnected terrestrial heterogeneous networks. In response, researchers introduced a centralized dynamic path planning algorithm deployed at the control station, aimed at improving network latency and throughput. Wu et al. (2018) delved into the joint optimization of UAV trajectory, user scheduling, and association to maximize the minimum downlink throughput for terrestrial users. A survey on 3D UAV placement and trajectory optimization is presented in Lakew et al. (2020), also exploring the existing challenges and research issues. Demiane et al. (2020) focused on using UAVs in disaster scenarios with compromised communication infrastructure to accurately locate potential survivors. The approach involves collecting RSSI data from mobile devices in different cells of varying importance. The study formulates and solves two subproblems: identifying strategic waypoints for UAV positioning and constructing an optimal UAV trajectory. However, challenges surrounding the reliability of wireless signals in disaster zones, ensuring robust communication between the UAV and the server, and accurately locating victims in rapidly changing and unpredictable conditions pose significant hurdles. Numerous techniques have been suggested for solving the localization problem in UAV networks, with the majority relying on distance measurement methods such as trilateration and bilateration (Lee and Scholtz 2002; Gezici et al. 2005). However, these methods often face challenges like flip ambiguity, introducing substantial measurement errors due to environmental noise affecting the accuracy of distance measurements between nodes (Zhang et al. 2012). The high mobility of UAVs in network routing protocols necessitates enhanced location accuracy at frequent intervals. UAV nodes, characterized by limited transmission range, dynamic links, and constrained battery power, require special consideration for developing energy-efficient routing protocols. The localization method in the routing protocol serves the purpose of swiftly determining the precise location of any node. Existing localization methods vary in terms of LA, computation cost, and error rate, with categorizations based on characteristics like static versus mobile nodes, anchor-based versus anchor-free, sparse versus dense network, indoor versus outdoor, and range-based versus range-free (Guo et al. 2019). Range-based localization methods, known for higher location accuracy and lower error rates, are preferred in a broader range of applications compared to range-free localization methods. A swarm intelligence-based localization (SIL) and clustering (SIC) scheme for emergency communications in UAV networks is presented in Arafat and Moh (2019*a*). The 3D SIL algorithm, using particle swarm optimization (PSO), improves convergence time and LA with lower computational costs. It also outperforms typical routing protocols in packet delivery, delay, and overhead, while consuming less energy and prolonging network lifetime.

## 3.5. Critical insights and gaps in existing studies

A robust channel model is essential for effective link design and evaluation in multi-UAV networks, especially in disaster scenarios where reliable communication is vital. While UAV-to-ground links share similarities with satellite-to-ground communications, they also possess unique aspects specific to UAV operations that must be carefully considered. Factors such as obstacles, ground station height, and UAV altitude significantly influence line-of-sight probability and signal propagation, thus impacting path loss and fading characteristics. Multipath components, which vary with UAV altitude, contribute to the severity of fading and delay distortion. Additionally, the relative difference in velocities between communicating entities can induce a Doppler shift, which varies based on UAV speed and altitude. Antenna patterns, influenced by UAV material and structure, play a critical role in signal reception and transmission. Thus, channel modelling must encompass diverse environmental conditions, including terrain, obstacles, and reflective surfaces, to accurately represent real-world scenarios. Future studies should explore a wide range of UAV-to-ground communication scenarios, considering various velocities, antenna configurations, and time-varying or time-invariant channel characteristics. Hybrid deterministic/stochastic models may provide more accurate representations of UAV-to-ground channels, incorporating multipath clustering and spatial consistency tracking.

The type of traffic flow within a network, whether real-time, periodic, or delay-tolerant, significantly influences network design. For missions like search and rescue, coordination and data sharing are crucial. Centralized decision-making includes the exchange of location and heading direction, while online decisions require bidirectional communication. Decentralized missions require the exchange of timestamps and maps. Distance between units is another important factor affecting communication links. Cellular technologies such as LTE, WiMAX, and UMTS are suitable for longer distances, but they rely on fixed infrastructure, which in disasters may not be available. Shorter distances often rely on ZigBee and WiFi due to their suitability and availability. Existing research underscores the superiority of 802.11 mesh networking over cellular for small networks. However, as networks grow, WiFi emerges as a viable option due to its scalability. Yet, for very large networks, WiFi alone may not suffice, prompting exploration of alternative technologies. In critical scenarios like disaster missions, where real-time data transmission is vital, the feasibility of using WiFi for large-scale aerial coordination within the latency bounds needs to be examined. Additionally, longer distances impact UAV energy consumption, prompting consideration of cellular handover-like schemes. Studies across IEEE 802.11 standards consistently demonstrate WiFi's ability to support various

**Fig. 4.** (*a*) UAV-swarm assisted edge computing. (*b*) Edge computing-assisted UAV swarm.






applications with fewer multi-hops. Nonetheless, unresolved issues persist for modern UAV applications relying on WiFi. Emerging alternatives enable unidirectional communication, but bidirectional support for diverse data types remains limited. LoRaWANs, with their standalone and hybrid schemes, are being debated regarding their suitability for UAV communication.

## 4. Data processing and decision-making

Effective decision-making is critical in all stages of disaster management, influencing the success of rescue missions and related events (Alsamhi et al. 2022). Handling the complexity of big data analysis during disasters calls for computational intelligence and real-time algorithms. These technologies enable swift decision-making, analyze diverse data structures, extract relevant information, and present insights through various strategies (Donratanapat et al. 2020). As UAVs are often limited in size and payload capacity, on-board data processing must strike a balance between processing capabilities and energy efficiency to ensure optimal flight endurance and mission success. With the rise of multi-UAV swarm systems, data processing takes on a whole new level of complexity. In swarm-based architectures, UAVs collaborate and coordinate their actions to accomplish shared objectives. This requires seamless communication and distributed decision-making among the swarm members. Each UAV in the swarm may possess different data processing capabilities, necessitating intelligent task allocation and load balancing to optimize the overall performance of the swarm. During disaster situations, efficient data processing becomes vital to derive actionable insights from the collected data promptly. One approach to process data during disaster situations is by leveraging remote servers. These servers process the information, conduct complex analyses, and deliver valuable outputs back to the UAVs or disaster response teams. By offloading data processing tasks to remote servers, it reduces the computational burden on the UAVs themselves. As a result, UAVs can conserve onboard resources, such as processing power and battery life, which are critical for prolonged and efficient mission execution.

