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SURVEY

Optimized Routing of UAVs Using Bio-Inspired Algorithm in FANET: A Systematic Review

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ABSTRACT Flying Ad hoc Network (FANET) is a self-organizing wireless network that constitutes swarms of flying nodes, namely Unmanned Aerial Vehicles (UAV), and communicates in close proximity. It has various distinguishing characteristics that set it apart from other ad hoc networks, posing some issues, particularly in routing. UAVs are highly dynamic and have frequent topology changes. Hence, the network urges an efficient routing technique to coordinate the node swarms and enhance the evaluation metrics of the network. The biological behavior of various living organisms, such as animals, insects, microbes, and humans, inspires researchers to solve various routing problems in ad hoc networks. Decentralized self-organized swarms of UAVs closely resemble the biological system. Therefore, the Bio-Inspired Algorithms (BIA) resolve a wide range of routing challenges in FANET. A Systematic Literature Review (SLR) is adopted to survey FANET routing methods based on non-hybrid and hybrid BIAs to properly comprehend the existing bio-inspired strategies used in FANET routing. The review will be beneficial for the researchers in the specified area. To our knowledge, no SLR has been conducted about the FANET routing protocol that employs BIA. This paper examines 1) the characteristics and features of existing routing algorithms, 2) the need of both non-hybrid and hybrid BIA for effective and optimal routing, 3) an analysis of the method's simulation tools, evaluation metrics and mobility models, 4) the current issues and scope of the study related to the specified method.

INDEX TERMS Bio-inspired algorithm (BIA), flying ad hoc networks (FANET), metaheuristic optimization, systematic literature review (SLR), unmanned aerial vehicle (UAV).

I. INTRODUCTION

The Flying Ad hoc Network (FANET) is a rapidly advancing wireless ad hoc network comprised of Unmanned Aerial Vehicle (UAV) nodes. UAVs are becoming vital in many real-world applications, including surveillance and reconnaissance, extending wireless coverage, search and rescue, geographic mapping, precise crop monitoring, and intelligent transportation systems. One of the most intriguing research areas in recent years has been the collaboration of FANETs with other ad hoc networks, such as the integration of FANETs with Vehicular Ad Hoc Networks (VANET), to increase transportation efficiency. The widespread distribution of VANET nodes causes frequent communication breakdowns. During the period of disconnection, UAVs can serve as relay nodes, allowing for two-way communication to be re-established between vehicles and UAVs. The notion of Cognitive Radio (CR) has proven indispensable to intelligent transportation systems.

Numerous smaller UAVs are preferable to a few large ones since the former are less expensive, more portable, and take less time to deploy. Quick mobility, low node

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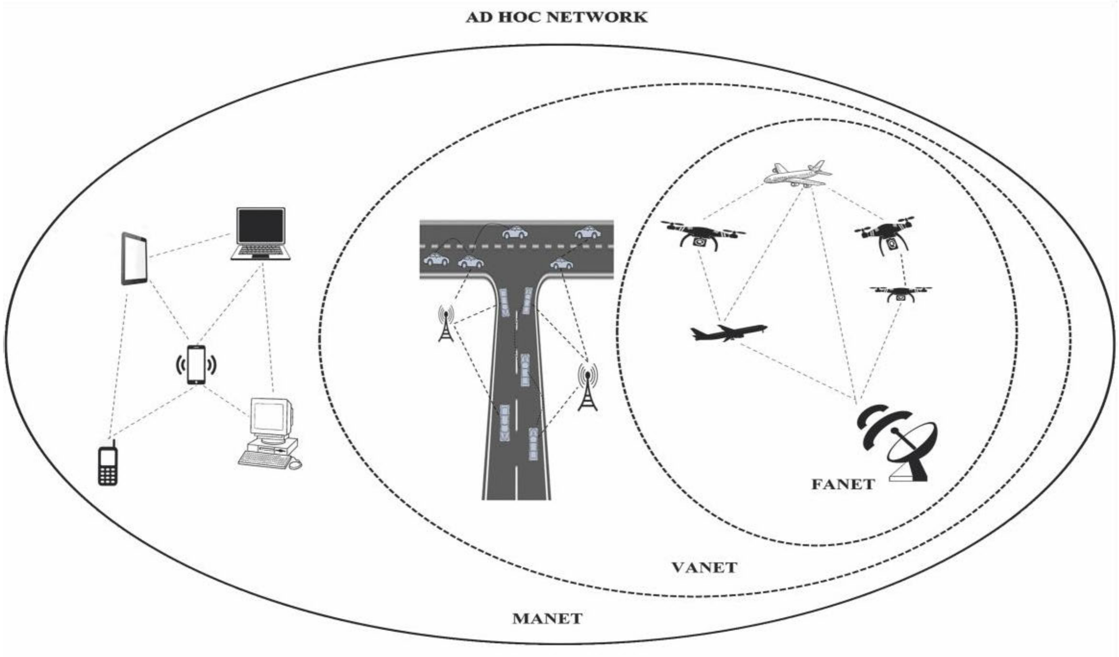

FIGURE 1. Relationship of MANET, VANET and FANET.

density, frequent topology changes, and mobility models are some of the inimitable features that make the FANET route more challenging. Due to the unique properties of FANET, unmanned aerial vehicles (UAVs) cannot simply employ the routing protocols designed for Mobile Ad hoc Networks (MANETs) and VANET [1]. Fig. 1 shows how the three types of ad hoc networks (MANET, VANET, and FANET) are related to one another.

The FANET routing requirements are more intricate than MANET and VANET [2]. The capabilities of the existing routing systems may not adequately meet their necessities. Hence further research is needed to develop an efficient routing system for FANET.

The current situation has signalled the transition from conventional optimization approaches to an entirely new species. An innovative method for tackling the corresponding optimization has arisen from the study of biological systems. These approaches are referred to as bio-inspired techniques or methods, and they continue to expand, surpass the constraints of conventional methods and are generally recognized in both academic and professional domains. The term ''bio-inspired optimization'' refers to a spectrum of optimization techniques inspired by biological systems, including Ant Colony Optimization (ACO), Bee Colony Optimization (BCO), the Bat Algorithm (BA), and the Krill Herd (KH) algorithm [3].

Bio-Inspired optimization Algorithms (BIA) are robust competitive strategies developed based on the principles and inspiration from biological systems. Adaptability, self-learning, and robustness are some qualities that enable them to accomplish complicated tasks autonomously. The issues encountered in engineering technology are not linear and bound by several nonlinear constraints, offering numerous challenges to finding the ideal solution, such as time and high-dimension requirements. Consequently, recent advancements employ BIA, providing a feasible strategy for resolving arduous optimization challenges and addressing the limitations of conventional optimization methods.

When considerably a large FANET environment is considered, BIAs are more effective due to the similarity of finding the path by numerous UAV nodes and the collective activity of bio-organisms to meet their day-to-day needs. It can solve computational, manage frequent topology changes, and reroute without human involvement. Moreover, bio-inspired strategies could bolster resilience to sustain the performance of routing during network disturbances. The features of the BIA mentioned above have inspired researchers to implement FANET routing with BIA. The focus for this review has narrowed to FANET routing with BIA instead of describing the classical routing algorithms of existing literature surveys of FANET. This study exemplifies the routing protocols, taxonomy, mobility models and simulation tools associated with bio-inspired approaches. Rather than concentrating on Bio-inspired techniques, this survey attempted to analyze various Bio-Inspired Algorithms (BIAs) utilized in FANET routing. For this reason, the study has been meticulously organized as a Systematic Literature Review (SLR) using the strict SLR methodology.

The methodology known as Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) [4] is the foundation for the systematic review of this study. PRISMA was chosen over other existing protocols due

TABLE 1. Comparison of existing surveys on FANET routing.

Publication Year	References	FANET Characteristics	FANET routing models	Routing Taxonomy	Mobility Models	Open research issues and future work	Number of Bio-Inspired Routing Protocols discussed	SLR Paper
2014	[2]		√			√	0	
2015	[9]	√	√			√	0	
2017	[10]	√	√	√	√	√	0	
2018	[11]	√	√			√	0	
	[8]	√	√				3	
2019	[12]	√				√	0	
	[13]	√	√	√		√	0	
	[5]	√	√	√	√	√	3	
	[14]	√	√	√	√	√	0	
	[15]	√	√		√		0	
	[6]	√	√	√	√	√	2	
	[16]					√	4	
	[17]	√	√	√		√	0	
	[18]		√			√	0	
2020	[19]		√			√	0	
	[20]	√	√	√	√		0	
	[21]		√			√	0	
	[22]	√	√	√	√	√	0	
	[23]		√	√		√	0	
	[24]				√		0	
2021	[25]					√	0	
	[7]	√	√			√	0	
2022	This Paper	√	√	√	√	√	16	√

to its comprehensiveness and capacity to increase review consistency.

The three phases of this SLR are outlined in Section III. First phase includes defining the goals, formulating research questions, and establishing review protocols. The second phase is to conduct a search using query strings and to choose applicable articles by following the inclusion and exclusion criteria. The review findings are reported in the last phase of the process.

Moreover, Table 1 compares contrasts and summarizes selected literature reviews to further highlight this SLR's novelty. According to the table, there have been no comprehensive studies on FANET routing based on the BIA.

The primary goal of the proposed SLR is to disseminate recent advancements in the theoretical outcomes of BIA based FANET routing in a thorough, unbiased manner by recognizing essential research possibilities for future studies. This article provides a statistical overview of the BIAs currently implemented in FANET routing.

The primary contributions made by this SLR are the following:

- An insight of the characteristics as well as routing methods of FANET that developed with various BIA.
- A taxonomy for bio-inspired-based FANET routing is devised.
- Mobility models associated with biologically inspired FANET routing algorithms are deeply analyzed.
- A statistical analysis of simulators and a detailed analysis of evaluation metrics are performed.
- The challenges and scope of BIA based FANET routing are discussed in an effort to give a direction for future research.

In contrast to this paper, most existing studies do not appear to have performed a comprehensive analysis of which BIAs have been implemented in FANET routing so far [5], [6], [7], [8].

The remaining portions of this paper are organized as follows: Section II summarizes FANET and its current routing strategies. The research methodology of SLR is presented in Section III. A discussion of the results of this review is provided in Section IV. The conclusion of this paper is given in Section V. Fig. 2 details the overall structure of the paper.

The expansion of abbreviations used in this paper is mentioned in Appendix A.

II. FANET OVERVIEW AND RELATED WORK

Wireless networks are classified into two types: i) infrastructure-dependent networks (Single-Hop wireless networks) and ii) infrastructure-less (multi-hop wireless networks) [26]. The detailed classification is given in Fig. 3. The former has wired permanent gateways, and bridges will serve as base stations. Wireless Local Area Network (WLAN) is one of these networks' applications. In contrast, the nodes in the latter type of network, often known as ad hoc, are dynamic and are connected arbitrarily. Its nodes can function as routers.

UAVs collaboratively communicated by forming an ad hoc network called FANET. One of the primary design factors for a multi-UAV network is maintaining a communication link between UAVs. In many applications, tiny or micro-UAVs are used as they can fit into small location where larger drones cannot. They also have the advantage of hovering above a

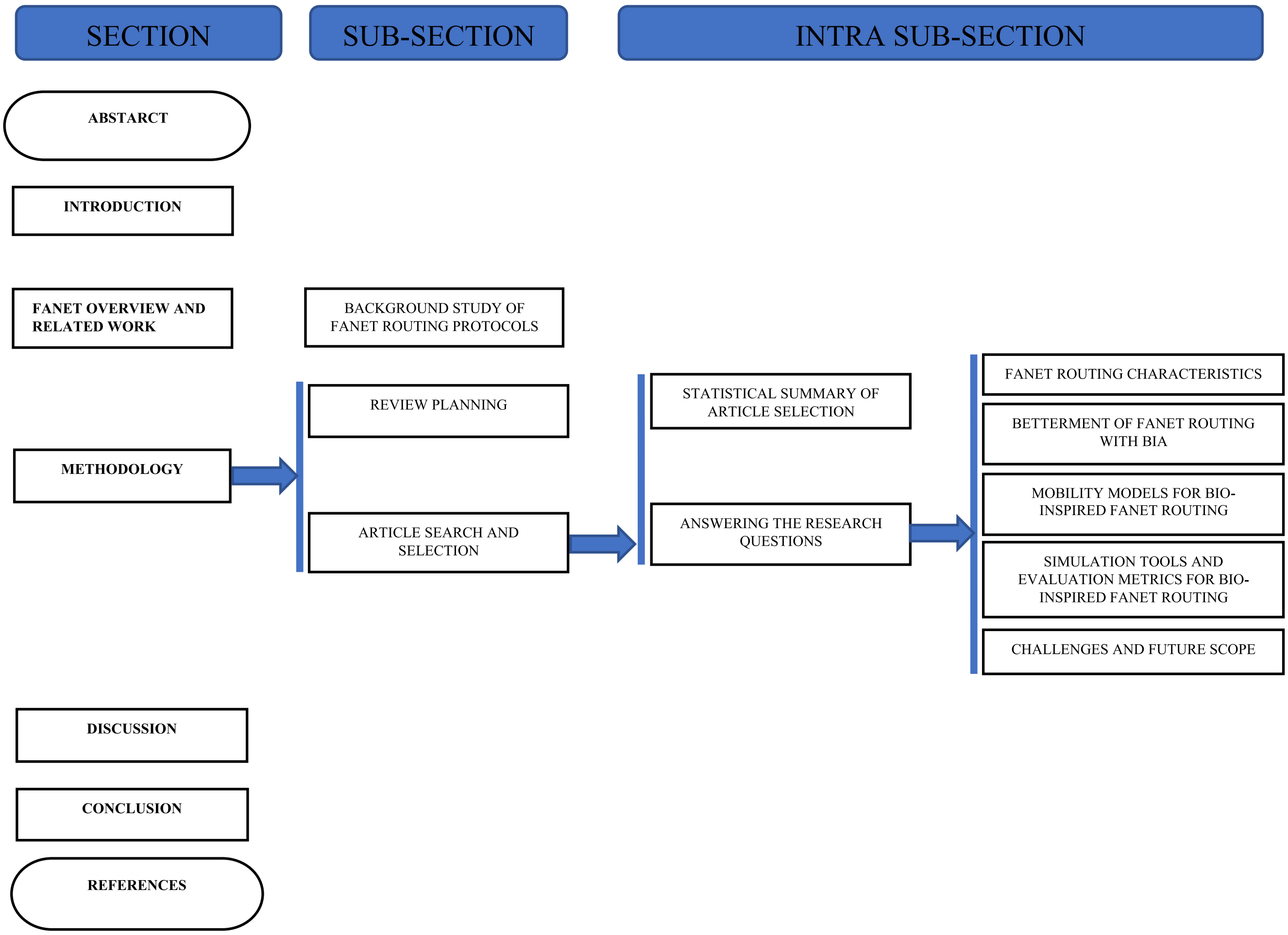

FIGURE 2. Structure of the Paper.

specified spot. Despite their tiny size, they are subjected to the following limitations: i)

They are limited to use small sensors because of the low weight of their payload. ii) The operating range is constrained by the communication link. iii) The Micro-UAV power source is limited [27]. For tiny UAVs, the hardware on board must be lighter, smaller, and low power consumption due to its size and weight restrictions, which can be significant [11]. Fig. 4 illustrates the architecture of FANET. It consists of UAVs, a High-Altitude Platform (HAP) or a Low-Altitude Platform (LAP) station, satellites, and Ground Control Stations (GCS) [28].

