International Journal on
Drones
Volume 1, Issue 1, 2025
January—June
DOI (Journal): 10.37591/IJD
https://journals.stmjournals.com/ijd
Review IJD

Drone Swarms: An Overview and Working in Network Control Systems

Angshuman Chakraborty[1,*], Trupa Sarkar[2]

Abstract

The review of multi-agent systems, including drone swarms, has gained momentum due to their ability to exhibit cooperative behavior. Automating the control of a drone swarm poses substantial challenges due to the diverse wireless, networking, and environmental constraints each drone faces. To address these challenges, we treat drone swarms as Networked Control Systems (NCS), integrating the overall system control within a wireless communication network. This approach relies on a strong interconnection between networking and computational systems to effectively support crucial control functions, including data collection and exchange, decision-making, and the distribution of actuation commands. Our literature review indicates a scarcity of review papers focusing on the design of drone swarms as Networked Control Systems (NCS). In this review, we provide an extensive overview of the development of self-organized drone swarms as Networked Control Systems (NCS) through the integration of networking and computational systems. We detail the characteristics of these proposed components with respect to their networking and computational features, and assess their integration to improve drone swarm performance. Furthermore, we propose a possible design approach and identify several open research challenges associated with the integration of networking and computing in drone swarms as Networked Control Systems (NCS).

Keywords: Drone swarms; networked control systems; wireless networks; in-network computing, Unmanned aerial vehicle

INTRODUCTION

An Unmanned Aerial Vehicle (UAV) swarm or fleet is made up of several drones cooperating to achieve a common goal. Each drone in the swarm is equipped with a set of rotors enabling vertical take-off, landing, and hover capabilities (VTOL). Control of the drones can be either manual through remote operations or autonomous using onboard processors [1]. Drones were first created for military use, but they are currently finding use in civilian settings as well. Their affordability and versatility make them ideal for innovative research projects and future commercial uses, enhancing efficiency in various fields. Drones within swarms can be categorized in several ways. Figure 1 depicts fully autonomous and semi-autonomous swarms. Alternatively, swarms can be classified as single-layered, where each drone acts independently, or multi-layered, with hierarchical leadership structures where higher-layer drones oversee lower layers. Data collection and processing tasks are typically allocated to each drone within the swarm, leveraging onboard computing power for real-time execution, with more intensive processing handled by a central server or cloud-based system.

***Author for Correspondence**
Angshuman Chakraborty
E-mail: ans_22@rediffmail.com

[1]Associate Professor, Department of ECE, Tripura Institute of Technology, Narsingarh, Tripura, India
[2]Assistant Professor, Department of ECE, Tripura Institute of Technology, Narsingarh, Tripura, India

Received Date: July 19, 2024
Accepted Date: November 30, 2024
Published Date: January 16, 2025

Citation: Angshuman Chakraborty, Trupa Sarkar. Drone Swarms: An Overview and Working in Network Control Systems. International Journal on Drones. 2025; 1(1): 13–35p.

APPLICATION AREAS

Advancements in UAV sensor capabilities have expanded the potential applications of drones, leading to the development of new services in unmanned operations. This section briefly explores the prominent application areas of drones.

Security, Survey, Monitoring, and Surveillance

UAVs have traditionally been pivotal in military surveillance missions. Their versatility and cost-effectiveness have also found extensive use in aerial surveys and monitoring across diverse sectors such as geophysics and agriculture [1, 2]. For instance, monitoring a facility or environment often necessitates real-time updates on detected movements, particularly after office hours. Conducting thorough manual surveillance in large areas demands considerable manpower. In contrast, a swarm of drones can efficiently cover and monitor regions with minimal human intervention, promptly alerting a central base station upon detecting movement.

Leisure Pursuit

In our modern world, lightweight UAVs weighing less than 55 pounds are increasingly popular for recreational purposes [1]. They also serve critical roles in disaster management, environmental mapping, and search and rescue operations.

Disaster Management

During natural disasters, UAVs can access hazardous or remote locations, providing essential assessments and enabling effective response strategies. For instance, in wildfires, a swarm of drones equipped with fire extinguishers can swiftly survey and suppress fires over large areas, reducing risks to human lives.

Environmental Mapping

UAVs are actively employed in mapping diverse environments, contributing significantly to fields like cartography and archaeology [3].

Search and Rescue (S&R)

Unmanned Aerial Vehicles (UAVs) are vital tools in S&R operations because they can detect and help people in peril by using real-time aerial imagery.

Drones equipped with basic first aid kits can be deployed quickly to provide immediate medical assistance, potentially saving lives before traditional rescue teams arrive.

CLASSIFICATION OF UAVS

In the market, UAVs vary in their configurations, including the number of propellers/rotors, as shown in Table 1 [4]. Drones are also categorized based on size (nano, mini, regular, or large), range (very close, close, short, mid, or endurance), and equipment. Commonly equipped features include cameras, stabilizers, sensors, Global Positioning System (GPS), and First Person View (FPV) systems with accompanying FPV goggles.

Table 1. Number of propellers/rotors.

Based on Propellers	
Tricopter 3	3
Quadcopter 6	4
Hexacopter 3	6
Octocopter	8
Based on Structure	
Fixed-Wing	long endurance and fast flight speed
Fixed-Wing Hybrid	VTOL and long endurance flight
Single Rotor	VTOL, hover, and long endurance flight
Multirotor	VTOL, hover, and short endurance flight

Fixed-wing hybrid drones combine manual gliding with automation but are still in developmental stages, lacking efficiency in both hover and forward flight. They are notably used commercially by Amazon for delivery purposes.

In contrast, single rotor drones exhibit greater mechanical complexity and operational risks such as vibration and large rotating blades. They require skilled operators and are costly, yet they excel in handling heavier payloads like LiDAR sensors. Some are even powered by gas motors for extended endurance.

Among UAV types, multirotors are the most affordable and easier to construct. They are widely employed for tasks such as photography and video surveillance, available in configurations like tricopters, quadcopters, hexacopters, or octocopters (Table 1). However, they are less suitable for large-scale aerial mapping and long-distance monitoring due to limitations in speed, flight time, and energy efficiency. Typically, multirotor drones offer up to 30 minutes of flight time with a standard lightweight payload such as a camera. The quadcopter, in particular, stands out as the most prevalent UAV type based on its configuration with four propellers, forming the focus of our subsequent discussions.

DYNAMICS AND FLYING MECHANISMS

Consider an autonomous and adaptive quadcopter, characterized as an under-actuated system with four input engines and propellers that enable control over roll, pitch, yaw, and thrust, providing six degrees of freedom for movement [2]. The propellers, or rotors, have fixed-pitch mechanically movable blades (Figure 2(a)), meaning their pitch remains constant during rotation.

Stable flight necessitates precise control of the motor throttles. Control algorithms continuously adjust the throttle based on feedback to manage roll, pitch, yaw, and thrust. Yaw controls the stability of rotation around the vertical (Z-axis), pitch controls lateral tilting (Y-axis), and roll controls longitudinal tilting (X-axis).

Figure 2(b) illustrates two common rotor configurations: the '+' and 'X' patterns. In both configurations, opposite rotors rotate in the same direction, while the others rotate oppositely. The 'X' pattern offers greater stability and rotational acceleration compared to the '+' arrangement [5]. The '+' design facilitates maneuverability, suitable for sports flying, while the 'X' setup is ideal for aerial photography, keeping propellers out of the frame.

Figure 3 depicts a hierarchical swarm of quadcopters operating under a leader-subordinate model. A single user controls the swarm's movement and formation via a leader drone using a remote control interface. This self-organizing structure employs multi-agent control principles, with drones communicating wirelessly within and across hierarchical levels. Higher-level leader drones interface with ground-based servers for data sharing and mission objectives distribution.

MECHANICAL DESIGN

To ensure controlled movement amid disturbances, quadcopters require a well-balanced design and adaptive computing platform. Constructing an effective control system involves developing a dynamic model that accounts for all forces acting on the drone at any given time interval.

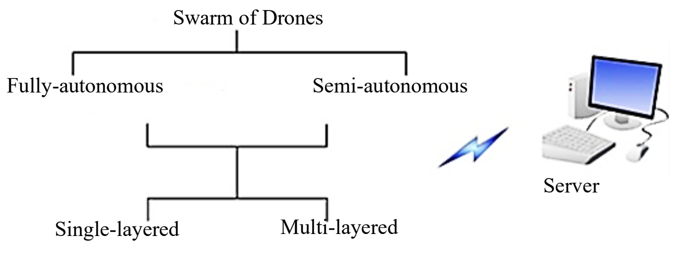

Figure 1. Classifications of swarms.

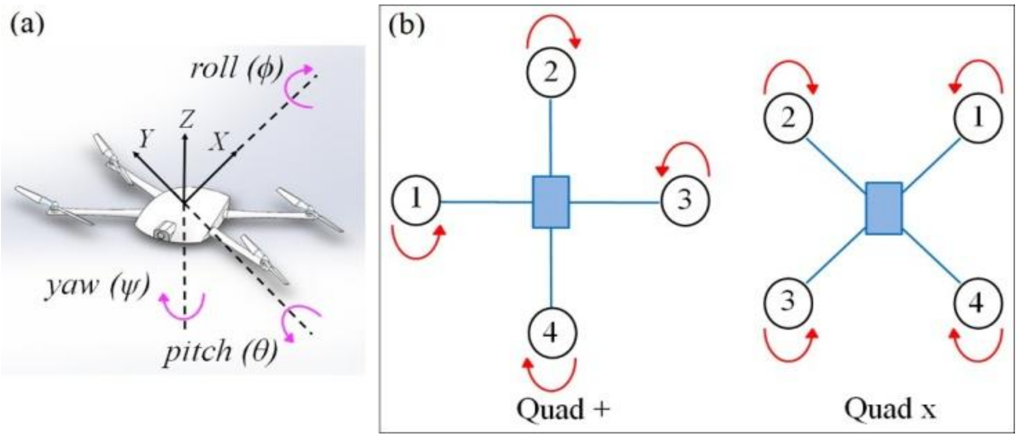

Figure 2. (a) Movement about axes, (b) Configuration of a quadcopter.