Among the recent UAV swarm-enabled edge computing applications, a prominent focus of research has been on utilizing UAV swarms as Mobile Edge Computing (MEC) servers (Zhang et al. 2020*a*; Abrar et al. 2021; Zhan et al. 2021). In this paradigm, specific UAVs within the swarm are equipped with computing capabilities, effectively acting as MEC servers. These UAVs can process data locally or offload computation to other UAVs within the swarm. This concept, referred to as UAV swarm-assisted edge computing, as shown in Fig. 4*a*, enables decentralized data processing, reducing reliance on distant central servers and minimizing communication delays. It is particularly advantageous for applications requiring real-time data analysis and decision-making. Another paradigm involves UAV swarms as users seek computing services from nearby servers due to their inherent limitations in size and computational capabilities (Zhou et al. 2020), as shown in Fig. 4*b*. In this scenario, UAVs constantly interact with edge computing resources, leveraging optimization methods to handle switch-overs. Swarm optimization is also resistant to noise and uncertainty in the optimization problem, making it appropriate for real-world applications in uncertain environments. Furthermore, because they are population-based methods, these algorithms can explore several solutions in parallel, providing a good balance between exploration and exploitation of the search space. This feature increases the likelihood of finding the global optimum rather than the local optimum, which is very useful when dealing with nonlinear and multi-modal situations. Some of the widely used optimization algorithms include PSO, ant colony optimization (ACO), bee colony optimization (BCO), firefly algorithm (FA), gray wolf optimization (GWO), and glow-worm swarm algorithm (GSO) (Vanitha and Padma 2014). A comparison of all the swarm optimization algorithms across various parameters like computational complexity, convergence speed, merits, and limitations is presented in Table 3.

Innovative approaches incorporating information technology, artificial intelligence, ICT tools, and ML are instrumental in enhancing all stages of disaster response (Chamola et al. 2021; Hernandez et al. 2022; McEnroe et al. 2022). The application of AI techniques in disaster management encompasses various ML and DL methods. ML methods, including SVM, NB, DT, RF, LR, and KNN, are employed. DL methods involve diverse artificial neural network architectures like convolutional neural networks (CNNs), MLP, recurrent neural networks (RNNs), LSTM, transformers, and GANs (Yu et al. 2018; Arinta and Andi 2019; Sun et al. 2020). ML and DL facilitate the utilization of extensive and intricate datasets to develop predictive systems and aid in disaster response and recovery. These techniques leverage the manipulation of diverse data types from multiple sources to identify patterns, offering valuable insights otherwise challenging to discern. Munawar et al. (2021) provide an overview of recent progress in flood management, particularly in the post-disaster phase, emphasizing developments in image processing, artificial intelligence (AI), and integrated approaches. The authors have also focused on reviewing the history of flood events and responses in Munawar et al. (2022), emphasizing the utilization of AI techniques for flood risk mitigation. It proposed an AI/ML-based early flood warning system for aged care facilities in the Hawkesbury-Nepean region, incorporating UAV and path planning for timely disaster response and evacuation. Linardos et al. (2022) aim to offer an overview of research studies conducted since 2017, focusing on the application of ML and deep learning (DL) methods in disaster management. Specific areas of interest include disaster and hazard prediction, risk and vulnerability assessment, disaster detection, early warning systems, disaster monitoring, damage assessment, post-disaster response, and relevant case studies. Additionally, the work analyzed recently developed ML and DL applications in the field of disaster management. A detailed survey of MI/AI schemes for disaster management is detailed in Sun et al. (2020), providing thorough insights about the role of these techniques at different phases of the disaster. The work has also identified potential challenges for these techniques to be explored by the research community.

### 4.1. Critical insights and gaps in existing studies

UAVs rely heavily on their computational capabilities for data processing and decision-making. However, not all proposed solutions are applicable in disaster scenarios due to their reliance on factors like network connectivity, bandwidth, and infrastructure. Implementing onboard image processing is a viable solution, particularly crucial in such scenarios, facilitating tasks like structural damage assessment and hazard identification. In large-scale disasters like floods or wildfires, remote sensing technologies enable UAVs to gather valuable data over vast areas, aiding in rapid damage assessments and response coordination. Techniques like data fusion and compression optimize data transmission, reducing latency. In smaller to medium-scale disasters, photogrammetry creates detailed 3D maps, offering insights into structural integrity and terrain changes. Furthermore, ML algorithms enhance real-time decision-making across all disaster scenarios, trained on extensive datasets for tasks like object detection and survivor identification. However, concerns arise regarding predictions beyond available data and the evolving nature of hazards, challenging the reliance on AI for resource deployment in disaster management. Despite these challenges, developing powerful and cost-effective AI-based tools remains an emerging area of research, aiming to improve analysis accuracy and speed.

In scenarios where UAVs face resource limitations, such as storage and processing power, data offloading to external systems becomes necessary to conserve onboard resources and extend mission duration. Various data offloading schemes, including transmission to cloud servers or ground stations, have been discussed in the literature. While this may introduce latency compared to onboard processing, it proves effective in disaster missions. However, for latency-critical missions like search and rescue, UAV-based edge computing techniques offer a more efficient solution. By integrating UAVs with high onboard processing capabilities, while lower end UAVs forward the data for analysis, bandwidth usage and latency are minimized, ensuring efficient data handling in congested or unreliable communication networks. Edge computing devices enable UAVs to leverage their onboard processing capabilities to solve complex data tasks without relying on external infrastructure, supporting response efforts in remote or inaccessible areas. Though HAPs are considered for data offloading, practical implementations are in their early stages. Challenges like intelligent HAP-UAV channel modelling and security need extensive research. Balancing energy efficiency and security, along with automatic switch-over schemes during node failures, is crucial for uninterrupted data flow in real-time missions. Integrating these advancements into the network infrastructure can significantly enhance disaster mitigation efforts.

## 5. Data routing schemes

When the distance between a UAV and a ground station surpasses the communication range, an alternative UAV can act as a relay to maintain connectivity between them. However, the challenges of an unstable wireless link, frequent topology changes, and the high mobility of UAVs make traditional MANET routing protocols impractical for UAV networks. Asadpour et al. (2014) observed the shortcomings in a majority of the MANET routing protocols, notably prolonged convergence time and high routing overhead, hindering their adaptability to the dynamic nature of aerial networks. Highlighting the specific characteristics of microaerial networks,

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**Table 3.** Comparison of swarm optimization algorithms.

