Bio-inspired Routing Algorithms for UAV-based Networks: A Survey

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Abstract — Rapid technological advancements, exponential growth, and unique characteristics are the key factors that enhance the usefulness of unmanned aerial vehicles (UAVs) in diverse applications, including military, agricultural, commercial, and communications-related fields. The use of UAVs for communication is a recent development that has become a topic of significant interest shown by researchers. A flying ad hoc network (FANET) made up of numerous UAVs cannot be developed without implementing an effective cooperative networking model that enables secure information sharing between UAVs. To achieve reliable and robust communication using FANETs, various design- and routing-related issues must be addressed in an appropriate manner. The use of bio-inspired algorithms for data routing in FANETs may be a promising direction, due to their ability to communicate efficiently in a swarm of devices. This work explores various bio-inspired routing algorithms proposed for transmitting data in UAV-based networks. Furthermore, their performance is evaluated and compared using routing metrics. All unresolved research concerns and prospective study avenues are examined based on the outcomes of the investigation conducted.

Keywords — bio-inspired routing protocols, FANET, routing protocols in FANETs, UAV

1. Introduction

The emergence of unmanned aerial vehicles (UAVs), ranging in size and capable of flying at any altitude, has become essential for a variety of existing and emerging applications. They are used in civilian and military settings, transport goods, take aerial photographs, manage traffic flows, participate in search and rescue operations, conduct surveillance missions and are parts of communication networks [1], [2]. Vehicles of this type may play multiple roles, e.g. those of aerial base stations, wireless relay systems or mobile sensors, owing to ease of their integration and flexibility [3], [4].

In a flying ad hoc network (FANET), drones can operate autonomously or cooperate as part of a specific mission [5], [6]. In stand-alone applications, UAVs can act as flying sensors or relay nodes communicating with ground control stations (GCS) or sink nodes.

However, their efficiency in performing various tasks is limited due to their mobility, interference, sparse coverage, the need for line of sight (LOS) communication, and limited energy supply [7].

Using multi-UAV or multi-drone systems can alleviate some of these limitations [8]. The need for enhanced protection and secure data transmission, together with improved overall network performance, is increasing the reliance on UAVs for coordination, collaboration and cooperation [9]. Adding more flying nodes enhances the range or size of the network used for transmission purposes in FANETs [10], which are more efficient than standalone UAV systems due to their scalability.

A FANET has few nodes directly linked to the infrastructure and each node operates in a mesh network [11]. A mesh network refers to a distributed communication network, where every node acts as both a transmitter and a receiver, forwarding information to other nodes. The nodes dynamically mesh together to create a dynamic, adaptive and self-organizing network that supports strong communication in dynamic mobile networks, such as FANETs, even when some nodes fail or change their location.

Nodes can use single-hop or multi-hop routing to connect to a GCS [12]. Multi-hop communication is a mechanism by which information is passed from a source node to a destination node via several intermediate nodes. Each node forwards the information to the next, facilitating communication across greater distances or beyond obstructions, thus increasing coverage and dependability within dynamic mobile networks. Efficient inter-node communication encourages collaboration and cooperation among flying nodes. In these ad hoc networks, the efficiency and credibility of the routing system determine how reliably communication may be conducted.

However, designing an effective communication system architecture for FANETs is a challenge. In FANET, every node participates in an ad hoc network, but only a few are connected to the infrastructure [13]. At the same time, the nodes can communicate with the GCS using single or multi-hop routing [14]. Due to their dynamic nature and deployment in demanding environmental conditions, FANETs require superior characterization compared to conventional ad hoc networks [15].

Reliable communication in an ad hoc network depends solely on the efficacy and trustworthiness of the routing protocol employed. A routing algorithm is a set of rules or procedures used by the nodes to determine the optimal path for transmitting data packets across the network to their destination. It accounts for factors such as node mobility, network topology changes, link quality, and energy constraints to ensure efficient and reliable multi-hop communication in dynamic environments. Each ad hoc network has specific characteristics and challenges that need to be tackled when deploying it for in a particular application. Due to such unique characteristics as highly dynamic nature, resource limitations, uneven distribution, unpredictable movement, and deployment in complicated and harsh settings, networking protocols must be modified [16].

The design of FANETs mobility models and routing protocols is complicated [17]. Over the past few years, researchers have investigated several issues related to FANETs and have proposed many routing protocols and mobility models, especially for addressing frequent link interruptions triggered by dynamic and abrupt node mobility. Initially, some routing protocols from conventional ad hoc networks were modified to match the needs of FANETs.

1.1. Related Work

Bio-inspired routing protocols for FANETs have been the subject of increased research interest in the recent years due to the typical challenges posed by the high degree of mobility, dynamic topology, and energy limitations of UAVs. Bio-inspired algorithms, mimicking natural systems such as insect colonies, animal behavior, and evolutionary processes, have been investigated to solve these challenges by offering adaptive, scalable, and energy-efficient routing solutions. Furthermore, a limited number of scientific papers specifically address bio-inspired routing protocols for FANETs. Therefore, it is necessary to draw insight from the broader literature on general network-related issues, communication architectures, routing protocols, routing challenges specific to FANETs, and traditional ad hoc networks.

The authors of [18] performed an in-depth survey of bio-inspired routing techniques used in vehicular ad hoc networks (VANETs), comparing 48 algorithms across four categories. Their categorization framework demonstrated that bio-inspired techniques resulted in lower delays and higher packet delivery rates than those achieved with the use of legacy protocols in urban vehicular environments. Through large-scale simulations, the authors illustrated the adaptability of these protocols to dynamic topologies and their robustness under varying vehicular velocities. The paper is highly relevant to FANETs, as the shared challenges include high mobility, which VANET protocols naturally support through topology dynamics at high velocities; decentralization, where bio-inspired processes enable self-organizing routing and satisfy QoS demands, e.g., those more typical of delay-sensitive applications.

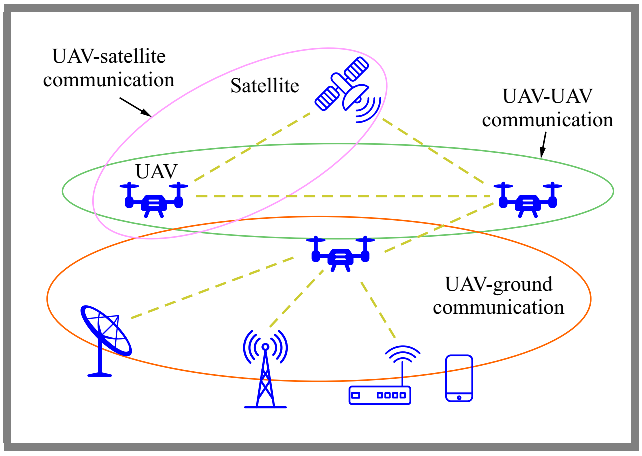

Fig. 1. FANET communication architecture.

In [19], a comprehensive review of new features, design challenges, and directions in the case of UAV-supported networks is presented. The paper is not explicitly focused on bio-inspired routing; however, its explanation of UAV communication constraints and remedies provides a starting point for researchers who plan to extrapolate VANET-inspired or biologically inspired solutions to FANETs.

Bio-inspired algorithms have been extensively researched for FANET routing, and valuable observations about their application have been presented in [20]. The research compares FANET with VANET and mobile ad hoc network (MANET) based on node mobility, density, and topology variation, and compares AntHocNet and BeeAdHoc with traditional protocols, like ad hoc on-demand distance vector (AODV) routing and dynamic source routing (DSR). It considers various parameters, e.g. scout ID, remaining energy for bee algorithms and pheromone-based parameters (e.g., α, β, ρ, η) for ant algorithms. NS-2.35 simulations were performed to illustrate performance under different scenarios, making the review of utmost importance for FANET routing studies.

In [21], a comprehensive review of FANET routing protocols is presented, dividing them into adaptive, proactive, reactive, and hybrid schemes. The paper includes swarm-based schemes, like those based on glowworm swarm optimization (GSO), that use bio-inspired ideas to cope with high dynamics and scarce energy. The authors contrast such schemes based on mobility parameters (e.g. speed, distance), link lifetime, location, available energy, and QoS parameters, such as packet delivery rate and delay, employing mobility models such as the random waypoint and random walk models. Their research emphasizes the flexibility of bio-inspired solutions for FANETs, although further studies are required on the details of specific protocols in order to solve 3D routing problems.

In their systematic review, the authors of [22] examine the use of bio-inspired algorithms for routing in FANETs. The research utilizes a systematic literature review to categorize bio-inspired routing techniques into hybrid and non-hybrid categories, focusing on their self-organizing and decentralized characteristics, which are particularly relevant to the high mobility and dynamic topology of UAV swarms. Compared to other existing algorithms, such as AntHocNet and BeeAdHoc, as well as traditional protocols, such as AODV and GPSR, the review also demonstrates their efficiency in improving packet delivery ratio (PDR), latency, and throughput.

Paper [23] introduces a comprehensive taxonomy of FANET routing protocols, such as topology-based, position-based, hierarchical, swarm-based and delay-tolerant networks (DTN) protocols. Swarm-based protocols, which utilize bio-inspired approaches, are contrasted based on their ability to handle

Tab. 1. List of acronyms and abbreviations used.

Acronym	Meaning	Acronym	Meaning
2D	Two-dimensional	HOPNET	Hybrid ant colony optimization routing
3D	Three-dimensional	HSCS	Hybrid self-organized clustering scheme
ACK	Acknowledgment	ID	Identification number
ACO	Ant colony optimization	IoT	Internet of Things
AI	Artificial intelligence	KH	Krill herd
AIS	Artificial immune system	LOS	Line of sight
AODV	Ad hoc on-demand distance vector	MAC	Media access control
APAR	Ant colony optimization-based polymorphism aware routing	MANETs	Mobile ad hoc networks
BAT-COOP	Bat algorithm using cooperation technique	PDR	Packet delivery ratio
BIA	Backward information ant	PeSOA	Penguin search optimization algorithm
BICSF	Bio-inspired clustering protocol for FANETs	PICA	Physarum-inspired clustering algorithm
BIR-SLB	Bio-inspired routing to support multimedia traffic in emergency conditions in FANET	PSO	Particle swarm optimization scheme
BR-AODV	On-demand routing using the Boids of Reynolds protocol	QoS	Quality of service
CH	Cluster head	RC	Route congestion
CH_DEC	Cluster head declaration	RREP	Route reply
CM	Cluster member	RREQ	Route request
CR	Cognitive radio	RS	Route stability
DF	Dragonfly scheme	RSF	Route selection function
DSR	Dynamic source routing	SI	Swarm intelligence
FANET	Flying ad hoc network	SIC	Swarm intelligence-based clustering
FEA	Forward exploration ant	SIL	Swarm intelligence-based localization scheme
GA	Genetic algorithm	SIL-SIC	Swarm intelligence-based localization and clustering
GCS	Ground control stations	SNRC	Signal-to-noise ratio combining
GSO	Glowworm swarm optimization	U2G	UAV-to-GCS
GW-COOP	Gray wolf algorithm using cooperative diversity technique	U2S	UAV-to-satellite
GWO	Grey wolf optimizer	U2U	UAV-to-UAV
HBA	Honey badger algorithm	UAVs	Unmanned air vehicles
HC	Hop count	VANETs	Vehicular ad hoc networks

high mobility and 3D routing. The paper introduces a novel taxonomy for reinforcement learning-based routing, contrasting the single-agent and multi-agent models. Although the lecture given does not mention specific parameters or simulators, the qualitative comparison with existing surveys highlights the prospect of bio-inspired protocols in FANETs, particularly for addressing dynamic topology issues.

The biologically inspired computation uses natural phenomena and available computer programs intended for solving various open research challenges. Therefore, this literature survey aims to study multiple bio-inspired routing protocols for FANETs and uncovers unresolved research issues. This work may serve as a reference point for those interested in solving open research challenges regarding efficient data routing in FANETs.

The paper is divided into six sections. Section 2 presents an outline of the FANET communication architecture, while Section 3 describes issues related to routing design. Section 4 discusses and compares various bio-inspired routing protocols. Section 5 provides a comparative analysis of bio-inspired routing protocols. Section 6 addresses several open research issues and future scopes. The article is concluded in Section 7. The acronyms and abbreviations used in this study are listed in Tab. 1.

2. FANET Communication Architecture

A consistent communication architecture in FANETs is essential because of the critical design requirements for internode and intra-node communications. Each UAV or flying node participating in these networks can act as a source or destination. However, node-to-node communication exposes constraints such as frequent link disconnections, network fragmentation, and packet losses. Therefore, all FANET communications must follow a well-designed communication model to overcome these problems.

Furthermore, nodes can cooperate to cope with dynamic topology and networks can be reorganized using relay nodes. As illustrated in Fig. 1, the following three types of communication dominate in FANETs: UAV-to-UAV (U2U), UAV-to-GCS (U2G), and UAV-to-satellite (U2S).

In various application scenarios, UAVs communicate directly with one another by exchanging topology control messages. However, when the nodes are outside of each other's transmission range, multi-hop communication becomes essential to extend network coverage to specific areas of interest. LOS U2U communication is typically prevalent due to the minimal obstacles between UAVs flying in open-sky space.

However, there are areas for improvement associated with LOS U2U communication, such as the requirement for separate frequency bands for each pair and the challenges in critical remote missions where LOS communication is not guaranteed, mainly when UAVs fly in urban areas or mountainous regions [24].

A group of UAVs can be efficiently controlled through a fixed infrastructure on the ground, known as GCS, by exchanging topology updates and control messages using U2G communications [25]. LOS U2G communication remains dominant even at high elevations. However, UAVs flying at lower altitudes encounter numerous obstacles, decreasing the likelihood of LOS communication with GCS [26].

UAVs are frequently stationed in complex environmental settings, such as mountainous landscapes, water tanks, and forest areas, where GCS support is not feasible. Moreover, when a FANET suffers from severe network fragmentation and is unable to maintain connectivity with the GCS, centralized control is required to ensure permanent connectivity [27]. Allowing U2S communications can solve the issue by serving as a centralized controlled relay and providing LOS coverage [28].

Satellite communication is beneficial for critical data exchanges between drones and for transmitting information collected to the GCS positioned at a distant location on the ground [29]. However, this is costly, as maintaining communication with satellites requires additional hardware and expenses [30].

3. FANET Routing Objectives

Several issues must be overcome in a stable and reliable network before UAVs can be deployed efficiently. FANET communication protocols, especially routing protocols, have been explored to a comparatively lesser degree [31]. Although researchers have proposed many routing schemes for traditional ad hoc networks to address their characteristics and non-continuous connectivity, these protocols are not able to meet the communication needs of FANETs [32]. Therefore, effective routing schemes must be developed considering their distinctive characteristics. For efficient utilization of network resources, FANET routing schemes should be characterized by self-organizing and self-healing capabilities, robustness, and high proficiency.

The following routing goals must be considered when creating routing protocols for FANETs:

- Improving link stability. Link stability and lifespan are minimal due to the dynamic network topology, discontinuous connectivity, and highly fragmented networks [33]. Furthermore, FANET nodes are separated by comparatively longer distances, requiring frequent path discovery and link reestablishment processes [34]. Moreover, link stability depends on node density and the network's residual energy [35].
- Improving network coverage. In a FANET, the nodes are deployed at distant geographical locations, resulting in sparse networks [36]. Therefore, the nodes must have high transmission powers to provide efficient network coverage [37]. Otherwise, intermittent connectivity and a partitioned network will worsen coverage. Furthermore, making the network denser, for example in a multi-UAV communication scenario, improves network coverage [38].
- Improving quality of service (QoS) and routing performance. Lower link stability in a FANET requires frequent route discovery, which decreases routing performance [39]. Consequently, it is crucial to identify and select routes that have higher stability, longer lifespan, and fewer hops [40]. Furthermore, an increase in node density and transmission power can improve QoS [41].

4. Bio-inspired Routing Algorithms in FANETs

The network layer of the FANET communication model faces some critical challenges [42]. As stated earlier, FANET networking protocols should be developed and maintained with special attention paid to their specific characteristics and the complex environmental conditions in which they function.

Researchers proposed various routing protocols to adapt and satisfy conflicting design challenges, with high node mobility resulting in dynamic topology [43], efficient energy consumption [44], frequent link discontinuation [45], low security, poor scalability, and intelligent usage of allocated bandwidth and UAV resources [46].

However, fulfilling these requirements in a single protocol is nearly impossible. Hence, differentiating FANET routing protocols based on the deployment scenario is necessary. Based on the concepts, the central idea, the issues that need to be resolved and the techniques adopted, FANET routing protocols can be classified as network topology-aware, node position-aware, bio-inspired, stochastic, and beacon-less opportunistic. Given their versatility, adaptability, and potential

Tab. 2. Bio-inspired algorithms available.

Name	Description
Ant colony optimization (ACO) [55]	A probabilistic method in which graph-based solutions are utilized to solve issues related to route discovery. The pheromone-based information exchange mechanism of biological ants is used to find the optimal solution
AntNet routing [63], [64]	A routing scheme in which a group of mobile agents, sometimes known as artificial ants, attempts to establish connections between pairs of nodes by simultaneously scanning the network and exchanging data to update the routing tables
Artificial bee colony (ABC) [91]	It provides an optimal way to handle swarm-based communication by simulating the behavior of a honey bee swarm
Bacterial foraging optimization (BFO) [92]	A method of evolutionary optimization based on Escherichia coli bacteria's foraging behavior
Bees' wangle dance [76], [77]	A special dance by honey bees creates a precise, coded message to communicate the distance and direction of a new food source from the hive
Boids of Reynolds [68]	Boids are used to model the movement of an object in 3D and provide their geometric abilities
Bat echolocation [81]	The echolocation characteristics of bats are employed to sense the internode distance and surrounding obstacles. Also, they can differentiate between food/prey
Dragonfly scheme (DF) [79]	The DF algorithm makes use of dragonflies' static and dynamic swarming behaviors. Route-finding optimization is achieved through the application of both exploration and exploitation techniques
Glowworm swarm optimization (GSO) [52]	A technique for solving an optimization problem based on the luciferin value estimated by simulating the movement of a glowworm swarm around a luminescent quantity
Gray wolf optimizer (GWO) [56]	Gray wolves' leadership hierarchy is employed to implement cooperation in sparse networks
Honey badger algorithm (HBA) [89]	A metaheuristic optimization scheme modeled after the foraging habits of honey badgers, which are renowned for their tenacity and adaptive food search strategies
Krill herd (KH) [53], [54]	It mimics the herding behavior of individual krill and is capable of resolving a wide range of optimization issues across several domains
Moth flame optimization (MFO) [93]	A mechanism based on moths' innate transverse-orientation navigation method. Moths can fly fairly effectively at night, keeping a constant angle towards the moon
Penguin search optimization algorithm (PeSOA) [90]	An algorithm for metaheuristic optimization influenced by social behavior and cooperative hunting strategies of penguins, particularly their efficient foraging patterns in harsh environments
Physarum polycephalum (PP) [86]	An optimization technique derived from a single-celled fungus that demonstrates resource allocation efficiency and flexibility by self-organizing mycelium networks in complex natural environments
Particle swarm optimization (PSO) [59]	An optimal solution is obtained by iteratively improving the initial solution as per the required quality. The best local and global positions are explored by moving the particle swarm according to a mathematical formula in the search space
Red deer optimization (RDO) [94]	A metaheuristic optimization technique inspired by the strange mating habits of Scottish red deer in the breeding season
Swarm intelligence-based clustering (SIC) [60]	It offers an alternative method to achieve clustering in the absence of central control
Swarm intelligence-based localization (SIL) [58]	Provides a mechanism for the localization of highly mobile in a 3D environment

for efficient data routing, this study is limited to bio-inspired routing protocols within FANETs.