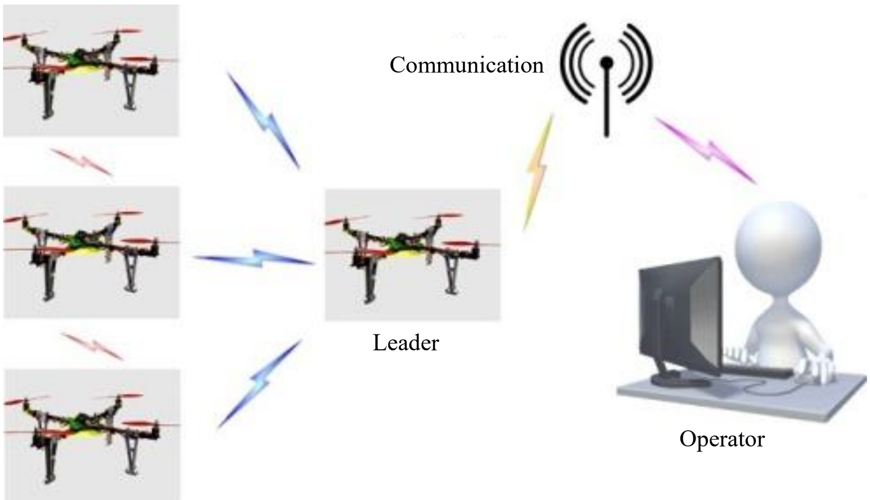

Figure 3. EXample of a hierarchical swarm of drones.

A battery-powered quadcopter, comprises of a mainframe base, Electronic Speed Control (ESC), Inertial Measurement Unit (IMU), central microcontrollers, electric motors, radio transmitters and receivers, batteries, sensors, and four rotors mounted on arms of the drone [6].

Electronic Speed Controllers (ESCs)

Brushless DC motors used in quadcopters require precise speed and direction control, which is mostly dependent on ESCs. They convert PWM signals from flight controllers into varying levels of electric power to adjust motor speed. This helps in precise control over the quadcopter's movement in the x-y plane. Position drift caused by slight motor speed variations can be compensated using feedback control systems.

Inertial Measurement Unit (IMU)

The IMU comprises accelerometers and gyroscopes. Accelerometers measure acceleration forces such as gravity along each axis, aiding in altitude determination. Gyroscopes measure angular rotation rates around each axis, enabling precise tracking of the quadcopter's orientation and movement.

Additional Sensors for Precision Control

- *Barometer:* Measures atmospheric pressure changes to determine altitude variations accurately.
- *Magnetometer:* Detects magnetic fields to determine heading direction, essential for navigation.
- *Altitude Sensors:* Provide real-time altitude data, complementing barometric measurements for improved accuracy.

Obstacle Detection and Avoidance Sensors

- *Ultrasonic Sensors:* Used for low-altitude operations to detect obstacles by emitting sound waves and measuring their reflection time.
- *Infrared Range Finders:* Detect proximity to objects based on infrared reflections.
- *LiDAR (Light Detection and Ranging):* Uses laser pulses to create high-resolution maps of surroundings, crucial for precise obstacle avoidance and mapping applications.

Camera

Cameras mounted on quadcopters serve multiple purposes:

- *Visual Feedback:* Provides real-time video feedback for situational awareness.
- *Image Recognition and Processing:* Enables identification of objects and terrain features.
- *3D Obstacle Identification:* Helps in detecting obstacles in three-dimensional space.
- *Indoor/Outdoor Facility Navigation:* Assists in navigating complex indoor and outdoor environments.

Global Positioning System (GPS)

GPS modules provide accurate positioning, velocity, and time information. They are essential for outdoor navigation, path planning, tracking, and localization tasks in surveillance and mapping missions.

Multi-Sensor Integration and Fusion

Combining data from multiple sensors (multi-sensor fusion) enhances reliability and accuracy in object detection, obstacle avoidance, and navigation tasks. This integration optimizes the quadcopter's performance in various operating conditions.

In [7], classical control techniques (P, PI, PD, and PID) were simulated on a quadcopter, highlighting the suitability of PD and PID controllers for steady-state stabilization, while P and PI controllers showed limitations. Similarly, [8] demonstrated successful flight tests using a gravity-compensated PID approach for altitude and attitude control of a tilt-wing UAV. Meanwhile, [9] proposed a PID cascade control architecture for trajectory tracking in a 3D environment, emphasizing its effectiveness during disturbances.

For micro aerial vehicles like quadrotors, [10] implemented a backstepping nonlinear control approach and Model Predictive Control (MPC) for precise trajectory generation and hover stability. Comparatively, [11] compared Backstepping and Sliding Mode Control (SMC) for micro quadrotors, noting SMC's robustness under high perturbations and Backstepping's effectiveness in orientation control.

Other studies focused on specific applications: [12] used Backstepping for autonomous take-off and landing, [13] enhanced altitude control with a Kalman filter and sensor fusion, and [14] applied pole placement with Kalman filtering for dynamic feedback linear control.

Visual feedback control strategies were explored in [15], where nested saturations showed superior performance in vehicle stability and energy consumption compared to backstepping and SMC methods. [16] explored PI, LQG, and SDRE algorithms for angular rate, attitude, and velocity stabilization in an aerial model autopilot.

Additionally, [17] employed Lyapunov functions and pole placement methods for stability and altitude control in an indoor micro quadcopter, while [18] analyzed UAV longitudinal dynamics using LQR for pitch control. [19] compared PID, LQR, LQG, and SMC techniques, highlighting SMC's minimal overshoot and steady-state error in pitch control.

Numerous advanced techniques are employed for UAV control, such as PID control, adaptive control, Boltzmann-Hamel equations, and various sensing and navigation methods [20–23]. These include marker recognition algorithms [24, 25], vision-based systems [26,27], and wireless communication [28–30]. Memory-based controllers [31], brain emotional learning-based intelligent controllers [32], and learning-based methods like fuzzy logic [33], neural networks [34], and iterative reinforcement learning [35–38] are also utilized. This discussion primarily focuses on the technologies of linear and model-based nonlinear controllers from a control engineering perspective.

In the realm of adaptive control, [39] proposed a model reference adaptive control scheme for altitude control of a miniature quadcopter, showing consistent performance across different payloads. Lastly, [40] implemented a two-stage robust controller for motion control in quadcopters, ensuring robust performance in the face of uncertainties and disturbances.

AUTONOMOUS SWARMS

A swarm of UAVs equipped with intelligent monitoring systems can efficiently cover designated target areas by utilizing multiple drones operating concurrently. This section discusses key characteristics of autonomous drone swarms.

BATTERY SWAPPING/RECHARGING

In missions requiring prolonged flight durations, an automated battery exchange system for individual drones or clusters is critical. Addressing data continuity during battery swaps, [40] introduced an autonomous refilling concept featuring hot battery swapping. This method involved supplying external power to a drone at a charging station, facilitating onboard data processing and communication with the base station while the drone remained docked. The system utilized a portable rocker arm and revolving carousel with four charging batteries, completing the entire swap process in approximately 60 seconds from landing to takeoff. Initially designed for a single quadcopter with a 15-minute flight capability, it could fully recharge a depleted battery in about 45 minutes. For swarms, [41] proposes expanding the charging station's capacity to handle multiple drones simultaneously, including leader and worker/slave configurations.

SMART ENERGY MANAGEMENT AND AUTOMATED MAINTENANCE

With the rise of UAV swarms, efficient energy management and automated maintenance have become crucial. In [42], researchers developed an autonomous Ground Recharge Station (GRS) that enhances single UAV charging efficiency through improved electrical contacts and a balancer mechanism to ensure proper circuit connectivity between the drone and recharging station. For swarm operations, the system includes a prioritization algorithm to manage charging sequence based on drone priority levels, ensuring higher priority drones receive charging precedence over lower priority ones.

ROBUSTNESS AGAINST COLLISIONS

Pico Quadcopter Design

In [43], researchers developed an 11 cm pico quadcopter weighing 25 g, capable of carrying up to 12 g of payload, including a small RF camera. The quadcopter was equipped with a 2 g carbon fiber cage designed to protect the device during collisions, enabling quick recovery. Smart control was facilitated by a custom autopilot board. Experimental tests included delta leader-follower and square formation flights, demonstrating robust performance even in dense formations. The quadcopters proved resilient to collisions at speeds up to 4 m/s.

Collision Avoidance Algorithm

In [15], a collision avoidance algorithm based on Model Predictive Control (MPC) was developed for reliable trajectory prediction during emergency evasive maneuvers. Simulations encompassed various collision scenarios, including one-on-one and one-to-many patterns. Flight tests with two helicopters validated the algorithm's effectiveness in averting face-to-face collision courses.