| Algorithm | Particle swarm optimization (PSO) | Ant colony optimization (ACO) | Bee colony optimization (BCO) | Firefly algorithm (FA) | Gray wolf optimization (GWO) | Glowworm swarm optimization (GSO) |
|---|---|---|---|---|---|---|
| Inspired from | Flocking behaviour of birds | Foraging behaviour of ant species | Foraging behaviour of honey bees | Flashing pattern of fireflies | Pack of grey wolves chasing their prey | Bio-luminescence behaviour of glowworm |
| Parameters | Current velocity, personal best, global best | Pheromone update | Velocity and position based on source | Attractiveness of firefly | Position update of omega wolves | Luciferin update |
| Computational complexity | $O$(NT) | $O$(NS) | $O$(NS) | $O$(2NS) | $O$(NS) | $O$(NS) |
| Memory | No | Yes | No | No | Yes | No |
| Search techniques | Mutation and selection | Mutation and selection | Mutation and selection | Mutation | Mutation and selection | Mutation |
| Convergence speed | Fast | Slow | Slow | Fast | Slow | Slow |
| Scalability | Poor | Good | Poor | Good | Good | Good |
| Merits | Good diversity | Suitable to solve mix variable problems, have feedback system | Suitable to solve high-dimensional constrained problems | Good exploration, can easily escape from local minima | Strong versatility, reduces operational time for high-dimensional problems | Suitable for solving multi-dimensional optimization problems with equality and inequality constraints |
| Limitations | Gets trapped easily in local minima for high-dimensional problems | Uncertain convergence time | Unable to provide complete optimal solution | Not good at exploitation, have low diversity | Prone to local stagnation, limited exploration, less accurate | Poor accuracy, easily trapped in local minima |

particularly the availability of GPS data, the work proposed a better approach to mobile ad hoc networking (BATMAN), emphasizing the potential of geographical routing. Nevertheless, the paradigm required further refinement to optimize its functionality. An optimized way-points (OPWP) algorithm based on message ferry route design is discussed in Tariq et al. (2006). This algorithm is designed for sparse MANETs, offering efficient performance without necessitating real-time collaboration between nodes and the ferry. The OPWP ferry route consists of strategically selected waypoints and associated waiting times, tailored according to the node mobility model. Delay-tolerant networks (DTN) allow nodes to store messages until forwarding is possible, a mechanism known as store–carry–forward (SCF). This enhances routing robustness in the face of disruptions. DTN is primarily designed for sparse networks with infrequent contact opportunities, making it less efficient in well-connected networks. Many DTN routing schemes resort to packet replication to reduce delivery delays and increase delivery probability. However, this replication introduces substantial storage and bandwidth overhead, potentially diminishing performance in well-connected networks.

A hybrid MANET-DTN routing approach designed to enhance the performance of a MANET routing protocol is discussed in Raffelsberger and Hellwagner (2013) by incorporating local packet buffers. This protocol stores data packets in the absence of an end-to-end path and sends them when a route is identified. Despite its benefits, this scheme may experience significant delays due to the absence of a mechanism for advancing data delivery when no end-to-end path is available. Aung et al. (2017) introduced a data-delivery solution for opportunistic networks, consisting of two main algorithms: store–carry–cooperative forward routing and information epidemic control. The data forwarding algorithm involves proactive monitoring by nodes, utilizing direct and two-hop cooperative forwarding opportunities, and adaptively switching between cooperative and reactive SCF routing. Additionally, an information epidemics control algorithm is proposed for earlier control signal distribution and a faster recovery rate, with the effectiveness studied using the susceptible-infected-recovered model. In a disaster scenario, a forwarding-based protocol like a geographic routing protocol may be more suitable (Huda et al. 2012; Fajardo et al. 2014). Location-aware message delivery (LMD) is introduced in Huda et al. (2012) as a communication solution for short messages among individuals in disaster-stricken areas. Emphasizing power conservation and message delivery ratio as crucial design goals, the authors presented LMD as a routing protocol capable of exchanging messages without network infrastructure or a continuous end-to-end path. The system performs well beyond certain node density levels, making it a preferable option over energy-consuming multi-copy strategies for communication in disaster-stricken areas. To address challenges posed by limited UAV battery capacity and unpredictable network connectivity in disaster sites, Yang et al. (2019) investigated an energy-efficient multi-hop data routing algorithm for UAV-aided medical assistance. Prioritizing quality-of-service, the research focuses on minimizing energy consumption, considering transmission rate, time delay, and UAV swarm life cycle. Harounabadi et al. (2015) introduced a trajectory-aware geographical (TAG) routing for cognitive radio ad hoc networks featuring UAV nodes. TAG utilizes trajectory information from UAVs and ensures that a UAV is not chosen as the next hop if it is expected to fly inside a primary user (PU) region or in close proximity to it. This approach is designed to safeguard real-time packets from potential delays caused by PU activity. Shumeye Lakew et al. (2020) have reviewed UAV classification metrics and deployment issues, serving as a basis for classifying FANET communication architecture. It proposed a new taxonomy for routing protocols in FANETs, providing thorough discussions and comparative studies.

A location-aided delay-tolerant routing (LADTR) protocol for UAV networks, specifically designed for post-disaster operations, is presented in Arafat and Moh (2018). The protocol incorporates location-awareness and utilizes an SCF technique. Notably, ferrying UAVs are introduced for efficient SCF, marking the first instance of their use for routing in UAV networks. This innovation aims to enhance connection paths between searching UAVs and ground stations, thereby reducing end-to-end delays and improving packet delivery ratios. A dynamic priority packet scheduling scheme designed for maintaining high QoS in post-disaster UAV-assisted MANETs is discussed in Gao et al. (2021). The scheme considers not only the current packet delay but also anticipates the impact of future transmissions on priority assignment. The Gauss–Markov Mobility Model is employed to capture the dynamic characteristics of nodes. Additionally, the scheme integrates factors such as node movement, topology instability, and time-varying channel quality into the priority assignment process. Table 4 summarizes routing protocols tailored for UAV networks in disaster environments, and the state-of-the-art schemes are outlined in Table 5.

## 5.1. Critical insights and gaps in existing studies

Designing a routing protocol for reliable communication in UAV networks poses significant challenges due to high mobility, dynamic topology, and uneven UAV distribution. In missions like search and rescue, minimizing latency and ensuring high data transmission rates are crucial. While achieving zero delay is impractical, efforts focus on minimizing latency within certain limits. Proactive routing protocols, which require frequent table updates, may not be ideal for highly dynamic environments. In contrast, reactive protocols like BATMAN offer efficiency, however, with potential limitations in packet size. To address frequent link disconnections, the store-carry-forward technique is proposed in literature by having nodes carry packets until finding a suitable neighbour; however, this approach, particularly in sparse networks, can introduce delays. Greedy forwarding-based schemes select the next node based on the minimum distance, but they may fail to find closer nodes, leading to local minimum problems. Multi-hop AODV-based protocols are noted for their adaptability to harsh conditions with minimal overhead and have been extensively investigated.