UAVs are crucial in many real-world applications [29], including traffic monitoring, extending wireless coverage, search and rescue, geographic mapping, precision crop monitoring, and shipping [30]. UAVs are often referred to as drones. The Internet of Drones (IoD) and its applications are rapidly escalating [31]. IoD is a tiered network control architecture. Its primary goal is to coordinate drones in a restricted space and provide wayfinding services between nodes [32].

FANET has a varied environment and has distinct operational characteristics. This necessitates special routing techniques for data delivery. The detailed discussion of the characteristics is as follows:

(i) Node Mobility: UAVs change their location within a minimum span of time, which can affect the communication between the nodes [14].

(ii) Topology change: The topology often changes due to increased node mobility and network link interruptions in FANET [11].

(iii) Power Consumption: Since the tasks done by UAVs are complex and communicated collaboratively, the power consumption of the node is high [13].

(iv) Localization: High mobility and continual change in topologies of UAV nodes necessitate localization for short periods [33].

(v) Node Density: The count of nodes per square meter. FANET exhibits the least node density of MANET and VANET [8]. Since UAVs are flying nodes, the distance maintained by them is large, and the node density becomes sparse.

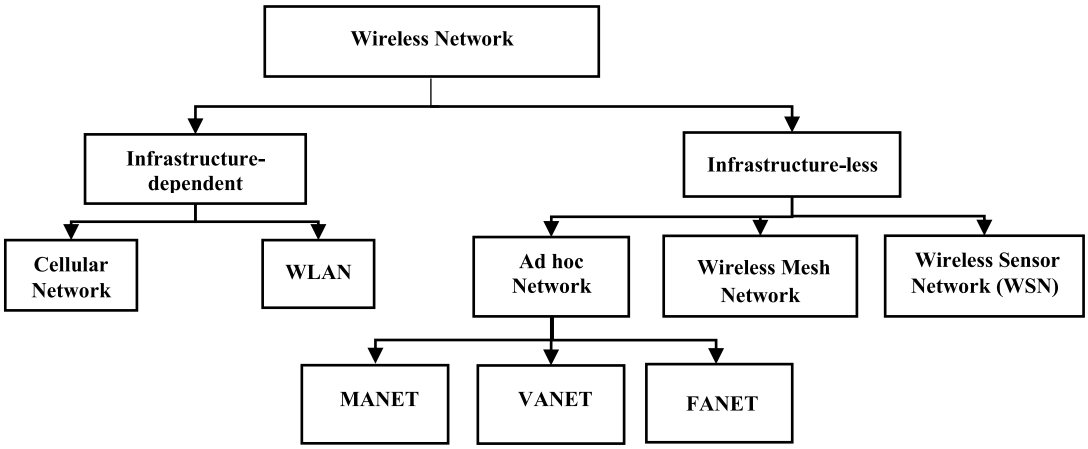

FIGURE 3. Classification of Mobile wireless networks.

(vi) Radio Propagation: Nodes in MANET and VANET are typically on the ground, whereas the nodes in FANET will be far away from the ground. So, UAVs are primarily reliant on LoS pathways [11].

(vii) Mobility Model: Nodes in FANETs are dynamic. Hence, during each simulation, selecting a suitable mobility model is necessary. The mobility model mainly helps estimate the network's performance to obtain the results as realistically as possible before an actual deployment [34].

(viii) Communication range (coverage):

UAVs efficiently cover a broad region in real-time scenarios. UAVs can provide temporal connectivity to ground users without disruption of ground infrastructure.

According to the employed application, UAVs use various positioning techniques to provide good coverage [5].

(ix) Frequency: 0.9 GHz and 2.4 GHz are the commonly used bands in UAV communications and are unlicensed and one of the reasons for the congestion with other communication systems. The 5.9 GHz frequency is ideal for avoiding disruption with other bands, particularly with IEEE 802.11p [5].

(x) Environment: Although UAVs are far from the ground, large barriers, reflections from the ground, climatic conditions, etc., can disrupt UAVs communication [35].

(xi) UAV platform constraints: Many limitations are imposed on FANET connection terminals by the UAV platform, such as size, weight, and energy consumption.

Minimizing the possibility of data loss in the FANET environment necessitates using an efficient routing system to direct data packets. The routing methods, including Store-Carry and Forward, Greedy Forwarding, Path Discovery, Single Path, Multi-Path, and Prediction, are used in FANETs [36].

In addition, test beds or simulators are typically used to investigate and evaluate FANET protocols. Models of mobility mimic the real-world behavior of nodes in a FANET setting. They demonstrate the movement of UAV over time as well as the dynamic position, acceleration, and velocity of the FANET nodes. These models determine whether or not a proposed protocol is useful in a certain setting. The five types of mobility models are random, time-based, path-based, group-based, and topology-based. A summary of the aforementioned mobility models' characteristics, uses, and underlying ideology are provided in [5].

A. BACKGROUND STUDY OF FANET ROUTING PROTOCOLS

FANET characteristics discussed so far conveys an existing complexity in designing a routing protocol by fulfilling all the constraints, such as rapid topology change, power source and security. As a result, the categories of FANET routing protocols vary depending on the network's condition. Fig. 5 shows the FANET routing categorization based on the routing techniques mentioned below [6], [10], [33].

1) TOPOLOGY BASED

In the topology-based category, the data packets are sent with topology information. Knowledge of the routing path is also needed beforehand for the transmission.

Topology-based routing is further classified as flat and hierarchical or cluster-based routing.

a: FLAT ROUTING PROTOCOLS

Based on how the UAVs in the network acquire and store the routing information, flat routing is divided into proactive, reactive, and hybrid routing.

i) Proactive Routing (table-driven) Protocols: Proactive routing techniques maintain track of all network routes. Each node registers its route information with every other node in the network. These protocols regularly communicate control data between nodes, maintaining the latest paths for each node in the network. They are organized based on methods they employ, such as prediction-based and heuristic, as well as their goals to meet the demands and problems of FANET routing. The event involving sharing or exchanging packets and highly dynamic network bandwidth may cause network congestion. Therefore, proactive routing can only

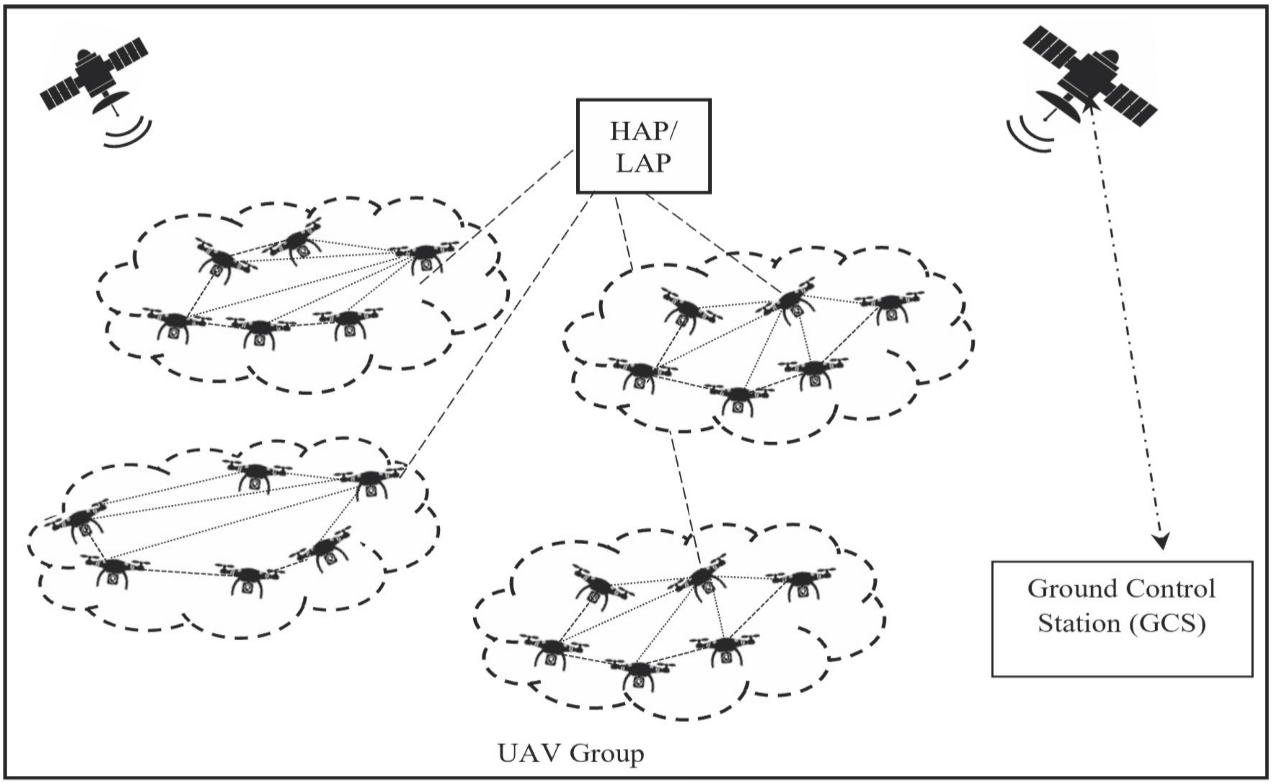

FIGURE 4. FANET Architecture.

be appropriate for FANET when there has been a significant upgrade. OLSR, DSDV, TBRPF and BATMAN are some of the proactive routing protocols.

Among various types of OLSR algorithms, energy-efficient and sturdy routes are formed in the network with OLSR+, an improved fuzzy logic-based OLSR algorithm [37]. Among the four phases of OLSR+, the discovery of neighboring nodes is its first phase. During this phase lifetime of the UAVs' link is calculated efficiently depending on the quality of the link, the distance between the nodes, speed and direction of motion of the nodes. Multipoint relay (MPR) nodes are chosen in the second phase with a fuzzy technique. As MPR, this process selects the node with the highest degree of connectivity with neighbor nodes, the lowest residual energy, and the most extended link lifespan. While the third phase discovers network topology, and route power and lifetime are added as new fields to the message. A routing table is calculated in the final step. It reduces delay and improves energy consumption with a higher packet delivery rate and throughput than G-OLSR and OLSR. Nevertheless, the routing overhead for OLSR+ is more compared with G-OLSR.

ii) Reactive (on-demand) Routing Protocols: The reactive protocol will only initiate a route discovery process when a node has to deliver data packets. It is intended to solve the bandwidth and power consumption limitations of proactive routing solutions by reducing the route management overhead. Furthermore, excessive delay and latency are frequent issues for this protocol. Reactive routing approaches are appropriate for applications with a small to moderate number of UAVs that can tolerate the communication delay involved with route construction.

iii) Hybrid Routing Protocols: Hybrid routing protocols benefit from combining proactive and reactive routing techniques to implement hybrid routing strategies. Hybrid routing addresses the significant latency caused by route research in reactive schemes and the routing overhead problem in proactive routing methods. In applications involving a small number to several UAVs in a single layer, incorporating heterogeneous nodes in a multi-layer, hybrid protocols such as Link Stability Estimation based Preemptive Routing (LEPR) and Hybrid Routing Algorithm (HRA) can be employed.

B. HIERARCHICAL (CLUSTER-BASED) ROUTING PROTOCOLS

An increase in network size causes the generation of extensive routing messages by flat routing protocols. Cluster-based or hierarchical routing fits the situation where the network size and presence of heterogenous nodes are large. As far as the heterogeneity of the nodes is concerned, hierarchical routing is an apt approach by reducing networks' congestion and enhancing network scalability. The routing has challenges, including cluster head selection and cluster management.