Ultrasound Localization for Collision Avoidance

Authors in [44] employed an affordable ultrasound localization method to create a collision avoidance system for commodity hardware quadcopters operating in Global Navigation Satellite Systems (GNSS) denied areas. Experimentation in two dimensions involved three quadcopters and at least two stationary anchors. The system's operational range was limited to a maximum distance of 12 m between anchors and quadcopters.

Quadcopter-based Surveillance Systems

Quadcopter-based surveillance systems are increasingly prominent due to advancements in maneuverability and payload capacity. Researchers are exploring various applications and technologies to enhance their effectiveness:

Swarm-based Surveillance and Target Tracking

In [45], algorithms were tested on a quadcopter swarm for surveillance and target tracking. Modeling the swarm as a multi-agent system aimed to optimize cooperation and ensure mission safety. Their path tracking approach facilitated smooth navigation in dense environments.

Autonomous Path Planning with Dynamic Grids

In [46], a scalable dynamic grid concept for cooperative quadcopters enabled efficient environment coverage. A nonlinear optimization approach determined optimal flying altitudes, ensuring comprehensive area surveillance. Additionally, [47,48] demonstrated quadcopter swarms' capabilities in object localization and tracking.

Swarm Design, Management, and Optimization

[49] utilized Organic Computing principles to develop a framework for designing and controlling quadcopter swarms. This IoT-enabled platform supported efficient interaction between operators and swarms, enhancing performance in 3D swarming applications.

Hovering Performance and Stability

Ensuring stable hovering and synchronized flight mechanisms is crucial. [50] implemented a two-stage controller to maintain individual drone stability and formation synchronization, even under single drone failure conditions.

Communication Reliability

Reliable communication is essential for mission success. [50] developed a motion-driven packet forwarding algorithm for micro aerial vehicle networks, ensuring connectivity over larger areas. Meanwhile, [51] employed the Takahashi Self Deployment algorithm to establish ad-hoc networks among quadcopter swarm agents. [52] utilized bandwidth-efficient coordination algorithms over 3G/4G networks to enable real-time coordination of UAV swarms across wide areas.

This restructuring aims to highlight each study's contributions and their significance in advancing quadcopter-based surveillance systems. For further reading on advanced sensor integration techniques and object detection methodologies in quadcopters, references [53], [54], and [55] provide comprehensive literature reviews and discussions on these topics.

CONTROLLING OF DRONES

Drone swarms, where multiple drones collaborate to efficiently cover large geographic areas, have garnered significant attention. Projects like the Low-cost UAV Swarm Technology [56] and initiatives by the Chinese Electronics Technology Group [57], showcased at events like the Farnborough air show in 2016, highlight efforts to enhance drone system impact through coordinated efforts. This coordination promises broader coverage, increased flexibility, and enhanced redundancy, essential for robust operations [58].

In a drone swarm, each drone functions as a simple agent within a networked control system. These agents operate collectively in a multi-agent system, leveraging network and computational integration to distribute simple behaviors across all drones. This integration enables collaborative behaviors capable of tackling complex tasks [59].

Addressing technical challenges, researchers focus on advancements in wireless communications and computational performance critical for decentralized flight control operations [60]. However, most current systems rely on centralized control, posing scalability and security limitations. Wireless environments, prone to channel variations and potential attacks, further challenge swarm functionalities like collision avoidance and formation control. A shift towards self-organizing properties becomes crucial, reducing dependency on centralized controllers that require frequent swarm status updates [61].

Successful self-organized drone swarm operations hinge on tightly integrating networking and computational systems [61]. Traditionally studied in isolation, their symbiotic relationship enhances network robustness. For instance, adaptive networking systems can optimize transmission channels and end-to-end paths based on computational predictions of wireless link quality or intermittently available paths, mitigating issues like packet loss due to shadowing effects [62].

The goal of this paper is to present a thorough examination of the process of creating self-organizing drone swarms as networked control systems, with a focus on the coupling effects and integration of networking and computational systems. It identifies key research challenges and open issues critical for advancing drone swarm technologies.

RELATED WORK

Despite the broad applicability of drone swarms, significant challenges remain in automating, securing, and scaling their operations. One approach involves Software-Defined Networking (SDN), where a centralized controller makes operational decisions for all drones in the swarm [63].

In contrast, efforts exploring interactive deployment strategies focus on either the networking system or the computational system [64, 65], overlooking their intricate interactions critical for comprehensive swarm control. Emerging network architectures like Named Data Networking (NDN) [66], Information Centric Networking (ICN) [67], and Named Function Networking (NFN) [68] aim to address mobility and computation distribution challenges inherent in IP-based solutions. These paradigms facilitate seamless mobility support and efficient task computation through content-based data forwarding and dynamic task management strategies [69].

This review underscores the need for integrated networking and computational systems to advance drone swarms as networked control systems, identifying key research challenges and opportunities in this evolving field.

The features of Named Function Networking (NFN), particularly its support for in-network task execution, autonomous function computation, and resolution of computing strategies and dynamic processes, make it ideal for designing networking protocols. These protocols are crucial for controlling, computing, and managing distributed systems like drone swarms. For instance, dynamic in-network execution of network resources is made possible by a Named Function as a Service (NFaaS) architecture built on NFN [70]. This framework connects network nodes and deploys forwarding strategies for message queries encompassing network functions. Comparably, Named Data Networking (NDN) NFN services use data packets to compute outcomes and distribute them across the network to numerous clients from a single data source [71].

Another protocol framework, Named Data Networking Function Chaining (NDN-FC), integrates information-centric networking technology into Internet of Things (IoT) platforms [72]. This architecture combines Service Function Chaining with NDN to support in-network execution, enhancing the efficiency of IoT networks by facilitating a variety of resourceful functions.

Drone Swarms as Networked Control Systems

Drone systems are typically mission-oriented, varying in scale and complexity, necessitating different network deployment strategies. A drone system may have a single drone or a collection of non-interacting drones connected to a ground control center for smaller, more straightforward missions. Larger-scale missions benefit from multiple interactive drones forming a drone swarm, leveraging consensus and swarm intelligence (Figure 3). Highly complex missions may involve multiple drone swarms connected via ground or satellite platforms for information sharing. In these scenarios, a drone swarm can be conceptualized as a Networked Control System (NCS) [73].

Networked Control System Model

A drone swarm can be modeled as an NCS, comprising computational systems (drones) interconnected through a communication network. An NCS is a closed-loop computational system controlled via a communication network, where control and feedback messages are exchanged among system units or agents in the form of information packets transmitted through the network. The functionality of an NCS relies on two fundamental elements:

- Computational systems equipped with sensors for data gathering, decision-making capabilities (e.g., flight control), and actuators for executing commands.
- A communication network that facilitates information transmission by using modules, standards, and protocols (such media access control and routing).

Each drone in a swarm is fitted with onboard computers that handle data processing and may run various micro-services for specific functions, including sensing, decision-making, and actuation.[74]. Operating as an NCS, a drone swarm evaluates outcomes and adjusts its behavior in a closed-loop fashion typical of NCSs. This enables drones to function as a collective of agents working towards common goals, exhibiting emergent behaviors where simple individual actions contribute to complex problem-solving [75]. In order to enable two major strategies—non-interactive and interactive interactions—the deployment of drone swarms primarily depends on wireless and networking technologies for delivering specialized data and control orders among drones or between drones and ground control.

NON-INTERACTIVE APPROACH TO DEPLOYMENT

Every drone under a non-interactive deployment technique connects directly to a ground control center. This station monitors the drones' status, including their location, sensor conditions, and network configurations. It also makes decisions and issues commands such as setting new waypoints.

This strategy creates a unified network structure where each drone forms a closed-loop control system, optimizing its operations independently. Communication remains essential as drones interact continuously with the ground control for tasks such as perception, communication, computation, and control.

Network Topology

In this deployment strategy, drones rely entirely on the ground controller for control and coordination. Efficient uplinks and downlinks are crucial, enabling the ground controller to relay flight instructions to the drones and collect data from them. In scenarios involving multiple drones, direct communication between drones or via the ground controller is not supported, as illustrated in Figure 4.

Communication and Technologies in Non-Interactive Deployment Strategy

In a non-interactive deployment strategy, each drone maintains a bidirectional communication link with a ground control system, facilitating direct transmission of application-specific data and control commands. This strategy is typically suitable for small-scale applications with limited coverage ranges.

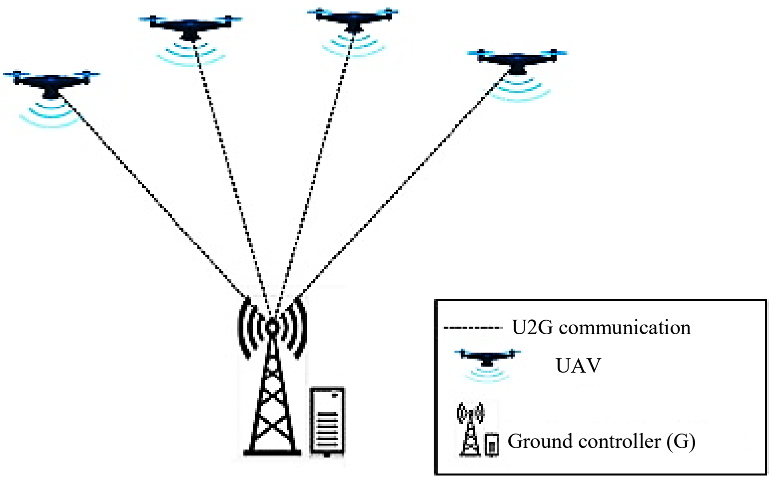

Figure 4. Non-interactive deployment.