**Table 4.** Routing protocols for a multi-UAV network in a disaster environment.

| Classification | Routing protocol |
|---|---|
| Reactive | • Ad hoc on-demand distance vector (AODV)<br>• Location-aided routing (LAR)<br>• Temporally-ordered routing algorithm (TORA)<br>• Associativity-based routing (ABR) |
| Opportunistic | • Opportunistic routing protocol (ORP)<br>• Multi-copy opportunistic routing (MCOR)<br>• Cooperative communication-based opportunistic routing (CCOR)<br>• Geographic and opportunistic routing (GEAR)<br>• Spray and wait (SnW) |
| Ad hoc | • Centralized routing<br>• Decentralized routing<br>• Collaborative routing |
| Delay-tolerant networks (DTNs) | • Epidemic routing<br>• Spray and wait routing<br>• PRoPHET routing<br>• MaxProp routing<br>• Message ferry routing |
| Wireless mesh network (WMN) | • Hybrid wireless mesh protocol (HWMP)<br>• Better approach to mobile adhoc networking (BATMAN)<br>• Optimized link state routing (OLSR)<br>• Hybrid wireless mesh protocol v2 (HWMPv2)<br>• Multi-gateway routing (MGR)<br>• Proactive routing protocol for mesh networks (BMF)<br>• Distance routing effect algorithm for mobility (DREAM) |

**Table 5.** A brief analysis of the literature on routing schemes.

| Reference | Description |
|---|---|
| Arafat and Moh (2018) | Introduced the location-aided delay-tolerant routing (LADTR) protocol for post-disaster UAV networks, employing ferrying UAVs to enhance store-carry-forward technique, improving connection paths, reducing delays, and increasing packet delivery ratio |
| Fu et al. (2022) | Introduced a UAV Routing System (UAVRS) to determine optimal routes for inspecting damages and monitoring transmission lines and roads in real time for distribution networks |
| Faiz et al. (2024) | Proposed a framework optimizing a two-echelon vehicle routing problem using ground vehicles to transport drones for delivering medical aid to trapped populations |
| Mohammed Ahmed et al. (2021) | Evaluated the efficiency of routing protocols (AODV, DSR, OLSR, and ZRP) in disaster scenarios for UAVs communication mesh, addressing challenges to enhance network performance |
| Yin et al. (2017) | Introduced a greedy and position-assisted routing protocol for highly mobile UAVs, mitigating transmission delay challenges |
| Arafat and Moh (2019*b*) | Reviewed UAV network routing protocols, categorizing them and conducting a qualitative comparison based on features, characteristics, and performance |
| Yang et al. (2019) | Examined challenges in UAV-aided disaster management and proposed an energy-efficient routing algorithm ensuring quality-of-service, while addressing issues such as limited UAV battery capacity and unstable network connectivity |
| Khan et al. (2018) | Focused on topology-based routing protocols, reviewing their features, pros, and cons. Evaluates selected protocols through simulation analyses for end-to-end delay, throughput, and network load |
| Bousbaa et al. (2020) | Explored fleet routing in FANETs and proposed a geo-cast protocol mitigating UAV mobility challenges, enhancing average delay, packet delivery, and throughput |

Position-based routing schemes offer an alternative approach for disaster missions, where every node shares its position with others in the network. However, in pure geographic-based routing schemes, the periodic transmission of beacons to update positions results in significant network overhead. Various alternative protocols have been studied to address this issue, but practical testing remains limited. Moreover, these schemes rely on GPS locations to determine the next node, leading to drawbacks in global accuracy and security, such as susceptibility to GPS spoofing attacks in highly mobile networks. From our analysis, it is evident that there is no single protocol suitable for all types of disasters.

Instead, a combination of protocols tailored to specific disaster scenarios may be considered. For instance, proactive protocols may be suitable for smaller networks with limited mobility, while position-based protocols are preferred for larger networks with high mobility. Position-based routing offers advantages such as reduced overhead and scalability, as the next hop is chosen based on positions. However, the complexity of position-based protocols is higher compared to proactive ones, as beacons need to be transmitted frequently. Despite the multitude of protocols discussed in the literature, many focus on theoretical improvements rather than practical application, overlooking the importance of aligning with specific mission requirements. Furthermore, protocols that meet security requirements are often underexplored, highlighting the ongoing need for research in routing protocols for critical missions with dynamic network topologies.

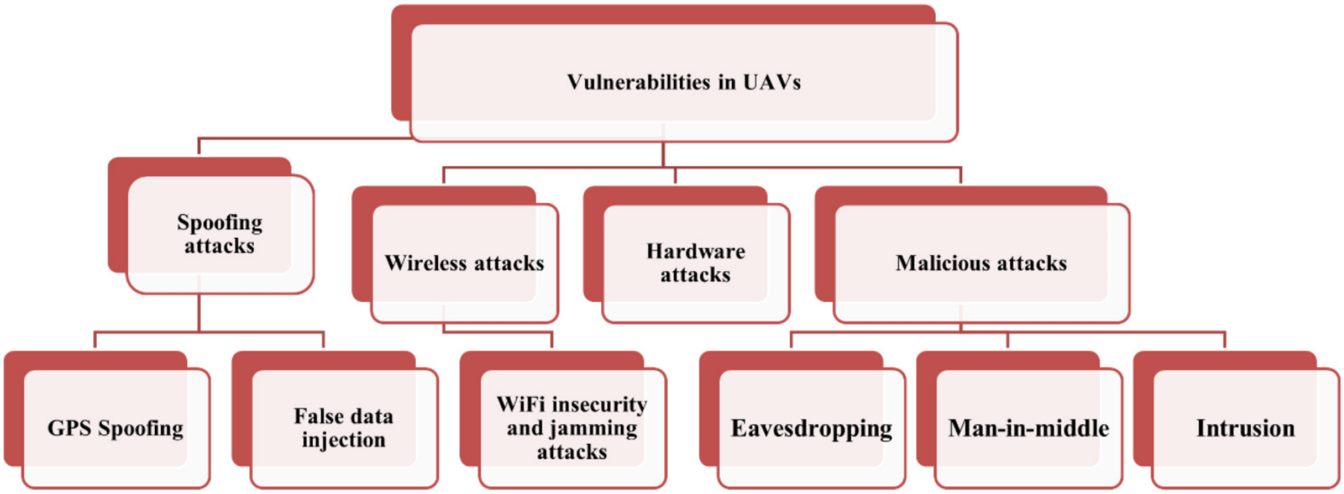
AI-based routing is a growing trend, leveraging ML algorithms for optimal route selection based on network perceptions. However, frequent topology changes challenge predictions, prompting research into node-based position predictions to reduce reliance on network topology. Further research is needed to fully harness the potential of AI-based solutions, integrating advanced ML algorithms for path planning, routing, and resource allocation. Computational complexity and power consumption must be considered, especially for battery-powered UAVs. Connectivity issues due to limited UAV range and battery drain necessitate energy-based predictions and lightweight protocols. Integrating online path planning algorithms can minimize connectivity issues, particularly in static mission areas like search and rescue or wildfire monitoring. Sophisticated AI approaches that can predict nodes, environments, and connectivity quality can address network challenges comprehensively. Lightweight protocols incorporating energy efficiency and connectivity optimization can further enhance UAV network performance.