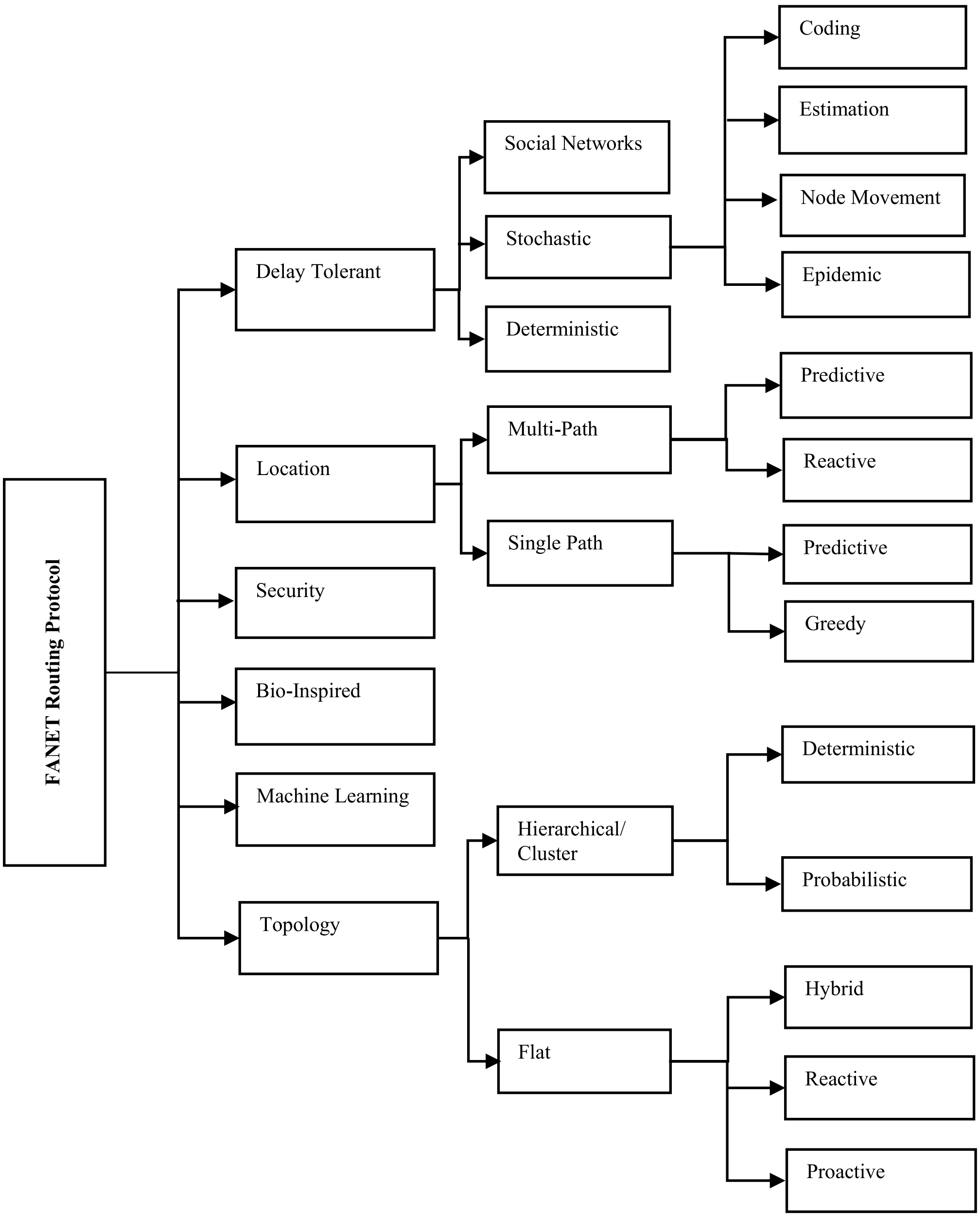

FIGURE 5. Taxonomy of FANET Routing.

Applications involving UAVs in single-layer with multi-group and multi-layer with multi-group communication architectures are better suited for hierarchical (cluster-based) routing algorithms. The probabilistic method makes the selection of cluster heads (CH) arbitrary. FANET routing is suitable for this routing approach, while in the deterministic process, CHs are elected based on the information of neighboring nodes.

Mobility Prediction Clustering Algorithm (MPCA), Predictive Routing, Mobility Prediction Clustering Routing (MPCR), Cluster-Based Location-Aided Dynamic Source Routing (CBLADSR), Energy Aware Link-based Clustering (EALC) [38], Localization Multi-hop Hierarchical Routing (IMRL), Cluster based reactive routing protocol (CRR) and Traffic-Differentiated Routing (TDR) are some of the hierarchical or cluster-based protocols [6].

1) MACHINE LEARNING

Recent improvements in FANET routing algorithms include various Machine Learning (ML) principles. Supervised Learning, Unsupervised Learning and Reinforcement Learning (RL) are the three types of ML [39]. Dynamicity and the complex nature of FANET make Unsupervised and supervised learning inappropriate responses during routing. Since distributed routing algorithms handle problems similar to those described in reinforcement learning problems, it is feasible to explore the learning algorithms underlying different routing techniques in a single framework [40]. Since RL can constantly learn about the routing methods without any data set, it is suitable for FANET by desirably controlling the unpredictable environment.

RL is appropriate to govern the unpredictable environment in a preferred manner for FANET as it can continuously learn about the routing methods without any data set. The traditional RL works well with small-scale FANETs. The learning algorithm cannot successfully perform when figuring out the best routing strategy for the network because of the vastness of the state and action regions and the slow convergence speed of the learning algorithm. ML is vital in solving various FANET issues related to communication, resource management, security, and position [41].

The Q-routing technique [42] is a packet routing algorithm that encapsulates a reinforcement learning module within every network node. Each node only uses a local connection to maintain precise data on which routing choices result in the shortest delivery times. A Q-learning algorithm can be efficiently applied to develop a routing protocol in many ad hoc networks, including FANETs. Although Q-learning determines the optimum route based on the shortest path or the number of hops, it also takes the nodes' energy and traffic load into account at relay nodes.

Q-FANET [43] is an enhancement version of the Q-learning routing protocol for FANETs. The suggested method combines the most effective strategies and components from Q-learning based multi-objective optimization Routing protocol (QMR) and Q-Noise+, two distinct Reinforcement Learning-based routing protocols. The idea was to create a new protocol architecture by merging and altering features of these foundation protocols to suggest a protocol that better fits the dynamic behavior of FANETs while enhancing network performance and dependability.

2) BIO-INSPIRED

BIA is one of the heuristic techniques that mock the methodology of nature and works with several unpredictable decisions. BIA is effective in resolving the complexity of the optimization methods that are difficult to understand. In FANET, many algorithms are implemented with BIA, which increases their efficiency compared to other existing algorithms. AntHocNet and BeeAdHoc are BIA-based FANET algorithms, and these algorithms are examined, evaluated, and studied in comparison to the existing FANET algorithms, AODV, DSDV, and DSR [44]. According to the findings, AntHocNet performs well in terms of the delivery of packets and the end-to-end latency. In contrast, BeeAdHoc performs better in the throughput and the routing overheads.

The ability of individual UAV nodes to collaborate to complete tasks is one of the characteristics of a BIA-based routing protocol. The multi-relay notion of the iBAT- COOP routing protocol [36] makes substantial attempts to achieve the functionality mentioned above. It is utilized to select an optimal route, ultimately improving the SNR and link conditions. Deployment of UAVs in the agricultural field is getting popular. RSoBIR (Recruiting Strategies over Bio-inspired Routing) and RSoLSR (Recruiting Strategies over Link State Routing) are used to manage UAVs in farming, mainly to locate and eliminate parasites, these two approaches appear more efficacious [45].

The delay-tolerant networking strategy is implemented using the dPSO-U routing method, which is utilized by the UAV team and is based on Particle Swarm Optimization (PSO). If PSO particles are DTN-networked UAVs, then it is advised to use the dPSO-U strategy to inspect an area during a disaster [46].

In the paper [47], the authors suggested a routing strategy for FANET based on bee colonies, and they used the Markov mobility model to anticipate when a link would expire. Compared to GPSR and LAR-3D, the mentioned methods greatly enhance the packet delivery ratio and end-to-end latency. The routing protocol, known as GW-COOP [48], takes care of the requirements for flying nodes by utilizing Gray Wolf Optimizer (GWO), and it keeps the link between the source and the destination alive with the assistance of two relays. The experiment results show that the protocol works better than the BAT-FANET and BAT-COOP protocols.

In addition, utilizing BIA in clustering UAV nodes produces an efficient route plan that establishes reliable communication between the nodes. The Red Deer Optimization Algorithm Inspired Clustering-based Routing Protocol (RDOAICRP) [17] uses a route discovery function that considers the number of neighbouring nodes, the measurement of separation between the UAVs, and remaining energy guarantees efficient communication. It determines the remaining power of each node to maintain the cluster functioning. In the paper [49], the authors offer another clustering method for FANET called Moth Flame Optimization (MFO). In the study, the route identification function is used to select a route that considers both the remaining energy of the nodes and their Euclidean distance from one another. The Fruit Fly Optimization Algorithm (FFOA) improves the functionality and efficiency of clustering with K-Means and is compared to other optimization approaches, such as comprehensive learning particle swarm optimizer (CLPSO), classification of Compositional-Aware COrrelation NETworks (CACONET), Grey Wolf Optimization Based Clustering In Vehicular Ad-Hoc Networks (GWOCNET), and Energy-aware Cluster-based Routing in FANETs ECRNET [50]. These comparisons are made according to various performance characteristics that the FFOA exhibits.

3) SECURITY

With its dynamic nature, wireless and broadcast communication in FANET networks are more prone to various attacks and urges for better security mechanisms [33]. Several security schemes of Ad-Hoc networks, including cryptographic algorithms, intrusion detection methods and reputation-based techniques, can be used in UAV networks [14].

By embodying geographical leashes, hash chains, and public-key cryptography into the AODV protocol, a security protocol named SUAP is developed for FANETs. Moreover, DOLSR improves security since it is resistant to interference. AODV security, AODVSEC, is the routing protocol that ensures security among the reactive protocol category [51].

4) LOCATION

Forwarding decisions in location-based routing are based on the relative location of the destination node in the FANET environment, and no need to maintain the route information [52]. Usually, GPS is used to locate the node position. Reactive Location Service (RLS), Grid Location Service (GLS) and Hierarchical Location Service (HLS) are used to calculate the position of the destined node. Location-based routing protocols consist of single-path and multipath routing strategies.

a: SINGLE PATH

These protocols pick a unique path for transmitting messages from sender to receiver. These procedures may fail at any moment, causing significant delays.

Single-path protocols consist of greedy and predictive techniques. The former approach chooses nearby receiving nodes as relay nodes to avoid no-hop situations in data transmission. The latter uses direction, velocity and location to predict the future position of UAV nodes.

b: MULTIPATH

Efficient data distribution requires many paths to minimize bottlenecks, load balancing, and dependable communication concerns. Multipath enables the forwarding of a packet to the recipient over many paths, reducing the likelihood of the aforementioned network problems. Reactive and predictive techniques are utilized in multi-path routing. On-demand path establishment to destination and load balancing of the network is done in multipath with reactive technique, while the predictive method uses prediction in UAV node movement.

With jamming-resilient multipath routing protocol, also known as JarmRout [53], the overall network performance of FANETs is preserved despite deliberate jamming, interruption, and failures (isolated and localized). Using link quality, traffic load, and spatial distance schemes, JarmRout is designed.

5) DELAY TOLERANT

Implementation of this protocol may overcome the Intermittent disconnection of UAV nodes and delay caused in routing. The protocol leverages the store carry mechanism in Delay Tolerant Network (DTN) to deliver messages successfully. Location-aided delay tolerant routing (LADTR) [54]. The following three classifications of DTN are concerned with FANET.

a: DETERMINISTIC ROUTING

In delay-prone networks, the deterministic technique generates patterns using time-dependent graphs and discovers the shortest space-time route. Deterministic routing is suitable for networks with predictable topologies. In addition, the deterministic approach presumes that all spatial and temporal linkages between nodes are known and understood.

b: STOCHASTIC

The stochastic routing protocol was the first to transmit data using a probabilistic local broadcast paradigm [55]. It is possible to achieve a close link between lower network layers by modeling channel properties. Additionally, the model decided on routing based on instantaneous feedback from each communication. Rather than describing the set of links that each packet must travel, the Stochastic protocol detects local broadcast transmission of each node's stochastic outcome and generates an ideal route based on this immediate feedback. Since the approach is based on the local knowledge of a node, it lends itself effectively to distributed implementation. Physical layer factors and the network layer routing function are combined by modifying transmission types to improve the routing decisions of this method.

The agility and features of FANET exacerbate the difficulties of packet forwarding. A stochastic packet forwarding algorithm (SPA) [56] is suggested for FANETs, allowing for the efficient transport of data packets to their destination. In SPA, the packet sender examines each potential drone for next-hop forwarding based on several network characteristics before picking the drone based on the forwarding probability. SPA has four exciting aspects. First, entropy weight theory assigns weights to network measurements. Thus, SPA may be changed for applications with diverse network characteristics like high or low connection throughput and movement speed. Second, the forwarding probability will randomly choose the forwarding node. Thus, any forwarding candidate node may participate in packet forwarding. Stochastic forwarding node selection may provide conditional load balancing. Third, regularly broadcasted HELLO messages containing geographical location and mobility information may assist packet senders in immediately noticing the change of forwarding candidate nodes and re-evaluating all candidate nodes for packet forwarding. Fourth, SPA designers consider extension and flexibility. Thus, SPA may easily include real-time network measurements. Network traffic should be balanced across all forwarding nodes to prolong node and network lifespan. The limits of SPA are (i) it can only deliver data packets to one forwarding node. (ii) FANET nodes are mobile faster; therefore, the packet sender may not have a neighbor to transfer the data packet.

Epidemic routing propagates data around the network by utilizing node mobility. The merits of epidemic routing are low latency and a higher success rate. Some challenges with epidemic routing are more extended connections, reduced network load and larger buffers. When nodes' movements cannot be tracked, information gathered by the node is broadcast to all nodes.