However, it has notable limitations: the ground control station serves as a single point of failure for the entire network, potentially leading to network shutdowns. Additionally, transmission delays may occur due to the long wireless links required to cover larger areas. From a communication standpoint, the effectiveness of a non-interactive strategy hinges on precise air-to-ground channel modeling, antenna design, and mobility patterns.

Major Technologies

In this deployment strategy, drones autonomously gather data from themselves and their surroundings. This data is then transmitted to a ground control station for processing. The results of these computations are sent back to the drones and used by local actuators for decision-making and control purposes.

Communication Technologies

Cellular technologies like LTE offer enhanced system capacity, extensive coverage, high data rates, and low-latency deployment capabilities [76]. LTE, for example, supports data rates ranging from 0.07 to 1 Gbps and can cover distances up to 350 km using flexible spectrum.

In contrast, Low Power Wide-Area Networks (LPWAN), such as LoRaWAN, provide connectivity over broad areas using unlicensed frequency bands, characterized by low data rates, minimal power consumption, and lower throughput [77]. For instance, LoRaWAN offers data rates varying from 0.3 kbps to 50 kbps [77].

Computational Systems

In terms of computational systems, this deployment strategy can leverage precise mobility models or path planning algorithms such as Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Bee Colony Optimization (BCO) to optimize drone operations and decision-making processes.

INTERACTIVE DEPLOYMENT STRATEGY

Drone swarms that employ an interactive deployment method function independently, adjusting their course and other aspects of their environment—including nearby drones—based on their perceptions. This strategy fosters coordinated operations through cooperative sensing, monitoring, and information sharing among drones, enabling them to reach a consensus on optimal mission execution and navigate obstacles effectively. Communication in an autonomous drone swarm relies on a network system independent of a ground controller, except for emergencies.

In a fully autonomous system, drone swarms utilize airborne networks with strong line-of-sight capabilities, facilitating robust data transmission and enabling drones to generate suitable routing tables for decision-making based on nearby drone interactions. This localized operation, characteristic of self-organized systems, avoids the need for a centralized view of the entire swarm, which is advantageous in dynamic environments.

Regardless of the airborne network's topology, designing a reliable wireless communication system is crucial for enabling efficient swarm operations under dynamic propagation conditions [78]. Therefore, an interactive deployment strategy enables a more flexible swarm with higher density and extended range compared to a non-interactive approach.

Network Topology

Drones utilizing an interactive deployment method can speak with one another directly or via multiple hop linkages. [79]. As a result, the network topology can vary in complexity, ranging from ground-based communication networks to multiple air-to-air communication networks. The network in the latter scenario could be as simple as a single cluster or as complicated as a big flat ad hoc network with several clusters.

Infrastructure-Based Network

An infrastructure-based network in interactive deployments mirrors non-interactive deployment topologies (Figure 1), where all drones establish direct connections with a ground control station. The distinction lies in the ability of drones in interactive deployments to communicate with each other through the ground station, which acts as a central relay for all communications. However, relying solely on the ground controller to relay control information can lead to a less robust system due to its vulnerability as a single point of failure.

Decision-Making Process

In terms of decision-making, interactive deployments can adopt centralized or decentralized approaches. In a centralized approach, the ground controller makes decisions based on information gathered from all drones. In contrast, a decentralized approach allows each drone to make independent decisions based on shared information among drones via the ground controller, which acts solely as a relay in this scenario.

Cluster-Based Network

In a cluster-based network configuration, each drone connects to a designated cluster head, either predefined during system deployment or dynamically selected based on swarm status [80]. The cluster head manages communication within its cluster, serving as a central point through which all intra-cluster communications are routed. However, relying heavily on a cluster head can potentially create bottlenecks within the drone swarm, leading to congestion and increased latency.

This configuration can scale to include multiple clusters, with each cluster having its own designated cluster head. In both single and multiple cluster scenarios, cluster heads are responsible for establishing inter-cluster communication and managing communication between clusters and the ground control station.

Decision-Making Process

In a cluster-based network, decision-making can be decentralized, allowing drones to make individual decisions or reach consensus through communication with other drones via their respective cluster heads. This distributed decision-making capability is facilitated by drones communicating not only with the ground control but also directly with each other through the cluster heads. Figure 2 gives an example of a network with a multi-cluster topology made up of individual clusters.

Ad hoc-Based Network

In an ad hoc-based network deployment, drones communicate via one-hop or multi-hop wireless connections, typically organized in a flat structure without relying on cluster heads [81]. This method lessens the effect that a single node failure can have on the system as a whole.. The strategy also reduces downlink bandwidth and latency requirements due to shorter communication links between drones.

ADVANTAGES

The ad hoc-based network deployment strategy offers several advantages:

- *Scale-Up:* It supports scaling the network size efficiently.
- *Fault Tolerance:* It provides resilience to failures of individual nodes.
- *Device Autonomy:* Drones operate autonomously without strict hierarchical control.
- *Flexibility and Cost-Effectiveness:* Setting up such networks is flexible and less expensive compared to structured approaches [56].

NETWORK COVERAGE AND ORGANIZATION

Compared to cluster-based networks, an ad hoc network configuration allows packets to be routed over a number of hops, allowing the drone swarm's coverage to expand considerably. [82]. However, managing routing in a flat organization may lead to scalability challenges, prompting the organization of the ad hoc network into multiple separate clusters. Each cluster may then operate independently as a single ad hoc network, potentially requiring one or more cluster heads to act as gateways. Figure 3 depicts the general topology of several ad hoc networks that could combine to create an ad hoc network configuration based on clusters.

Major Technologies

Modeling a drone swarm as a Networked Control System (NCS) necessitates addressing communication requirements to ensure maximum system performance over an airborne wireless network. Problems including message mistakes, fading channels, delays, and transmission failures can severely impair system performance as a whole.

Effective wireless technologies are essential to connect all drones and facilitate robust interaction between them [83]. Technologies suitable for interactive strategies include IEEE 802.11 [84], 3G/LTE [85], and satellite communications [86]. However, alternative networking solutions must be explored further, considering drones' mobility and power limitations. The networking system must operate reliably in the face of irregular connections and device challenges while meeting delay and throughput requirements for various services. Communication protocols designed for closed-loop control systems face challenges in providing necessary guarantees, highlighting the need for robust and stable wireless solutions.

A substitute networking system ought to include routing protocols that can provide safe paths for data transfer from the point of origin to the final destination. Existing literature discusses various routing protocol families suitable for effective drone communications, including Swarm Intelligence-based, Position-based, and Topology-based protocols.

In interactive deployment strategies, computational resources are distributed across drones and the ground control station. This distribution requires careful task allocation to facilitate decision-making processes effectively.

System Components

Drone swarms integrate networking and computational systems to enable closed-loop operations within the Networked Control System (NCS). The operational chain involves sensing to gather environmental data and a networking system to transmit this data within the swarm for computation. Furthermore, the networking system ensures computational results reach drones needing information to adjust swarm behavior. This section looks at the networking system and the computational system, which are the core components of a drone swarm. It analyzes their characteristics, needs, and difficulties.

Networking System

A communication graph is established by the networking system to facilitate data exchange between drones and between drones and ground infrastructure. It plays a crucial role in ensuring closed-loop operations by facilitating data flow among sensing, decision-making, and actuation components, which may be distributed across different drones to enable cooperative sensing. For example, one drone sensing a new obstacle can relay this information to another drone capable of computing an appropriate action, which in turn coordinates with additional drones to navigate around the obstacle.

Communication within a drone swarm is essential not only for sharing observations, tasks, and control information but also for enhancing coordination and safety among drones. Due to drone energy limits and outside variables such wireless shadowing and sporadic connection availability, robust networking presents difficulties because the communication requirements vary greatly throughout applications.

The following subsections delve into analyzing the networking system's requirements, constraints, and considerations regarding its fundamental properties crucial for optimizing drone swarm operations.

Networking Demands

The data traffic in drone swarm operations can be categorized into two main types: command and control traffic, and coordination traffic [87].

- *Command and Control Traffic:* This type enables ground control to monitor and influence drone behavior, as well as receive status updates from drones.
- *Coordination Traffic:* This involves information crucial for cooperation among drones and collision avoidance.

In addition to these operational traffic types, drone communications may also include payload data, such as observations from onboard sensors like video cameras and data generated and consumed by payloads.

Regarding air-to-ground communication links, the International Telecommunications Union (ITU) and the 3rd Generation Partnership Project (3GPP) classify both command and control communication and payload communication for safe drone operations based on throughput, reliability, and latency requirements, as outlined in Table 1. These performance standards aim to ensure timely communication, processing, and coordinated movements in real time. While these standards primarily address centralized air-to-ground links (Figure 1), similar quality expectations should apply to air-to-air links between drones.

Networking Challenges

The mobility of drones, including changes in altitude and speed, presents inherent challenges for reliable communication due to the intermittent nature of wireless links and varying mobility patterns during missions. This mobility leads to an unstable network topology and introduces difficulties such as the Doppler effect and antenna alignment issues among neighboring drones, potentially decreasing network transmission performance. But drone mobility can also be used to increase bandwidth and transmission capacity by integrating store-carry-and-forward (SCF) capabilities into drones [88].