## 6. Security challenges and approaches

Given the inherent broadcast vulnerability in wireless communications, ensuring security is paramount for current and future wireless network designs. The attention in research has increasingly turned to physical layer security, distinct from traditional key-based cryptographic techniques (Mukherjee et al. 2014). Unlike upper-layer methods, physical layer security safeguards wireless data transmissions without relying on secret keys and intricate algorithms, rendering it more suitable for large-scale decentralized networks (Liu et al. 2017). Recent research explores the potential of full-duplex techniques at the source or legitimate destination, aiming to double spectral efficiency. To identify the research gaps in the above methods, a secure transmission scheme is designed for UAV wiretap channels in the presence of a full-duplex active eavesdropper in Liu et al. (2017). Two major contributions of the work include a derived compact expression for the hybrid outage probability, considering short-distance LoS links in UAV-aided communication systems, and the determination of an optimal power allocation factor at the source to minimize the hybrid outage probability. From the comprehensive survey on security and safety considerations presented in Altawy and Youssef (2017) for civilian applications, the potential attacks associated with a UAV network in disaster response scenarios are identified and listed in Fig. 5. The primary security challenge in communication protocols for UAVs lies in securing data transmitted over vulnerable connections like WiFi. UAVs typically transmit data to ground stations via wireless links that are susceptible to attacks. To safeguard against interception, encryption schemes such as the advanced encryption standard are commonly used. However, its efficiency in real-time applications, particularly with high data transfer rates, poses challenges (Heron 2009). Another significant security concern is potential attacks on UAVs, aiming to seize control or disrupt communication with the ground control station (GCS). Attack methods include jamming, spoofing, and false data injection attacks. A comprehensive literature review on UAV security is presented in Shafique et al. (2021), examining vulnerabilities in existing protocols and proposing potential solutions. It analyzes threats, including WiFi insecurity, jamming attacks, and fuzzing attacks, outlining how these vulnerabilities can be exploited. The study also emphasizes risks in packet forwarding and routing protocols within UAVs, highlighting potential threats to security.

In the context of disaster response and management, the spread of false or manipulated information can have serious consequences. It can lead to misinformation and confusion and hinder the effectiveness of emergency response efforts. To protect data transmission, various symmetric cryptographic and steganographic methods have been proposed in the literature (Naji et al. 2009; Vegh and Miclea 2014). However, securely distributing and managing the keys becomes a complex task in symmetric schemes, particularly in large-scale systems, making it susceptible to various attacks, including brute-force attacks. This paved the way for asymmetric cryptographic schemes, where key exchange was made possible through the Diffie–Hellman key exchange algorithm (Boneh no date). This algorithm establishes a session key between communicating entities, ensuring secure data transmission once the session key is in place. In Wang et al. (2023), an innovative, secure, and energy-efficient data sharing scheme for urban drone rescue networks is presented. The approach employs a lightweight, infrastructure-free blockchain framework to ensure data security and trace misbehaviour at disaster sites. In Wesson et al. (2014), a data authentication protocol employing an asymmetric key algorithm technique is proposed to verify the authenticity of data received by the UAV, distinguishing between communication from the authentic ground station and potential eavesdroppers. In Sahingoz (2013), a public-key exchange protocol enables sensor nodes to authenticate each other before communication. Two nodes act as communicating parties, exchanging encrypted messages with public and private keys. In Valentin-Alexandru et al. (2019), a trust-based protocol is proposed where sensors are assigned trust values. The UAV combines these values and avoids communication with sensors having negative trust values. In Yoon et al. (2017), an authentication protocol for UAV security is proposed. The UAV is authenticated based on comparing received data with

**Fig. 5.** Security attacks on the UAV network in a disaster scenario.






maintained indexes, allowing take-off for successful authentication and disconnecting communication for unsuccessful attempts. Challenges of this scheme include high bandwidth, cost, and processing time for large data. A detailed review of various authentication schemes is presented in Zhou et al. (2020), Shafique et al. (2021), and Pandey et al. (2022).

To address the challenges posed by jamming GPS signals, adopting alternative navigation methods becomes essential. Wu and Johnson (2010) proposed a vision and inertial navigation system, enabling autonomous navigation for drones in situations where GPS signals are unavailable. Existing research on vision-based navigation is comprehensively reviewed in Balamurugan et al. (2017), and it is concluded that a visual odometry-based approach is more efficient in terms of memory and computational power. The authors also proposed a modular multi-sensor data fusion technique designed for UAV navigation in GPS-denied environments. Similar to GPS signals, the attackers can jam or spoof the position and velocity broadcasts of the

UAVs, potentially causing collisions or redirecting the drone to a desired location to physically capture it. To mitigate this challenge, De Melo et al. (2021) introduced a system designed to validate the identity and location of UAVs. It combines a public-key authentication method with a movement plausibility check for groups of UAVs. This method periodically assesses the credibility of neighbouring UAV locations, providing enhanced security by detecting intruders deviating from expected trajectories.

Another significant security concern in UAV networks is intrusion attacks. A concise survey of state-of-the-art intrusion detection systems (IDS) in the context of networked UAV environments is presented in Choudhary et al. (2018). The classification is based on various factors, including information gathering sources, deployment strategies, detection methods, detection states, IDS acknowledgment, and intrusion types. Various authentication schemes are studied in the literature to overcome the challenge of intrusion attacks. The concepts of blockchain for authentication mechanisms were explored in Jensen et al. (2019) and Lv et al. (2021). While blockchain technology offers advantages such as data confidentiality and entity validation, making it suitable for trust-sensitive applications, certain limitations were identified (Shafique et al. 2021). In larger networks, the blockchain may grow to a size that makes it impractical for agents to maintain a complete record. Additionally, the time required to process a new block could be deemed inefficient, particularly in UAVs that typically operate with an average flight autonomy of approximately 25 min. In response to the identified challenges, a UAV network identity authentication scheme is presented in Li et al. (2019) that relies on the elliptic curve ECC algorithm (Li 2002). The system utilized ECC digital certificates as proof of identity for authorized access. Authentication of drone identity is achieved through the application of the elliptic curve-based ECDSA signature algorithm (Johnson et al. 2001), chosen for its efficiency in terms of computation and resource consumption. Subsequently, the ECDH exchange algorithm (Haakegaard and Lang 2015) is employed to generate a session key for secure UAV communication. To address the issues identified with existing ECC-based protocols, such as inflexibility and backward security issues, a lightweight authentication protocol over elliptic curve is proposed in Zhang et al. (2023). It ensures backward secrecy of session keys, provides flexibility, and exhibits minimal time cost compared to other authentication methods, enhancing overall security. Table 6 outlines the recent studies on security aspects of UAV networks.