Intermediate nodes assess the chances of outgoing packets reaching the intended destination. With the estimation method, intermediary nodes will save the packet and be forwarded only after selecting when and to whom the packet will be forwarded. Probabilistic Routing Protocol using History of Encounters and Transitivity (PRoPHET) [57] is one of the routing protocols designed for networks with delay-tolerant features that use delivery estimation. For reconnection, nodes may either quietly wait reactively to reconnect with the other node or proactively search for a different node. Network throughput can be enhanced by implementing network coding in routing. Relay nodes combine incoming packets and broadcast them as a single new outflow packet to maximize the data contained in the outflow packet.

c: SOCIAL NETWORKS

Social-based approaches successfully predict and manage the dynamics of DTNs by using typically stable social traits, making them more promising than opportunity-based routing for DTNs [58]. In rare circumstances, a forecast may not come true. However, performance may be improved in several scenarios by combining mobility patterns and geographic profiles with social-based measures or with more traditional opportunity-based metrics. On the other hand, in some instances, a poor mix of several routing indicators might impair performance. Some applications of such routing in FANET provide interaction over a petroleum drilling program or communication around a location prone to natural disasters.

Moreover, a brief overview of the advantages and disadvantages of the FANET protocols mentioned above and their applications is presented in Table 2 [5], [57], [59]. For applications, routing protocols are selected based on their advantages. For example, the applications like traffic monitoring and cooperative transportation of objects use proactive routing protocol since rapid route discovery and reliable packet delivery are its advantages.

Even though standard routing algorithms operate well with FANET, the intricacy of its routing might cause the network's performance to deteriorate. However, this may be mitigated by using optimization techniques that improve the Quality of Service (QoS) parameters of UAV networks. Swarms of mini-UAVs are more successful than traditional methods in covering broad areas. After deploying flocks of airborne nodes, UAVs collaborated to perform tasks, attracting academics' attention and motivating them to use the BIA in FANET routing [60].

In general, bio-inspired networking strategies utilize computational methods to solve various networking problems. In recent years, several networking challenges in routing, congestion management, security etc., have been addressed by introducing solutions that are inspired by biological processes. BIA have been utilized to handle the network related issues. Furthermore, the striking similarity between the various communication scenarios that occur in networking and the regular communication between animals is the fundamental factor that drives the development of bio-inspired networking approaches. In addition, biologically inspired techniques offer optimal solutions while reducing the complexity involved. As a result, to have a better understanding of why bio-inspired procedures are necessary for FANET routing, a comprehensive review is required.

The succeeding paragraph will explain each step of the review process in depth.

III. RESEARCH METHODOLOGY

In contrast to other literature reviews, SLR is a structured process that does a complete, in-depth literature analysis on a specified topic with less bias. According to the SLR criteria in [61], the methodology for this review paper was created by merging numerous discrete procedures into the following three-phase process:

Phase 1: Planning- In this phase, research questions are specified, and a review protocol is developed (See Section A).

Phase 2: Conducting- Once the protocol has been finalized, the SLR executes this phase and implements the search strategy of the protocol. The steps involved in this phase include the formulation of search strings, the selection of databases to search records, the initial selection of papers based on the titles and abstracts of articles, the finalization of articles based on inclusion/exclusion criteria, and combining the analyzed records to answer the research questions. Section B discusses in detail about the entire process involved in this phase.

Phase 3: Reporting- This is the concluding phase in a systematic review, comprising disseminating the results of the review in a report form. Research findings can be published in a technical report, such as a chapter of a doctoral dissertation, in peer-reviewed journals, or in conference papers.

A. REVIEW PLANNING

In the "planning" phase, the goals of this review are translated into specific Research Questions (RQ) [4], [61]. RQs will be used to find primary studies to understand and summarize evidences about the non-hybrid and hybrid BIA implemented in FANET routing. In this context, five research questions were devised from the goals or objectives of this SLR. The goals and RQs that will lead this study are outlined in Table 3. Based on [61], a protocol is created for this systematic review. The protocol is evaluated externally in advance of its actual implementation.

TABLE 2. Summarization (application, advantages and disadvantages) of fanet routing protocols.

Protocols	Advantages	Disadvantages	Application
Proactive	• Rapid route discovery. • Reliable packet delivery.	• Routing Overhead is high. • Routing table updates often.	Traffic Monitoring Cooperative transportation of objects.
Reactive	• Reduced Routing Overhead. • Reduces resource use.	• Route discovery delays. • Heavy flooding causes network congestion.	Data collection in precision agriculture Post-disaster operation Remote sensing
Hybrid	• Fix reactive system latency and proactive routing overhead.	• Only suitable for hierarchical networks.	Reconnaissance Search and rescue Border Surveillance
Hierarchical or cluster based	• Predicting Link Failure. • a high rate of delivery. • robust connection, decreased packet losses.	• The level of layering and addressing is dependent on the benefit. • Traffic demand response is determined by meshing variables.	Battlefield applications Network coverage Cooperative Surveillance
Machine Learning	• Faster training; increased accuracy; and decreased average latency. • Used in both centralized and decentralized routing algorithms. • Frequently online-trained, responding to rewards from the surroundings.	• Pre-process is complex • Scalability has to be improved • Can't scale Q function table to larger networks.	Medical image processing Computer vision Natural language processing.
Bio-Inspired	• Avoids congestion and link breakages. • Improves memory storage and bandwidth. • Encourages the fragmentation of networks.	• Modelling complex behavioural patterns.	Searching for evading targets Battlefield applications
Security	• Prevents replay and alteration of routing control messages. • Protects against threats and discovery technique during flooded.	• For the resource-limited mobile nodes, public key cryptography is still extremely costly.	Internet of Drones (IoD) Intelligent Transportation System (ITS)
Location	• Low control overhead. • Low energy consumption. • Requires less memory. • Scalability. • Requires less maintenance.	• If the target node is in the same area, the same route is used, which leads to more power usage for specific nodes and some remained underutilized.	Hovering on a target.
Delay Tolerant	• Enhanced operations and awareness of the environment. • Considerable Latency. • Data rate is low. • Increased delivery ratio and delay.	• The performance of the DTN network is hampered by its limited resources. • Nodes have limited processing power and memory. • Low computing power and a non-replaceable battery.	Deep Space missions News delivery Voice-based communication application (walkie-talkies) Monitoring wildlife movement Web searching from buses

B. ARTICLE SEARCHING AND SELECTION

The "conducting" phase describes various procedures involved in searching and selecting pertinent articles in SLR. In this stage of SLR, it is necessary to identify the inputs as search phrases relevant to the study themes. These terms are then logically concatenated to create a query string that will search the selected seven online databases (IEEE, Web of Science (WoS), Scopus, Science Direct, Springer, Wiley, and ACM) for pertinent publications. In this stage, two search queries are developed: 1) "FANET" OR "UAV" AND "Hybrid" AND "Optimization" and 2) "FANET" OR "UAV" AND "Bio-inspired" AND "Hybrid" AND "Optimization" AND "Routing" AND "Algorithm".

Fig. 6 depicts the PRISMA-based article selection process, which includes searching records for this SLR. Each phase in conducting process utilizes inclusion and exclusion criteria, described in Table 4, for the search and selection of articles for this survey. In the identification stage, an initial search of 6712 records was searched through the online databases on 17 February 2022. The detail of these records was imported to the excel sheet and documented.

The search was restricted to publications that were published in the English language between the years 2000 and 2022. (inclusive). The outcome of the initial search is displayed in Table 5. After combining the articles and removing duplicate papers from the selected articles, the total number of records retrieved from the online databases namely, WoS, ACM, Science Direct, IEEE, Scopus, Wiley, and Springer are 637, 226, 2974, 503, 515, and 703, respectively. Several articles were irrelevant throughout this phase.

TABLE 3. Research questions with goals.

	Research Question	Goal
RQ1	What are the characteristics of FANET and how can it be differentiated from other ad hoc networks?	To give an insight into the characteristics that make FANET unique from MANET and VANET.
RQ2	How are routing characteristics in FANET improved with non-hybrid and hybrid BIA?	To identify and compare the characteristics of existing FANET routing with hybrid and non-hybrid BIA and to substantiate the improvement in performance with these techniques over existing routing protocols in FANET.
RQ3	What are the mobility models in FANET with BIA?	To identify and analyze the existing mobility models in FANET routing algorithms implemented with BIA.
RQ4	What is the role of Bio-inspired and hybrid Bio-inspired techniques in optimizing the routing metrics of FANET and how it is assessed?	To analyze the effect of BIA in FANET routing metrics and identify the simulation tools used for evaluating FANET metrics.
RQ5	What are the present research difficulties being examined, and the future research scope?	To perceive and identify the research gaps that need to be filled, along with possible future scope in this discipline.

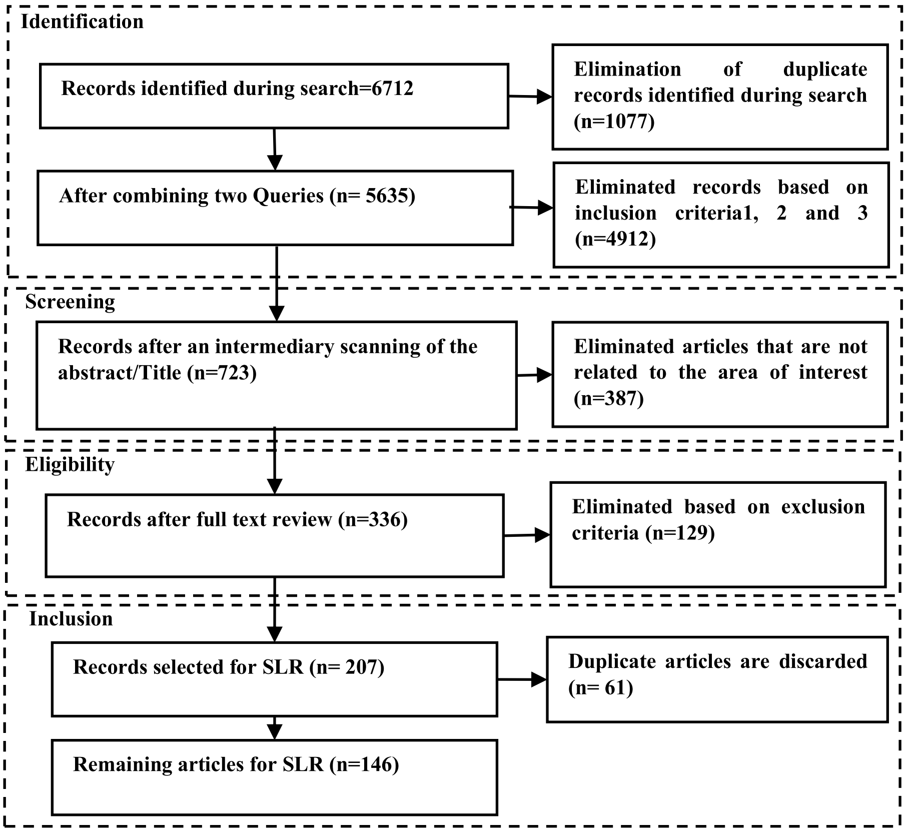

FIGURE 6. PRISMA Flow diagram of article selection.

During the screening step, an interim scan was conducted using the titles and abstracts of the papers, which resulted in the selection of 723 articles. After the intermediate screening of articles, 387 records were removed during the eligibility phase's quality scanning of the article. After removing 61 redundant articles, remaining 146 were thought to be pertinent for this SLR in the inclusion phase. In Fig. 7, a Venn diagram illustrates the range of distribution of the chosen articles.

C. STATISTICAL SUMMARY OF ARTICLE SELECTION

The articles that meet the requirements for inclusion are chosen for evaluation. 146 papers from journals, conference proceedings, and book chapters were examined using the data from 7 electronic databases. Fig. 8 depicts the percentage distribution of publications published between 2000 and 2022 according to their publication year. There were no publications between the years 2000 and 2006, as well as between 2008 and 2012. The graph demonstrates that the use

TABLE 4. Criteria for inclusion and exclusion.

	Criteria
Inclusion	1. Language of the publications must be in English.
	2. Range of the publication year of the articles from 2000 to 2022.
	3. Articles in the form of Journal, Conference or Book Chapter.
Exclusion	1. Articles not explicitly focusing on standard FANET routing or FANET routing based on non-hybrid as well as hybrid Bio-inspired.
	2. If an article is not entirely accessible from an online electronic database, then it will be excluded.

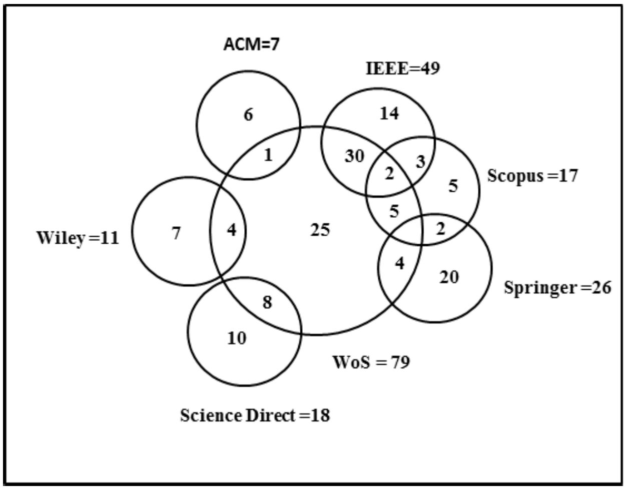

FIGURE 7. Venn Diagram.