In recent years, bio-inspired technology has gained prominence as a research focus due to its capability to address various optimization challenges and deliver high performance [47]. With its unique features and bottom-up methodology, it primarily handles network challenges such as congestion control, security, and routing [48]. The various evolutionary algorithms inspired by nature are used to solve issues related to communication networks. These belong to two classes of biologically inspired algorithms, namely swarm-based movement control algorithms and those that model the collective behavior of biological species [49].

Swarm intelligence (SI) refers to designing and implementing distributed problem-solving strategies inspired by social insect colonies and other animal societies that act collectively [50]. Researchers have proposed multiple bio-inspired algorithms based on swarm movement, mimicking honey bees, ant colonies, and bird flocks to provide an optimal solution to various networking problems [51].

Table 2 presents a range of bio-inspired algorithms that may effectively enhance routing efficiency in highly dynamic networks such as FANETs. The routing schemes based on bio-inspired algorithms proposed specifically for FANETs are mentioned in the upcoming subsection. These protocols are compared based on routing parameters such as adaptability, link stability, communication overhead, network coverage, efficiency, load balancing, security, and privacy to uncover open research issues.

4.1. Bio-Inspired Clustering Scheme for FANETs (BICSF)

BICSF is a clustering-based routing scheme for FANETs inspired by two biological algorithms: glowworm swarm optimization (GSO) [52] and krill herd (KH) [53], [54]. It comprises three phases: cluster formation, management, and maintenance. The GSO algorithm, aided by each UAV's residual energy and luciferin level, facilitates energy-efficient clustering and cluster head (CH) election.

Initially, as shown in Fig. 2a, each UAV autonomously calculates its fitness value F_i using:

$$L_i(t) = (1-\alpha)\, L_i(t-1) + \beta\, F\big(l_i(t)\big) \,, \tag{1}$$

$$E_{residual} = \sum_{i=1}^{n} \big(E_{initial}(i) - E_{current}(i)\big) \,, \tag{2}$$

$$F_i = \gamma\, E_{residual} + (1-\gamma)\, L_i(t) \,, \tag{3}$$

where for each glowworm i, $L_i(t)$ signifies its luciferin value, α represents the luciferin decay constant, β represents the luciferin perfection fraction, and $F\big(l_i(t)\big)$ is the glowworm goal function for the UAV i at current location l_i.

UAVs broadcast F_i, and the UAV with the maximum F_i becomes the CH. Low-energy UAVs (e.g. UAV 8 in Fig. 2a) are excluded to prioritize network longevity.

In the second phase, the KH algorithm ensures stability and efficient cluster management by modeling cluster members' communication and virtual positioning relative to the CH, inspired by krill swarming patterns. This guides alignment with the CH, ensuring cohesive and stable intra-cluster interactions. Genetic operators, including crossover and mutation, are utilized to optimize communication paths between members and enhance adaptability in response to dynamic topology changes.

Route selection employs a function that evaluates the count of adjacent UAVs, remaining energy, and the space between UAVs, ensuring efficient data transmission:

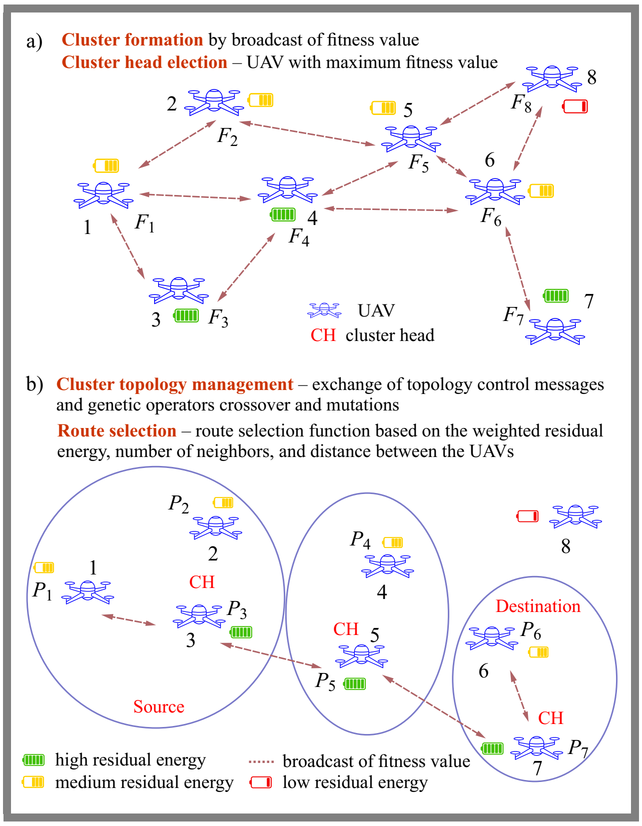

Fig. 2. BICSF algorithm demonstrating: a) cluster formation and cluster head election, and b) cluster topology management with route selection.

$$Route\ selection = \frac{\omega_1\, E_{residual}}{(\omega_2 \cdot N_i)(\omega_3 \cdot d)} \,, \tag{4}$$

where ω_1, ω_2, and ω_3 represent the weights associated with residual energy, N_i represents the count of UAVs in the neighborhood, and d is the distance between the UAVs.

After cluster formation, the CH manages intra-cluster communication by collecting and processing data from CMs and handles inter-cluster communication by forwarding data to neighboring CHs or the destination, as depicted in Fig. 2b. During the maintenance phase, UAV energy levels are periodically monitored. CMs with energy levels above a set threshold remain, while those below are removed as dead nodes, potentially necessitating re-clustering to sustain network performance.

The scheme described in [48] involves the following steps.

- UAVs initiate distributed clustering, each calculating fitness F_i based on luciferin and residual energy levels.
- Each UAV broadcasts a hello message with F_i.
- Upon receiving the messages, F_i builds, updates, and sorts a neighbor table. The table is continuously updated and sorted with the arrival of new hello messages.
- With three or more entries, the nodes check for the highest F_i. If it is the highest, they declare self-CH. Otherwise, they acknowledge the UAV with the highest F_i as CH, via a formation message.
- The remaining nodes join as CMs.

- The topology is periodically updated to ensure stability and energy efficiency.

The authors of [48] evaluated efficiency of BICSF against ant colony optimization (ACO) [55] and gray wolf optimizer (GWO) [56] approaches, demonstrating that BICSF requires less time for cluster formation compared to these alternatives. BICSF is highly adaptable, adjusting to dynamic node positions via bio-inspired algorithms. However, it exhibits low link stability due to the mobility of UAVs, which impacts reliability. It ensures a single stable route but lacks multiple routes, limiting fault tolerance. The scheme incurs high routing overhead resulting from frequent updates and computational complexity of GSO and KH. It requires substantial memory to route the data and is energy efficient during transmission, but lacks load balancing, leading to uneven energy depletion. BICSF does not prioritize privacy or security mechanisms, making the network susceptible to attacks such as data interception or unauthorized access.

The coverage of a BICSF network is based on clusters and can be expanded by CH using multi-hop communication. For the sake of enhancing cluster stability and reducing routing overhead, BICSF makes moderate assumptions about UAV mobility and selects highly reliable and connected UAVs as CHs. The UAVs are relocated to cover holes.

Area coverage is determined by clustering algorithms, making it computationally complex. By simulating krill movement to adapt to topological changes, the KH algorithm ensures stable coverage, and GSO iteratively optimizes the cluster assignments. Coverage is estimated by neighbor density using RSSI-based distance measurements. This approach incurs complexity of $O(n \log n)$ per cluster.

The advantages of BICSF are as follows:

- GSO helps in energy-efficient cluster management and makes the proposed protocol adaptable to topology changes.
- The KH-inspired clustering method ensures stable intra-cluster communication, even with limited node movement, thereby extending the lifespan of clusters.
- This scheme requires less cluster formation time and provides a longer cluster lifespan.

The limitations of BICSF can be summarized as:

- High routing overhead owing to frequent cluster head reelections.
- Limited scalability in dense UAV networks.
- Cluster instability under high mobility.
- Moderate computational complexity due to dynamic clustering using GSO and KH.
- No support for time-sensitive data delivery.

4.2. Swarm Intelligence-based Localization and Clustering (SIL-SIC)

SIL-SIC [57] is a hybrid of two bio-inspired techniques, namely the swarm intelligence-based localization (SIL) [58] and particle swarm optimization (PSO) [59] schemes. The SIL method analyzes the distance between existing connector nodes to estimate the destination's position that is randomly dispersed in a 3D search space. This scheme uses a bounding box approach to exploit the particle search space inside a restricted boundary.

Furthermore, the authors of [60] presented a clustering method based on PSO-based energy-proficient swarm intelligence (SIC). As shown in Fig. 3a, UAVs dynamically adjust their positions based on their local estimates and global information shared through the localization data within the swarm. UAVs evaluate their fitness value F_v based on multiple factors, including inter- and intra-cluster distances, the network's residual energy, and geographical locations. As depicted in Fig. 3b, UAVs with the highest F_v are selected as CHs.

The PSO method may introduce localization errors due to the random initial positions of particles, determined by their personal best p_{best} and information from neighboring particles, potentially leading to the exploration of unnecessary or irrelevant areas in the search space. Additionally, the g_{best} solution may converge prematurely, limiting exploration and resulting in suboptimal localization outcomes. The bounding box method enhances the efficiency in limiting the search space within a restricted boundary. The restricted search is marked by identifying multiple anchor UAVs within the communication range of an unknown UAV.

The objective of the SIC method is to maintain a uniform cluster size, as shown in Fig. 3c. UAVs iteratively update their distances and cluster centers to optimize node assignment using the following formula:

$$d = \sqrt{\left((x_2 - x_1)^2 + (y_2 - y_1)^2 + (z_2 - z_1)^2\right)}\,, \qquad (5)$$

where d is the distance between two UAVs and coordinates, x_1, y_1, z_1 and x_2, y_2, z_2 define the location of the first and second UAVs, respectively.

Clustering is done based on proximity to CH and inter-cluster distances. Additionally, maintaining the cluster size above a threshold value ensures a balanced cluster size. CMs are assigned to the nearest cluster. For instance, as shown in Fig. 3c, UAV 6 migrated to cluster 2 from cluster 1 to balance cluster sizes. After clustering, inter-CH data transmission is done using multi-hop routing [61], as depicted in Fig. 3d.

The scheme [57] involves the following steps:

- UAVs in the swarm start at random locations P_i with velocities V_i.
- Each UAV calculates its fitness value F_v using P_i and V_i. Optimal F_v = Personal best p_{best}.
- p_{best} is used to evaluate the best global position g_{best} for the entire swarm. Each UAV adjusts its trajectory according to its p_{best} and g_{best}.
- Center points are initialized randomly. These serve as the initial reference points for each cluster. Each UAV calculates its distance from different cluster centers using the Euclidean distance formula. The node is associated with a cluster with the nearest central point.

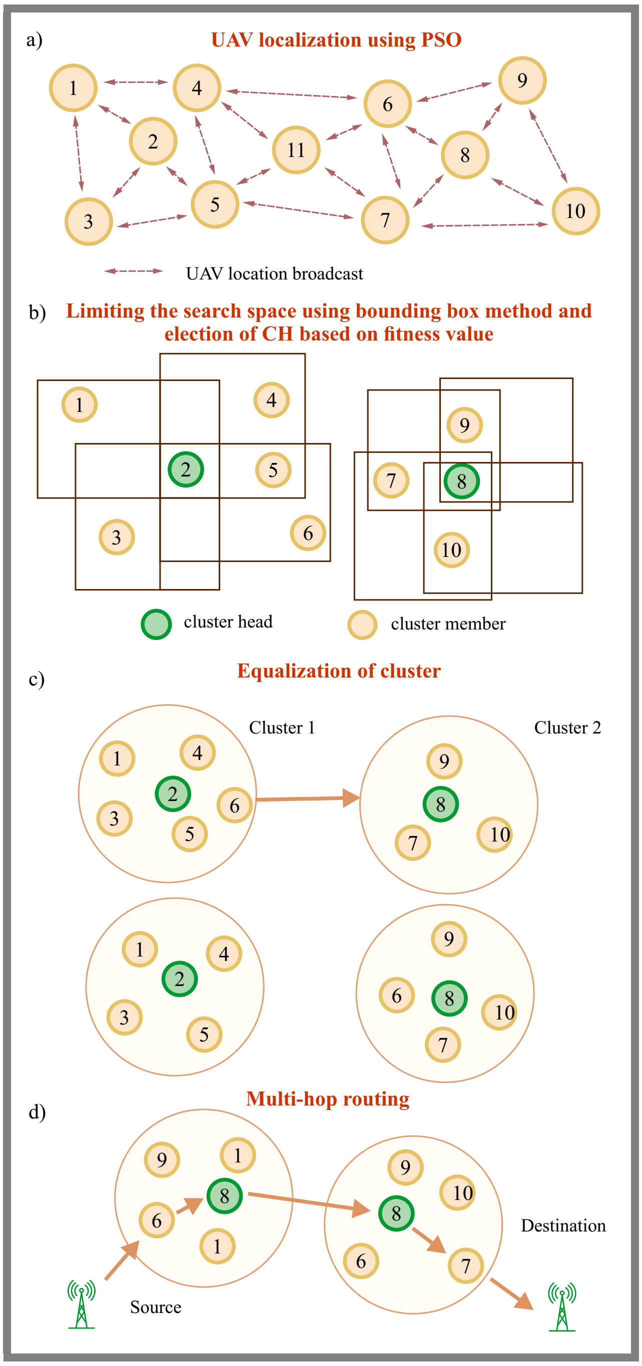

Fig. 3. Illustration of the SIL-SIC scheme for FANETs: a) dynamic position adjustment of UAVs in a 3D search space using SIL, b) CH selection based on F_v, c) cluster balancing with node migration, and d) multihop routing for data transmission.

- Inter-cluster distances are measured between all clusters and a distance matrix is constructed. This matrix stores the distances between each pair of clusters.
- Clusters are merged based on proximity until stable clusters are formed, ensuring efficient communication and swarm coordination.
- The optimal UAV is chosen as CH based on the UAV closest to the center of its cluster and the node with a higher residual energy.
- p_{best} and g_{best} are updated periodically.
- Data are transferred using multi-hop routing, where each CH communicates with the next CH to route data to GCS.

Based on simulation findings described in [57], due to its accurate localization, the SIC method outperforms conventional approaches in terms of routing overhead, packet delivery ratio (PDR), and average delay. SIL-SIC exhibits high adaptability and responds flexibly to network topology and UAV position modifications through its PSO-based clustering and routing approach, which enhances link stability and network coverage by optimizing UAV positions and communication paths. However, SIL-SIC focuses solely on single-path routing, limiting redundancy and fault tolerance.

Despite efforts to optimize overhead, SIL-SIC experiences considerable routing overhead due to the demands of the algorithms and frequent updates required to maintain dynamic clustering. The computational overhead of executing these algorithms and the storage requirements for particle positions and routing information contribute to space complexity. Frequent updates in positions and clusters can lead to significant energy consumption. Although SIL-SIC incorporates load-balancing features to evenly distribute the network load, it does not prioritize privacy or security mechanisms, leaving the network vulnerable to potential attacks, such as data intercepting or unauthorized access.

The 3D SIL algorithm, designed for emergency communication in highly mobile environments, utilizes PSO to determine the optimal location of the UAVs within a 3D bounded space, positioning them to cover the target area effectively. UAVs identify coverage holes through RSSI-based triangulation with anchor nodes. The SIC algorithm then clusters UAVs based on geolocation, inter- and intracluster distances, and RE. Clustering is utilized to partition the network into manageable clusters, with each cluster covering a portion of the operational area.

A pheromone-based coverage map is used to compute the coverage area. UAVs deposit virtual pheromones in visited areas, and low-pheromone regions cause member redistribution. Complexity $O(n^2)$ arises due to a pairwise comparison, which restricts deployment in emergency cases involving large sizes, where computational latency is higher.

The advantages of SIL-SIC can be summarized as:

- Use of the PSO scheme in SIL-SIC enables precise localization of UAVs.
- Effective clustering improves energy efficiency and extends network's life.

The limitations of such an algorithm are:

- High routing overhead due to swarm coordination and localization.
- Performance degrades with the addition of UAVs.
- Cluster instability due to high mobility.
- High computational overhead is incurred due to the PSO algorithm used for position estimation.
- Due to frequent clustering, time-sensitive data delivery is not supported.