## 6.1. Critical insights and gaps in existing studies

In the realm of highly dynamic UAV networks, traditional security methods relying on asymmetric approaches face challenges due to the absence of a central authority for issuing digital signatures and managing key storage. As a result, researchers have delved into alternative avenues such as distributed certificate-based techniques, pre-key distribution algorithms, and blockchain technology. Recently,

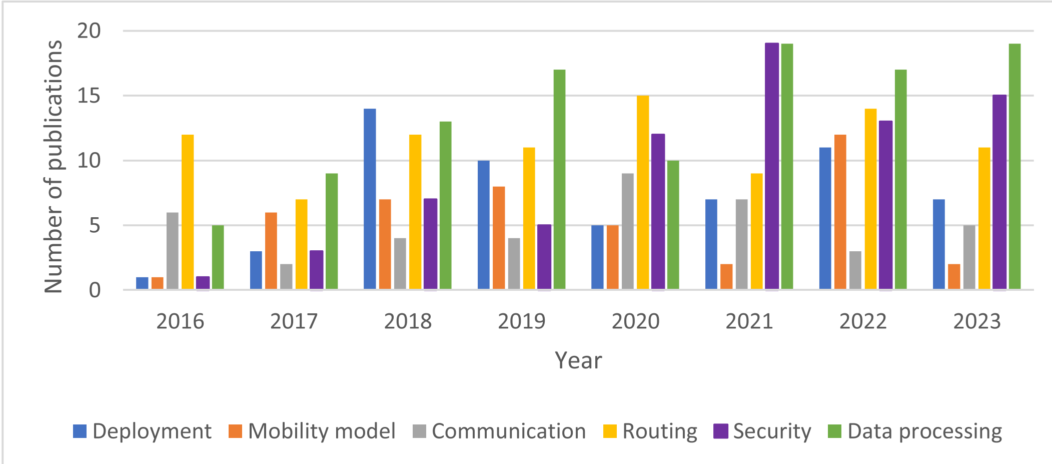
**Table 6.** A brief analysis of the literature on security approaches.

| Reference | Description |
|---|---|
| Rodday et al. (2016) | Demonstrated security vulnerabilities, potential man-in-the-middle attacks, and proposed countermeasures to enhance security and resilience |
| He et al. (2016) | Underscored the crucial need for communication security in UAVs, highlighting potential vulnerabilities and presenting a low-cost implementation of GPS spoofing and WiFi attacks |
| Abdallah et al. (2019) | Proposed a secure disaster surveillance UAV system considering energy constraints and limited computation, utilizing ring-learning with errors for confidentiality and data redundancy for accuracy in a two-tier cluster network |
| Sun et al. (2019) | Investigated physical layer security issues in UAV wireless communications, addressing eavesdropping vulnerabilities and proposing techniques like trajectory design and resource allocation, alongside applications of advanced technologies for improved security and spectral efficiency |
| Li et al. (2019) | Proposed a lightweight identity authentication method based on elliptic curve cryptography, ensuring two-way identity authentication and key consistency verification and providing a more secure and efficient solution compared to traditional methods |
| Wang et al. (2019) | Addressed the power allocation strategy for a UAV swarm-enabled aerial network to enhance physical layer security against eavesdropping |
| Ch et al. (2020) | Introduced a blockchain technology solution to enhance security and privacy for UAVs used in aerial surveying, employing elliptic curve cryptography and SHA for data integrity |
| Alladi et al. (2020*b*) | Introduced a lightweight mutual authentication scheme based on physical unclonable functions (PUFs) for securing communication between UAVs and ground station, addressing vulnerabilities, and providing formal security analysis |
| Abro et al. (2022) | Examined evolving UAV applications, focusing on detection, classification, and tracking advancements while addressing security and privacy concerns through control signal jamming and proposing strategies to enhance UAV security and privacy |
| Iqbal (2021) | Explored for intelligent defense mechanisms within UAV operating systems, examining existing security issues, proposing solutions, and discussing research challenges for secure UAV operating systems |
| Tsao et al. (2022) | Surveyed security and privacy issues in UAVs, focusing on FANETs. Categorizes threats and defense mechanisms, analyzes UAV routing protocols, and discusses research challenges and future directions |
| Pandey et al. (2022) | Conducted a comprehensive survey on security issues in UAV-aided networks, addressing cyber threats, privacy concerns, and mitigation techniques, while integrating key wireless communication technologies and emerging topics like machine learning and blockchain |
| Asghar Khan et al. (2022) | Addressed security and privacy concerns in UAV-enabled intelligent transportation systems by proposing a privacy-preserving authentication scheme combining hyperelliptic curve cryptography, digital signature (Asghar Khan et al. 2022), and hash function |

hardware-driven solutions like physically unclonable functions (PUFs) have garnered attention for their potential to enhance security for mobile UAVs. Despite their theoretical exploration, practical implementation remains limited in existing studies. Security considerations within UAV networks vary depending on factors like network size and deployment environment. Solutions tailored to specific applications are necessary since generic approaches like data encryption cannot address diverse threats such as GPS spoofing or jamming attacks. Addressing each attack separately is imperative, necessitating measures like alternative localization methods and secure handover mechanisms. While UAVs offer line-of-sight communication, this also exposes vulnerabilities, with data confidentiality at risk due to interception by rogue UAVs. Different mission types face distinct security challenges; for instance, disaster surveillance missions may encounter eavesdropping or man-in-the-middle attacks, while search and rescue operations are susceptible to GPS spoofing and denial of service. Incorporating security into routing protocols and exploring physical layer security techniques are avenues for mitigating these risks.

ML approaches, including CNNs and RNNs, offer promise for detecting anomalies and intrusions. However, their adoption introduces computational complexity, posing challenges for battery-powered UAVs. Cloud offloading schemes mitigate this but add complexity and cost, particularly concerning data security in disaster scenarios. Software-defined networking introduces delays and single points of failure, making it less suitable for low-latency missions. Distributed and multi-controller approaches offer alternatives, while lightweight encryption schemes and optimized cryptographic protocols can enhance scalability and efficiency. Blockchain-enabled security techniques show potential in managing tasks and securing swarm UAV networks, yet they suffer from computational delays, a major concern in resource-constrained UAVs. Fog computing techniques have garnered attention for their applicability in low-latency missions, offering the capability to handle large data volumes while providing quality of service, scalability, adaptivity, reduced platform dependency, and low latency. This makes them well-suited for missions like disaster mitigation, as they offer security against threats such as GPS spoofing, hijacking, eavesdropping, and denial of service attacks. Despite these advantages, fog computing has not been fully explored and has limitations, including a lack of task sharing and inter-layer resourcing. Task sharing can distribute the workload evenly, enhancing network lifetime, while inter-layer resourcing facilitates interaction and data offloading among heterogeneous devices. Addressing these

**Fig. 6.** Literature survey chart.




challenges could enhance the suitability of fog computing for UAV networks.