Drone systems are also subject to actuator failures and inherent uncertainties, including parametric variations in mass, inertia, velocity, altitude dynamics, elevation angles, and random aircraft noise during flight. External disturbances such as weather conditions and uncertainties related to wireless channel properties further impact system performance. Large-scale and small-scale fading phenomena, common in air-to-ground and air-to-air communications, pose significant challenges:

- *Large-scale Fading:* Includes free-space fading, attenuation, and shadowing. Free-space fading reduces transmission strength over line-of-sight (LOS) paths due to reflection and absorption effects from the Earth's surface [89]. Attenuation occurs as signals weaken over distance and through atmospheric conditions such as rain and gases [90]. Rainfall can scatter and diffract signals, increasing attenuation and transmission delays, while gases absorb wave energy, leading to severe propagation attenuation dependent on environmental factors [91, 92].

- *Shadowing Effect:* Caused by UAV bodies and misaligned antennas, impacting air-to-ground links particularly at lower altitudes due to obstacles like buildings and terrain, which obstruct LOS paths and degrade communication efficiency [93].

Moreover, the frequency bands used for drone communication (e.g., 2.4 GHz, 3.4 GHz, 5.8 GHz) are susceptible to environmental conditions such as buildings, trees, and distance between antennas, influencing drone control systems' ability to coordinate swarm movements. Higher frequency carriers may suffer from increased signal attenuation and packet loss due to their reduced ability to penetrate obstacles compared to lower frequency bands [89].

These challenges highlight the complexities involved in ensuring reliable and efficient communication for drone swarms, necessitating robust solutions tailored to dynamic operational environments.

Small-Scale Fading and Related Effects

In wireless communications, small-scale fading is brought on by interactions between the transmitter and receiver signals, which lead to reflection, scattering, and diffraction effects. The size, form, and texture of items in the surrounding environment have an impact on these effects.:

- *Reflection:* Occurs when signals bounce off objects on the Earth's surface, such as trees, causing propagation in line-of-sight (LOS) channels to split into multiple paths [94]. Drones' airframes and flat mountain slopes can also reflect signals [95].
- *Diffraction:* Results from obstacles like forest vegetation that diffract LOS propagation waves, creating additional signal paths [96].
- *Scattering:* Objects within the ground station area scatter LOS paths, affecting drone communications at altitudes above ground level [97].

These phenomena can significantly degrade signal propagation, leading to signal loss in extreme cases. Additionally, air-to-ground communications may experience interference from neighboring cells like macro-cells and pico-cells, reducing channel capacity and throughput [98].

These factors underscore the challenges in maintaining reliable and robust communication links for drone operations, particularly in dynamic and varied environmental conditions.

Networking Advances: Fading and Interference Mitigation

In addressing the challenges posed by wireless reliability issues in drone systems, several mitigation strategies can enhance wireless reliability, throughput, and minimize delays, crucial for maintaining high-quality channel propagation within drone swarms.

FADING AND INTERFERENCE MITIGATION

Higher Altitude Operation

Drones can operate at higher altitudes above ground stations and tall buildings, reducing the potential for interference with terrestrial radio cells and improving visibility to multiple cells [99]. This approach helps mitigate wave interference between drone-to-ground and inter-cell communications.

Wireless Beamforming

Utilizing wireless beamforming has been studied extensively to mitigate inter-cell interference. Reducing inter-cell and inter-sector channel interference and fading is the goal of beamforming technology, which is especially successful at millimeter-wave (mmWave) frequencies. By focusing transmission energy directionally, beamforming enhances spectral efficiency, energy efficiency, and overall throughput [100].

Benefits

Increases spectral efficiency and energy efficiency.

Considerations

Beamforming designs must balance between creating narrow beams, which require precise alignment but reduce interference, and broad beams, which simplify beam alignment but may cause excessive channel interference.

These advancements in fading and interference mitigation technologies represent significant strides in overcoming the challenges posed by wireless communication in drone operations.

Effective Antenna Placement and Configuration

In drones, antenna placement, design, and configuration are critical for efficient data exchange, especially considering their rapid mobility. Drones in motion can be equipped with omni-directional antennas, although their signal strength and throughput may be compromised. To mitigate this, multiple lightweight antenna systems with dual-polarized and cross-polarized MIMO configurations can be used, enhancing signal quality and channel capacity during maneuvers.

Drones can serve as aerial base stations to improve wireless coverage through multi-hop cooperation, capturing and transferring data to ground stations. This approach overcomes wireless constraints like shadowing, blockages, and signal attenuation, enhancing network spectrum efficiency, throughput, and reliability.

To address challenges such as actuator failures, system uncertainties, and external disturbances, a thorough control design is crucial for ensuring flight reliability, safety, and fault tolerance. Control solutions need to manage flight orientations, elevation angles, speed, and direction to enhance performance. Examples of effective strategies include finite-time fault-tolerant adaptive robust control, which handles systems with saturation constraints to ensure reliable control and precise tracking, and distributed consensus tracking control, which deals with multiple actuator faults, parametric uncertainties, and external disturbances in quadrotors.

Computing System

Computation within a drone swarm functions similarly to a networked control system (NCS), where simple data inputs can lead to complex decision-making. Developing an effective computational system requires investigating the best decision-making strategies based on the deployment strategy and intelligence algorithms used.

Self-Organized Decision Making

While all drones can manage basic flight control, only highly autonomous ones make mission-critical decisions without ground control. In a swarm, decision-making can be centralized or distributed. Centralized control suits low-autonomy swarms, reducing energy use and simplifying design, while high-autonomy swarms benefit from distributed control for better robustness and scalability. In complex scenarios, swarms self-organize, sharing data to make autonomous decisions and maintain connectivity (Figure 5).

Self-organizing algorithms facilitate this process. The control architecture is decentralized, with each UAV making independent decisions that collectively lead to emergent behavior, unaffected by scale changes or node removal. The decision-making process is divided into Perception, Decision, and Action stages. UAVs gather positional and velocity data, optimize decisions based on modeling, and execute the best possible actions, ensuring continuous coordination and optimization [101].

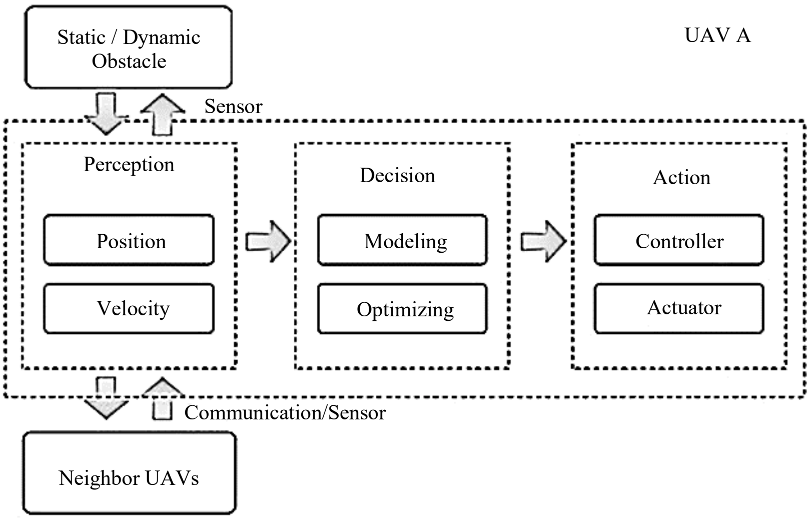

Figure 5. Self-organizing decision-making procedures.

Swarm Intelligence

The objective of swarm intelligence is to enable drone systems to perform sophisticated and complex behaviors through cooperation, organization, and information sharing. In a swarm intelligence system, simple agents (drones) interact locally with each other and their surroundings. This method emulates biological systems, where agents (such as ants or bees) follow basic rules without centralized control, resulting in the emergence of collective behaviors. Swarm intelligence algorithms focus on controlling drone swarms using two primary strategies: optimization and consensus. This article examines various optimization techniques, including Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Bee Colony Optimization (BCO), as well as consensus methods, with particular emphasis on the Paxos and Raft algorithms [102].

PSO, proposed by Kennedy and Eberhart in 1995, is inspired by the flocking behave Proposed by Kennedy and Eberhart in 1995, Particle Swarm Optimization (PSO) draws inspiration from the flocking behavior of birds. It facilitates collaboration among drones to find optimal solutions to problems, such as avoiding obstacles. The PSO algorithm works by continuously adjusting the velocities and positions of drones within the solution space. Through the exchange of information, drones are guided towards optimal positions in relation to their neighbors, fostering strong cooperative behavior for improved collective performance or of birds. It enables drones to cooperate in searching for the best solution to a problem, such as obstacle avoidance. The PSO algorithm continuously updates the velocities and positions of drones in the solution space. By sharing this information, the algorithm allows drones to move towards optimal positions relative to their neighbors, maintaining strong bonds for collective performance [103].

Computing and Networking Integration

In drone swarms, creating a closed-loop system requires a tight coupling between computational and networking systems, implying mutual influences and dependencies. Understanding these consolidated system effects is crucial for optimizing the scarce resources each drone has for sensing, computation, and networking tasks.

Networking Supporting Computing

Networking significantly supports the computational system by creating a topology that enables data exchange among drones in the swarm. The networking system transports data required by the computational system, while each drone shares its computational outcomes through the network to achieve consensus. This makes the performance of the networking system crucial for real-time data tasks.