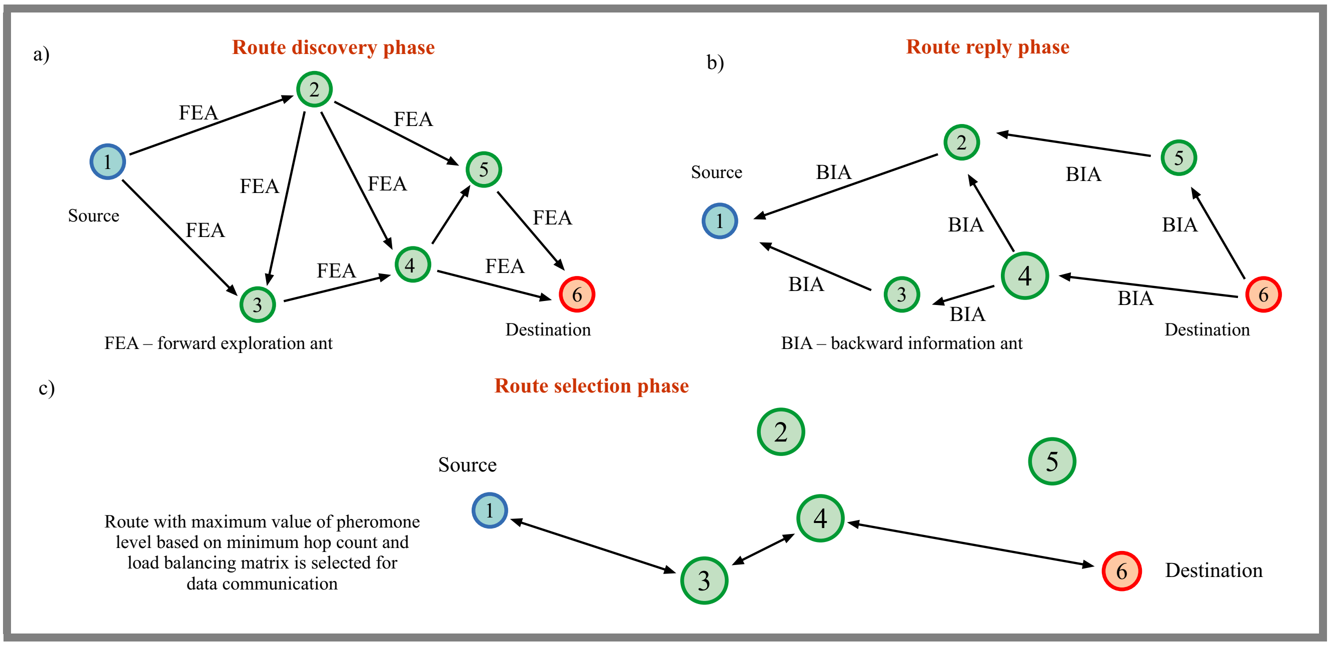

Fig. 4. BIR-SLB scheme for FANETs demonstrating: a) route discovery phase, b) route reply phase, and c) route selection phase.

4.3. Bio-inspired Routing to Support Multimedia Traffic under Emergency Conditions in FANETs (BIR-SLB)

BIR-SLB is a bio-inspired routing scheme that employs multi-objective optimization metrics, focusing on shortest path and load-balancing [62]. These metrics evaluate potential routes and select the most optimal one for routing multimedia traffic. The proposed approach inherits certain behaviors from the AntNet routing protocol [63], [64].

Specifically, in very dynamic networks, such as UAV-based mesh networks, identifying the optimal path is challenging due to constant changes in topology. To address this, BIR-SLB optimizes the routing process by decreasing path length while considering the traffic load across the routes. This guarantees that the network will continue to function effectively even in high-traffic situations.

The scheme comprises three phases:

Route exploration. In the first phase, the source drone initiates probabilistic forward exploration ant (FEA) communication to explore potential paths toward the destination (as shown in Fig. 4a). FEA packets traverse various routes, collecting vital network information such as hop count (HC), link quality, and available bandwidth. This phase allows drones to probe the network and identify viable routes.

Route reply. In the second phase, after an FEA packet reaches its destination, the destination generates a backward information ant (BIA) packet that retraces the explored route back to the source (as depicted in Fig. 4b). During this reverse traversal, BIA collects and relays critical performance metrics, such as latency, energy consumption, and network congestion at each node. This phase ensures that the source drone receives valuable feedback to evaluate the quality and efficiency of each path.

Route reinforcement and load balancing. In the final phase, the BIA packet incrementally updates the pheromone levels on each link as it follows the reverse route to the source (as illustrated in Fig. 4c). The pheromone concentration reflects the reliability, energy efficiency, and traffic load of each route. Routes with higher pheromone levels are reinforced and are more likely to be selected for future transmissions. This phase dynamically balances network load by distributing traffic across multiple paths, promoting routes that are not only shorter but also energy efficient and less congested, and thus optimizing overall network performance.

The scheme described in [62] proceeds as follows:

- UAVs are deployed in the emergency area. Each source UAV broadcasts an FEA message towards the destination.
- FEA packets travel probabilistically, exploring potential routes to the destination.
- When the destination receives the FEA message, it confirms this by generating a BIA message.
- The BIA backtracks to the source following the reverse path of the original FEA message.
- The source node chooses the most efficient path to route its multimedia data based on the optimal values of link quality, pheromone value, and HC.
- This process is repeated periodically, ensuring that the network can adjust to changes in topology caused by UAV movement or link alteration failures.

The authors of [62] evaluated the performance of BIR-SLB by comparing it with link-state routing protocols [65]. They observed that the proposed scheme is more adaptable and requires less overhead than link-state routing, which has the maximum flow and a single shortest path.

BIR-SLB is highly adaptable and efficiently handles changes in network topology and node position. It benefits from high link stability because it focuses on path length optimization, leading to more reliable connections. However, BIR-SLB does not support multiple routes, which limits redundancy and fault tolerance within the network. Due to the minimal use of control messages, the scheme keeps a low routing overhead, leading to a balanced path length and traffic load.

Furthermore, the availability of optimal routes leads to low computational and communication overheads. This scheme does not emphasize energy efficiency, privacy, and security, making networks vulnerable to security threats.

Designed for multimedia support in dynamic environments, BIR-SLB balances load distribution through an ant-inspired mechanism. BIR-SLB implements pheromone-based coverage estimation where "coverage ants" deposit virtual pheromones, proportionally to RSSI measurements during path exploration. The buffered data is forwarded to uncovered regions via ants.

The ACO algorithm is utilized to identify coverage holes, i.e. regions with pheromone values below adaptive thresholds. The algorithm executes $O(k \cdot n)$ operations per agent (k – number of iterations, n – number of agents) for the map convergence with bandwidth overhead due to periodic re-broadcasts of the pheromone table in mobile environments.

The advantages of BIR-SLB are:

- Due to the availability of many routes to distribute calls, BIR-SLB can handle many calls and efficiently distribute call requests among the UAV-based network.
- Due to the low cluster build time, this protocol shows better route exploration and scalability.

The limitations of BIR-SLB can be summarized as follows:

- Less effective in dense networks.
- Route instability due to high mobility of the UAV.
- No support for real-time packet delivery, limiting its applicability to emergency scenarios.

4.4. On-demand Routing Using Boids of Reynolds Protocol (BR-AODV)

BR-AODV is a biologically inspired upgrade of the traditional AODV routing scheme [66] for UAV-based networks [67]. The proposed scheme merges AODV, a conventional reactive routing protocol, with the Reynolds Boids [68] algorithm to ensure dynamic path connectivity and route maintenance during data transmission.

The protocol operates an on-demand basis, as routes are discovered only when needed rather than maintaining pre-established routes. This approach helps reduce unnecessary overhead, making the protocol more efficient for UAV networks, where nodes frequently move and change their positions.

The node activity monitoring process is illustrated in Fig. 5a. A timer is connected to each UAV inside the network for monitoring purposes. After a silence period T, UAVs become active or inactive. This is the period in which an UAV neither transmits nor receives any data. The remaining rules are as follows:

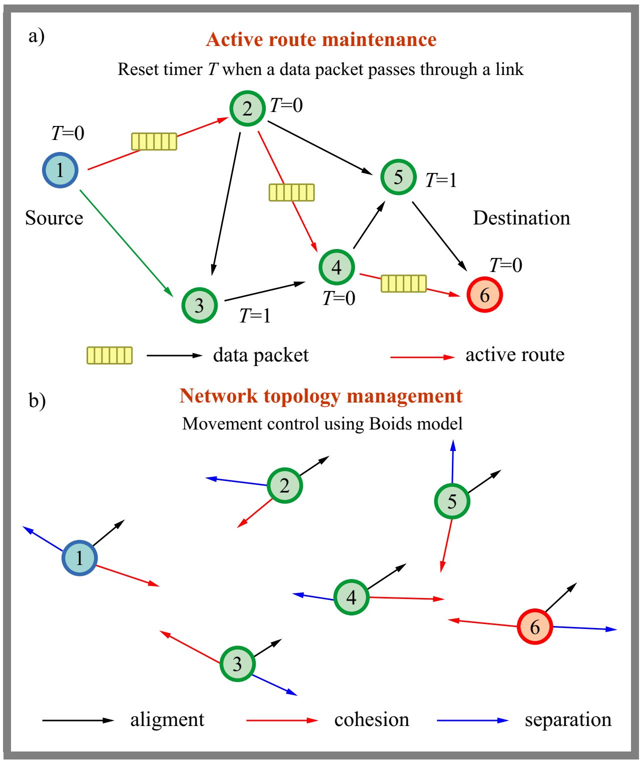

Fig. 5. Illustration of the BR-AODV scheme for FANETs: a) active route maintenance and b) network topology management.

- If silence period T exceeds threshold T_{max}, the UAV is marked as inactive.
- If $T \leqslant T_{max}$, the UAV remains active.
- The timer value is reset to 0 whenever the UAV under consideration sends or receives a message. Otherwise, the value is incremented by 1.

The status of UAVs is checked regularly. Routes through active UAVs are selected for data forwarding. During data transmission for active links, the movement of UAVs is controlled using the Reynolds Boids. The Boids of Reynolds rules are based on distance, cohesion (tendency to remain closer to neighbors), and alignment (velocity and direction toward the neighbors) between the communicating UAVs in the neighborhood, as described in Fig. 5b.

The key objective of the BR-AODV scheme is to maintain connectivity for a route during data transfer [69]. The AODV protocol is augmented with a control module based on Reynolds Boids to track UAVs' movement and counter issues observed in AODV. UAVs can determine their participation in multiple active paths. If so, they must decide their future movements by avoiding any route disconnection.

The scheme [67] involves the following sequence of steps:

- In a swarm, each UAV initializes its parameters such as its unique identifier (MAC or IP address), position P_i, and velocity V_i.
- The UAVs broadcast a hello message, signal strength, V_i, P_i.

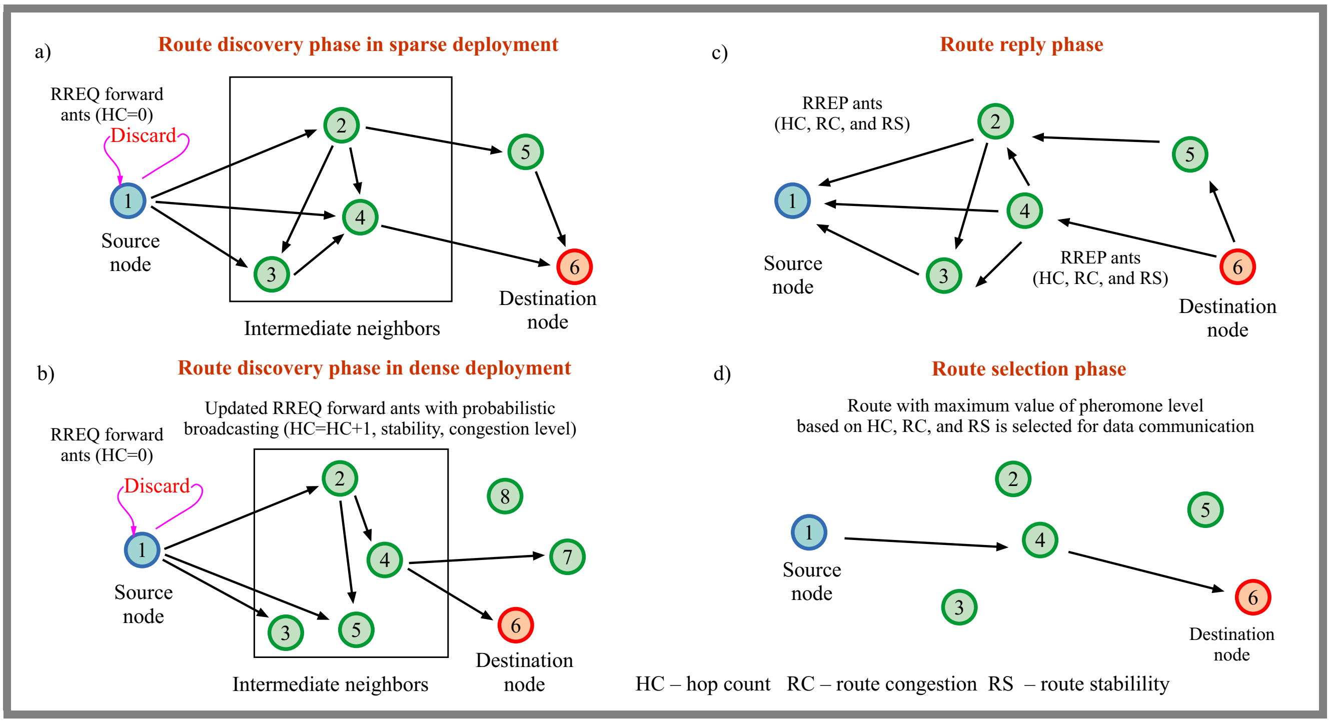

Fig. 6. APAR routing process for FANETs demonstrating the following: a) route discovery phase in sparse deployment, b) route discovery phase in dense deployment, and c-d) route reply and selection phase.

- The UAV identifies nearby UAVs based on signal strength and distance. If a UAV is within radio range, it is added to the list of neighbors.
- The source UAV transmits an RREQ packet to find a path to the destination. If intermediate UAVs do not have a recorded path, they forward the message.
- Once the destination is reached or an intermediate UAV with a known route to the destination is found, it responds with an RREP.
- Each UAV keeps track of whether it is active or inactive based on a timer, denoted by T. If a UAV has been transmitting or receiving packets within time $T \leqslant T_{max}$, it is marked active. If the UAV has been idle for more than T_{max}, it is marked inactive.
- Active UAVs behave like Boids and adjust their movements, applying alignment, cohesion, and separation.
- The route is checked for being active. If all nodes in the path are active, the route is marked as active. If any node in the path becomes inactive, the path is considered inactive. The process is started over to identify an alternative route.
- The UAVs periodically exchange hello messages and update neighbor tables to maintain active routes.
- The UAVs communicate multihop, forwarding data from one UAV to another until they reach the destination or gateway.

BR-AODV is highly adaptable, as the Boids model efficiently manages UAV movements and network routing decisions. The scheme also achieves high route stability, leading to reliable connections. Nevertheless, support for multipath routing is still missing, resulting in low fault tolerance. Owing to the poor scalability of the distance-based approach, the scheme suffers from low network coverage in the case of dispersed networks. BR-AODV has a significant routing overhead due to the combination of the Boids of Reynolds scheme with the traditional AODV routing protocol.

However, the scheme is energy efficient because of route optimization and low redundancy, as shown by the Boids model. BR-AODV also incorporates load-balancing mechanisms by dispersing traffic flow among the routes equally. Unfortunately, BR-AODV does not provide any protection against common security threats.

The scheme suffers from low network coverage, particularly in the case of dispersed networks. Tailored for on-demand routing in dynamically positioned UAVs, BR-AODV integrates RSSI-based coverage mapping during route discovery. This method mimics bird flocks, in which UAVs prevent coverage gaps by realigning to remain within range, thereby preserving group cohesion, separation, and alignment through connectivity while transmitting data.

BR-AODV ensures the coverage of the operational area, since the UAVs maintain their connections in order to form an integrated network. A fitness function evaluates coverage using neighbor counts and path loss models. The computational burden includes $O(m \cdot p)$ (m – node count, p – generations) for neighbor checks during route requests, resulting in latency in low-density networks when updating coverage maps. The computational complexity arises from the need to simulate flocking behavior and dynamically adapt routes, ensuring robust coverage in FANETs.

The advantages of BR-AODV include the following:

- The Boids of Reynolds scheme provides active path connectivity and efficient route maintenance, increasing throughput and reducing packet loss.
- This scheme shows low end-to-end delay, especially for high network traffic loads.

The known limitations of BR-AODV are as follows:

- High routing overhead due to reactive route discovery.
- Poor scalability due to latency spikes in dense networks.
- Poor link stability due to high UAV movements.
- Does not support time-sensitive communication.

4.5. Ant Colony Optimization-based Polymorphism Aware Routing (APAR)

The highly dynamic network topology of FANETs makes standard routing strategies unsuitable for meeting their unique requirements and complex application scenarios. Furthermore, using the hop count as the only route metric makes it impossible to guarantee a consistent PDR in real-time battlefield scenarios. To overcome these challenges, the authors of [70] proposed APAR, which integrates the ant colony optimization (ACO) scheme with the dynamic source routing (DSR) protocol [71]. The algorithm comprises three phases.

Route exploration phase. The authors of [70] proposed two route exploration techniques, with both of them based on network node density, to minimize the broadcast storm during the route creation phase. In sparse deployments, as illustrated in Fig. 6a, a source node without route information in its cache forwards a route request (RREQ) to all nearby stable nodes. Stable nodes are defined as those with high link quality and low mobility, which ensures reliable communication.

Upon receiving the RREQ, intermediate nodes update critical information such as HC, congestion, and stability, and then forward the updated RREQ to their stable neighbors. This process continues until the RREQ arrives at its destination or an intermediary node with a known path, which then transmits a route reply (RREP) back to the source. A probabilistic broadcasting strategy is employed in dense deployments, as illustrated in Fig. 6b.

Upon receiving an RREQ, each intermediate node calculates probability p of forwarding the RREQ based on the number of mutual and unique stable neighbors compared to the previous hop, reducing redundant broadcasts and minimizing the broadcast storm.

Route response and selection phase. Upon receiving the RREQ, the destination responds with an RREP source containing information on the HC, route congestion (RC) and route stability (RS) (see Fig. 6c). After receiving the RREP, the source node calculates the pheromone value for each path according to these metrics and chooses the path with the highest pheromone value for data transmission (see Fig. 6d).

Route maintenance phase. For route maintenance, the DSR topology control packets are modified to include extra information about the route, such as the UAVs' speed, antenna gain, transmitting power, address, and load level. The signal intensity of the received control packet is used to assess stability of the connection between two UAVs.

Channel load is determined as the percentage of time the medium is busy and is calculated as:

$$Channel\ load = \frac{busy\ time}{busy\ time + idle\ time} \times 100\% \,. \quad (6)$$

Buffer utilization is determined by the ratio of the current queue length to the maximum queue length in the media access control (MAC) layer. The level of congestion is evaluated based on both channel load and average buffer occupancy. The ACO algorithm manages routes – those with declining pheromone levels or increased congestion are discarded. This dynamic path management ensures efficient data transfer routes across the network.