Privacy concerns, alongside security, are paramount in UAV systems, necessitating measures to prevent unauthorized access and mitigate privacy leakage. However, detecting and identifying malicious UAVs is a critical challenge, with existing literature lacking comprehensive studies on algorithms for detecting spying actions in specific areas of interest. While watermark-based schemes have been proposed for detection (Nassi et al. 2019), their applicability is limited to UAVs within the range of Wi-Fi first-person view. In scenarios involving multiple UAVs, distinguishing between legitimate and malicious ones becomes increasingly challenging, underscoring the need for extensive research in security fields. Additionally, ensuring security during UAV flight missions requires forensic analysis, but collecting real-time data from each UAV and conducting thorough testing to identify security breaches poses logistical challenges. Addressing these challenges necessitates future research efforts aimed at developing robust detection algorithms and enhancing forensic analysis capabilities within UAV systems.

# 7. Future research directions

The preceding discussions clearly show that UAVs have the possibility of significantly increasing the efficiency of disaster management operations by providing critical situational awareness and delivering relief and supplies to affected areas. Despite the benefits provided by UAVs and technology advancements, the research on UAV-swarm networks is still in its infant stage, and there are many open issues that need to be addressed and investigated. The difficulties range from regulatory issues to technical constraints, and they can have a considerable impact on the effectiveness of UAV-based disaster mitigation efforts. In this context, it is critical to evaluate and comprehend the issues connected with UAV-based disaster mitigation to devise effective solutions and exploit the full potential of these technologies. Figure 6 represents the current research trend, deduced from the average number of research publications in the domain of UAV networks for disaster applications over the last five years (2016–2023).

## 7.1. Cyber-physical security

UAV networks face significant security issues, such as wire-tapping, malicious attacks, jamming, and control signal forgery. These vulnerabilities may compromise mission-critical data and UAV operation security. While security has been a focal point in recent research, there is a need for further exploration into the implementation and hardware resource requirements of existing schemes. The impact on payload capacity and computational resources can significantly affect UAV battery life and mission accomplishment.

The major attacks that predominate in a disaster environment are eavesdropping, signal jamming, intrusion attacks, and physical capture attacks. Eavesdropping, to a greater extent, can be mitigated through lightweight cryptographic techniques, but they are yet to be tested and analyzed on UAV swarms. To enhance intrusion detection in computer networks with high bandwidth and data traffic, researchers have turned to ML and DL algorithms. However, the effectiveness of these schemes needs to be thoroughly investigated in terms of training and precision. To mitigate physical capture attacks, PUFs are gaining popularity and will definitely receive major attention in the coming years. PUFs are devices that generate responses based on intrinsic variations (McGrath et al. 2019). A striking feature that is explored for physical security is that, any attempt to tamper with the PUF, such as micro-probing, renders it useless. However, existing research on these devices is confined to theoretical simulations, with insufficient consideration given to the impact of temperature variations and other environmental factors (Alladi et al. 2020*a*; Garcia-Bosque et al. 2020). PUF can also add uniqueness and randomness to key generation and will definitely receive major attention in the coming years. The ability of these devices to mitigate other attacks is also to be explored. Thus, continuous research and collaboration are required to keep up with increasing security concerns in the field of UAVs.

Furthermore, future research directions should investigate countermeasure approaches to mitigate jamming attacks in UAV relay schemes. The RL approach (Zhang et al. 2020*b*) is a promising avenue, leveraging RL and transfer learning to optimize relay signal power against jamming, even without prior knowledge of network topology and signal models. Exploring the scalability, robustness, and real-world applicability of such countermeasure techniques would be instrumental in enhancing the security of drone communication networks. Some of the other research perspectives may include the development of AI-driven security solutions capable of adapting to evolving threats, exploring less-computationally intensive blockchain technology for secure data sharing among UAVs, and addressing privacy concerns through privacy-preserving algorithms. Additionally, further research to strengthen physical security measures for UAVs could mitigate the risks associated with unauthorized access and tampering.

## 7.2. Routing issues

UAVs typically operate in low-density environments with high mobility, leading to frequent changes in network topology and disconnections among communication nodes. This instability adversely affects routing efficiency and performance, making the design of routing protocols challenging. It is obvious that traditional routing protocols designed for MANETs and VANETs are not sufficient in UAV networks due to the high mobility and frequent changes in topology. While existing schemes in the literature have individually succeeded in incorporating parameters like hop count, link quality, congestion, and energy efficiency, a standardized routing scheme that integrates all these factors to ensure low overhead and a high packet delivery rate during disaster scenarios is yet to be established. The existing approaches, such as SCF, indeed led to the nodes not requiring to maintain continuous routing table for the routes, but it has added overhead to the transmission process. Further, achieving a high packet delivery ratio during disasters with routing protocols may still result in mission failures due to adverse effects from malicious replays and false signalling. Additionally, many state-of-the-art protocols are simulation-based, and the mobility rates considered may not always align with real-time scenarios. Testing and evaluating these protocols in real-time disaster-like scenarios are essential for standardization. Therefore, to fully harness the UAV network potential, routing requires substantial attention. Factors such as inter-node synchronization, heterogeneity, energy efficiency, collision avoidance, decentralized control, communication range management, and real-time decision-making are also to be further investigated in the routing process. A notable and pioneering work involves the integration of security measures into routing protocols to ensure the robust protection of data traffic. Existing works (Yadav et al. 2017; Patil et al. 2020) still need to be deeply investigated, and future directions in this line of research could explore advanced cryptographic techniques, anomaly detection mechanisms, and intrusion prevention strategies within routing protocols. Additionally, the development of lightweight and efficient security protocols tailored to the resource constraints of UAVs would further enhance the applicability of this approach in real-world scenarios.