In a pure IP networking solution, like those using mobile ad hoc routing protocols, each drone must know which other drones to communicate with for functions like collision avoidance. Because each drone must keep and update a certain amount of state information, this may cause scalability and performance difficulties. Using a networking architecture based on named data objects—which enables drones to retrieve necessary data even when they are unsure of its location within the swarm—is one possible approach. This approach can enhance performance by reducing delays through caching but requires two-level operations: fetching data and discovering the needed computational function.

Given energy constraints, not all drones can run all computational functions for the swarm's control. A more efficient solution involves a networking system capable of resolving computational functions rather than just data names. The Named Function Network (NFN) allows requesters to be agnostic about the swarm's status, enhancing self-organization as drones only store local information. It should be noted that NFN relies on the swarm's complete trust, which is not always the case. Thus, an NFN-based system should transparently evaluate computational function results to ensure reliability and security.

Computing Supporting Networking

The computational system can significantly enhance networking in various scenarios. Environmental changes, such as altitude or terrain variations, can impact channel models and network performance. To enhance networking performance, the computational system may measure and model the wireless channel and classify it based on predetermined rules. Research has aimed to embed computation into the networking system to boost performance. High latency and low transmission rates are reduced using intelligent algorithms such as P4-assisted constraint operations. These functions focus on data plane operations, such as aggregating acknowledgment messages, supporting multicast, improving routing decisions, scaling forwarding based on current conditions (e.g., link quality, drone mobility), and reducing communication overhead considering communication cost constraints. In a drone swarm, communication security and data protection are crucial due to wireless channel hazards. The functioning of the swarm can be jeopardized by misbehavior and information leaks, which can also cause bodily harm. The integration of computing within the swarm facilitates the processing of data and traffic at a line-rate within the network, while also offering security and privacy features such as intrusion detection, attack prevention, and incident analysis.

Introducing a computational system enhances decision-making, helping drones better control their networking based on their properties and environmental status.

OPEN RESEARCH ISSUES

Integrating Networking and Computing

Combining discrete computational processes with continuous networking processes is challenging. Both systems continuously estimate the swarm's best behavior under specific conditions with strict spatial-temporal constraints. Modeling a drone swarm as a networked control system (NCS) requires considering the influence of time, which is often neglected in event or agent models. Additionally, some networking functions based on best-effort service do not align with NCS requirements for high reliability. Due to the distributed nature of drone swarms, various devices are used by system components, which means that synchronization, handling of timing and network state irregularities, and network delay management are required.

Resource Constraints

Drones have limited resources, especially when it comes to services like pattern recognition and video processing that demand a lot of computing power. Using concepts like mobile edge computing, computation offloading can help with these issues. By shifting work to neighboring ground infrastructure, game theory, in conjunction with resource scheduling and job allocation systems, can accomplish a trade-off between computation time and energy consumption.

Resource Management

Efficient resource management in drone swarms, given limited resources, may require cooperation to increase efficiency. Assigning tasks to various drones to achieve parallel processing goals is challenging.

Energy Efficiency

Networking systems consume more energy than computational systems in drones. Extending the drone system's lifetime and communication capability is crucial. Increasing the lifespan of individual drones and the swarm as a whole requires effective coordination of networking and computational systems.

This process requires cooperation among drones, which is complicated by their motion characteristics and the tight coupling between networking performance and swarm behavior.

Security Issues

Drone swarms face increased security issues compared to traditional NCS. Operating in open spaces, drones are more accessible to third parties. Additionally, wireless communication infrastructure is harder to secure than wired infrastructure. Since drones are more vulnerable to malicious attacks than wired NCS, further research into drone security is necessary.

CONCLUSION

Drone swarms and networked control systems (NCSs) are gaining significant attention. The development of drone swarms as NCSs is anticipated to improve their performance when confronted with environmental and operational difficulties. The purpose of this review is to further our understanding of drone swarms as NCSs. In order to implement two different deployment techniques, we first analyze the topologies and technologies needed. The review also describes the two fundamental building blocks of any drone swarm: networking and computational systems. We provide a thorough analysis of how to integrate these components to achieve a self-organized swarm system.

We show that addressing the main obstacles in developing drone swarms as NCSs may be achieved by constructing a networking system that does not rely on identifying hosts (e.g., drones) but rather concentrates on computational functions deployable on any drone. Utilizing a networking system capable of resolving on-demand computation expressions composed of named data and functions transparently for each drone enhances the self-organization properties of the swarm.

REFERENCES

1. Boriceanu AM. The use of unmanned aerial vehicles for monitoring purposes in civilian applications. Review of the Air Force Academy. 2021(1):17-26.
2. Luukkonen T. Modelling and Control of Quadcopter, Aalto University, Espoo, Finland, 2011.
3. Špinka O, Kroupa S, Hanzálek Z. Control system for unmanned aerial vehicles, 5th IEEE International Conference on Industrial Informatics (INDIN), Vienna, Austria, 2007, pp. 455–460.
4. Tahir A, Böling J, Haghbayan MH, Toivonen HT, Plosila J. Swarms of unmanned aerial vehicles—a survey. Journal of Industrial Information Integration. 2019 Dec 1;16:100106.
5. Thu KM, Gavrilov AI. Designing and modeling of quadcopter control system using L1 adaptive control. Procedia Computer Science. 2017 Jan 1;103:528-35.
6. Vanin M. Quadrocopter Manual, KTH Royal Institute of Technology, 2014.
7. Navajas GT, Prada SR. Building your own quadrotor: A mechatronics system design case study. In2014 III International Congress of Engineering Mechatronics and Automation (CIIMA) 2014 Oct 22 (pp. 1-5). IEEE.
8. Liu Y, Montenbruck JM, Stegagno P, Allgöwer F, Zell A. A robust nonlinear controller for nontrivial quadrotor maneuvers: Approach and verification. In2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) 2015 Sep 28 (pp. 5410-5416). IEEE.

9. Beck H, Lesueur J, Charland-Arcand G, Akhrif O, Gagné S, Gagnon F, Couillard D. Autonomous takeoff and landing of a quadcopter. In2016 international conference on unmanned aircraft systems (ICUAS) 2016 Jun 7 (pp. 475-484). IEEE.
10. Asadpour M, Hummel KA, Giustiniano D, Draskovic S. Route or carry: Motion-driven packet forwarding in micro aerial vehicle networks. IEEE Transactions on Mobile Computing. 2016 May 3;16(3):843-56.
11. Bouabdallah S, Murrieri P, Siegwart R. Design and control of an indoor micro quadrotor. InIEEE International Conference on Robotics and Automation, 2004. Proceedings. ICRA'04. 2004 2004 Apr 26 (Vol. 5, pp. 4393-4398). IEEE.
12. Hetényi D, Gótzy M, Blázovics L. Sensor fusion with enhanced Kalman Filter for altitude control of quadrotors. In2016 IEEE 11th International Symposium on Applied Computational Intelligence and Informatics (SACI) 2016 May 12 (pp. 413-418). IEEE.
13. Grzonka S, Grisetti G, Burgard W. Towards a navigation system for autonomous indoor flying. In2009 IEEE international conference on Robotics and Automation 2009 May 12 (pp. 2878-2883). IEEE.
14. Pfeifer E, Kassab Jr F. Dynamic feedback controller of an unmanned aerial vehicle. In2012 Brazilian Robotics Symposium and Latin American Robotics Symposium 2012 Oct 16 (pp. 261-266). IEEE.
15. Shim DH, Sastry S. An evasive maneuvering algorithm for UAVs in see-and-avoid situations. In2007 American Control Conference 2007 Jul 9 (pp. 3886-3891). IEEE.
16. Sundqvist J, Ekskog J, Dil BJ, Gustafsson F, Tordenlid J, Petterstedt M. Feasibility study on smartphone localization using mobile anchors in search and rescue operations. In2016 19th International Conference on Information Fusion (FUSION) 2016 Jul 5 (pp. 1448-1453). IEEE.
17. Pearce C, Guckenberg M, Holden B, Leach A, Hughes R, Xie C, Hassett M, Adderley A, Barnes LE, Sherriff M, Lewin GC. Designing a spatially aware, automated quadcopter using an Android control system. In2014 Systems and Information Engineering Design Symposium (SIEDS) 2014 Apr 25 (pp. 23-28). IEEE.
18. Lee GH, Fraundorfer F, Pollefeys M. RS-SLAM: RANSAC sampling for visual FastSLAM. In2011 IEEE/RSJ International Conference on Intelligent Robots and Systems 2011 Sep 25 (pp. 1655-1660). IEEE.
19. Baek JY, Park SH, Cho BS, Lee MC. Position tracking system using single RGB-D Camera for evaluation of multi-rotor UAV control and self-localization. In2015 IEEE International Conference on Advanced Intelligent Mechatronics (AIM) 2015 Jul 7 (pp. 1283-1288). IEEE.
20. Achtelik M, Zhang T, Kuhnlenz K, Buss M. Visual tracking and control of a quadcopter using a stereo camera system and inertial sensors. In2009 International Conference on Mechatronics and Automation 2009 Aug 9 (pp. 2863-2869). IEEE.
21. Blösch M, Weiss S, Scaramuzza D, Siegwart R. Vision based MAV navigation in unknown and unstructured environments. In2010 IEEE International Conference on Robotics and Automation 2010 May 3 (pp. 21-28). IEEE.
22. Yang R, Wang X. Vision control system for quadcopter. In2013 IEEE third international conference on information science and technology (ICIST) 2013 Mar 23 (pp. 261-264). IEEE.
23. Berrahal S, Kim JH, Rekhis S, Boudriga N, Wilkins D, Acevedo J. Unmanned aircraft vehicle assisted WSN-based border surveillance. In2015 23rd International Conference on Software, Telecommunications and Computer Networks (SoftCOM) 2015 Sep 16 (pp. 132-137). IEEE.
24. Shetti K, Vijayakumar A. Evaluation of compressive sensing encoding on ar drone. In2015 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA) 2015 Dec 16 (pp. 204-207). IEEE.
25. Andaluz VH, Chicaiza FA, Meythaler A, Rivas DR, Chuchico CP. Construction of a quadcopter for autonomous and teleoperated navigation. In2015 Conference on Design of Circuits and Integrated Systems (DCIS) 2015 Nov 25 (pp. 1-6). IEEE.