The step-by-step breakdown of the routing procedure for the scheme from [70] is as follows:

- In a UAV swarm, for data communication, a UAV checks its route cache for any existing routes that can be used for transmission.
- If such routes exist, the optimal path is selected for information transmission. If no valid route exists, the route discovery process is continued.
- The source node broadcasts RREQ packets to all stable neighboring nodes in sparse formations.
  - Intermediate nodes receiving RREQ check routing loops and update the control packet with HC, stability, and congestion level.
  - If an intermediate node possesses a route to the destination, it initiates the RREP process.
  - If not, it forwards the RREQ to its stable neighbors.
  - Upon receiving RREQ, the destination node updates the route information and returns the RREP to the source.
- Each intermediate node calculates broadcast probability p for dense deployment based on the number of mutual and unique stable neighbors and forwards RREQ accordingly. Upon receiving RREQ, the destination updates the route information and returns the RREP to the source.
- The destination generates an RREP containing HC, RC, and RS and returns it to the source along the same route.
- Intermediate nodes receiving an RREP forward it to the source. If an intermediate node has a path upon receiving the RREQ, it converts it to an RREP and sends it to the source.
- After receiving the RREP, the source node extracts HC, RC, and RS and calculates the pheromone level for each route.
- The route with the highest pheromone level is selected for data transmission.
- The protocol maintains multiple routes with varying levels of pheromones. If the primary route fails due to inactive nodes, backup routes are utilized without restarting the route discovery process.

The authors of [70] compared the performance of APAR with DSR, hybrid ant colony optimization routing (HOPNET) [72],

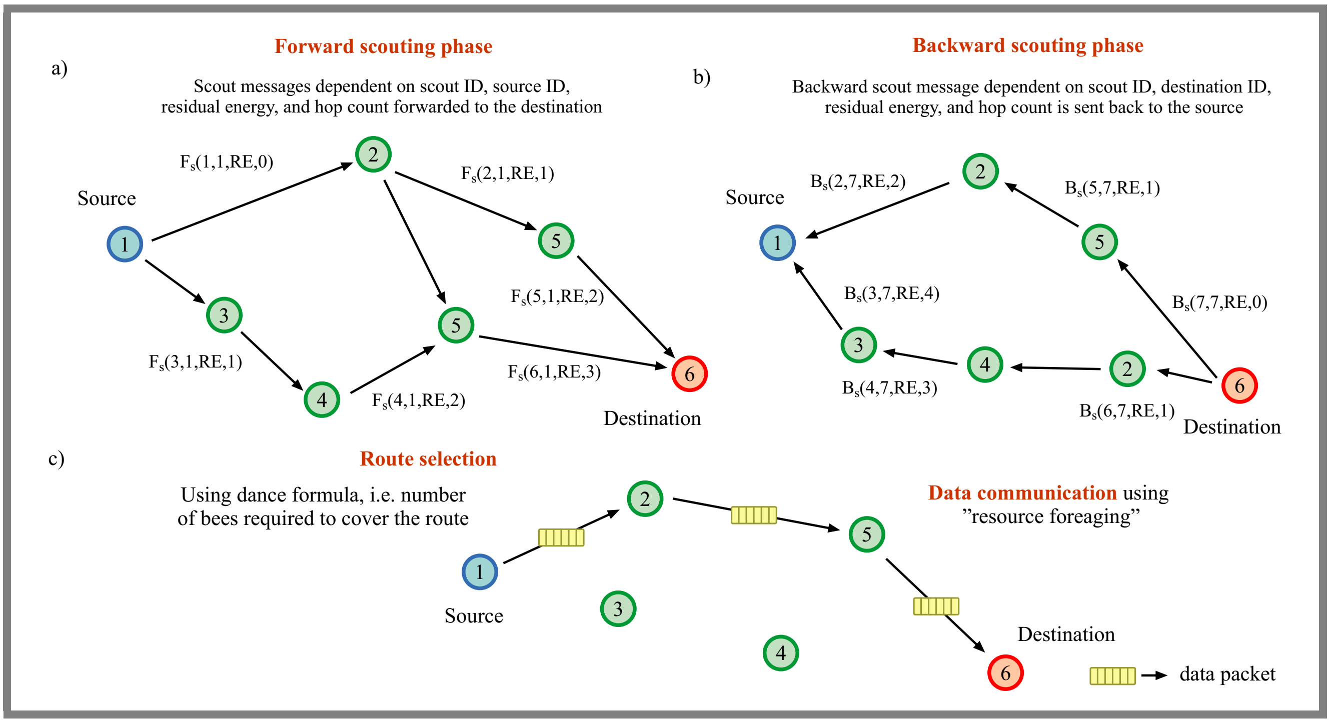

Fig. 7. Illustration of the BeeAdhoc scheme for FANETs: a) forward scouting phase, b) backward scouting phase, and c) route selection phase.

and Ant-DSR [73] algorithms. APAR exhibits high PDR, low average end-to-end delay, and low routing overhead compared to these schemes. Due to the quick topology adjustments of ACOs, APAR is highly adaptable. It also provides a high degree of link stability and scalability by using pheromone values to reinforce successful routes.

However, it suffers from high routing overhead and moderate energy efficiency due to the computational complexity and extra communication overhead required for pheromone updates. APAR effectively distributes traffic over the network, resulting in improved efficiency and reliability. Nevertheless, the protocol does not take into account privacy and security.

Solving polymorphic formations with ACO, APAR utilizes pheromone trails as a route stability method, where ants discover high-coverage routes. With the inclusion of DF and GSO, HSCS improves flexibility, allowing the network to efficiently adapt to dynamic node locations and topologies.

A polymorphic ACO algorithm computes the probability of coverage through Bayesian inference [74] on an ant exploration data. Computational complexity $O(m \cdot n)$ for (m – paths and n – ants) arises from the iterative optimization required to maintain robust coverage.

The advantages of the APAR protocol can be summarized as follows.

- The ACO algorithm provides a stable route by sensing pheromone levels in routes.
- It is applicable in both sparse and dense application scenarios, as different routing schemes were employed accordingly.
- Network performance degradation can be reduced by utilizing the pheromone volatilization property in routes.

The limitations of APAR include:

- High computational overhead of multipath exploration.
- Slow convergence in dense networks.
- Poor link stability due to high UAV movements.
- Lack of support for low-latency applications.

4.6. BeeAdhoc Routing Protocol

The BeeAdhoc routing protocol, introduced in [75], is a bio-inspired mechanism designed to manage the movement in FANETs. Grounded in swarm intelligence (SI), BeeAdhoc draws inspiration from honey bees' collective movement and foraging behavior to enable efficient data routing.

The protocol relies on frequent message exchanges utilizing two distinct message types: scouts and foragers. Scouts operate on demand to identify new paths to the destination. In the forward scouting phase, depicted in Fig. 7a, the source node broadcasts a forward scout message F_s containing the scout identification number (ID), sender ID, residual energy (RE) and hop count (HC).

Intermediate nodes update this information and relay it to neighboring nodes toward the destination. When F_s are received, the destination node responds with a backward scout message B_s comprising the scout ID, destination ID, HC, and RE, which retraces the route to the source, as depicted in Fig. 7b. The final route is selected based on a dance-inspired formula modeled after the bee waggle dance [76], [77], which evaluates the number of UAVs required to cover the path (see Fig. 7c).

Data transmission employs foragers, mirroring the resource-transportation behavior of bees. The routing procedure, as detailed in [77], unfolds as follows:

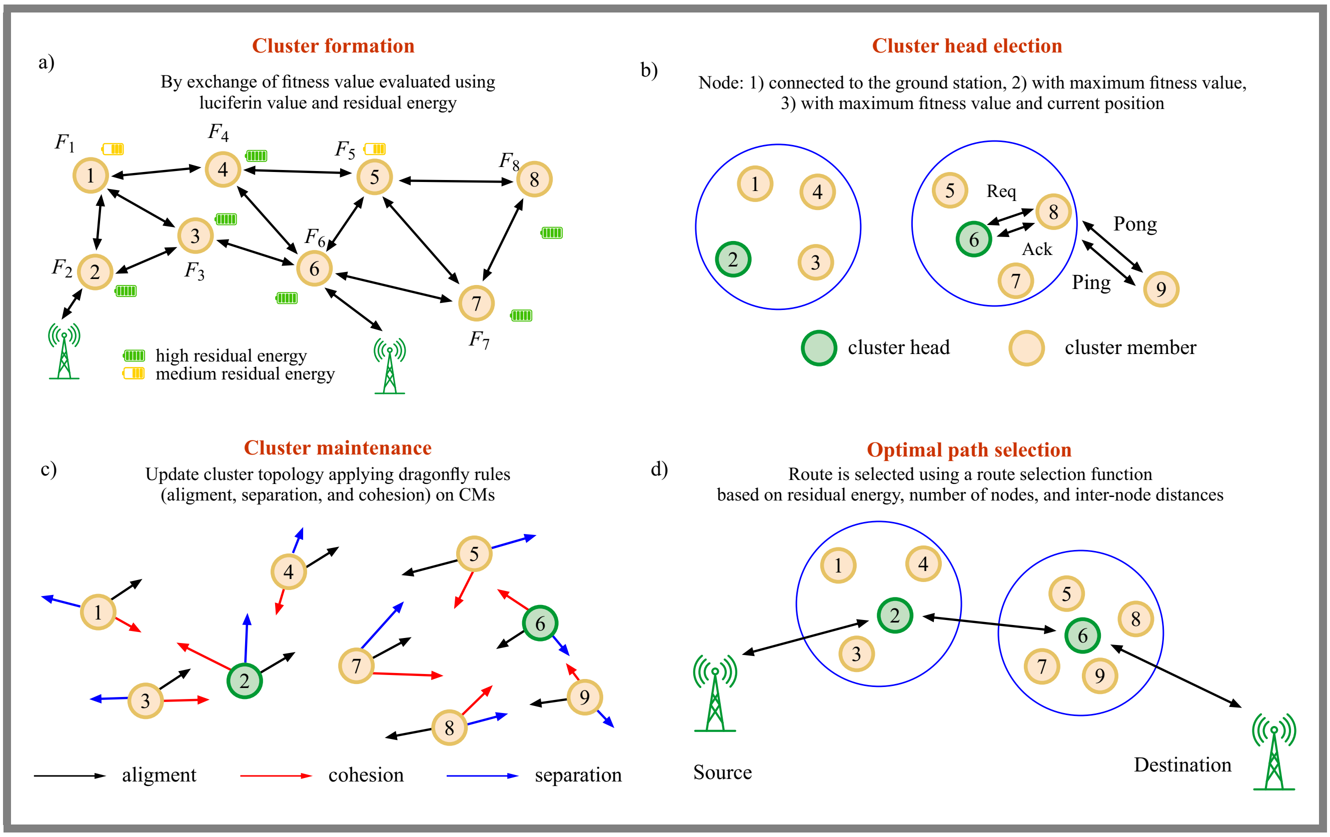

Fig. 8. HSCS scheme for FANETs: a) cluster formation, b) cluster head election, c) cluster maintenance, and d) optimal path selection.

- The sender node in a swarm transmits an F_s (scout ID, Sender ID, RE, HC) toward the destination.
- Intermediate nodes receive the F_s, update its contents, and forward it to neighboring nodes closer to the destination.
- Upon receiving the F_s, the destination node generates a backward scout message B_s (scout ID, destination ID, HC, RE), which backtracks the route to the sender.
- During data transmission, a packet from the transport layer arrives at the packing floor.
- A packer agent is instantiated to store the data packet temporarily. The packer searches the “dance floor” for an available forager to transport the packet to the destination. If a suitable forager is found, the packet is transferred and the packer terminates. If no forager is available, the packer waits briefly for a returning forager; if none arrives, a scout is deployed to discover a new route.
- Foragers acquire the entire route from a scout or another forager and transmit data relying on the multihop process.
- For TCP transmissions, the forager at the destination waits to be piggybacked.
- For UDP, the forager may become stranded at the destination and unable to return. To mitigate this, the swarm embeds multiple foragers, some in the header and others in the payload, to replenish resources at the destination.
- Upon returning to the source, the forager performs a “dance” to recruit additional foragers, reflecting the quality of the traversed path.

This scheme is highly adaptable, and the foraging behavior improves link stability. Furthermore, BeeAdhoc incurs a high routing overhead due to its high computation and communication requirements. Privacy and security are not prioritized, making the network vulnerable.

Network coverage is reduced due to the emphasis on local clustering. Optimized for energy efficiency in moderate mobility, BeeAdHoc uses bee scouts to discover routes to uncovered areas. Scout bees divide the terrain, and foragers evaluate coverage through path redundancy checks.

A flower pollination model maps coverage using scout bee trajectories. This incurs $O(s \cdot d)$ messaging overhead (s – scouts, d – destinations), resulting in severe accuracy degradation in urban canyons where sector misalignment causes coverage overestimation. Computational load increases exponentially with terrain difficulty and dense networks.

The advantages of the BeeAdhoc protocol include:

- It is energy efficient due to imitation of honey bees’ foraging behavior and low transmission of control packets.
- Honey bees’ foraging behavior results in efficient and consistent cluster formation and a low re-clustering rate.
- Due to its simple implementation, this technique is appropriate for many network situations.

The limitations of BeeAdhoc are as follows:

- High computational overhead from multipath exploration.
- Poor scalability due to proliferation of control packets.

- Poor link quality in large networks, as it suffers from a longer end-to-end delay.
- No priority scheduling for real-time data.

4.7. Hybrid Self-organized Clustering Scheme (HSCS)

To counteract the dynamic topology and limited resources of FANETs, the authors of [78] proposed the HSCS routing protocol. HCHS is a hybrid of the dragonfly scheme (DF) [79] and GSO algorithms, consisting of three essential phases: cluster formation, cluster management, and cluster maintenance. Such an approach facilitates effective communication among drones within the network. The GSO method is used for clustering and CH election process, while the DF scheme monitors CMs' mobility.

During clustering, as shown in Fig. 8a, each node evaluates its fitness based on luciferin values and residual energy levels. A cluster is formed by broadcasting the fitness value in the neighborhood. The fitness values and connectivity of the GCS are evaluated for the purpose of CH selection. If a single node within a cluster maintains a connection to the GCS, that node is selected as the CH, while the remaining nodes become CMs.

On the contrary, if multiple nodes are connected to the GCS or no nodes are connected, the CH is elected based on the maximum fitness value, as depicted in Fig. 8b. A node must broadcast a PING control message to the CH if it wants to join a cluster. A CM must forward an REQ control message to its CH if it receives the control message. Upon receiving the REQ message, the CH must send an acknowledgment (ACK) to the CM, and the CM will respond with a PONG message to the new node.

Furthermore, as explained in Fig. 8c, during the cluster management phase, the protocol facilitates effective coordination between CM and the CH, ensuring adherence to swarm behavior within the cluster. This coordination is achieved through a next-hop selection function that fosters overall network stability. The process is governed by DF rules, prioritizing alignment, cohesion, and separation.

These principles direct the movement of CMs, ensuring that they remain connected to the CH while maintaining optimal distances between themselves. This approach prevents collisions and fosters effective communication within the cluster. During the cluster maintenance phase, the status of CMs is periodically evaluated to ensure network stability. Nodes with energy levels that are lower than a threshold value are identified and removed from the cluster. Additionally, an alternative route is determined.

Finally, the optimal route is selected using a route selection function (RSF) based on key parameters such as node count, residual energy, and inter-node distances. The optimal value of RSF ensures low energy consumption. The route selection process depicted in Fig. 8d frees the protocol from multiple routes. The process outlined in scheme [80] is as follows:

- Each UAV calculates its fitness F_v (connectivity, residual energy, and luciferin value).
- UAVs exchange hello messages to discover their neighbors. If no UAVs are connected to the BS, the node with $\max(F_v) = CH$. If multiple UAVs are connected to the BS, the node with $\max(F_v) = CH$.
- The CH initializes the formation of the cluster, and neighboring nodes join as CMs.
- The CH applies DA rules (alignment, cohesion, and separation) and updates the cluster topology table based on the positions of its members.
- For data transfer, UAVs employ the RSF algorithm to determine the best route to the target. RSF analyzes aspects such as connection quality, HC, and RE.
- The data are communicated using the optimal route.

HSCS integrates bio-inspired techniques to optimize network organization and routing. CHs monitor member dropout rates to detect holes. By combining DF and GSO, HSCS improves adaptability, enabling the network to adjust efficiently to dynamic node positions and topology changes.

The protocol achieves high link stability due to its hybrid solution, which optimizes both clustering and routing paths in dynamic topologies to improve connections. Cognitive IoT-optimized HSCS supports a PSO coverage optimizer that attempts to cover the minimum number of uncovered grids using fitness functions. Minimizing communication, but with $O(n \cdot i)$ (n – nodes, i – iterations) complexity, it drains batteries on long-duration missions, resulting in reconstruction errors that are greater than those in high-mobility cases.

However, HSCS supports the establishment of multiple routes by leveraging its clustering approach. Multiple paths can be maintained within and between clusters, enhancing redundancy and fault tolerance. The network coverage ratio is high, as the hybrid clustering approach effectively manages more extensive and dispersed network areas.

HSCS suffers from high routing overhead due to high computational and communication complexity. Owing to its high computational complexity, energy efficiency performance is moderate. HSCS effectively manages network traffic but does not provide privacy and security, leaving the network open to security threats.

The advantages of the HSCS routing technique may be summarized in the following manner:

- Due to the fewer topology control messages, this scheme provides low routing overhead and high energy efficiency.
- The proposed scheme shows efficient cluster management due to the use of the DA algorithm for tracking CMs.
- Due to the nature of self-optimization, HSCS improves link stability.

HSCS suffers from the following limitations:

- High routing overhead due to complex computations for hybrid clustering and cognitive decision-making.
- Cluster formation latency with high mobility.
- Not optimized for multimedia traffic.