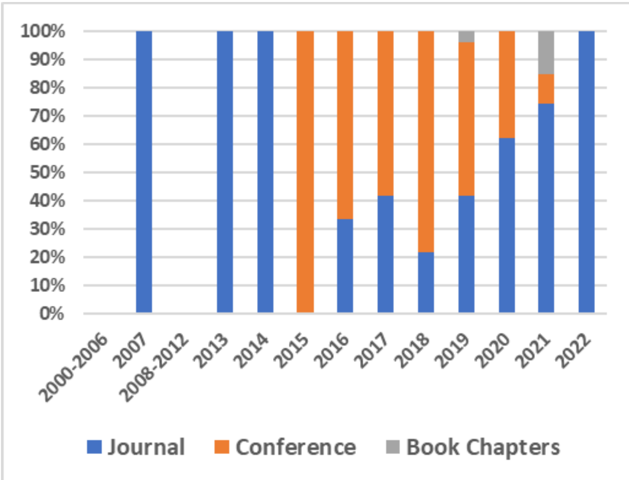

FIGURE 8. Year wise percentage distribution of selected Journal, Conference and Book Chapters.

of bio-inspired approach for FANET routing did not become prevalent until around the year 2012. Book chapters are less relevant to the designated field than conferences and journals. 100% of the articles in 2007, 2013, 2014, and 2022 were from journals; however, in 2015, there were just conference papers published. In contrast to the overall number of papers, most articles were published in journals and conferences in 2021 and 2018, respectively.

The distribution of articles across different online databases is illustrated in Fig. 9. The number of relevant articles retrieved from IEEE is higher than those collected from other databases, with WoS placed second and ACM falling in last. According to the diagram in Fig. 10, journals make up 54% of the total records that were included, while conference papers account for 41%, and book chapters make up the remaining 5%.

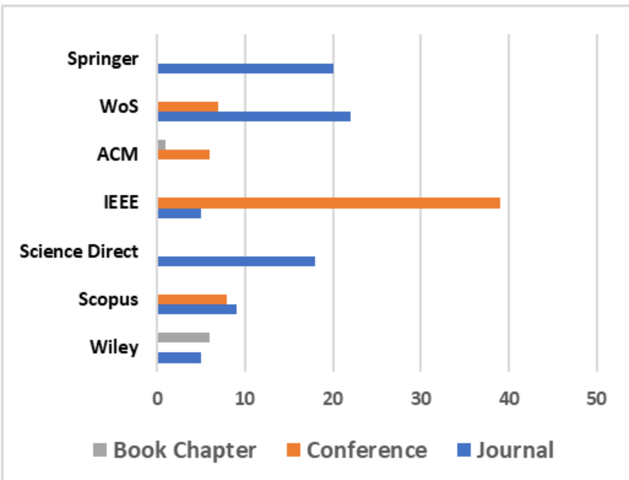

FIGURE 9. Distribution of Book Chapter, Journal and Conference articles among online databases.

1) ANSWERING THE RESEARCH QUESTIONS

The outcomes of conducting phase of the SLR agree with the established research questions pertaining to the selected papers based on the selection criteria. Research questions (RQ1-RQ5) were addressed in this subsection. The first research question (RQ1) examined the unique qualities of FANET and sought to explain how they set it apart from

TABLE 5. Initial search result.

Sl No	Data Base Name	Initial search (Total Count)			Count after Screening
		Search Query1	Search Query2	Count after the elimination of duplicates	
1	IEEE	503	315	503	173
2	Web of Science (WoS)	643	373	637	154
3	Scopus	516	2	515	142
4	Science direct	2910	310	2974	124
5	Springer	69	16	77	64
6	Wiley	609	159	703	45
7	ACM	227	60	226	21
			TOTAL COUNT	5635	723

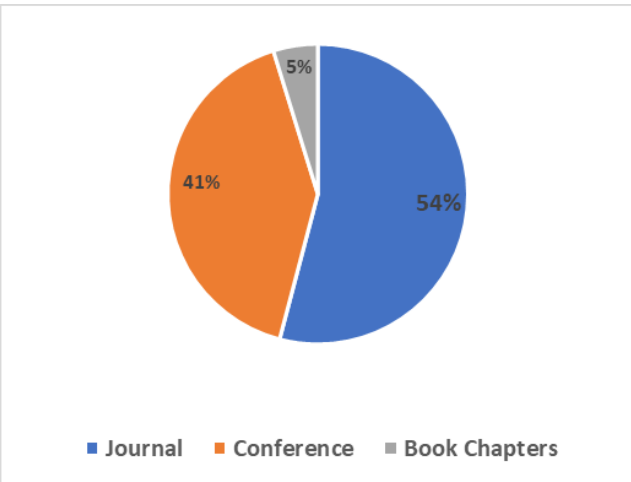

FIGURE 10. Overall percentage distribution of Book Chapters, Journal and Conference articles selected for this review.

other ad hoc networks, while the second (RQ2) aims to provide evidence that these techniques would improve upon FANET's pre-existing routing performance. Concerning the third research question (RQ3), the main focus is to identify and analyze the current mobility models used by FANET routing using BIA. Research question 4 (RQ4) focuses on identifying the simulation tools used to evaluate FANET routing metrics and analyzing the impact of BIA on those metrics. In particular, the research possibilities (gaps) for future researchers working in FANET routing with BIA methodologies are highlighted and emphasized in the fifth research question (RQ5).

a: FANET'S ROUTING CHARACTERISTICS

RQ1 is addressed in this section. Every FANET mission or application is distinct from others, and these differences are considered when choosing a suitable working approach [30]. Within this SLR's collected data, there are 16 papers that focus on discussing the properties of FANET. Section II of the paper also discusses the traits, and Table 6 summarizes the general FANET characteristics cited in the selected articles.

Table 7 presents a comparison of FANET, MANET, and VANET, highlighting the characteristics that distinguish FANET from the other two types of ad hoc networks [44], [5], [20], [62], [9], [63], [11], [36], [64], [15], [10]. The comparison reveals that UAV nodes have more mobility and power consumption than the other two types, while their topologies change more frequently.

b: BETTERMENT OF FANET ROUTING WITH BIA

Recent advancements in research highlight the significance of strategies inspired by biological behavior in FANET routing. This section addresses the second research question (RQ2) by analyzing various bio-inspired methods, including a classification of these methods. The bio- inspired technique is a subcategory that falls under the population-based approach. Even though Fig. 11 presents a taxonomy of FANET routing based on a metaheuristic optimization technique, the focus of this discussion will be on BIA. BIAs specified in Fig. 11 are summarized in Table 8.

A metaheuristic optimization technique is a higher-level approach that can identify an ideal solution. Utilizing this strategy, one can avoid settling for local optimal solutions. Complex problems, such as NP and NP-hard, can be tackled with the assistance of optimization techniques. The term "heuristic" refers to arriving at a solution through trial and error or by following rules that have ambiguous definitions, whereas the term "meta" alludes to anything of a higher order. In contrast to heuristic algorithms, the metaheuristic strategy is most helpful in rapidly locating a solution that is very close to the ideal. Based on the

TABLE 6. Characteristics of FANET.

	Node mobility	Topology change	Power Consumption	Localization	Node Density	Radio Propagation Model	Mobility Model	Communication range	Frequency band	Environment
[13]	√	√	√							
[15]	√	√	√	√	√	√				
[11]		√				√	√	√		
[14]	√	√	√	√	√	√	√			
[33]	√	√		√	√	√	√		√	
[7]	√		√					√		√
[22]	√		√	√	√		√	√		
[64]	√	√	√	√	√	√	√			
[35]	√		√		√			√		√
[5]	√		√	√	√	√		√	√	
[10]	√	√	√		√		√	√		
[34]	√	√	√			√				
[8]	√	√			√		√			
[65]	√	√	√							
[17]	√	√	√	√	√	√	√			
[36]		√	√	√	√	√	√			

findings of both single-point and population-based investigations, the metaheuristics methodology classifies search as either population-based or trajectory-based. Population-based techniques include Game Theory Optimization, Swarm Intelligence, and Evolutionary Computation Techniques.

The "Nature Inspired Methods," a subclass of Swarm Intelligence (SI), is divided into BIA and non-BIA categories.

Among the types mentioned above, BIAs associated with UAV routing in the FANET environment is the primary focus of this work. Information processing in nature takes place in a highly efficient distributed, deterministic, and uncontrolled system. Therefore, this work employed a bio-inspired optimization approach and examined its classification based on social and food-searching behavior since it replicates the behavior of swarms of UAV nodes.

BIA is classified according to the social behavior & foraging of living organisms such as Animals, Insects and Microbes. Some of the BIA are discussed below. Since the goal of this review was to develop an SLR for FANET routing based on BIA, a summary of each algorithm with its benefits and drawbacks is presented.

i)Animals

Krill: Krill Herd Optimization (KHO) [66] algorithm is motivated by how krill move in groups. The position of a krill fluctuates over time based on three factors: foraging behaviour, random diffusion, and movement triggered by the presence of other krill. Crossover and mutation, two adaptive evolutionary operators, are also introduced.

Several parameters for each metaheuristic algorithm must be fine-tuned for optimal performance. The suggested algorithm employs real-world pragmatic investigations to derive the coefficients and meticulously replicates the krill's behaviour. Therefore, only the time interval has to be adjusted while adjusting the KHO algorithm (Time interval is a fixed value between 0 and 2.). In contrast to previous algorithms inspired by nature, this is a significant benefit of the suggested approach. But to fine-tune the KH algorithm's parameters for each issue, it is recommended to use an appropriate meta-optimization approach.

Advantages

- The KH algorithm employs stochastic random search. Hence derivative information is unnecessary.
- Depending on its fitness, each agent may contribute to the relocation.
- Each neighbour has an enticing or repulsive influence on the krill's movement. Consequently, these impacts may serve as a local search for each particular krill.
- The food location decided by the fitness levels of all krill individuals is considered an approximation of the global optimal.

Disadvantage:

- The fundamental features, such as induced and foraging movements of the KHO algorithm, are more complicated than those of the standard swarm intelligence algorithm, PSO.

TABLE 7. Characteristics' comparison (manet, vanet, FANET).

Characteristics	MANET	VANET	FANET
Mobility	Slow (Speed 2m/s)	Higher than MANET (Speed on highways and urban are 20-30 m/s and 6-10m/s respectively)	Higher than VANET (Speed 0-100 m/s)
Topology change	Very less	Depends on traffic.	Frequent
Power Consumption	Medium	Low	Higher
Localization	Global Positioning System (GPS), beacon nodes or proximity-based techniques.	GPS, Assisted GPS or Differential GPS.	GPS, Assisted GPS or Differential GPS, GPS with Inertial Measurement Unit.
Density of nodes	Lower	Higher	Least
Radio Propagation	Above the ground	Nearest to the ground	Farther above the ground
Mobility Model	Random	Predictable	Usually predetermined; Autonomous UAVs have different models (Semi-random)
Communication range	Small Coverage	Small Coverage	Large Coverage
Frequency	30 MHz to 5 GHz	5.9 GHz	Between UAV is 5GHz Between UAV and the ground station is 2.4 GHz
Environment	Ground obstacles (terrain) cause interference	Depends on traffic.	Primarily used in free space.

Application:

Image processing and solving phase equilibria problems.

Wolf: Grey Wolf Optimizer (GWO) [67], [68], modelled after grey wolves (Canis lupus), imitates the leadership structure and hunting mechanism of grey wolves in the wild. For replicating the leadership structure, four sorts of grey wolves, including alpha, beta, delta, and omega, are used. In addition, the three primary phases of hunting—searching for prey, surrounding it, and attacking it—are incorporated.

Advantage:

- GWO excels at unconstrained and confined problems.
- Low computation cost.

Disadvantage:

- Low solving accuracy, poor local searching, and sluggish convergence.

Application:

Utilized in terrain positioning assisted underwater route planning and in decreasing fuzzy control system parametric sensitivity.

Bat:

The Bat Algorithm (BA) [69] is based on bats' echolocation behaviour. Even in total darkness, microbats can locate their prey and distinguish between various species of insects because of their echolocation abilities.

Idealized principles used in the BAT algorithm are i) Bats utilize echolocation to gauge distance and distinguish food from background obstacles. ii) Bats fly randomly with a velocity at a set frequency, wavelength, and loudness to find prey. They may automatically modify the wavelength (or frequency) and pulse emission rate r (varies [0,1] based on target proximity). iii) It is presumed that the loudness range extends from a high to a low fixed value, even if it fluctuates.

The process for updating the velocities and locations of bats is comparable to the typical particle swarm optimization since the frequency regulates the speed and range of the particle movement. BA may be seen as a blend of conventional particle swarm optimization with intense local search governed by the loudness and pulse rate.