## 7.3. Joint computation, communication, and control

Integration of space, air, and ground communications is a current development in aerial networks. The joint computation, communication, and control challenge in UAVs involves optimizing and coordinating these three aspects for efficient and reliable UAV operations. UAVs often face limitations in on-board computational resources, reliable communication links, and precise control systems, which adds latency in mission execution. The challenge arises due to the interconnected nature of these elements, where computation affects communication and control, and vice versa. Overcoming this challenge requires a holistic approach, incorporating advanced algorithms for computation, communication protocols, and control systems. Technologies such as edge computing, MIMO communication, adaptive control, and intelligent decision-making play a crucial role in addressing this challenge and unlocking the full potential of UAVs in disaster scenarios. This integration has the potential to create a seamless and pervasive connectivity environment for the efficient communication and exchange of data between various platforms, such as satellites, HAPs, UAVs, and ground communication systems. However, innovative solutions are required to overcome the inherent challenges of network heterogeneity in agent handovers and ensure the reliability of these integrated networks. Future research should delve into developing adaptive algorithms that dynamically distribute tasks and responsibilities among heterogeneous UAVs, taking into account their unique performance metrics. This involves designing intelligent decision-making frameworks capable of optimizing the utilization of resources across a diverse set of UAVs in a network. Researchers can explore the design of communication protocols that account for the diverse communication capabilities of UAVs. This involves developing adaptive routing algorithms that consider the bandwidth requirements of different UAVs and optimizing data transfer strategies based on the communication constraints present in the heterogeneous network. Various techniques for sensor fusion that integrate data from diverse sensors on UAVs to enhance the overall perception and information gathering capabilities of the network are to be extensively explored in the coming years to ensure accurate decision-making in heterogeneous environments.

The analysis of synchronization, resource allocation, and scheduling in drone networks highlights the importance of optimizing connectivity, especially in densely populated swarm configurations. As drones play a crucial role in relaying units to enhance networking solutions, future research should delve into advanced synchronization mechanisms to achieve optimal resource allocation and scheduling strategies. The throughput optimization for both A2A and A2G links poses challenges, particularly in the context of Internet of Drones (IoD) systems where various metrics need consideration. Addressing the computational complexity of solving optimization problems related to throughput maximization is crucial. Additionally, there is a need to explore energy-efficient solutions, given the trade-off between maximizing throughput and increased energy consumption, especially in battery-powered drones.

### 7.4. Energy-efficient coordination

Coordinating a swarm of UAVs for cooperative mission planning is a complex and challenging task. The problem becomes NP-hard as the size of the swarm and mission objectives increase, leading to exponential computational requirements. The UAV network is also affected by environmental changes, making real-time coordination difficult. Furthermore, the energy-constrained nature of UAVs raises concerns about energy-efficient coordination. Addressing these challenges requires decentralized approaches, hierarchical control, distributed optimization, learning-based methods, energy-aware routing, task allocation strategies, and dynamic resource management. Resolving these issues will enable effective deployment of UAV swarms in various applications, making continued research essential for advancement in this field. Therefore, future research should concentrate on developing energy-aware algorithms that consider the diverse energy constraints of UAVs. This involves designing optimization algorithms for task scheduling, path planning, and collaborative decision-making that account for variations in energy availability among heterogeneous UAVs, ensuring efficient use of resources throughout missions.

### 7.5. Trajectory optimization

Optimizing flight trajectories is challenging due to practical constraints on UAV networks deployed in disaster scenarios. To reduce communication delay, UAVs need to move close to ground users while maintaining interconnections with neighbouring UAVs. An optimal trajectory ensures end-to-end link connections and sufficient coverage of the target area. To achieve this, a dynamic trajectory control method is required, considering communication range, adaptive planning, collaborative decision-making, coverage, energy efficiency, real-time optimization, and safety. While some studies have addressed energy-efficient optimization, they often rely on generic energy consumption models, which may not be the most suitable fit for disaster scenarios. Disaster-stricken areas may have a more complex and dynamic environment with debris, damaged structures, and unpredictable terrain. Navigating through such areas requires advanced sensing and processing capabilities to detect and avoid obstacles. All these factors adversely affect the energy consumption rates of the nodes. While advancements in trajectory planning for UAV swarms and edge computing have proved effective individually, the integration of both areas, known as UAV swarm-enabled edge computing, is still relatively new and remains in its early stages of exploration.

### 7.6. Channel modelling

UAV-to-ground communication channels are more complex and susceptible to blockage than traditional ground communication channels due to their distinctive 3D space and time-variant characteristics. Conventional deterministic and stochastic models are inadequate for characterizing these channels, which depend on factors such as UAV altitude, type, elevation angle, and propagation environment. Further, the UAV network is highly dynamic. As UAVs move through the airspace, their relative motion with respect to the ground stations and other nodes causes a frequency shift in the signals transmitted and received. The Doppler effect can lead to fluctuations in signal frequencies, which further complicates the channel characteristics and requires careful consideration in channel modelling and communication system design. Developing an accurate and generic channel model for UAV-to-ground communications requires comprehensive simulations and measurements in various environments. Also, the lack of a standardized communication channel for UAV authentication and authorization poses challenges for FANETs. The initialization phase for UAVs could be streamlined with the implementation of a standardized communication channel. Moreover, as the number of UAVs in the network grows, so does the possibility of inter-UAV interference. This can result in decreased network performance and dependability. Researchers are investigating new interference management strategies, like beam-forming and interference cancellation, to help alleviate the consequences of interference in multi-UAV networks.

### 7.7. Deployment

One of the most critical challenges is designing the optimal 3D placement and flight path, as these factors significantly impact the performance of UAV-assisted wireless communications. The optimal altitude of UAV base stations and their flight trajectories depend heavily on environmental conditions, application scenarios, and the number of UAVs employed. While existing studies on UAV base station placement have shown promising results, further research is needed to optimize 3D UAV deployment, taking into account the unique features of UAVs. Many existing works on computing optimal UAV positions assume static UAV base stations, which is unrealistic in most cases. Therefore, designing a dynamic UAV base station deployment strategy for UAV-assisted wireless networks, considering UAV mobility and other constraints, presents an interesting research problem. Interdisciplinary collaboration and continuous innovation are necessary to overcome these hurdles and fully harness the potential of UAVs in diverse applications.

## 8. Conclusions

Unmanned aerial networks have proven remarkably effective in critical missions, reaching hard-to-access areas to provide essential assistance. While substantial research has been dedicated to this field, the absence of standardized schemes on communication, task scheduling, data processing, and trajectory optimization still remains a challenge in this domain. The vast scope of UAVs requires focused research in specific areas to address the intricate challenges unique to their diverse applications. The authors of the article have identified the prevailing research trends, emphasizing the prioritization of research in data processing capabilities and the security of both devices and data in the network. This article presents a substantial body of research, examining literature across various network aspects, including deployment, trajectory optimization, routing, and security. It also outlines research areas set to be extensively explored in the coming years. Each facet of these networks presents abundant opportunities for research exploration, particularly in mission-critical scenarios such as disasters.

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