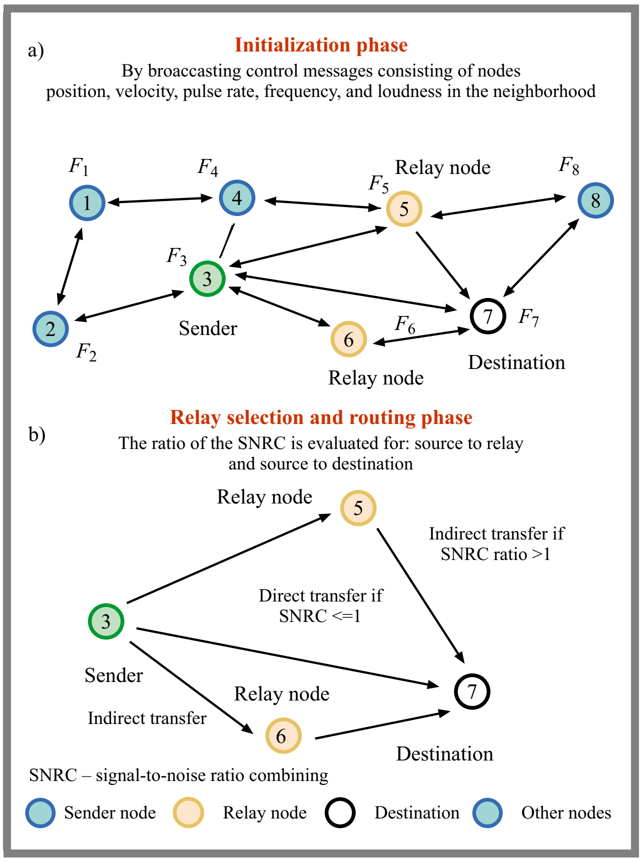

Fig. 9. BAT-COOP scheme for FANETs: a) initialization phase and b) relay selection and routing phase.

4.8. Bat Algorithm Using Cooperation Technique (BAT-COOP)

The authors of [81] proposed the BAT-COOP technique for FANETs to minimize transmission losses by decreasing end-to-end delay. To achieve this objective, bat echolocation [81] characteristics have been mimicked to induce cooperation features in the network. The algorithm comprises initialization, cooperation, as well as relay selection and routing. During the initialization phase, the nodes share their information by exchanging control messages consisting of the position, distance d, velocity v, pulse rate PR, frequency f, and loudness l in the neighborhood. Each node in the network evaluates its local optimal position, which is beneficial for intelligent selection of the next hop by the sender, as depicted in Fig. 9a. In the cooperation phase, the sender simultaneously forwards data to the destination and relay nodes.

Relay nodes forward the received data to the destination. Upon receipt of the data packets, the sink node merges the received signals and the power of the sender directly with the relay node [82]. Finally, during the relay selection and routing phase, a node with a higher cost value based on distances between nodes, signal-to-noise ratio, cost factor, and instantaneous link condition is selected for the relay. This is shown in Fig. 9b.

Following the selection of the relay node, the information is forwarded thereto. Data forwarding depends on signal-to-noise ratio combining (SNRC), which is evaluated for routes from the sender to the relay and from the sender to the destination. If the $ratio <= 1$, the data is transferred directly to the destination; otherwise, for a $ratio > 1$, the data is transferred to the relay node. During the indirect transfer, the relay node waits for a predefined hold time, during which redundant data packets are rejected at the destination, which is received from the sender directly or through the relay. When two relay nodes are available on the destination path, the relay node will not trigger cooperation. The needless forwarding of data packets has been successfully countered using the bat cooperation technique. The procedure described in scheme [81] includes the following steps:

- The system is initialized, with each node being aware of its position, velocity, frequency, pulse emission rate, and the best local position.
- The source node transmits its current position.
- Solutions for each node are generated by adjusting the pulse emission rate, while velocities and positions are updated based on the current best solutions discovered so far.
- The source generates a random number R and compares it with pulse emission rate r_i. If $R > r_i$, a solution is selected from the current best solutions; otherwise, a local solution is generated using random flight. Next, a fitness value is evaluated for each node; if it is worse than its local best, it is replaced with a new solution generated by random flight. If the new solution is better than the current one, it is accepted and the local best update is provided.
- After selecting the local best, a cost function $C_f\ (d, f, l)$ is evaluated, and the feasibility of a direct transfer is checked. If the direct transfer path is feasible and satisfies the cost function, the data is transferred directly from the source to the destination. Otherwise, the system selects the best relay node for the data transfer.
- If the destination receives multiple signals from the relay nodes, the SNRC scheme combines these signals, selecting the one with the highest SNR.

The BAT-COOP protocol employs a multi-hop routing strategy inspired by the cooperative behavior of bats to enhance network performance. BAT-COOP demonstrates high adaptability through its cooperative framework and efficiently handles dynamic network topology. Selecting optimal paths improves link stability and diminishes the chances of link failures. The protocol supports the establishment of multiple routs, thus improving redundancy and fault tolerance. Its multi-hop strategy and cooperative beam-focusing technique ensure extensive network coverage, making it suitable for larger operational areas.

However, BAT-COOP incurs significant routing overhead due to the computational demands of cooperative diversity techniques and frequent routing updates. Continuous message exchanges contribute to high communication overhead, while the storage and management of cooperative data structures result in elevated space complexity.

Energy efficiency remains moderate, as the cooperative approach increases energy consumption during multi-hop transmissions. The protocol integrates effective load-balancing mechanisms to distribute traffic evenly across the network. Despite its advantages, BAT-COOP prioritizes cooperative communication and network localization over privacy and security, potentially leaving the network vulnerable to security issues.

With cooperative diversity as its target in mobile FANETs, BAT-COOP utilizes cooperative relay probing, in which UAVs mimic signal pulses to identify coverage holes and node sparsity based on echo delays.

BAT-COOP employs a pulse-echo simulator model of coverage based on delay-sensitive sonar equations. Urban environments require $O(n \log n)$ complexity (n – number of bats), which increases in high-density areas. Unmodeled weather effects introduce accuracy errors in rain and fog conditions.

The advantages of the protocol are as follows.

- The approach suits dynamic networks, since the node count is regularly updated and shared.
- The scheme overcomes the issue of unnecessary forwarding of packets and reduces transmission losses.
- The scheme achieves better load balancing due to the use of forwarding nodes.
- The scheme suits sparse and dense networks in real-time application scenarios.

The limitations can be summarized as below:

- High routing overhead due to the computational complexity of cooperative routing.
- Limited scalability due to distributed cooperation.
- Not specifically designed to handle real-time packet delivery constraints.

4.9. Gray Wolf Algorithm Using Cooperative Diversity Technique (GW-COOP)

For efficient routing in FANETs, the authors of [83] proposed the GW-COOP approach that is based on the gray wolf optimizer (GWO) and uses the collaboration technique and the leadership hierarchy of gray wolves [84] to find the optimum path to the destination. The proposed scheme comprises two phases, namely initialization and routing.

As depicted in Fig. 10a, in the initialization phase, every node iteratively evaluates its fitness value based on energy level and distance from the destination. The nodes are ranked according to their position and fitness value. Next, the first three best options are identified during each iteration. The first best UAV is considered alpha, which is the sender node. Beta and delta nodes are the second and third best UAVs, respectively. The remaining nodes are regarded omega.

The sender can directly forward critical data to the sink during the routing phase. In the event of less critical data or a change in topology, the data can be sent through beta or delta relay nodes. Upon receiving a data packet from relay nodes, the enhanced signal-to-noise ratio combining (ESNRC) approach is used at the destination to consider higher strength signals, as shown in Fig. 10b.

The steps involved in scheme [83] are described below:

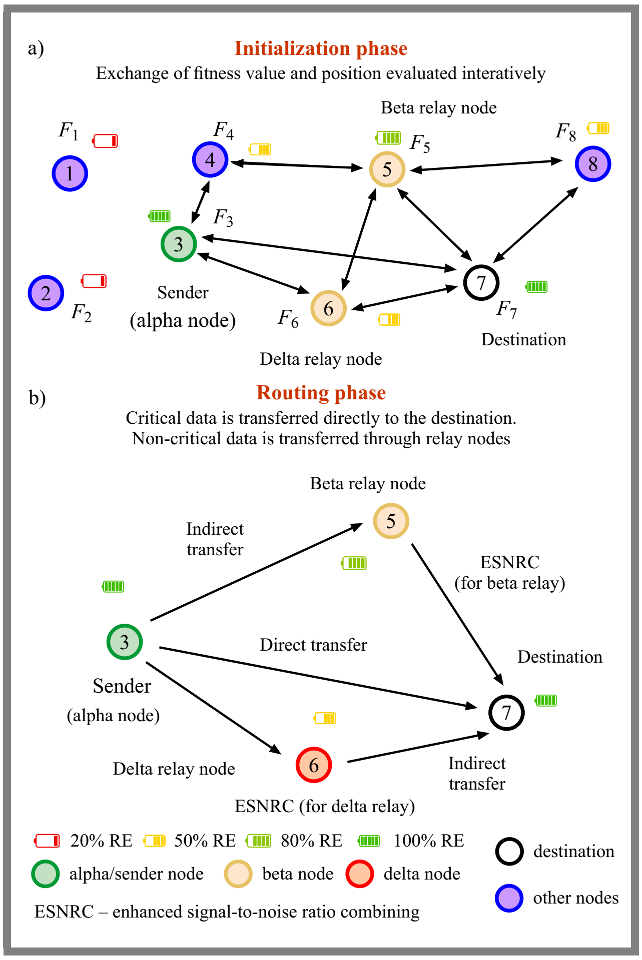

Fig. 10. Illustration of the GW-COOP scheme for FANETs: a) initialization phase and b) routing phase.

- UAVs are initialized randomly and each UAV evaluates its fitness value F_v iteratively, based on energy level.
- Based on F_v, the nodes are categorized as: α – first best solution, β – second best solution, δ – third best solution, and ω – the remaining solutions.
- The system iteratively searches for the best route based on the cost function.
- If critical data are detected, α is used as the direct path for communication. Otherwise, the cooperative phase is activated.
- Residual energy level is estimated for the source and potential relay nodes R_1 and R_2.
- A direct path is chosen if the source node has a higher residual energy than R_1 or R_2.
- Otherwise, a relay path is selected using the amplify-and-forward (AF) relay strategy at R_1 and R_2.
- Enhanced SNR combining is applied at the destination to improve reliability.

The performance of the proposed scheme was compared to BAT-COOP to evaluate its efficiency. Due to its incorporation of social hierarchy and cooperative diversity, the GW-COOP scheme outperforms BAT-COOP by showing lower transmission losses, improved adaptability, and more reliable communication. GW-COOP is highly adaptable, efficiently adjusting to changes in node mobility through its cooperative diversity approach.

The protocol supports multiple routes, enhancing redundancy and fault tolerance within the network. Network coverage is also high due to its multi-hop strategy, which facilitates extensive reach across larger areas. However, GW-COOP incurs relatively low routing overhead due to efficient cooperation mechanisms that minimize redundant data transmissions and optimize path selection, making the process of scaling up for large networks easy. The cooperative approach may result in higher energy consumption during multi-hop communications. GW-COOP effectively manages network load. However, it does not provide privacy and security.

Designed to target link-aware routing in high mobility, GW-COOP utilizes a gray wolf hierarchy for loss prediction during routing. "Alpha wolves" direct pack movement using fitness functions that evaluate coverage entropy from neighbor reports. Link quality thresholds trigger rerouting.

A social hierarchy-based search is used to minimize path loss. The $O(p \cdot n)$ complexity (p – pack size, n – generations) causes longer decision cycles in moderate-density networks.

The advantages of GW-COOP can be summarized in the following manner:

- The scheme employs fewer parameters and is easy to implement.
- It considerably minimizes transmission losses, resulting in reduced energy consumption, packet loss ratio, and link delay.
- The protocol offers better local exploration, as it employs a hierarchical pattern.
- It handles FANETs effectively due to the use of ESNRC.
- It offers reliable network communication, even in sparse deployment scenarios.

The limitations of GW-COOP include:

- Moderate routing overhead from gateway selection.
- Gateway congestion in large networks.
- Link instability during gateway failure.
- Time-window or latency-sensitive communication is not prioritized, limiting real-time performance.

4.10. Physarum-inspired Clustering Algorithm (PICA)

The authors of [85] proposed PICA – an innovative clustering algorithm designed explicitly for FANETs. The proposed scheme is based on the foraging behavior of physarum polycephalum (PP) silme mold [86]. PICA is known for its remarkable ability to form efficient networks and solve complex optimization problems. It utilizes a distributed multi-hop clustering approach that significantly improves forming and maintaining clusters within FANETs.

PICA is a two-stage process that includes cluster formation and maintenance. All nodes start in the initial IN state during cluster formation. The clustering process is depicted in Fig. 11a. Nodes establish their neighbor sets by exchanging hello

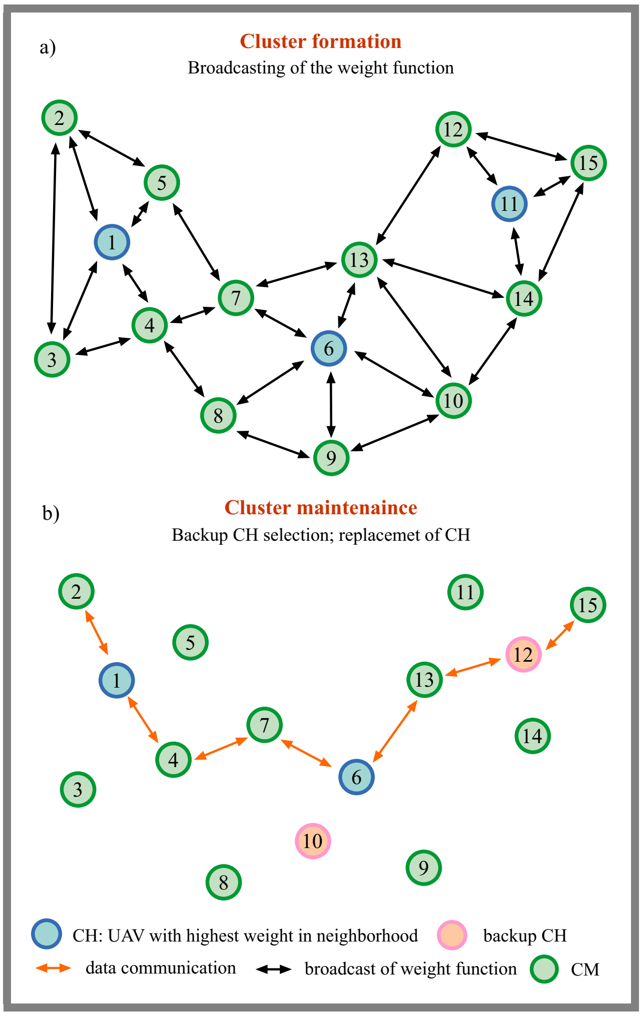

Fig. 11. Purpose of operation of the PICA scheme for FANETs demonstrating: a) cluster formation and b) cluster maintenance.

control packets and determining their weights using a W_f function that depends on the likelihood of the current node becoming a CH. These weights are subsequently shared with neighboring nodes in a second control message exchange round. If a node's neighbor set is populated and its probability of becoming a CH exceeds that of neighboring nodes, it is elected as the CH. The CH transmits a cluster head declaration (CH_DEC) to the surrounding nodes.

Nodes issue a join request (JOIN_REQ) to join the cluster after receiving a CH_DEC message, designating the node with the best virtual communication quality as their CH. It switches to CM after receiving a join response (JOIN_RESP). This multi-hop clustering structure optimizes cluster coverage by minimizing the frequency of switching between CMs and clusters.

During the cluster maintenance phase, procedures for detecting damage and merging clusters work to maintain the cluster's stability structure, while backup CHs are updated regularly, as illustrated in Fig. 11b. The CH periodically broadcasts the list of CMs. When this broadcast is received, any member with more than 60% of the CMs in its neighbor set determines its priority for possible election as a backup CH.

This priority is determined by factors such as the average virtual communication load with other nodes in the cluster and the member's remaining energy. The CH selects the member with the highest priority as the backup CH, and any updates regarding changes in the backup CH status are immediately broadcast to the cluster. To avoid selecting edge nodes, only nodes with strong connectivity to other cluster nodes are considered for backup CH selection. The step-by-step breakdown of the routing procedure for the scheme is as follows [85]:

- UAVs initiate the clustering process in a distributed manner. The source node shares hello control messages with its neighboring nodes.
- Each node assesses its weight function W_f, which relies on BeCH, and its likelihood of becoming a CH (BeCH).
- W_f is shared with the neighboring nodes during the second exchange of hello messages.
- If BeCH is the highest, the node changes its status to CH and invites nearby nodes to join the cluster; otherwise, it tries to connect to a nearby CH. If the node can connect to a CH, its state changes to CM. JOIN_REQ is forwarded and the cluster is joined if JOIN_RESP is received from CH. If the node cannot connect to any CH, it uses a multi-hop connection through another CM.
- A backup cluster head (BCH) is selected to take over if the current CH fails.
- If the clusters become too small, they merge with other clusters.

The algorithm considers several critical factors during the cluster formation process, including link stability, residual energy, and communication quality. PICA offers high adaptability and link stability levels by dynamically adjusting to network topology changes and mimicking PP's foraging behavior. This results in extensive network coverage and effective communication within clusters. However, PICA faces high computational and communication overhead challenges due to the complex computations and frequent updates required for accurate clustering.

In addition, storing pheromone levels and routing information contributes to increased memory overhead. While the algorithm aims for energy-efficient clustering and offers effective load balancing by distributing network load evenly, it does not inherently support multiple routing paths. Additionally, it does not prioritize privacy and security, leaving the network vulnerable to attacks.

Optimized for scalable clustering in highly mobile FANETs, PICA implements physarum-inspired multi-hop coverage trees. CHs utilize Levy flight patterns [87] to adjust their flights while exploring previously unexplored areas. CMs relay data across clusters to fill coverage gaps. The protocol prioritizes zones with low node density by triggering the CH redeployment when coverage holes are detected via RSSI decay.

A Levy flight coverage analyzer estimates coverage gaps, and CHs merge coverage maps via Levy flight, reducing communication overhead but requiring $O(m \cdot n)$ computations (m – clusters, n – waypoints).

The advantages of the PICA method include the following:

- PICA ensures the shortest paths between nodes, reducing communication latency and improving network performance.
- The algorithm can dynamically reconfigure itself in response to environmental changes, ensuring robust and flexible network connectivity.
- By optimizing the routing paths, PICA helps reduce energy consumption.

The limitations of PICA are presented below:

- High routing overhead due to computational complexity from multilevel clustering.
- Poor link stability in the case of highly dynamic networks.
- There is no dedicated mechanism for data delivery, limiting emergency communication support.