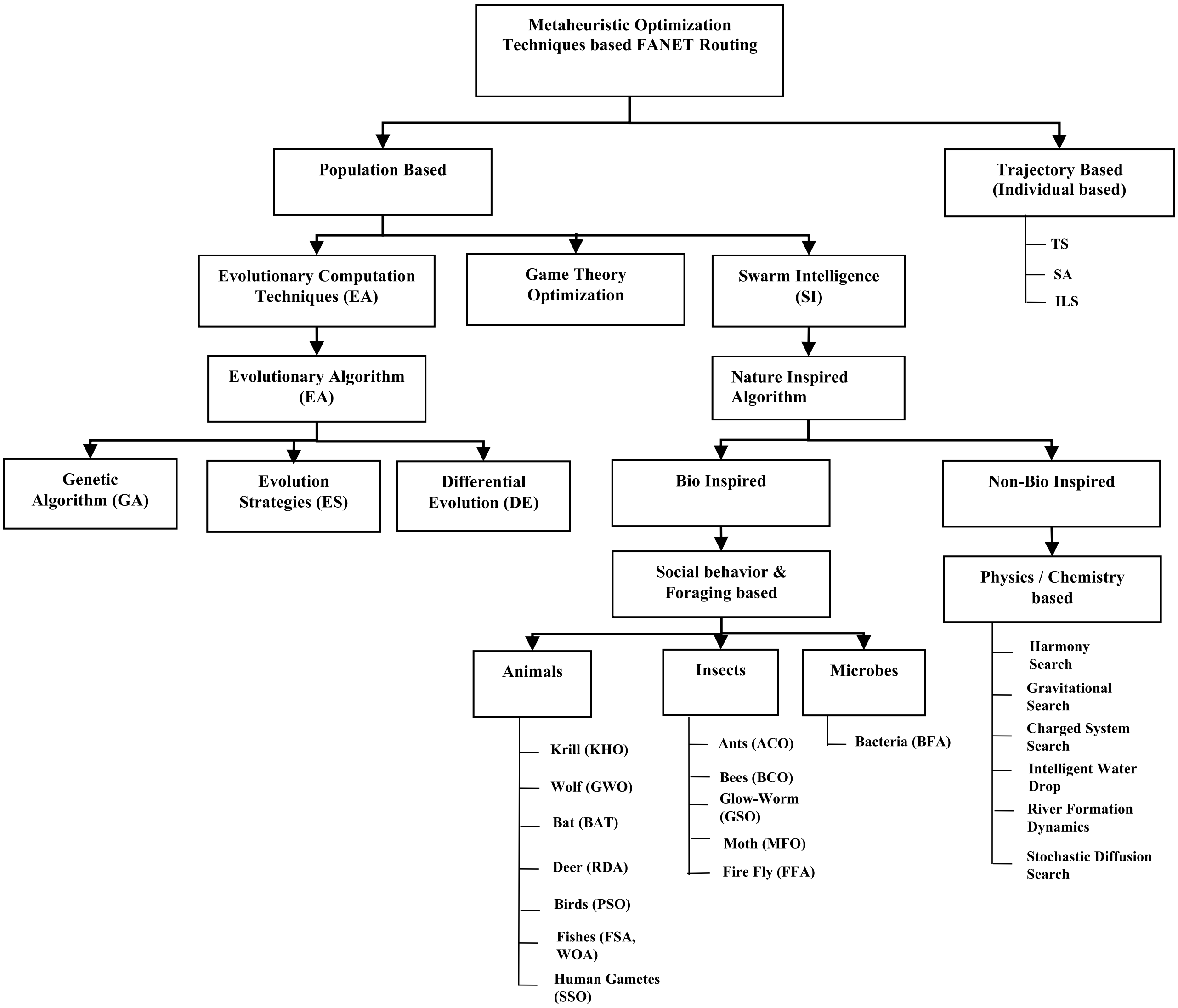

FIGURE 11. Taxonomy of Metaheuristic Optimization based FANET routing.

Advantage:
- Since it incorporates the best features of PSO, GA, and HS, BA may be more effective.
- It shows an appropriate mix of existing efficient algorithms and innovative features based on bat echolocation behaviour.

Disadvantage:
- The implementation is more complex.

Application:

Computational Geometry, Wireless Sensor Network (WSN), digital filter design, etc.

Red Deer: Red Deer Optimization Algorithm (RDA) [70] is a novel algorithm imitating the behaviour of Scottish red deer inspired by nature. The primary source of motivation for this meta-heuristic algorithm is the peculiar mating behaviour of Scottish red deer during the breeding season. The red deer algorithm (RDA) begins with an initial population of red deer (RDs). They are classified as either hinds or male RDs. A selection of the finest RDs in the population is called "male RDs," while the others are referred to as "hinds."

The first phase starts with the roaring of the male. Consequently, the roaring of male RD is the opposite of the local search in solution space to increase exploitation features. They are classified into two categories based on the loudness of a roaring phase. The commanders and stags of each harem then engage in a battle for harem ownership in the next stage. The conflict is a local search, and better alternatives are accepted. This stage focused mainly on the exploitation features.

After that, harems are constructed and assigned to commanders based on their relative strength. This step facilitates the algorithm's exploration phase. Consequently, the commander of a harem mates with a proportion of the hinds in his harem and a proportion of the hinds in another harem. Additionally, these levels have enhanced the exploring

TABLE 8. Metaheuristic optimization algorithms.

Reference	Metaheuristic Algorithms
[97]	Tabu Search (TS)
[97]	Simulated Annealing (SA)
[97]	Iterated Local Search (ILS)
[66]	Krill Herd Optimization (KHO)
[67]	Grey Wolf Optimization (GWO)
[70]	Red Deer Optimization (RDA)
[72]	Particle Swarm Optimization (PSO)
[75]	Fish School Optimization Algorithm (FSA)
[77]	Whale Optimization Algorithm (WOA)
[79]	Sperm Swarm optimization (SSO)
[80]	Ant Colony Optimization (ACO)
[82]	Bee Colony Optimization (BCO)
[98]	Glowworm Swarm Optimization (GSO)
[83]	Moth-Flame Optimization (MFO)
[85]	Fire Fly Algorithm (FFA)
[53]	Bacterial Foraging Algorithm (BFA)
[99]	Harmony Search
[100]	Gravitational Search
[74]	Charged System Search
[101]	Intelligent Water Drop
[102]	River Formation Dynamics
[103]	Stochastic Diffusion Search

characteristics. Regarding the breeding season, a stag should mate with the hind at the shortest distance, regardless of the size of the harem. This stage likewise focuses concurrently on the exploration and exploitation phases.

The RDA's mating process, which results in the progeny of RDs, is an additional crucial step. This phase corresponds to the creation of new solutions in the solution space. Regarding the categorization of the algorithm as an evolutionary one, the next generation of the algorithm is completed by allowing weak solutions a chance in the final stage.

Advantage:

- The RDA's approach, behaviour, and simulation results demonstrated exploration and exploitation.

Disadvantage:

- Requires stochastic processing-based theoretical analysis and mathematical modelling.
- Understanding and proving the convergence of RDA under particular cases will be crucial.

Application:

In solving engineering, computer science, and business problems [71].

ii) Birds

Particle Swarm Optimization (PSO) [72], [73]: The idea of employing PSO to improve nonlinear functions is presented. The two primary component approaches are the origins of particle swarm optimization. It links to artificial life (A-life) and the swarming theory, fish schooling, and flocking theory increasingly apparent. But it also connects to genetic algorithms, evolutionary programming, and evolutionary computation.

The term "swarm intelligence" is used explicitly by the authors in line with a work by Millonas, who created his models for applications in artificial life and articulated five fundamental principles of swarm intelligence. The first and foremost one is the proximity principle which states that the general populace should be able to do essential space and time

TABLE 9. Bio-Inspired based FANET routing.

Reference	BIA Used with FANET routing	Hybrid Algorithm	Problem identified	Solution	Disadvantage	Simulation tool used
[106]	Glowworm swarm optimization (GSO)	No	Time consumption in cluster formation.	Clustering is based on self-organization and optimization strategies.	Less efficient than hybrid.	MATLAB
[107]	ACO	No	Routing maintenance and residual energy of nodes.	Tuning parameters of routing algorithm.	Less efficient than hybrid.	The author developed a simulator.
[108]	AntHocNet and BeeAdHoc	No	Difficulty in finding an efficient and optimized solution for routing problems.	Solutions with BIA are more effective.	Less efficient than hybrid.	NS2
[92]	Hybrid gray wolf optimization (HGWO) method.	Yes	Expensive and high energy consumption due to GPS usage.	A flexible and energy-efficient clustering approach with node localization.	No Calculation for cluster heads' routing overhead.	MATLAB
[45]	ACO	No	Drones have limited resources	Network performance improves with scalable coordination strategies.	Topology is managed through a proactive method.	Developed application specific simulator.
[109]	ACO	No	Inadequate fuel and insecticide of UAVs.	Integration of bio-inspired methods in UAV recruiting processes.	High energy usage.	Designed especially for this application.
[65]	Bee Colony Algorithm	No	Unique characteristics with the 3D motion in FANET.	Implementation with BIA.	Hybrid BIA will result in a better convergence rate.	NS2
[110]	BAT-COOP	No	Unpredictable mobility model, recruitment strategy, and Quality of Service requirements.	Maximal data gathering by adequately placing the relay node and retransmitting to the target.	Only discusses network delay and transmission loss.	Not Specified
[111]	iBAT-COOP	No	UAVs are dynamic and highly mobile.	Implementation with BIA.	Calculation of error is not done.	Not Specified
[112]	Bee Colony Optimization Algorithm with Fuzzy	Yes	Lacks cognitive relays and maps for complicated missions.	Hybridization of Fuzzy based problem formulation with optimization techniques.	Limitation in storage space to enhance cognitive restoration and evaluation in UAVs.	MATLAB
[93]	HGSOFA	Yes	UAV's limited lifetime.	Hybrid metaheuristic algorithm.	Not comparing with the existing hybrid BIA on clustering with FANETs	MATLAB
[113]	HPSOGA	Yes	Challenges in the formation and restructuring of multi-UAV in 3-D space.	A hybridization of Particle Swarm Optimization (PSO) and Genetic Algorithm (GA).	Existing hybrid BIA with FANET are not compared.	Not Specified
[48]	GW-COOP	No	Dynamic topology.	A strategy for determining the best routes depending on energy, relay placement, and desired distance.	Efficiency can be increased with Hybrid BIA.	Not Specified

calculations. The second quality principle states that people should be able to react to environmental quality variables. According to the third principle of diversified response, the population should avoid committing its efforts to too restricted pathways. The population shouldn't alter its pattern of conduct each time the environment changes, according to the fourth principle of stability. The fifth principle of adaptation is that the population must be able to alter its

TABLE 9. ***(Continued.)*** **Bio-Inspired based FANET routing.**

[114]	Differential evolutionary algorithm with Metaheuristics based on flocking and stigmergy.	Yes	The design and management of biologically inspired metaheuristic method is challenging.	Stable communication through grouping and indirect coordination of UAVs.	Fault or loss of UAV nodes.	Not specified
[47]	Bee Colony	No	Less guarantee for link stability in FANET.	Routing algorithm with Gaussian Markov mobility model	Fewer convergence rates.	NS2
[115]	Glow worm Swarm Optimization (GSO) and Krill Herd (KH)	Yes	Restricted UAV battery power and dynamic topology changes.	Energy-efficient and extended cluster lifespan with an enhanced self-organization-based technique.	Routing overhead calculation for cluster head is not calculated.	MATLAB
[116]	Enhanced ACO Algorithm (eACO)	No	Coverage of larger geographical area is a challenging problem for traffic monitoring in remote areas.	Drone based FANETs utilizing an enhanced ant colony optimization technique for traffic monitoring in remote areas.	Efficiency is compared only with other ACO based algorithm.	NS2
[117]	Modified glowworm swarm optimization (MGSO) algorithm.	No	Unreliable cluster communication in FANET.	Clustering with metaheuristic methods for FANETs,	Evaluated only Consumption of energy and life time of clusters.	Not specified
[49]	Moth flame optimization.	No	The creation of networks is difficult due to the mobile UAV nodes.	FANET-based cluster management and routing technique with optimization methods.	Fewer convergence rates.	MATLAB
[91]	IPSO (Improved PSO)	No	Node positioning and data transfer in FANET.	Optimizing the localization of nodes and data communication in FANET with improved PSO (IPSO).	CH node's load is high.	MATLAB
[118]	Red Deer Optimization Algorithm	No	High power consumption and reduction in throughput of FANET due to its topology change.	UAVs' cluster routing with BIA minimizes instability due to its dynamicity.	Load of CH node is more significant.	MATLAB
[119]	Directional Particle Swarming Optimization (DPSO)	No	Difficulty in source-to-target linkages due to UAV's dynamicity.	Implementing a FANET routing algorithm with metaheuristic optimization methods.	Routing overhead is not computed.	Not specified
[120]	Firefly Algorithm with Fuzzy based.	Yes	Obtaining an appropriate instant for accomplishing a goal while avoiding barriers is a challenge in FANET.	A hybrid model was constructed utilizing the firefly method and the fuzzy algorithm to reach an ideal solution	Experimental work was done using a static barrier in this study.	MATLAB
[121]	Water Cycle Moth Flame Optimization (WCMFO) and Grey Wolf Particle Swarm Optimization (GWPSO)	Yes	Traditional methods suffer from high latency, limited throughput, and early node failure in UAV networks.	The status of the UAV may be accurately anticipated by estimating the UAV parameter vector intelligently.	Only energy consumption and alive node is considered.	MATLAB

behaviour mode when doing so is worthwhile financially. The fifth and fourth principles are opposites of each other.

The primary parameters of a classical PSO are the total number of particles and iterations, inertia weight, constriction factor, and cognitive and social behaviour coefficients

TABLE 9. ***(Continued.)*** **Bio-Inspired based FANET routing.**

[122]	Social Learning Particle Swarm Optimization (SLPSO)	Yes	The use of hybrid flocking control techniques may cause conflicting instructions, thereby decreasing mission performance.	Implementation with particle swarm optimization method	NA	Monte Carlo simulation model
[123]	eAntHocNet	No	The Dynamicity of the FANET routing protocol causes to amplify its complexity and diversity.	A nature-inspired routing protocol can overcome these challenges.	Efficiency can be enhanced by hybridizing with another BIA.	NS2

(c1 and c2). Thus, A desired accuracy or any other termination condition might be used instead of the total number of iterations. An n-dimensional hypersurface may be used to conceptualize the search space of an n-dimensional optimization problem. The appropriate settings for a meta-heuristic's parameters rely on how rough and smooth this hyperspace is in comparison [74].

The methodology and notion of particle swarm optimization follow above mentioned five criteria, and calculations in n-dimensional space performed in a sequence of time provide the basis of the paradigm. The personal best (pbest) and global best (gbest) quality criteria are getting a reaction from the populace. The distribution of responses between pbest and gbest guarantees a variety of responses. The population stays true to the stability principle by altering its state (mode of behaviour) only when gbest changes. Because it adapts to gbest changes, the population is adaptable [74].

The algorithm is developed in a few lines of code and needs the problem statement and a few parameters to solve it. This algorithm is philosophically associated with the philosophical school that enables knowledge to arise rather than attempting to impose it, emulates nature than attempting to control it, and attempts to simplify things.