26. Dasgupta R, Mukherjee R, Gupta A. A novel approach of sensor data retrieving using a quadcopter in wireless sensor network forming concentric circular topology. In2015 6th International Conference on Automation, Robotics and Applications (ICARA) 2015 Feb 17 (pp. 238-245). IEEE.
27. Filatova ES, Devyatkin AV, Fridrix AI. UAV fuzzy logic stabilization system. In2017 XX IEEE International Conference on Soft Computing and Measurements (SCM) 2017 May 24 (pp. 132-134). IEEE.
28. Dunfied J, Tarbouchi M, Labonte G. Neural network based control of a four rotor helicopter. In2004 IEEE International Conference on Industrial Technology, 2004. IEEE ICIT'04. 2004 Dec 8 (Vol. 3, pp. 1543-1548). IEEE.
29. Schoellig AP, Mueller FL, D'andrea R. Optimization-based iterative learning for precise quadrocopter trajectory tracking. Autonomous Robots. 2012 Aug;33:103-27.
30. Palunko I, Faust A, Cruz P, Tapia L, Fierro R. A reinforcement learning approach towards autonomous suspended load manipulation using aerial robots. In2013 IEEE international conference on robotics and automation 2013 May 6 (pp. 4896-4901). IEEE.
31. Wang W, Ma H, Sun CY. Control system design for multi-rotor mav. Journal of Theoretical and Applied Mechanics. 2013;51(4):1027-38.
32. Jafari M, Shahri AM, Shouraki SB. Attitude control of a quadrotor using brain emotional learning based intelligent controller. In2013 13th Iranian Conference on Fuzzy Systems (IFSC) 2013 Aug 27 (pp. 1-5). IEEE.
33. Öner KT, Çetinsoy E, Sirimoğlu EF, Hançer C, Ünel M, Akşit MF, Gülez K, Kandemir I. Mathematical modeling and vertical flight control of a tilt-wing UAV. Turkish Journal of Electrical Engineering and Computer Sciences. 2012;20(1):149-57.
34. Paiva EA, Soto JC, Salinas JA, Ipanaqué W. Modeling and PID cascade control of a Quadcopter for trajectory tracking. In2015 CHILEAN Conference on Electrical, Electronics Engineering, Information and Communication Technologies (CHILECON) 2015 Oct 28 (pp. 809-815). IEEE.
35. Bouabdallah S, Siegwart R. Backstepping and sliding-mode techniques applied to an indoor micro quadrotor. InProceedings of the 2005 IEEE international conference on robotics and automation 2005 Apr 18 (pp. 2247-2252). IEEE.
36. [36]Carrillo LG, Dzul A, Lozano R. Hovering quad-rotor control: A comparison of nonlinear controllers using visual feedback. IEEE Transactions on Aerospace and Electronic Systems. 2012 Oct 8;48(4):3159-70.
37. Abozaid MR. LQR Based a UAV Pitch Controller System Design. InThe Libyan Arab International Conference on Electrical and Electronic Engineering (LAICEEE) 2010.
38. Nair MP, Harikumar R. Longitudinal dynamics control of UAV. In2015 International Conference on Control Communication & Computing India (ICCC) 2015 Nov 19 (pp. 30-35). IEEE.
39. Emran BJ, Dias J, Seneviratne L, Cai G. Robust adaptive control design for quadcopter payload add and drop applications. In2015 34th Chinese Control Conference (CCC) 2015 Jul 28 (pp. 3252-3257). IEEE.
40. Liu H, Xi J, Zhong Y. Robust motion control of quadrotors. Journal of the Franklin Institute. 2014 Dec 1;351(12):5494-510.
41. Lee D, Zhou J, Lin WT. Autonomous battery swapping system for quadcopter. In2015 international conference on unmanned aircraft systems (ICUAS) 2015 Jun 9 (pp. 118-124). IEEE.
42. Leonard J, Savvaris A, Tsourdos A. Energy management in swarm of unmanned aerial vehicles. Journal of Intelligent & Robotic Systems. 2014 Apr;74:233-50.
43. Mulgaonkar Y, Cross G, Kumar V. Design of small, safe and robust quadrotor swarms. In2015 IEEE international conference on robotics and automation (ICRA) 2015 May 26 (pp. 2208-2215). IEEE.
44. Vedder B, Eriksson H, Skarin D, Vinter J, Jonsson M. Towards collision avoidance for commodity hardware quadcopters with ultrasound localization. In2015 International Conference on Unmanned Aircraft Systems (ICUAS) 2015 Jun 9 (pp. 193-203). IEEE.
45. [45]Leonard J, Savvaris A, Tsourdos A. Towards a fully autonomous swarm of unmanned aerial vehicles. InProceedings of 2012 UKACC international conference on control 2012 Sep 3 (pp. 286-291). IEEE.

46. Wallar A, Plaku E, Sofge DA. A planner for autonomous risk-sensitive coverage (PARCov) by a team of unmanned aerial vehicles. In2014 IEEE Symposium on Swarm Intelligence 2014 Dec 9 (pp. 1-7). IEEE.
47. Pestana J, Sanchez-Lopez JL, de la Puente P, Carrio A, Campoy P. A vision-based quadrotor swarm for the participation in the 2013 international micro air vehicle competition. In2014 International Conference on Unmanned Aircraft Systems (ICUAS) 2014 May 27 (pp. 617-622). IEEE.
48. Ma'Sum MA, Jati G, Arrofi MK, Wibowo A, Mursanto P, Jatmiko W. Autonomous quadcopter swarm robots for object localization and tracking. InMHS2013 2013 Nov 10 (pp. 1-6). IEEE.
49. von Mammen S, Tomforde S, Höhner J, Lehner P, Förschner L, Hiemer A, Nicola M, Blickling P. OCbotics: an organic computing approach to collaborative robotic swarms. In2014 IEEE Symposium on Swarm Intelligence 2014 Dec 9 (pp. 1-8). IEEE.
50. Niemoczynski B, Biswas S, Kollmer J, Ferrese F. Hovering synchronization of a fleet of quadcopters. In2014 7th International Symposium on Resilient Control Systems (ISRCS) 2014 Aug 19 (pp. 1-5). IEEE.
51. Alvissalim MS, Zaman B, Hafizh ZA, Ma'sum MA, Jati G, Jatmiko W, Mursanto P. Swarm quadrotor robots for telecommunication network coverage area expansion in disaster area. In2012 Proceedings of SICE Annual Conference (SICE) 2012 Aug 20 (pp. 2256-2261). IEEE.
52. de Souza BJ, Endler M. Coordinating movement within swarms of UAVs through mobile networks. In2015 IEEE International conference on pervasive computing and communication workshops (PerCom Workshops) 2015 Mar 23 (pp. 154-159). IEEE.
53. Chen Y. Industrial information integration—A literature review 2006–2015. Journal of industrial information integration. 2016 Jun 1;2:30-64.
54. Farahnakian F, Haghbayan MH, Poikonen J, Laurinen M, Nevalainen P, Heikkonen J. Object detection based on multi-sensor proposal fusion in maritime environment. In2018 17th IEEE International Conference on Machine Learning and Applications (ICMLA) 2018 Dec 17 (pp. 971-976). IEEE.
55. Haghbayan MH, Farahnakian F, Poikonen J, Laurinen M, Nevalainen P, Plosila J, Heikkonen J. An efficient multi-sensor fusion approach for object detection in maritime environments. In2018 21st International Conference on Intelligent Transportation Systems (ITSC) 2018 Nov 4 (pp. 2163-2170). IEEE.
56. Chen X, Tang J, Lao S. Review of unmanned aerial vehicle swarm communication architectures and routing protocols. Applied Sciences. 2020 May 25;10(10):3661.
57. Liu X, Yin D, Zhou Y, Liu Z, Wang Y. Dispatching and management methods for communication of UAV swarm. InProceedings of the 2nd International Conference on High Performance Compilation, Computing and Communications 2018 Mar 15 (pp. 61-67).
58. Chmaj G, Selvaraj H. Distributed processing applications for UAV/drones: a survey. InProgress in Systems Engineering: Proceedings of the Twenty-Third International Conference on Systems Engineering 2015 (pp. 449-454). Springer International Publishing.
59. Sun W, Tang M, Zhang L, Huo Z, Shu L. A survey of using swarm intelligence algorithms in IoT. Sensors. 2020 Mar 5;20(5):1420.
60. Engebråten S, Glette K, Yakimenko O. Field-testing of high-level decentralized controllers for a multi-function drone swarm. In2018 IEEE 14th International Conference on Control and Automation (ICCA) 2018 Jun 12 (pp. 379-386). IEEE.
61. Cook JA, Kolmanovsky IV, McNamara D, Nelson EC, Prasad KV. Control, computing and communications: technologies for the twenty-first century model T. Proceedings of the IEEE. 2007 Feb;95(2):334-55.
62. Gupta L, Jain R, Vaszkun G. Survey of important issues in UAV communication networks. IEEE communications surveys & tutorials. 2015 Nov 3;18(2):1123-52.
63. Wickboldt JA, De Jesus WP, Isolani PH, Both CB, Rochol J, Granville LZ. Software-defined networking: management requirements and challenges. IEEE Communications Magazine. 2015 Jan 16;53(1):278-85.