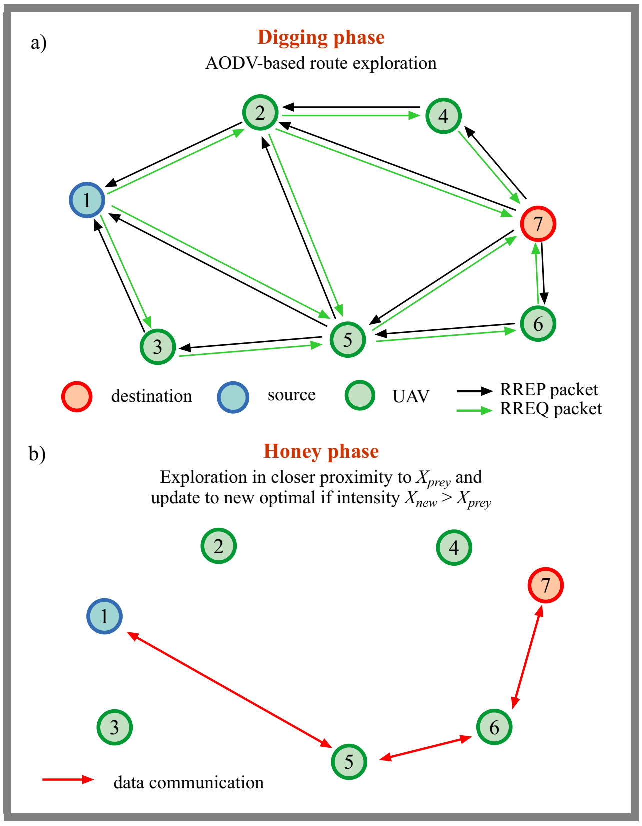

Fig. 12. HB-AODV scheme for FANETs: a) digging phase and b) honey phase.

4.11. Hybrid Optimization of the 2-opt Heuristic and Honey Badger Algorithm (HB-AODV)

To counteract the dynamic topology of FANETs, the authors of [88] proposed HB-AODV – a hybrid of the 2-opt heuristic and the honey-badger algorithm (HBA) [89]. The proposed scheme comprises two phases: initial solution construction and route optimization using HBA. During the initialization phase, routes are determined using the 2-opt heuristic, as represented in Fig. 12a. To explore the route to the destination, the source node initiates a route discovery process using RREQ and RREP control messages, in a way that is similarly to that employed in the traditional AODV scheme.

A source node broadcasts RREQ messages when it needs a path to the destination. Each RREQ packet is modified to include a path field, accumulating the node IDs of all intermediate nodes traversed. The destination node collects multiple RREQ packets from the same source-destination pair. Each unique record path forms an initial solution in the population. Then, all these records are represented as a graph, in which edges denote communication links. Path length is reduced by iteratively swapping edges. During the route optimization phase, as shown in Fig. 12b, a metaheuristic approach is applied to refine the initial solutions obtained from phase 1. The scheme continues exploring new paths while exploiting the available routes.

The goal is to identify the path with the fewest hops. This phase also includes route maintenance, which is used to repair inconsistent paths. If a link is detected, the route repair process is triggered to rapidly adapt to topology changes. This continuous optimization and maintenance ensure reliable communication and robust performance. The steps taken in scheme [88] are described below:

- Randomly initialize the positions of honey badgers (potential solutions) within the search space.
- Assess the fitness of each honey badger position based on HC, delay, and energy consumption.
- Store the honey badger position with the best fitness (i.e. the most promising route) as x_{prey} and its F_v as f_{prey}.
- Find the optimal solution. When stopping criteria such as reaching the maximum number of iterations or achieving the desired fitness are met, the algorithm yields the current best-results solution; otherwise, it continues to update variables and searches for a better solution.
- Calculate each honey badger intensity level I based on its F_v and P.
- Generate a random number r between 0 and 1. If $r < 0.5$, update the honey badger's position using an exploration equation. If $r \geqslant 0.5$, update the honey badger's position using an exploitation equation.
- Evaluate the fitness of the updated solution.
- If the new fitness f_{new} is better than the current best fitness f_{prey}, update it.

The authors of [88] assessed the performance of HB-AODV using a network simulator. They concluded that HB-AODV is superior to DSDV and AntHocNet in PDR and outperforms traditional protocols such as AODV, DSDV, and AntHocNet in terms of QoS metrics, including PDR, average end-to-end delay, and throughput.

The metaheuristic approach makes this scheme adaptable to dynamic topology, ensuring reliable communication. However, the scheme suffers from high routing overhead due to high computational and communication requirements. Route optimization makes the scheme energy efficient, but security and privacy issues are neglected.

Combining 2-opt heuristics and HBA for dynamic networks, HB-AODV employs genetic coverage optimization to prevent coverage holes. UAVs continuously monitor neighbor density via hello packets, and GA-optimized paths avoid low-connectivity zones by penalizing routes with low neighbor counts.

GA-driven Dijkstra's algorithm evaluates coverage using a fitness function combining path loss (Friis free-space model), node degree, and link stability index. The $O(p \cdot g)$ complexity (p – population, g – genes) incurs more computational overhead when optimizing 3D coverage with altitude variations.

The advantages of the scheme are as follows:

- The scheme shows better performance than traditional routing approaches.
- This scheme is highly adaptable and balances exploration and exploitation.

The limitations of HB-AODV are:

- High routing overhead due to the increased complexity of the hybrid mechanism.
- Limited scalability.
- Reactive routing delays persist, affecting responsiveness in dynamic scenarios.
- Not optimized for latency-sensitive applications, limiting real-time performance.

4.12. Adaptive Secure and Efficient Bio-inspired Routing Protocol (Penguin-AIS)

To provide secure routing in FANETs, the authors of [90] proposed Penguin-AIS, a hybrid penguin search optimization algorithm (PeSOA), and artificial immune systems (AIS). PeSOA provides optimal routes using penguin collaborative hunting strategies. The PeSOA routing process is initialized by clustering UAVs that are randomly dispersed in the search space, mimicking the spatial distribution of penguins. UAVs gradually refine their paths, converging towards an optimized solution, as depicted in Fig. 13a. In the next phase, the location is estimated through a fitness function and then adjusted using penguin foraging behavior. Additionally, UAVs can optimize their current location by exploring new regions.

PeSOA prioritizes security and privacy and employs AIS, a solution similar to the human immune system, capable of detecting and countering malicious activities, as shown in Fig. 13b. The step-by-step breakdown of the routing procedure for scheme [90] is as follows:

- The search area is initialized and velocity- and position-related restrictions imposed on the nodes are defined.
- The UAVs are divided into equal-sized groups and a group head (GH) is assigned to each group.
- The beacon coordinates are sent to GH to guide them to the search area. They then further search within their assigned sub-area, updating UAV positions as needed.
- Information is exchanged between the GH and the central command.

Tab. 3. Comparative analysis of bio-inspired routing systems.

Routing protocol	Goal of optimization	Network coverage context	Network coverage	Protocol-specific constraints	Mapped universal constraints	Timing constraints
BICSF	Network coverage enhancement	Assume moderate-density UAV swarms in open areas	Partial	High re-clustering overhead	C1↑, C3↑	Cluster maintenance window
SIL-SIC	Efficient localization and clustering	Focuses on emergency scenarios with dynamic node distributions	High	Localization delay in sparse networks	C1↑, C4↓	Emergency data delivery
BIR-SLB	Multimedia routing	Targets multimedia traffic in mobile emergency networks	High	QoS degradation under mobility	C2↓, C4↓	Multimedia frame delivery
BR-AODV	On-demand routing	Assumes uniform node distribution	High	Slow route recovery	C2↓, C4↓	Route recovery deadline
APAR	Stability-aware routing	Medium-density airspace	High	Slow convergence in large networks	C3↑, C4↓	Convergence time for node heterogeneity
BEEAdhoc	Bee foraging-inspired routing	MANET-adapted	Low	Energy-intensive path discovery	C1↑	Scout path discovery latency
HSCS	Self-organized clustering	Cognitive IoT (static-sensor interaction)	High	Cluster instability in dynamic environments	C2↓, C5↓	Cluster stabilization
BAT-COOP	Enhances cooperative diversity	Suburban environments	High	Weather-sensitive links	C5↓	Relay handshake window
GW-COOP	Link/loss-aware routing	Moderate mobility	High	High computational load	C1↑	Link-failure response time
PICA	Multi-hop clustering	Uniform FANETs	Partial	Multi-hop latency	C4↓	Multi-hop forwarding
HB-AODV	Hybrid optimization	Generic UAV networks	High	Complex parameter tuning	C3↑	Hybrid metric tuning latency
Penguin-AIS	Adaptive secure routing	Security-focused FANETs	High	Security-induced overhead	C1↑, C3↑	Security validation delay
C1 – energy, C2 – mobility, C3 – scalability, C4 – QoS, C5 – link stability, constraint violation (↑) constraint compliance (↓)						

- Each group checks if its assigned sub-area has been searched thoroughly.
- The central command checks that the entire search area has been covered. Otherwise, the search continues.
- The UAV nearest to the destination is updated and stored as the best global solution g_{best}.
- UAVs from completed groups can be redistributed to unfinished groups.
- Low-power UAVs are identified and sent for recharge.

The authors of [90] evaluated PeSOA's performance through simulations and concluded that the scheme exhibits adaptability, high PDR, and reduced average end-to-end delay due to optimized route discovery. The scheme also focuses on load balancing and energy efficiency.

However, the overall routing overhead is moderate due to efficient route discovery and low computation overhead. The scheme continuously monitors packets due to the integrated AIS, enabling the easy detection of any abnormal activity.

Additionally, the scheme provides high route stability and optimized single-route communication. UAVs emulate penguin hunting behavior, cooperatively "diving" into coverage gaps detected via encrypted neighbor discovery. The protocol prioritizes the coverage of the secure zone by isolating untrusted nodes and dynamically positioning UAVs to fill the holes identified through packet loss thresholds.

Providing secure routing for mobile UAVs, PeSOA uses penguin search-inspired thermal coverage mapping, where "huddles" collaboratively detect cold spots (coverage holes). Computational complexity is $O(p \cdot f + k)$ per iteration (p – penguins, f – fitness evaluations, k – grid cells).

The advantages of the scheme are:

- It is highly adaptable to dynamic topologies.
- It is secure and easily counterattacks due to the built-in AIS security mechanisms.

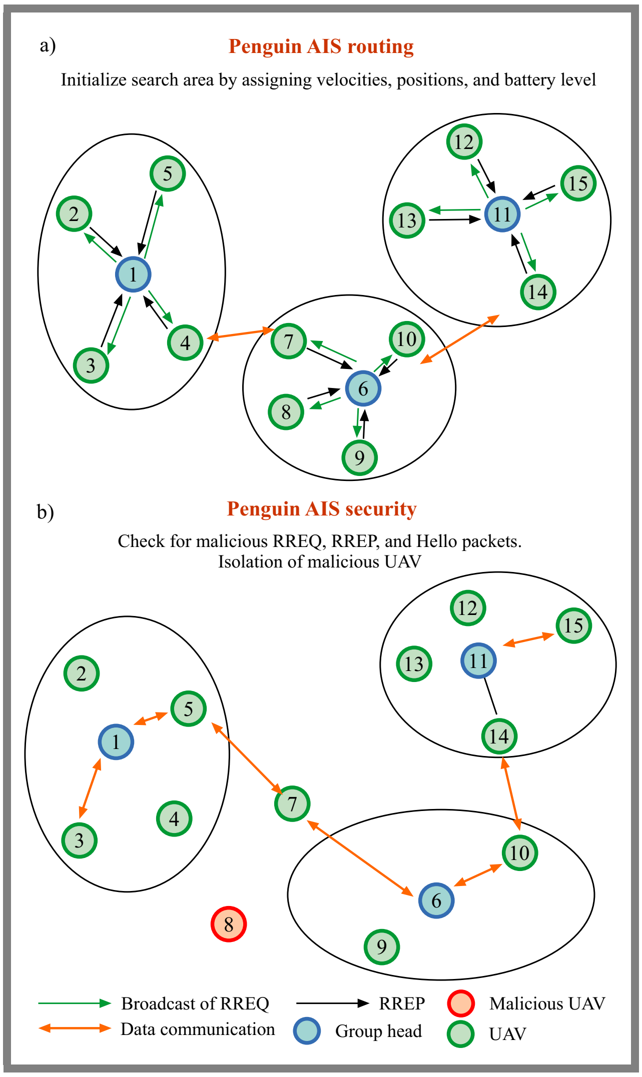

Fig. 13. PeSOA scheme for FANETs: a) routing phase and b) security phase.

The limitations can be summarized as:

- It suffers from moderate computational overhead due to adaptive and secure route selection.
- Poor scalability in dense networks.
- There is no explicit support for real-time traffic handling, limiting emergency communication support.

5. Comparative Analysis

The operational efficacy of bio-inspired FANET routing schemes is inherently related to network coverage characteristics, a dependency that is critically underexplored in the existing literature. Coverage heterogeneity (e.g. urban canyons, sparse deployments, altitude variations) induces profound performance divergences across protocols under identical mission scenarios. This section conducts a systematic comparative analysis of 12 state-of-the-art bio-inspired protocols, evaluating their resilience against: coverage-driven topological constraints (NLoS propagation, node density extremes, 3D mobility) and universal FANET limitations (C1 – energy, C2 – mobility, C3 – scalability, C4 – QoS, C5 – link stability), with its results presented in Tab. 3. By benchmarking protocol behaviors against these dual axes, we expose critical trade-offs, resilience gaps, and domain-specific suitability to guide protocol selection and future research. Table 3 analysis reveals intrinsic coverage-constraint couplings:

- BICSF incurs higher communication overhead than SIL-SIC in large swarms to counter mobility (C2) but achieves only partial coverage due to instability in ultra-dense/sparse deployments.
- BeeAdhoc reduces the delay in rerouting compared to BR-AODV at high speeds (C2) but exhibits low coverage efficacy due to non-adapted MANET mechanisms.
- BAT-COOP maximizes link stability (C5) by increasing retransmissions during weather disruptions. However, it ignores urban multipath fading.
- PeSOA's security measures increase resource requirements compared to lightweight protocols, but they are lower than those in clustering-intensive methods such as BICSF.

The routing protocols explicitly target dynamic FANET environments where UAVs exhibit significant positional changes. Optimization goals focus on maintaining routing stability despite 3D mobility, and all of the protocols address node displacement as a core challenge. Crucially, no protocol assumes static deployments, even GW-COOP's link-aware routing and PICA's multi-hop clustering prioritize adaptability to variations in velocity. This mobility-centric design imperative is evidenced by:

- **Mobility-specific mechanisms**. BeeAdhoc's scout bees relied upon for route rediscovery (high mobility), and BAT-COOP's echolocation used for relay handovers.
- **Universal constraint violations**. The 9/12 protocols violate C2 (mobility) due to delayed response to abrupt maneuvers.
- **Timing constraints**. Emergency data deadlines (SIL-SIC) and route recovery windows (BR-AODV) reflect real-time mobility adaptation needs.

Thus, all of the reviewed protocols fundamentally optimize data routing in networks with frequent UAV repositioning, not quasistatic deployments. Most importantly, altitude-related coverage variance – a characteristic of FANETs – is not addressed by 75% of the protocols (e.g. hybrid BR-AODV, PeSOA), which exacerbates urban shadowing attacks. These cross-protocol trade-offs, as reported, attest to the lack of Pareto-optimal solutions for all coverage-context constraints. Table 4 provides a comparison of the metrics harnessed in the analysis.

6. Open Challenges and Areas for Future Research

Bio-inspired routing protocols offer great potential to cater to the needs of FANET routing. FANETs have distinctive characteristics, including highly dynamic topologies, higher

Tab. 4. Comparison of metrics used in bio-inspired routing systems.

Routing protocol	Routing strategy	Bio-inspired algorithm	Routing function	Mobility model	Routing metrics								
					Adaptability	Link stability	Multiple routes	Computational overhead	Communication overhead	Memory overhead	Energy efficiency	Load balancing	Privacy and security
BICSF	Clustering	GSO, KH	Luciferin value	3D Gauss-Markov	Yes	Low	No	High	High	High	Yes	No	No
SIL-SIC	Clustering	PSO	Fitness function	Swarm waypoint	Yes	High	No	High	Mod.	High	Yes	Yes	No
BIR-SLB	Clustering	AntNet	Path length	Swarm based	Yes	Low	No	Low	Low	Low	No	Yes	No
BR-AODV	Distance-based	Boids of Reynolds	Velocity alignment	3D random walk	Yes	Low	No	High	High	High	Yes	Yes	No
APAR	On-demand reactive	ACO	Pheromone concentration	Random waypoint	Yes	Low	Yes	High	High	High	Mod.	Yes	No
BEE Ad hoc	Swarm intelligence	Bee's wangle dance	Swarm intelligence	Swarm based	Yes	Low	Yes	High	Mod.	High	Yes	Yes	No
HSCS	Clustering	DF, GSO	Luciferin energy level	Swarm based	Yes	High	No	High	High	High	Mod.	Yes	No
BAT-COOP	Multi-hop	Bats' cooperation	Pulse emission/reception	Swarm based	Yes	High	Yes	High	Mod.	High	Mod.	Yes	No
GW-COOP	Multi-hop	GWO	Fitness function	Swarm based	Yes	Low	Yes	Low	Low	Low	Mod.	Yes	No
PICA	Clustering	PP	Cluster head function	Swarm based	Yes	Low	No	High	High	High	Yes	Yes	No
HB-AODV	Multi-objective optimization	HBA	Fitness function	Swarm based	Yes	High	No	High	High	High	Yes	Yes	No
Penguin-AIS	Meta-heuristic optimization	PeSOA, AIS	Membership function	Swarm based	Yes	High	No	Mod.	Mod.	Low	Yes	Yes	Yes

node mobility, energy constraints, sparse deployment, limited processing capabilities, and complex application scenarios that require specific routing protocols. Various routing protocols have been proposed to fulfill these critical requirements, each with its advantages and limitations that ultimately lead to their failure.

Most bio-inspired protocols (10/12) (such as BICSF, BR-AODV, and APAR) have considerable computational burdens that stem from intricate biomimetic functions. These impose severe energy-scalability compromises (violating C1/C3 constraints).

BICSF's dynamic clustering shows significantly greater processing requirements than SIL-SIC, and BeeAdHoc's path discovery shows modest communication overhead despite significant memory needs. Most importantly, BIR-SLB achieves a uniformly low overhead. GW-COOP excels in communication and memory efficiency but with moderate energy costs, resulting in a significantly prolonged network lifetime in large swarms.

Verification-based optimizations validate the high memory overhead from localization caching in SIL-SIC, while BAT-COOP maintains moderate communication overhead using focused probing.

Some of the constraint-specific gaps are listed below:

- Cluster-based protocols (BICSF, SIL-SIC) optimize energy efficiency (C1) in terms of coverage limitation.
- Cooperative designs (BAT-COOP, GW-COOP) optimize link stability (C5), but GW-COOP shows instability during disruption (C5).
- Penguin-AIS alone implements adaptive encryption with moderate computation (C1) cost without sacrificing QoS (C4).
- Biohybrids, such as HB-AODV, demonstrate good QoS (C4) but lack multipath support and scalability (C3).