Advantage:

- The optimization of a particle swarm is simple and requires a few lines of code.
- Less parameter regulation.
- Beneficial for multi-objective optimization.

Disadvantage:

- Low-quality solution.
- Memory is required to update velocity.
- Convergence in the early stages.

Application:

Power System Optimization challenges, scheduling, vehicle routing, ANN tool durability forecasting, multi-objective, dynamic, QoS in ad hoc multicast, selective particle regeneration for data clustering.

iii) Fish

Fish School Optimization Algorithm (FSA) [68], [75], [76]:

Due to the large dimensionality of specific search spaces, search procedures may be time-consuming and inefficient if appropriate methods are not used. To promote mutual survival, fish schools, for example, benefit substantially from the enormous number of individuals they contain. Fish School Optimization Algorithm (FSA) is a unique algorithm for searching high-dimensional areas considering fish school behaviour. The Fish-School Search (FSS) algorithm comprises three operators: feeding, swimming, and breeding. Collectively, these operators (i) provide the evoked computation with extensive search capabilities, (ii) the capacity to automatically transition between exploration and exploitation, and (iii) a self-adaptive global direction for the search process.

A fish population conducts the search procedure in the FSS (limited-memory individuals). Each fish is a potential response to the issue. The effectiveness of a small number of the population's members influences the search recommendations in FSS. The knowledge of fishes' natural memory of their accomplishments—their weight—is essential as it can eliminate the need to keep a list of the best spots visited by each individual, as well as a record of their velocities and other factors. The concept of development through a combination of parental knowledge (after breeding) and some collective swimming (i.e., "reasoning") that chooses between various operating modes during the search process based on immediate outcomes is another critical component of FSS. The only information needed during reproduction is the parents' phenotypic and environmental information (i.e., actual offspring evolution).

FSS has to, at the very least, take into account guidelines like the following to cope with the high dimensionality and lack of organization of the search space: Simple calculations are required across the board, along with a variety of methods for storing distributed memories of previous computations, local computations (preferably within short radii), little centralized control (ideally none), and some individual variability.

Advantages:

- Exchanges local information to accelerate convergence, allows adaptive learning, decreases search computing cost, and may accelerate search due to individual differentiation.
- FSS performed well on multimodal functions despite its outstanding unimodal performance.

Disadvantage:

- The necessity to properly define the step used in some operators and evaluate the fitness function twice per fish per iteration.

Application:

Software test data generation, to identify weak characteristics hidden by noisy backgrounds and to identify stable paths in WSN routing.

Whale Optimization Algorithm (WOA) [68], [77] Humpback whales exhibit social behaviour that is modelled by the Whale Optimization Algorithm (WOA)with the bubble-net searching tactic as its basis. The WOA algorithm is based on how humpback whales typically forage using bubble nets. A humpback whale can't chase after and eat an oceanic school of fish because of its slow pace. These creatures use bubbles to catch fish. One or more whales create bubbles as they swim in a spiral motion around a school of fish. The radius of the spiralling movement becomes less as one gets closer to the water's surface; humpback whales attack when the fish pool is near the surface.

The WOA algorithm primarily employs the following mechanisms:

- Encircling the victim: Humpback whales can locate their prey. The WOA technique makes the assumption that the best candidate solution at this moment is either the target prey or really near the optimum since the location of the optimal design in the search space is unknown a priori. The other search agents will attempt to update their positions in favour of the best search agent once that agent has been identified.
- Bubble-net attack: The method assumes a 50 percent probability of selecting either the spiral model or the diminishing encircling mechanism to update the position of whales throughout optimization to simulate this simultaneous behaviour. Humpback whales also swim in a spiral pattern around their prey.
- Seeking the prey: The WOA algorithm uses a starting set of random solutions. Search agents change their positions when they iterate regarding the best outcome or a randomly chosen search agent. The value of an is changed from 2 to 0 to aid in exploration and exploitation.

The best option is selected for updating the position of the search agents when the search vector A is more than 1 and when A is less than 1. Depending on the amount of p, WOA may alternate between a spiral and a circular motion (p is a random number in the range [0,1]). The WOA algorithm is eventually terminated when a termination condition is satisfied.

Advantage:

- Adhere to fundamental ideas and easy-to-apply concepts.
- No requirement for gradient information.
- Avoids local minima.

Disadvantage:

- Applicable only to continuous problems, not discrete ones.

Application:

For solving the six structural engineering problems (welded beam, a pressure vessel design, a tension or compression spring, a 15-bar truss design, a 25- bar truss, and design of a 52-bar truss design) and in production optimization.

Human Gametes:

Sperm Swarm optimization (SSO):

The behaviour of sperm inspired SSO [78] as they fertilized the egg. It employs a collection of candidate solutions that move in a multidimensional search space domain to identify the best solution. The swarms simultaneously search for the optimal solution, the best sperm, on their paths. In other words, sperms evaluate the greatest value achieved to date (global best solution) and their personal best solution. Each sperm in SSO should alter its position based on its current velocity, location, distance to the personal best solution, and distance to the global best solution.

SSO may be thought of as a distributed behaviour method that can be used to address multi-dimensional issues. The inspiration for SSO came from the sperm's ability to travel forward in a swarm from a low-temperature region known as the cervix to fertilize the ovum (egg). The egg is waiting for the swarm to fertilize it in the Fallopian Tubes, a high-temperature zone that the sperm hunts for during this trip. One sperm remains in the end to fertilize the egg. The winner is the name of this sperm.

Assumptions On Sperm Movement Can Be Summarized As Follows:

- Based on the female reproductive system's pH value:

(1) It is 4.5–5.5 for a healthy vagina.

(2) During ovulation, the vagina's pH is 7–14, which is alkaline and non-toxic to the swarm and helps sperm to migrate.

(3) The pH of the female reproductive system's mucus is affected by the food consumed and the female's emotions. These considerations suggest a pH range of 7–14.

- Based on the temperature within the female reproductive system:

(1) Sperm seek warmer regions where the egg lives.

(2) The vagina's average temperature is 35.1–37.4 degrees Celsius, according to studies.

(3) In some instances, vaginal blood pressure might raise this temperature to 38.5 °C. These results indicate a temperature range of 35–38.5.

According to the study, vaginal temperature and pH affect sperm velocity and orientation.

The speed that sperm acquires after the ejaculation process inside the cervix zone is known as the sperm's initial velocity. Each sperm has a unique location in the cervix, and the pH level affects its velocity. The optimal solution that sperm can attain on its own is referred to as the personal best solution. The solution may be found by comparing the sperm's present position with its former location. The location will be remembered when the prior location is inferior to the present one. The sperm solution with the most advantageous location is known as the global best solution (location of egg) and replicates the value of the winner.

Each sperm in SSO does not have a memory that stores information about the temperature or pH of the location it has visited, for instance. The only thing that will be cached is the sperm's location. The location of each sperm is determined by multiplying the number of numerical factors, such as the pH, temperature, and ideal sperm solution, by one another. The new location is compared to the old location (the cached location), and SSO only replaces the old location with the new location if the new location is better [79].

Advantage:

- Accurate exploitation.
- Fast convergence, simplicity, and global optimal discovery.
- Intelligence underlies SSO, which may be used in science and engineering.
- SSO doesn't overlap calculations.
- SSO calculations are straightforward and beneficial.

Disadvantage:

- SSO quickly reaches a local minimum.

Application:

WSN problem optimization

v) Insects

Ant: In Ant Colony Optimization (ACO) [80], several artificial ants solve the issue and communicate about their effectiveness using a model of ant communication. Stigmergy serves as the primary source of inspiration for the ACO algorithm. An apparent example of stigmergy is the manner in which ants in a colony forage for food. During foraging, organisms seek to maximize food availability while minimizing energy expenditure. An ant colony's optimization activity that resembles foraging is accomplished by identifying the shortest path from the nest to any food source. In the wild, ants use a fundamental solution to this problem. This behavior inspired the ACO optimization method developed by Marco Dorigo in 1996. The Ant System is the first optimization theory using ant models, introduced in 1992.

In combinatorial optimization problems, the ACO method is appropriate. The goal is to find the best collection of variables from a limited set of values to maximize or reduce an objective. Moreover, most combinatorial tasks are NP-hard, and scaling up deterministic methods results in worse performance. ACO uses a method to avoid examining the entire search space and concentrate on promising sections, much like other heuristics and meta-heuristics. To tackle combinatorial optimization issues, ACO includes three steps [73].

Construction phase: Fake ants are created at this phase. An ant is thought to be a succession of states. For instance, exploring every node in a graph while searching for a small loop is the objective. Artificial ants are created from a restricted number of feasible solutions, n. Each ant may be regarded as a collection of values selected from the initial finite set. A component from the main set is selected and added to the artificial ant during the construction phase. The solution-creation mechanism guides the procedure.

Pheromone update phase: It replicates the natural deposition and evaporation of pheromones. It is utilized as a means of communication amongst ants.

Optional daemon action phase: The first two techniques allow artificial ants to adjust their paths based on pheromone concentration and node preference. However, since the mathematical model considers probabilities, the algorithm may lose an advantageous route. The daemon phase is used to prevent the loss of such brilliant ideas. For instance, recording each iteration's ideal path or including additional local searches into each artificial ant is feasible. Comparable elitism characterizes this stage of evolutionary algorithms. The intelligence of ants does not inspire this strategy. They might be considered a centralized control system that supports ACO in problem-solving.

Advantage:

- Capable of grouping and building routes.

Disadvantage:

- Pheromone-laying on ant trails is time-consuming.
- Susceptible to local optimum.

Application:

Travelling Salesman Problem (TSP), dynamic problem (network routing), continuous optimization and parallel processing implementations, vehicle routing, graph colouring and set covering, agent-based dynamic scheduling, digital image processing, classification problem (data mining), protein folding problem, Quadratic Assignment problem (QAP) etc [81].

Bees:

Bee Colony Optimization (BCO): Lui and Teodorovi developed the Bee Colony Optimization (BCO) [68], [82] metaheuristic designed by Lui and Teodorovi as a novel method for the study of swarm intelligence. The BCO approach is a "bottom-up" modeling tool that uses bees as a metaphor for developing new artificial agents and is motivated by natural bee behavior. The fundamental goal of the BCO is to build a multi-agent system (artificial bee colony) capable of solving challenging combinatorial optimization problems. The behavior of the artificial bee colony is a hybrid of that of natural bee colonies.

Despite various social insect species and behavioral diversity, insects may be capable of complex tasks. The finest example is the meticulous collecting and preparation of nectar. Every bee chooses to search for nectar by imitating a nestmate who has previously located a region of flowers. The "dancing floor" is a place in each hive where bees discover nectar sources and dance to entice their nestmates to join them. A bee must follow one of the bee dancers outside the hive to go to one of the nectar sources. As soon as it comes, the foraging bee gathers nectar, feeds it to a food storer bee, and then returns to the hive. The bee has three choices after giving up the food: (a) abandon the food source and revert to an uncommitted follower; (b) forage there forever without asking the nestmates for assistance; or (c) dance and ask the nestmates for assistance before going back to the food source. The chance is that the bee will choose one of the possibilities above. Within the dancing area, the bee dancers "promote" many restaurants. It is commonly accepted that "bee recruitment is always a result of the quality of the food source," even if the procedures by which the bee chooses which dancer to follow are not entirely understood.

In the last ten years, a few bee behavior-inspired algorithms have been developed (Bee System, BCO algorithm, ABC algorithm, MBO, Bees Algorithm, Bee Hive, Artificial Bee Colony, VBA algorithm). It is a meta-heuristic driven by honeybee foraging behaviour. It is a generic algorithmic framework that may address a range of optimization issues (management, engineering, and control) and can continually adapt this generic algorithmic framework to a particular situation. The idea of collaboration is the foundation of the BCO strategy. Artificial bees can be more effective and do things together that they couldn't do alone. Through sharing information and the hiring process, the BCO can step up its search efforts in the solution space's most promising areas. The BCO can broaden its search as appropriate.

Artificial bees serve as a representation of agents that work together to tackle challenging combinatorial optimization problems.

Advantages: Artificial bees depict agents who collectively tackle complicated combinatorial optimization problems.

Disadvantage:

- The BCO has not been extensively employed to solve real-world issues
- No theoretical findings to support BCO notions.

Application:

To maximize sentence similarity and extract data, optimizes robot cellular manufacturing system multi-objective designs and calculates the network's shortest route.

Glowworm: Glowworm Swarm Optimization (GSO) [83] starts with a swarm of agents randomly around the search region. Since they resemble glowworms, agents will be referred to as glowworms. In addition, they exhibit additional behavioural mechanisms not seen in their natural counterparts. As a consequence, the following three processes interact to provide the algorithm's fundamental functionality:

i) Fitness broadcast: Glowworms have a fluorescent pigment known as luciferin, the amount of which encodes their positions in the objective space. It thus enables them to emit light with an intensity proportionate to the optimal function value. It is presumed that the luciferin concentration of a glowworm, as measured by its neighbour, is not affected by distance.

ii) Positive taxis: Each glowworm is drawn to and goes toward a single neighbour whose glow is brighter than its own, and if there are numerous such neighbours available, it employs a probabilistic procedure to pick one of them.

iii) Adaptive neighborhood: Each glowworm employs an adaptive neighbourhood defined by a local-decision domain with a flexible range restricted by a hard-limited sensor range to detect neighbours. If j is in i's neighbourhood and has a greater luciferin level than j is i's neighbour.

Advantage:

- GSO efficiently solves extremely non-linear, multimodal optimization problems.
- GSO doesn't utilize velocities.

Disadvantage:

- GSO fails high-dimensional issues.
- Decision domains in glow worms' movement vary

dynamically in GSO.

- The method impedes convention speed and has delayed, subpar local search capability during iteration.

Application:

Truss structure design, benchmark functions applied to optimum power flow issues, mechanical design optimization issues, multi-objective optimization, optimal placement of FACTS devices, machine condition monitoring, and optimal location and capacity of distributed generating systems.