64. Hayat S, Yanmaz E, Muzaffar R. Survey on unmanned aerial vehicle networks for civil applications: A communications viewpoint. IEEE Communications Surveys & Tutorials. 2016 Apr 29;18(4):2624-61.
65. Ebeid E, Skriver M, Jin J. A survey on open-source flight control platforms of unmanned aerial vehicle. In2017 euromicro conference on digital system design (dsd) 2017 Aug 30 (pp. 396-402). IEEE.
66. Zhang, L.; Estrin, D.; Burke, J.; Jacobson, V.; Thornton, J.D.; Smetters, D.K.; Zhang, B.; Tsudik, G.; Massey, D.; Papadopoulos, C.; et al. Named data networking (ndn) project. In *Relatório Técnico NDN-0001*; Xerox Palo Alto Research Center: Palo Alto, CA, USA, 2010; Volume 157, p. 158.
67. Scherb C, Tschudin C. Smart execution strategy selection for multi tier execution in named function networking. In2018 IEEE International Conference on Communications Workshops (ICC Workshops) 2018 May 20 (pp. 1-6). IEEE.
68. Marxer C, Scherb C, Tschudin C. Access-controlled in-network processing of named data. InProceedings of the 3rd ACM Conference on Information-Centric Networking 2016 Sep 26 (pp. 77-82).
69. Scherb C, Grewe D, Wagner M, Tschudin C. Resolution strategies for networking the IoT at the edge via named functions. In2018 15th IEEE Annual Consumer Communications & Networking Conference (CCNC) 2018 Jan 12 (pp. 1-6). IEEE.
70. Król M, Psaras I. NFaaS: Named function as a service. InProceedings of the 4th ACM Conference on Information-Centric Networking 2017 Sep 26 (pp. 134-144).
71. Marxer C, Tschudin C. Result Provenance in Named Function Networking. InProceedings of the 7th ACM Conference on Information-Centric Networking 2020 Sep 22 (pp. 24-29).
72. Kumamoto Y, Yoshii H, Nakazato H. Real-world implementation of function chaining in named data networking for iot environments. In2020 IEEE International Workshop Technical Committee on Communications Quality and Reliability (CQR) 2020 May 14 (pp. 1-6). IEEE.
73. Gupta RA, Chow MY. Networked control system: Overview and research trends. IEEE transactions on industrial electronics. 2009 Nov 6;57(7):2527-35.
74. Chen W, Liu B, Huang H, Guo S, Zheng Z. When UAV swarm meets edge-cloud computing: The QoS perspective. IEEE Network. 2019 Mar 27;33(2):36-43.
75. Campion M, Ranganathan P, Faruque S. UAV swarm communication and control architectures: a review. Journal of Unmanned Vehicle Systems. 2018 Nov 29;7(2):93-106.
76. Kim Y, Kim Y, Oh J, Ji H, Yeo J, Choi S, Ryu H, Noh H, Kim T, Sun F, Wang Y. New radio (NR) and its evolution toward 5G-advanced. IEEE Wireless Communications. 2019 Jun;26(3):2-7.
77. Haxhibeqiri J, De Poorter E, Moerman I, Hoebeke J. A survey of LoRaWAN for IoT: From technology to application. Sensors. 2018 Nov 16;18(11):3995.
78. Cui Q, Liu P, Wang J, Yu J. Brief analysis of drone swarms communication. In2017 IEEE International Conference on Unmanned Systems (ICUS) 2017 Oct 27 (pp. 463-466). IEEE.
79. Mozaffari M, Saad W, Bennis M, Nam YH, Debbah M. A tutorial on UAVs for wireless networks: Applications, challenges, and open problems. IEEE communications surveys & tutorials. 2019 Mar 5;21(3):2334-60.
80. Cumino P, Maciel K, Tavares T, Oliveira H, Rosário D, Cerqueira E. Cluster-based control plane messages management in software-defined flying ad-hoc network. Sensors. 2019 Dec 21;20(1):67.
81. Bekmezci I, Sen I, Erkalkan E. Flying ad hoc networks (FANET) test bed implementation. In2015 7th International conference on recent advances in space technologies (RAST) 2015 Jun 16 (pp. 665-668). IEEE.
82. Rosário D, Arnaldo Filho J, Rosário D, Santosy A, Gerla M. A relay placement mechanism based on UAV mobility for satisfactory video transmissions. In2017 16th Annual Mediterranean Ad Hoc Networking Workshop (Med-Hoc-Net) 2017 Jun 28 (pp. 1-8). IEEE.
83. Park P, Ergen SC, Fischione C, Lu C, Johansson KH. Wireless network design for control systems: A survey. IEEE Communications Surveys & Tutorials. 2017 Dec 6;20(2):978-1013.
84. Macha Sarada D, Damodaram A. Review of 802.11 based Wireless Local Area Networks and Contemporary Standards: Features, Issues and Research Objectives. Glob. J. Comput. Sci. Technol. 2016;16.

85. Furht B, Ahson SA, editors. Long Term Evolution: 3GPP LTE radio and cellular technology. Crc Press; 2016 Apr 19.
86. Maral G, Bousquet M, Sun Z. Satellite communications systems: systems, techniques and technology. John Wiley & Sons; 2020 Apr 6.
87. Andre T, Hummel KA, Schoellig AP, Yanmaz E, Asadpour M, Bettstetter C, Grippa P, Hellwagner H, Sand S, Zhang S. Application-driven design of aerial communication networks. IEEE Communications Magazine. 2014 May 19;52(5):129-37.
88. Wei Z, Wu H, Huang S, Feng Z. Scaling laws of unmanned aerial vehicle network with mobility pattern information. IEEE Communications Letters. 2017 Feb 20;21(6):1389-92.
89. Khuwaja AA, Chen Y, Zhao N, Alouini MS, Dobbins P. A survey of channel modeling for UAV communications. IEEE Communications Surveys & Tutorials. 2018 Jul 16;20(4):2804-21.
90. Mahbub M. Uav assisted 5g het-net: A highly supportive technology for 5g nr network enhancement. EAI Endorsed Transactions on Internet of Things. 2020 Jul 16;6(22).
91. Giannetti F, Luise M, Reggiannini R. Mobile and personal communications in the 60 GHz band: A survey. Wireless Personal Communications. 1999 Jul;10:207-43.
92. Hemadeh IA, Satyanarayana K, El-Hajjar M, Hanzo L. Millimeter-wave communications: Physical channel models, design considerations, antenna constructions, and link-budget. IEEE Communications Surveys & Tutorials. 2017 Dec 14;20(2):870-913.
93. Holis J, Pechac P. Elevation dependent shadowing model for mobile communications via high altitude platforms in built-up areas. IEEE Transactions on Antennas and Propagation. 2008 Apr 3;56(4):1078-84.
94.] Malik WQ, Allen B, Edwards DJ. Impact of bandwidth on small-scale fade depth. InIEEE GLOBECOM 2007-IEEE Global Telecommunications Conference 2007 Nov 26 (pp. 3837-3841). IEEE.
95. Matolak DW, Sun R. Air–ground channel characterization for unmanned aircraft systems—Part III: The suburban and near-urban environments. IEEE Transactions on Vehicular Technology. 2017 Jan 26;66(8):6607-18.
96. Khawaja W, Guvenc I, Matolak D. UWB channel sounding and modeling for UAV air-to-ground propagation channels. In2016 IEEE global communications conference (GLOBECOM) 2016 Dec 4 (pp. 1-7). IEEE.
97. Cid EL, Alejos AV, Sanchez MG. Signaling through scattered vegetation: Empirical loss modeling for low elevation angle satellite paths obstructed by isolated thin trees. ieee vehicular technology magazine. 2016 Jul 29;11(3):22-8.
98. Zhang S, Liew SC, Chen J. The capacity of known interference channel. IEEE Journal on Selected Areas in Communications. 2015 Mar 25;33(6):1241-52.
99. Zhang C, Zhang W, Wang W, Yang L, Zhang W. Research challenges and opportunities of UAV millimeter-wave communications. IEEE Wireless Communications. 2019 Feb 13;26(1):58-62.
100. Sultan Q, Khan MS, Cho YS. Fast 3D beamforming technique for millimeter-wave cellular systems with uniform planar arrays. IEEE Access. 2020 Jul 1;8:123469-82.
101. Qiu Z, Chu X, Calvo-Ramirez C, Briso C, Yin X. Low altitude UAV air-to-ground channel measurement and modeling in Semiurban environments. Wireless Communications and Mobile Computing. 2017;2017(1):1587412.
102. Mehrabi M, Lafond S, Wang L. Frame synchronization of live video streams using visible light communication. In2015 IEEE International Symposium on Multimedia (ISM) 2015 Dec 14 (pp. 128-131). IEEE.
103. Chang T, Watteyne T, Pister K, Wang Q. Adaptive synchronization in multi-hop TSCH networks. Computer Networks. 2015 Jan 15;76:165-76.