These overhead properties place inherent limitations on real-world deployment of resource-constrained UAV platforms. In addition, bio-inspired schemes, e.g. artificial bee colony (ABC) [91], bacterial forage optimization (BFO) [92], moth flame optimization (MFO) [93], and red deer optimization (RDO) [94] are still unexplored.

Therefore, more research and innovation are necessary to explore the use of these algorithms and effectively address the complexities of FANET routing [95].

These trade-offs emphasize the importance of choice of an environment-sensitive protocol in FANET deployments. Some of the open research issues will be discussed in the next subsection.

6.1. Dynamic Topology and Sparse Deployment

High mobility of nodes leads to frequent topological changes in the network, resulting in sporadic connectivity [96]. Additionally, nodes can enter and exit sparsely deployed networks when necessary. Several routing protocols have attempted to counter these challenges [97], but most protocols, including bio-inspired routing schemes, fail to ensure proper network coverage. Routing protocols must be designed with increased adaptability and better topology management to counter intermittent connectivity issues. High PDR, reduced end-to-end delay, quick route recovery, reduced overhead of control messages, and high reliability must be supported as well.

6.2. Security Attacks and Data Encryption

Most FANET routing schemes have been designed considering intermittent connectivity, without taking into consideration security threats. Flying nodes are deployed in very harsh or complex situations where they remain unattended, making them easy to capture or be victimized by attackers [98]. Most bio-inspired protocols do not have the provision to provide security and privacy. Under the military application scenario, data transmission must be performed securely and must be protected by suitable encryption algorithms.

Consequently, in the event of a node capture attack, the attacker will need some time to decode the secret information. Therefore, FANET routing protocols must be designed with data encryption in mind, to provide relevant security levels.

6.3. Realistic Mobility Models and Simulation Environment

Although several node mobility models have been presented in the literature, further improvements are still required to simulate nodes in a real-world scenario, with a variable degree of movement in 3D space and multiple mobility models [99]. Furthermore, simulation tools can be designed to predict the node's future locations precisely.

6.4. Energy-efficient Routing with Energy Harvesting

The flying nodes in FANETs are battery powered, with the energy utilized for node mobility, hovering, data processing, payloads, and transmission to intermediate nodes or sink nodes [100]. The amount of residual energy affects each of these operations.

Furthermore, in complex environmental application scenarios, UAVs remain unattended for a long time [101]. Due to the non-availability of any power recharging systems, efficient energy management becomes the most critical routing design issue for future research. Therefore, residual energy of UAVs must be considered when designing routing protocols, especially for FANETs. Additionally, various power transfer schemes and energy harvesting techniques using renewable energy sources should be considered.

6.5. Networking Protocols and the Use of AI

The useful life of FANETs depends on the use of the appropriate networking protocols [102]. Depending on the application scenario and the density of the nodes, the communication protocols must be adaptable and dynamic for improved network throughput, such as selecting wireless technology or the cognitive radio (CR) [103] technique.

Furthermore, principles of artificial intelligence (AI), such as reinforcement learning and deep learning, can enhance system performance by learning from experience [104]. Through reinforcement learning, AI methods can find the optimal node positions and movements. Consequently, UAVs can self-organize to choose optimal routes during flight.

6.6. Cross-layer Architecture

Adopting cross-layer architecture strategies has garnered substantial research interest in improving data communication and network performance, especially while addressing the challenges posed by erroneous link state information caused by the drones' 3D movements occurring in highly dynamic environments [105].

Multiple studies indicate that routing protocols have been designed for conventional layered or hierarchical network architectures. Although the layered network architecture has achieved acceptable performance in a traditional wired network model, it is not on par with the unique requirements of FANETs. Therefore, a cross-layer architecture design will be a fascinating choice allowing to meet FANETs' unique requirements and efficient data routing. Additionally, such a system allows data sharing and feedback among its different layers.

6.7. Load Balancing

In FANET routing protocols, including bio-inspired routing schemes, the source node forwards data packets to intermediate nodes using greedy forwarding or through optimal algorithms, such as those identifying the shortest or lowest cost path, without considering the load of the next receiver, thus reducing network performance due to generating congestion over a particular route.

Therefore, forwarding data packets according to varying traffic loads can increase network throughput. In view of the above, the ability to design load-sensitive routing protocols [106] for FANETs is another critical issue for future research.

6.8. QoS and Standards

QoS is necessary for specific FANET applications where different types of data, such as on-demand, real-time audio and video, as well as video streaming, can be communicated over the network [107]. Therefore, the network must ensure the essential QoS to meet predetermined service constraints, such as delay, bandwidth, and packet loss. In addition, FANET communication must be standardized to make it universally acceptable.

7. Conclusions

This study explored the efficiency of bio-inspired routing algorithms in overcoming communication obstacles in FANETs. Its main objective was to identify bio-inspired routing algorithms that balance adaptability, scalability, and security for reliable data transmission in UAV-based networks.

We examined several FANET routing protocols utilizing bio-inspired algorithms, drawing inspiration from swarm behaviors such as ACO, ABC, BFO, DF, GSO, GWO, HBA, KH, MFO, PeSOA, PP, PSO, and RDO. Our analysis evaluated their efficiency in addressing critical FANET routing design issues, encompassing adaptability, energy efficiency, link stability, and security considerations.

While many bio-inspired routing protocols exist, our findings reveal that most exhibit trade-offs affecting critical characteristics that are essential for effective FANET routing. The PeSOA scheme is the most promising routing protocol, covering all routing metrics. In contrast, many available schemes suffer from high routing overhead and lack focus on load balancing and network security.

Furthermore, the application of bio-inspired schemes such as ABC, BFO, MFO, and RDO remains unexplored. Finally, several open research issues were identified based on the advantages, limitations, and comparative studies; these issues must be considered before developing robust, reliable, and application-specific FANET routing protocols.

References

[1] H. Zhao, H. Wang, W. Wu, and J. Wei, "Deployment Algorithms for UAV Airborne Networks Toward On-demand Coverage", *IEEE Journal on Selected Areas in Communications*, vol. 36, no. 9, pp. 2015–2031, 2018 (https://doi.org/10.1109/JSAC.2018.2864376).

[2] J. Kwak, J.H. Park, and Y. Sung, "Emerging ICT UAV Applications and Services: Design of Surveillance UAVs", *International Journal of Communication Systems*, vol. 34, no. 2, article no. e4023, 2021 (https://doi.org/10.1002/dac.4023).

[3] S.-Y. Park, C.S. Shin, D. Jeong, and H. Lee, "DroneNetX: Network Reconstruction Through Connectivity Probing and Relay Deployment by Multiple UAVs in Ad Hoc Networks", *IEEE Transactions on Vehicular Technology*, vol. 67, no. 11, pp. 11192–11207, 2018 (https://doi.org/10.1109/TVT.2018.2870397).

[4] L. Ferranti, L. Bonati, S. D'Oro, and T. Melodia, "SkyCell: A Prototyping Platform for 5G Aerial Base Stations", *2020 IEEE 21st International Symposium on "A World of Wireless, Mobile and Multimedia Networks" (WoWMoM)*, Cork, Ireland, 2020 (https://doi.org/10.1109/WoWMoM49955.2020.00062).

[5] I.U. Khan *et al.*, "Smart IoT Control-based Nature Inspired Energy Efficient Routing Protocol for Flying Ad Hoc Network (FANET)", *IEEE Access*, vol. 8, pp. 56371–56378, 2020 (https://doi.org/10.1109/ACCESS.2020.2981531).

[6] J. Zhang, J. Yan, and P. Zhang, "Multi-UAV Formation Control Based on a Novel Back-stepping Approach", *IEEE Transactions on Vehicular Technology*, vol. 69, no. 3, pp. 2437–2448, 2020 (https://doi.org/10.1109/TVT.2020.2964847).

[7] A. Srivastava and J. Prakash, "Future FANET with Application and Enabling Techniques: Anatomization and Sustainability Issues", *Computer Science Review*, vol. 39, art. no. 100359, 2021 (https://doi.org/10.1016/j.cosrev.2020.100359).

[8] G. Skorobogatov, C. Barrado, and E. Salamí, "Multiple UAV Systems: A Survey", *Unmanned Systems*, vol. 8, no. 02, pp. 149–169, 2020 (https://doi.org/10.1142/S2301385020500090).

[9] I. Valiulahi and C. Masouros, "Multi-UAV Deployment for Throughput Maximization in the Presence of Co-channel Interference", *IEEE Internet of Things Journal*, vol. 8, no. 5, pp. 3605–3618, 2020 (https://doi.org/10.1109/JIOT.2020.3023010).

[10] A. Pandey, P.K. Shukla, and R. Agrawal, "An Adaptive Flying Ad-hoc Network (FANET) for Disaster Response Operations to Improve Quality of Service (QoS)", *Modern Physics Letters B*, vol. 34, no. 10, art. no. 2050010, 2020 (https://doi.org/10.1142/S0217984920500104).

[11] M.A. Al-Absi, A.A. Al-Absi, M. Sain, and H. Lee, "Moving Ad Hoc Networks – A Comparative Study", *Sustainability*, vol. 13, no. 11, article no. 6187, 2021 (https://doi.org/10.3390/su13116187).

[12] Y. Cheriguene *et al.*, "COCOMA: a Resource-optimized Cooperative UAVs Communication Protocol for Surveillance and Monitoring Applications", *Wireless Networks*, pp. 4429–4445, 2022 (https://doi.org/10.1007/s11276-022-03031-8).

[13] X. Zhu, F. Vanegas, and F. Gonzalez, "An Approach for Multi-UAV System Navigation and Target Finding in Cluttered Environments", *2020 International Conference on Unmanned Aircraft Systems (ICUAS)*, Athens, Greece, pp. 1113–1120, 2020 (https://doi.org/10.1109/ICUAS48674.2020.9214062).

[14] A. Guillen-Perez, A.-M. Montoya, J.-C. Sanchez-Aarnoutse, and M.-D. Cano, "A Comparative Performance Evaluation of Routing Protocols for Flying Ad-hoc Networks in Real Conditions", *Applied Sciences.*, vol. 11, no. 10, art. no. 4363, 2021 (https://doi.org/10.3390/app11104363).

[15] M. Nemati *et al.*, "Non-terrestrial Networks with UAVs: A Projection on Flying Ad-hoc Networks", *Drones*, vol. 6, no. 11, art. no. 334, 2022 (https://doi.org/10.3390/drones6110334).

[16] G. Amponis *et al.,* "A Survey on FANET Routing from a Cross-layer Design Perspective", *Journal of Systems Architecture*, vol. 120, p. 102281, 2021 (https://doi.org/10.1016/j.sysarc.2021.102281).

[17] A.H. Sawalmeh and N.S. Othman, "An Overview of Collision Avoidance Approaches and Network Architecture of Unmanned Aerial Vehicles (UAVs)", *International Journal of Engineering and Technology*, vol. 7, 2018, (https://doi.org/10.14419/ijet.v7i4.35.27395).

[18] S. Bitam, A. Mellouk, and S. Zeadally, "Bio-inspired Routing Algorithms Survey for Vehicular Ad Hoc Networks", *IEEE Communications Surveys & Tutorials*, vol. 17, no. 2, pp. 843–867, 2014 (https://doi.org/10.1109/COMST.2014.2371828).

[19] Y. Zeng, R. Zhang, and T.J. Lim, "Wireless Communications with Unmanned Aerial Vehicles: Opportunities and Challenges", *IEEE Communications Magazine*, vol. 54, no. 5, pp. 36–42, 2016 (https://doi.org/10.1109/MCOM.2016.7470933).

[20] A.V. Leonov, "Applying Bio-inspired Algorithms to Routing Problem Solution in FANET", *Bulletin of the South Ural State University. Series Computer Technologies, Automatic Control, Radio Electronics*, vol. 17, no. 2, pp. 5–23, 2017 (https://doi.org/10.14529/ctcr170201).

[21] M.F. Khan, K.-L.A. Yau, R.M. Noor, and M. A. Imran, "Routing Schemes in FANETs: A Survey", *Sensors*, vol. 20, no. 1, art. no. 38, 2020 (https://doi.org/10.3390/s20010038).

[22] T.R. Beegum, M.Y.I. Idris, M.N.B. Ayub, and H.A. Shehadeh, "Optimized Routing of UAVs Using Bio-inspired Algorithm in FANET: A Systematic Review", *IEEE Access*, vol. 11, pp. 15588–15622, 2023 (https://doi.org/10.1109/ACCESS.2023.3244067).

[23] M.J. Almansor *et al.*, "Routing Protocols Strategies for Flying Ad-hoc Network (FANET): Review, Taxonomy, and Open Research

Issues", *Alexandria Engineering Journal*., vol. 109, pp. 553–577, 2024 (https://doi.org/10.1016/j.aej.2024.09.032).

[24] N. Kumar, D. Puthal, T. Theocharides, and S.P. Mohanty, "Unmanned Aerial Vehicles in Consumer Applications: New Applications in Current and Future Smart Environments", *IEEE Consumer Electronics Magazine*, vol. 8, no. 3, pp. 66–67, 2019 (https://doi.org/10.1109/MCE.2019.2892278).

[25] A. Orsino *et al.*, "Effects of Heterogeneous Mobility on D2D- and Drone-assisted Mission-critical MTC in 5G", *IEEE Communications Magazine*, vol. 55, no. 2, pp. 79–87, 2017 (https://doi.org/10.1109/MCOM.2017.1600443CM).

[26] A.A. Khuwaja *et al.*, "A Survey of Channel Modeling for UAV Communications", *IEEE Communications Surveys & Tutorials*, vol. 20, no. 4, pp. 2804–2821, 2018 (https://doi.org/10.1109/COMST.2018.2856587).

[27] N.K. Tomar *et al.*, "FANet: A Feedback Attention Network for Improved Biomedical Image Segmentation", *IEEE Transactions on Neural Networks and Learning Systems*, vol. 34, no. 11, pp. 9375–9388, 2022 (https://doi.org/10.1109/TNNLS.2022.3159394).

[28] N.H. Motlagh, T. Taleb, and O. Arouk, "Low-altitude Unmanned Aerial Vehicles-based Internet of Things Services: Comprehensive Survey and Future Perspectives", *IEEE Internet of Things Journal*, vol. 3, no. 6, pp. 899-922, 2016 (https://doi.org/10.1109/JIOT.2016.2612119).

[29] M. Bacco *et al.*, "Reliable M2M/IoT Data Delivery from FANETs via Satellite", *International Journal of Satellite Communications and Networking*, vol. 37, no. 4, pp. 331–342, 2019 (https://doi.org/10.1002/sat.1274).

[30] G. Sun, D. Qin, T. Lan, and L. Ma, "Research on Clustering Routing Protocol Based on Improved PSO in FANET", *IEEE Sensors Journal*, vol. 21, no. 23, pp. 27168–27185, 2021 (https://doi.org/10.1109/JSEN.2021.3117496).

[31] G.A. Kakamoukas, P.G. Sarigiannidis, and A.A. Economides, "FANETs in Agriculture – A Routing Protocol Survey", *Internet Things*, vol. 18, art. no. 100183, 2022 (https://doi.org/10.1016/j.iot.2020.100183).

[32] L. Gupta, R. Jain, and G. Vaszkun, "Survey of Important Issues in UAV Communication Networks", *IEEE Communications Surveys & Tutorials*, vol. 18, no. 2, pp. 1123–1152, 2015 (https://doi.org/10.1109/COMST.2015.2495297).

[33] X. Li and J. Yan, "LEPR: Link Stability Estimation-based Preemptive Routing protocol for Flying Ad Hoc Networks", *2017 IEEE Symposium on Computers and Communications (ISCC)*, Heraklion, Greece, 2017 (https://doi.org/10.1109/ISCC.2017.8024669).

[34] J. Agrawal, M. Kapoor, and R. Tomar, "A Novel Unmanned Aerial Vehicle-Sink Enabled Mobility Model for Military Operations in Sparse Flying Ad-hoc Network", *Transaction on Emerging Telecommunication Technologies*, vol. 33, no. 5, art. no. e4466, 2022 (https://doi.org/10.1002/ett.4466).

[35] M. Xu *et al.*, "Improving Traditional Routing Protocols for Flying Ad Hoc Networks: A Survey", *2020 IEEE 6th International Conference on Computer and Communications (ICCC)*, Chengdu, China, 2020 (https://doi.org/10.1109/ICCC51575.2020.9345206).

[36] S.N. Karam *et al.*, "Inspection of Unmanned Aerial Vehicles in Oil and Gas Industry: Critical Analysis of Platforms, Sensors, Networking Architecture, and Path Planning", *Journal of Electronic Imaging*, vol. 32, no. 1, art. no. 011006, 2022 (https://doi.org/10.1117/1.JEI.32.1.011006).

[37] M.H. Siddiqi *et al.*, "FANET: Smart City Mobility off to a Flying Start with Self-organized Drone-based Networks", *IET Communications*, vol. 16, no. 10, pp. 1209–1217, 2022 (https://doi.org/10.1049/cmu2.12291).

[38] A. Eroğlu and E. Onur, "Revisiting Slotted ALOHA: Density Adaptation in FANETs", *Wireless Personal Communication*, vol. 124, no. 2, pp. 1711–1740, 2022 (https://doi.org/10.1007/s11277-021-09428-6).

[39] S.K. Maakar *et al.* "Performance Evaluation of AODV and DSR Routing Protocols for Flying Ad hoc Network Using Highway Mobility Model", *Journal of Circuits, Systems and Computers*, vol. 31, no. 1, art. no. 2250008, 2022 (https://doi.org/10.1142/S0218126622500086).

[40] J. Souza *et al.*, "A Proposal for Routing Protocol for FANET: A Fuzzy System Approach with QoE/QoS Guarantee", *Wireless Communications and Mobile Computing*, vol. 2019, art. no. 8709249, 2019 (https://doi.org/10.1155/2019/8709249).

[41] A. Chriki, H. Touati, H. Snoussi, and F. Kamoun, "FANET: Communication, Mobility Models and Security Issues", *Computer Networks*, vol. 163, art. no. 106877, 2019 (https://doi.org/10.1016/j.comnet.2019.106877).

[42] G. Secinti, P.B. Darian, B. Canberk, and K.R. Chowdhury, "SDNs in the Sky: Robust End-to-end Connectivity for Aerial Vehicular Networks", *IEEE Communications Magazine*, vol. 56, no. 1, pp. 16–21, 2018 (https://doi.org/10.1109/MCOM.2017.1700456).

[43] H.R. Hussen, S.-C. Choi, J.-H. Park, and J. Kim, "Performance Analysis of MANET Routing Protocols for UAV Communications", *2018 Tenth International Conference on Ubiquitous and Future Networks (ICUFN)*, pp. 70–72, Prague, Czech Republic, 2018 (https://doi.org/10.1109/ICUFN.2018.8436694).

[44] I. Mahmud and Y.-Z. Cho, "Adaptive Hello Interval in FANET Routing Protocols for Green UAVs", *IEEE Access*, vol. 7, pp. 63004–63015, 2019 (https://doi.org/10.1109/ACCESS.2019.2917075).

[45] C. Li, L. Zheng, W. Xie, and P. Yang, "Ad Hoc Network Routing Protocol Based on Location and Neighbor Sensing", *2018 IEEE International Conference on Computer and Communication Engineering Technology (CCET)*, pp. 1–5, Beijing, China, 2018 (https://doi.org/10.1109/CCET.2018.8542225).

[46] R. Fan *et al.*, "Optimal Node Placement and Resource Allocation for UAV Relaying Network", *IEEE Communications Letters*, vol. 22, no. 4, pp. 808–811, 2018 (https://doi.org/10.1109/LCOMM.2018.2800737).

[47] N. Palmieri and A. Serianni, "Overhead Analysis of a Bio-inspired Routing over FANET", *2022 30th Telecommunications Forum (TELFOR)*, Belgrade, Serbia, 2022 (https://doi.org/10.1109/TELFOR56187.2022.9983785).

[48] A. Khan, F. Aftab, and Z. Zhang, "BICSF: Bio-inspired Clustering Scheme for FANETs", *IEEE Access*, vol. 7, pp. 31446–31456, 2019 (https://doi.org/10.1109/ACCESS.2019.2902940).

[49] A. Yadav, A. Shastri, and S. Verma, "Experimental Analysis of ACO with Modified Firefly and Modified Genetic Algorithm for Routing in FANETs", in *Optical and Wireless Technologies: Proceedings of OWT 2021*, Springer, pp. 81–87, 2022 (https://doi.org/10.1007/978-981-19-1645-8_9).

[50] Z. Zhang, K. Long, J. Wang, and F. Dressler, "On Swarm Intelligence Inspired Self-organized Networking: Its Bionic Mechanisms, Designing Principles and Optimization Approaches", *IEEE Communications Surveys & Tutorials*, vol. 16, no. 1, pp. 513–537, 2013 (https://doi.org/10.1109/SURV.2013.062613.00014).

[51] A.K. Kar, "Bio Inspired Computing – A Review of Algorithms and Scope of Applications", *Expert Systems with Applications*, vol. 59, pp. 20–32, 2016 (https://doi.org/10.1016/j.eswa.2016.04.018).

[52] K.N. Kaipa and D. Ghose, "Glowworm Swarm Optimization: Algorithm Development", in *Glowworm Swarm Optimization*, pp. 21–56, 2017 (https://doi.org/10.1007/978-3-319-51595-3_2).

[53] A.H. Gandomi and A.H. Alavi, "Krill Herd: A New Bio-inspired Optimization Algorithm", *Communications in Nonlinear Science and Numerical Simulation*, vol. 17, pp. 4831–4845, 2012 (https://doi.org/10.1016/j.cnsns.2012.05.010).

[54] G.-G. Wang, A.H. Gandomi, A.H. Alavi, and D. Gong, "A Comprehensive Review of Krill Herd Algorithm: Variants, Hybrids and Applications", *Artificial Intelligence Review*, vol. 51, pp. 119–148, 2019 (https://doi.org/10.1007/s10462-017-9559-1).

[55] M. Dorigo, M. Birattari, and T. Stutzle, "Ant Colony Optimization", *IEEE Computational Intelligence Magazine*, vol. 1, pp. 28–39, 2006 (https://doi.org/10.1109/MCI.2006.329691).

[56] N.A. Al-Aboody and H.S. Al-Raweshidy, "Grey Wolf Optimization-based Energy-efficient Routing Protocol for Heterogeneous Wireless Sensor Networks", *2016 4th International Symposium on Computa-*

tional and Business Intelligence (ISCBI), Olten, Switzerland, 2016 (https://doi.org/10.1109/ISCBI.2016.7743266).

[57] M.Y. Arafat and S. Moh, "Localization and Clustering Based on Swarm Intelligence in UAV Networks for Emergency Communications", *IEEE Internet of Things Journal*, vol. 6, pp. 8958–8976, 2019 (https://doi.org/10.1109/JIOT.2019.2925567).

[58] G.A. Amran *et al.*, "Efficient and Secure WiFi Signal Booster via Unmanned Aerial Vehicles WiFi Repeater Based on Intelligence Based Localization Swarm and Blockchain", *Micromachines*, vol. 13, art. no. 1924, 2022 (https://doi.org/10.3390/mi13111924).

[59] C. Zhou, H.B. Gao, L. Gao, and W.G. Zhang, "Particle Swarm Optimization (PSO) Algorithm J", *Application Research of Computers*, vol. 12, pp. 7–11, 2003.

[60] W. Bin and S. Zhongzhi, "A Clustering Algorithm Based on Swarm Intelligence", *2001 International Conferences on Info-Tech and Info-Net. Proceedings (Cat. No. 01EX479)*, Beijing, China, 2001 (https://doi.org/10.1109/ICII.2001.983036).

[61] O.T. Abdulhae, J.S. Mandeep, and M. Islam, "Cluster-based Routing Protocols for Flying Ad Hoc Networks (FANETs)", *IEEE Access*, vol. 10, pp. 32981–33004, 2022 (https://doi.org/10.1109/ACCESS.2022.3161446).

[62] F. De Rango, M. Tropea, and P. Fazio, "Bio-inspired Routing over FANET in Emergency Situations to Support Multimedia Traffic", *Proc. of the ACM MobiHoc Workshop on Innovative Aerial Communication Solutions for FIrst REsponders Network in Emergency Scenarios*, pp. 12–17, 2019 (https://doi.org/10.1145/3331053.3335033).

[63] B. Baran and R. Sosa, "A New Approach for AntNet Routing", *Proc. of Ninth International Conference on Computer Communications and Networks (Cat. No. 00EX440)*, pp. 303–308, 2000 (https://doi.org/10.1109/ICCCN.2000.885506).

[64] R. Sosa and B. Baran, "AntNet routing algorithm for data networks based on mobile agents", *Revista Iberoamericana de Inteligencia Artificial*, vol. 5, pp. 75–84, 2001 [Online] Available: (https://www.redalyc.org/pdf/925/92551210.pdf).

[65] P. Jacquet *et al.*, "Optimized Link State Routing Protocol for Ad Hoc Networks", *Proc. of IEEE International Multi Topic Conference, 2001. IEEE INMIC 2001. Technology for the 21st Century*, pp. 62–68, 2001 (https://doi.org/10.1109/INMIC.2001.995315).

[66] I.D. Chakeres and E.M. Belding-Royer, "AODV Routing Protocol Implementation Design", *Proc. of 24th International Conference on Distributed Computing Systems Workshops*, pp. 698–703, 2004 (https://doi.org/10.1109/ICDCSW.2004.1284108).

[67] N.E.H. Bahloul, S. Boudjit, M. Abdennebi, and D.E. Boubiche, "Bio-inspired on Demand Routing Protocol for Unmanned Aerial Vehicles", *2017 26th International Conference on Computer Communication and Networks (ICCCN)*, Vancouver, Canada, 2017 (https://doi.org/10.1109/ICCCN.2017.8038487).

[68] C.W. Reynolds, "Flocks, Herds and Schools: A Distributed Behavioral Model", *Proc. of the 14th Annual Conference on Computer Graphics and Interactive Techniques*, pp. 25–34, 1987 (https://doi.org/10.1145/37401.37406).

[69] R.G. Braga, R.C. Da Silva, A.C. Ramos, and F. Mora-Camino, "Collision Avoidance Based on Reynolds Rules: A Case Study Using Quadrotors", *Information Technology-New Generations*, vol. 558, pp. 773–780, 2018 (https://doi.org/10.1007/978-3-319-54978-1_96).

[70] Y. Yu *et al.*, "Ant Colony Optimization Based Polymorphism-aware Routing Algorithm for Ad Hoc UAV Network", *Multimedia Tools and Applications*, vol. 75, pp. 14451–14476, 2016 (https://doi.org/10.1007/s11042-015-3240-y).

[71] D.B. Johnson, D.A. Maltz, and J. Broch, "DSR: The Dynamic Source Routing Protocol for Multi-hop Wireless Ad Hoc Networks", *Monarch Project at Carnegie Mellon University*, 2001 [Online] Available: (https://www.cse.iitb.ac.in/~mythili/teaching/cs653_spring2014/references/dsr.pdf).

[72] J. Wang, E. Osagie, P. Thulasiraman, and R.K. Thulasiram, "HOPNET: A Hybrid Ant Colony Optimization Routing Algorithm for Mobile Ad Hoc Network", *Ad Hoc Networks*, vol. 7, pp. 690–705, 2009 (https://doi.org/10.1016/j.adhoc.2008.06.001).

[73] M. Aissani, M. Fenouche, H. Sadour, and A. Mellouk, "Ant-DSR: Cache Maintenance Based Routing Protocol for Mobile Ad Hoc Networks", *The Third Advanced International Conference on Telecommunications (AICT'07)*, Morne, Mauritius, 2017 (https://doi.org/10.1109/AICT.2007.14).

[74] A.M. Ellison, "Bayesian Inference in Ecology", *Ecology Letters*, vol. 7, pp. 509–520, 2004 (https://doi.org/10.1111/j.1461-0248.2004.00603.x).

[75] H.F. Wedde *et al.*, "BeeAdHoc: An Energy Efficient Routing Algorithm for Mobile Ad Hoc Networks Inspired by Bee Behavior", *Proc. of the 7th Annual Conference on Genetic and Evolutionary Computation*, pp. 153–160, 2005 (https://doi.org/10.1145/1068009.1068034).

[76] J.R. Riley *et al.*, "The Flight Paths of Honeybees Recruited by the Waggle Dance", *Nature*, vol. 435, pp. 205–207, 2005 (https://doi.org/10.1038/nature03526).

[77] S. Dong, T. Lin, J.C. Nieh, and K. Tan, "Social Signal Learning of the Waggle Dance in Honey Bees", *Science*, vol. 379, pp. 1015–1018, 2023 (https://doi.org/10.1126/science.ade1702).

[78] F. Aftab, A. Khan, and Z. Zhang, "Hybrid Self-organized Clustering Scheme for Drone Based Cognitive Internet of Things", *IEEE Access*, vol. 7, pp. 56217–56227, 2019 (https://doi.org/10.1109/ACCESS.2019.2913912).

[79] Y. Meraihi, A. Ramdane-Cherif, D. Acheli, and M. Mahseur, "Dragonfly Algorithm: A Comprehensive Review and Applications", *Neural Computing and Applications*, vol. 32, pp. 16625–16646, 2020 (https://doi.org/10.1007/s00521-020-04866-y).

[80] S. Mirjalili, "Dragonfly Algorithm: A New Meta-heuristic Optimization Technique for Solving Single-objective, Discrete, and Multi-objective Problems", *Neural Computing and Applications*, vol. 27, pp. 1053–1073, 2016 (https://doi.org/10.1007/s00521-015-1920-1).

[81] G. Jones and B.M. Siemers, "The Communicative Potential of Bat Echolocation Pulses", *Journal of Comparative Physiology A*, vol. 197, pp. 447–457, 2011 (https://doi.org/10.1007/s00359-010-0565-x).

[82] S. Hameed *et al.*, "An Improved iBAT-COOP Protocol for Cooperative Diversity in FANETs", *Computers, Materials & Continua*, vol. 67, pp. 2527–2546, 2021 (https://doi.org/10.32604/cmc.2021.013896).

[83] S. Hameed *et al.*, "Link and Loss Aware GW-COOP Routing Protocol for FANETs", *IEEE Access*, vol. 9, pp. 110544–110557, 2021 (https://doi.org/10.1109/ACCESS.2021.3101361).

[84] R.O. Peterson *et al.*, "Leadership Behavior in Relation to Dominance and Reproductive Status in Gray Wolves, Canis Lupus", *Canadian Journal of Zoology*, vol. 80, pp. 1405–1412, 2002 (https://doi.org/10.1139/z02-124).

[85] S. Yang *et al.*, "Bio-inspired Multi-hop Clustering Algorithm for FANET", *Ad Hoc Networks*, vol. 154, art. no. 103355, 2024 (https://doi.org/10.1016/j.adhoc.2023.103355).

[86] X. Zhang *et al.*, "An Improved Physarum Polycephalum Algorithm for the Shortest Path Problem", *The Scientific World Journal*, pp. 1–9, 2014 (https://doi.org/10.1155/2014/487069).

[87] A.M. Reynolds and C.J. Rhodes, "The Lévy Flight Paradigm: Random Search Patterns and Mechanisms", *Ecology*, vol. 90, pp. 877–887, 2009 (https://doi.org/10.1890/08-0153.1).

[88] A. Kout *et al.*, "A Hybrid Optimization Solution for UAV Network Routing", *Engineering, Technology & Applied Science Research*, vol. 13, pp. 10270–10278, 2023 (https://doi.org/10.48084/etasr.5661).

[89] F. A. Hashim *et al.*, "Honey Badger Algorithm: New Metaheuristic Algorithm for Solving Optimization Problems", *Mathematics and Computers in Simulation*, vol. 192, pp. 84–110, 2022 (https://doi.org/10.1016/j.matcom.2021.08.013).

[90] A. Beghriche, "An Adaptive Secure and Efficient Bio-inspired Routing Protocol for Effective Cooperation in FANETs", *Ingénierie des Systèmes d'Information*, vol. 28, pp. 49–66, 2023 (https://doi.org/10.18280/isi.280106).

[91] F.S. Abu-Mouti and M.E. El-Hawary, "Overview of Artificial Bee Colony (ABC) Algorithm and its Applications", *2012 IEEE Interna-*

tional Systems Conference SysCon 2012, Vancouver, Canada, 2012 (https://doi.org/10.1109/SysCon.2012.6189539)

[92] K.M. Passino, "Bacterial Foraging Optimization", in: *Innovations and Developments of Swarm Intelligence Applications*, pp. 219–234, 2010 (https://doi.org/10.4018/978-1-4666-1592-2.ch013).

[93] S. Mirjalili, "Moth-flame Optimization Algorithm: A Novel Nature-inspired Heuristic Paradigm", *Knowledge-Based Systems*, vol. 89, pp. 228–249, 2015 (https://doi.org/10.1016/j.knosys.2015.07.006).

[94] A.F. Fard and M. Hajiaghaei-Keshteli, "Red Deer Algorithm (RDA); A New Optimization Algorithm Inspired by Red Deer's Mating", *International Conference on Industrial Engineering*, Tehran, Iran, 2016.

[95] A. Meier and J.S. Thompson, "Cooperative Diversity in Wireless Networks", *6th IEE International Conference on 3G and Beyond,* Stevenage, UK, 2005.

[96] V.A. Maistrenko, L.V. Alexey, and V.A. Danil, "Experimental Estimate of Using the Ant Colony Optimization Algorithm to Solve the Routing Problem in FANET", *2016 International Siberian Conference on Control and Communications (SIBCON)*, Moscow, Russia, 2016 (https://doi.org/10.1109/SIBCON.2016.7491805).

[97] A. Heidari, N.J. Navimipour, M. Unal, and G. Zhang, "Machine Learning Applications in Internet-of-drones: Systematic Review, Recent Deployments, and Open Issues", *ACM Computing Surveys*, vol. 55, pp. 1–45, 2023 (https://doi.org/10.1145/3571728).

[98] O. Ceviz, S. Sen, and P. Sadioglu, "A Survey of Security in UAVs and FANETs: Issues, Threats, Analysis of Attacks, and Solutions", *IEEE Communications Surveys & Tutorials*, 2024 (https://doi.org/10.1109/COMST.2024.3515051).

[99] H. Yang and Z. Liu, "An optimization routing protocol for FANETs", *EURASIP J. on Wireless Communications and Networking*, art. no. 120, 2019 (https://doi.org/10.1186/s13638-019-1442-0).

[100] S. Bharany *et al.*, "Wildfire Monitoring Based on Energy Efficient Clustering Approach for FANETS", *Drones*, vol. 6, art. no. 193, 2022 (https://doi.org/10.3390/drones6080193).

[101] D. Bein, W. Bein, A. Karki, and B.B. Madan, "Optimizing Border Patrol Operations Using Unmanned Aerial Vehicles", *2015 12th International Conference on Information Technology-New Generations*, Las Vegas, USA, 2015 (https://doi.org/10.1109/ITNG.2015.83).

[102] K. Mariyappan, M.S. Christo, and R. Khilar, "Implementation of FANET Energy Efficient AODV Routing Protocols for Flying Ad Hoc Networks FEEAODV", *Materialstoday Proceeding*, 2021 (https://doi.org/10.1016/j.matpr.2021.02.673).

[103] N. Mansoor *et al.*, "Cognitive Radio Ad Hoc Network Architectures: A Survey", *Wireless Personal Communications*, vol. 81, pp. 1117–1142, 2015 (https://doi.org/10.1007/s11277-014-2175-3).

[104] A. Hussain *et al.*, "Taking FANET to Next Level: The Contrast Evaluation of Moth-and-ant with Bee Ad Hoc Routing Protocols for Flying Ad Hoc Networks", *ADCAIJ: Advances in Distributed Computing and Artificial Intelligence Journal*, vol. 10, pp. 321–337, 2021 (https://doi.org/10.14201/ADCAIJ2021104321337).

[105] H.S. Mansour *et al.*, "Cross-layer and Energy-aware AODV Routing Protocol for Flying Ad Hoc Networks", *Sustainability*, vol. 14, art. no. 8980, 2022 (https://doi.org/10.3390/su14158980).

[106] R. Khaleghnasab *et al.*, "An Energy and Load Aware Multipath Routing Protocol in the Internet of Things", *Management Strategies and Engineering Sciences*, vol. 7, pp. 1–15, 2020 (https://doi.org/10.61838/msesj.7.3.1).

[107] P. Kaur, A. Singh, and S.S. Gill, "RGIM: an Integrated Approach to Improve QoS in AODV, DSR and DSDV Routing Protocols for FANETS Using the Chain Mobility Model", *The Computer Journal*, vol. 63, pp. 1500–1512, 2020 (https://doi.org/10.1093/comjnl/bxaa040).

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