Moth

Moth-Flame Optimization (MFO): Moth-Flame Optimization (MFO) [68], [83], [84] is a proposed paradigm for optimization that takes inspiration from nature. This optimizer was motivated mainly by moths' inherent transverse orientation navigating method. Moths can fly quite efficiently at night, maintaining a steady angle to the moon and covering long distances in a straight line. However, these insects are trapped in a futile or lethal loop around artificial lights. In order to accomplish optimization, the behaviour is mathematically modeled.

The MFO technique makes the assumption that moths represent the potential solutions and that the moths' spatial locations serve as the problem's variables. By altering their location vectors, the moths may thus fly in one dimension, two dimensions, three dimensions, or hyper dimensions. Because the MFO method is based on populations, an nxd matrix is used to represent the set of moths (n - number of moths; d - number of dimensions). The fitness values corresponding to n moths are kept in an array.

The fitness value is the return result from each moth's fitness (objective) function. The position vector of each moth is sent to the fitness function, which generates an output assigned to each moth as its fitness value. Flames are a crucial component of the proposed approach. We consider a matrix nxd similar to the moth matrix, where n is the number of moths and d is the number of variables. Also expected is the existence of a 1xn array, where n is the number of moths, for storing the necessary fitness values for the flames.

The method to update moths and fires in each cycle makes them different. The moths are the real searchers; they travel around the search area, and their current best position is among the flames. In other words, flames may be flags or pins that moths drop while scouring the search area. Each moth examines the surrounding area to update a flag (flame) if a better solution is discovered. A moth never errs while using this process to choose the optimal answer.

The following are some remarkable findings for this model:

i)By varying the t parameter, a moth may converge to any location in the neighbourhood of the flame. The t specifies how near the next position of the moth should be to the flame (t = -1 is the closest place to the flame, while t = 1 is the furthest).

ii)The lower t, the closer to the flame.

iii) As the moth nears the flame, the frequency of position updates on both sides increases.

Advantage:

Flexibility, simplicity, and ease of implementation

Exploration-exploitation balance.

disadvantage:

MFO's high parameter count makes implementation difficult.

MFO is inefficient in community discovery problems for extensive networks.

Convergence with ease.

Applications:

Benchmark optimization, chemical, economic, image processing, medical applications, networks, power dispatch problems, and engineering optimization. Parameter extraction of the diode in a solar cell.

FireFly:

FireFly Algorithm (FFA):

Most of the firefly species flash rhythmically. Flashes vary by species. Bioluminescence produces the flashing light, and the fundamental roles of such communication systems are still contested. Bright flashes attract mating partners (communication) and prey. Flashing may also alert predators that fireflies taste unpleasant. The signal system that unites both sexes includes the rhythmic flash, pace, and duration. Some tropic fireflies may coordinate their flashes, establishing biological self-organization. The Firefly Algorithm (FA) employs three perfect rules: One firefly will be attracted to another firefly regardless of gender since 1) all fireflies are unisex and 2) attractiveness is inversely correlated with brightness; the less attractive one will migrate toward the more attractive one. The luminosity and attraction are inversely correlated, and both will decrease as the distance between them grows. A firefly will migrate randomly if there isn't a brighter one nearby. 3) the landscape of the objective function affects or determines a firefly's brightness. The brightness might be proportional to the value of the objective function for a maximizing issue. The fitness function in genetic algorithms may be used to define other types of brightness [85].

The inverse square law states that the amount of light at a given distance r from the light source is constant. That is to say, in terms of I ∞1/r2, the light intensity I drop as the distance r rises. Air also absorbs light, which weakens as the distance between objects grows. These two elements work together to make most fireflies only visible from a short distance at night, often a few hundred meters, which is sufficient for fireflies to communicate. Additionally, a firefly's attractiveness β is determined by other fireflies' perceptions, which change depending on how close they are to it. The following form of attractiveness is used to prevent singularity:

$$\beta = \beta_0 \exp[-\gamma r^2] \tag{1}$$

where, β_0 is the attractiveness at distance r = 0 and γ is the light absorption coefficient. In this case, the Cartesian separation of the two relevant fireflies is denoted by r. However, the time delay along a route may also be utilized as the "distance" for other optimization issues like routing. Consequently, depending on the nature of the issue, r should be understood in the broadest and most relevant manner. It is feasible to structure the flashing light to link it to the objective function that has to be improved, which opens up the possibility of creating novel optimization methods [86].

Advantage:

FA can handle multimodal functions more naturally and efficiently than particle swarm optimization.

Disadvantage:

Acquires a lot of time to get the optimal parameter values.

Application:

To solve mono alphabetic substitution cipher.

Microbes:

Bacterial Foraging Algorithm (BFA): The foraging behaviour of Escherichia coli (also known as E. coli) bacteria is imitated by the recently developed evolutionary optimization algorithm known as BFA. Passino first presented the Bacterial Foraging Optimization Algorithm in 2002. Instead of being an individual activity, foraging is a phenomenon of a bacterial colony. The three main processes of BFA are reproduction, elimination-dispersal, and chemotaxis. In this context, a cell-to-cell communication system is built to imitate the biological behaviour of bacterial movement (swim/tumble). Chemotaxis is the action of bacteria collecting in nutrient-rich locations in an unplanned manner. Natural selection is the basis for reproduction since, in this process, only the best-adapted bacteria tend to survive and pass on their genetic traits to the following generations, while the less-adapted ones usually die. Elimination-dispersal events randomly choose portions of the bacterial population to reduce and disperse into arbitrary locations in the environment; this way, the algorithm ensures the species diversity and avoids becoming sucked into local optimum conditions, improving the capability of a global search [87].

BFA has successfully solved optimization issues in power systems and economic load dispatch. BFA simulates how E. coli bacteria migrate across the human gut in search of nutrient-rich environments. E. coli bacteria move in a manner that combines swimming and tumbling motions. Swimming means travelling in a straight line in a specific direction while tumbling means changing direction randomly. In a neutral medium, a bacterium alternates between swimming and tossing motions [88].

TABLE 10. Simulators and evaluated Metrics in FANET.

Reference	Simulation Tool Used	Metrics Evaluated
[115]	MATLAB	Cluster building time and lifetime, energy consumption, delivery success probability
[112]		Average transfer time and cognitive overheads, Network efficiency, Convergence time
[93]		Cluster building time, energy consumption, First node death analysis
[106]		Cluster building time and lifetime, energy consumption, delivery success probability
[49]		Energy consumption, Cluster lifetime, Throughput, Packet delivery ratio
[91]		Positioning and Clustering Performance.
[118]		Cluster building time and lifetime, energy consumption, delivery success probability.
[120]		Path Length and time of Experiment and Simulation.
[121]		Energy consumption, Alive node analysis
[124]		Packet Delivery Ratio, End-to-End Delay, Network Lifetime, and Transmission Loss
[125]		Number of clusters, cluster building time and lifetime and energy consumption.
[126]		Probability of collisions, average convergence, Computational power and cost
[127]	MATLAB and NS2	Route setup success rate (RSSR), Average Path Lifetime (APL), Hop Count (HC), Successful Data Delivery Ratio (SDDR), Successful Throughout Without Retransmissions (STWR), and average network delay
[108]	NS2	Throughput, End-to-End delay, Routing overheads.
[65]		Throughput, End-to-End delay, Routing overheads.
[47]		Packet delivery rate and reduces the end-to-end delay.
[116]		Network lifetime and number of received packets
[123]		Packet Drop Rate (PDR), throughput, packet received ratio, average end to end delay
[44]		Packet Delivery Ratio (PDR), End-to-End delay, Throughput, Goodput, Overheads
[36]		Packet Delivery Ratio (PDR), End-to-End delay, Throughput
[31]	OMNET++	Packet delivery ratio, packet delivery latency, number of ferried data packets.
[128]		Packet loss percentage
[129]		Number of connected components, Node Degree, Number of bridges, Maximum clique length, node colors.
[130]	NS3 and Gazebo	Packet Delivery Ratio (PDR), end-to-end delay, Normalized Routing Load (NRL)
[131]	NS3	End-to-end delay, throughput, packet delivery ratio
[132]		Transmission delay, transmission overhead, Packet delivery ratio, Throughput
[133]		End-to-end delay, Throughput

The "artificial potential field approach" used in autonomous vehicle guiding is comparable to the methods used by bacteria to find food. Foraging and cooperative management of swarms of UAVs deployed in military (or commercial) applications have obvious parallels: Animals and creatures are represented by UAVs, social foragers are groups of cooperative UAVs that can interact with one another, nutrients represent targets, risks are represented by pernicious compounds and the environment is represented by a battleground [53].

Advantage:

- Individualized BFA is more adaptable, versatile, and resilient.
- Individual-based BFA is more advantageous than population-based BFA for solving complicated optimization problems that are dynamic, multi-objective, or multi-constrained.

Disadvantage:

- BFA has a number of drawbacks, including low convergent performance and decreased performance with rising problem search space dimensionality and complexity.

Application [89]:

- Optimization of power system stabilizers.
- PID controller tuning of an AVR.
- The use of BFA in subjects like social science, decision science, business economics, operations research management science, materials science, neurosciences, medical informatics, etc., has received scant attention.

Moreover, collective animal, insect, and microbial foraging behavior is the primary inspiration for BIA in FANET. Several optimization techniques are named after animals, such as the Krill, the Wolf, the Bat, the Deer, the Birds, the Fishes, etc.; examples include KHO, GWO, BAT, Red Deer Optimization, PSO, FSA, and WOA. Algorithms such as ACO, BCO, GSO, MFO, and FFA draw inspiration from insects, much like BFA does with bacteria. As a result, the effectiveness of the FANET routing protocol can be enhanced by employing bio-inspired or hybrid techniques.

However, as a result of the analysis performed on the selected papers of this survey, both hybrid and non-hybrid BIA-based UAV routing algorithms are summarized in Table 9. The table revealed that 16 of the total selected articles are non-hybrid BIAs like ACO, BCO, BA, GSO, etc., that implement with FANET. BIAs are combined with other BIAs or metaheuristic algorithms like fuzzy, GA, differential evolution, etc., to form hybrid algorithms. The hybrid approach was utilized in five studies using BIAs, and the hybridization technique was applied in five articles with other optimization strategies using BIA.

Moreover, BIA can be used to solve typical issues in FANET routing. It can be accomplished through clustering, adjusting parameters, localization, and other methods. Thus, FANET routing using BIA enhances its features and has shown to be more effective than other ad hoc networks. Electrical and bio-inspired technologies are coupled to develop a cluster-based communication model with a mobility model that maintains a constant connection and decreases UAV energy consumption [90]. IPSO [91] and HGWO [92] are examples of BIA that aid FANET localization and energy usage. The performance of FANET routing, on the other hand, degrades due to frequent topology changes. The existing routing protocols will be enhanced to suit better the requirements of node mobility mode and topology change.

Additionally, hybrid BIA improves performance with FANET routing compared to non-hybrid BIA. The selection of cluster heads in FANET in HGSOFA [93], a hybrid BIA with GSO and FA, is optimized for energy efficiency. HSSOGSA [94] is the combination of sperm swarm optimization (SSO) and gravitational search algorithm (GSA). The hybrid method outperformed SSO and GSA in faster convergence by avoiding local minima with a higher convergence rate. Consequently, recent research demonstrates that hybrid and non-hybrid BIA are among the effective optimization techniques that help to enhance FANET's characteristics significantly and thereby maximize its routing performance.

c: MOBILITY MODELS FOR BIO-INSPIRED FANET ROUTING

It is vital to model the movement of FANET nodes due to their high mobility and frequent directional changes. Therefore, mobility models reflect the movement of UAVs across time, considering their position, velocity, and direction. These models are crucial for assessing how effectively routing protocol functions. Depending on the application, many mobility models might be selected. This study helps summarize and analyze the mobility models used in FANET's BIA-based routing. Random Way Point Mobility Model (RWPM), ii) Reference Point Group Mobility Model (RPGMM), iii) Gaussian Markov Mobility Model (GMMM), iv) Particle Swarm Mobility Model (PSMM) and v) Distributed Flocking Model (DFM), the mobility models used in the publications selected for this study that pertain to our area of interest. In Fig. 12, a pie chart provides an overview of the mobility models employed in BIA-based FANET routing.

i) RWPM

A random waypoint mobility model is a fundamental paradigm that is simple to evaluate and implement and is one of the major reasons for the model's broad adoption in simulations. For the initial stage of this approach, network nodes will remain in the same position for a predetermined fixed value called pause time. When the timer expires, the MN picks a target randomly within the virtual environment and speed is assigned to be evenly distributed between the minimum and maximum rates. When it reaches the destined node, it stops for a certain amount of time before resuming the operation [14]. The node produces three movements: turning right, left, and straight. RWPM causes the nodes to prefer to congregate close to the center of the simulation region because nodes frequently choose or pass through the core region at random. However, a fixed number of neighbors is required for each node throughout the simulation [95]. Due to the inability of UAV nodes to maintain the same position, RWPM is subject to numerous constraints in FANET [6].

ii) RPGMM

According to this model, a team relationship causes the network to split into numerous groups, each exhibiting a different mobility pattern [96]. The group center, which also determines the group's trajectory, specifies the motion characteristics of a group. While it is moving, a node is randomly positioned close to its reference point. This reference point system's advantages are the freedom of movement of nodes arbitrarily and group mobility.

iii) Gaussian MARKOV Mobility Model (GMMM)

A single tuning parameter was used to create the Gauss-Markov Mobility Model, which can adjust to varying levels of unpredictability. The node's position and speed will be changed from their initial settings at predetermined intervals. If the relevant parameters are given, it simulates real-world movement patterns. This benefits by moving the nodes farther from the simulation space's edges. When a node moves

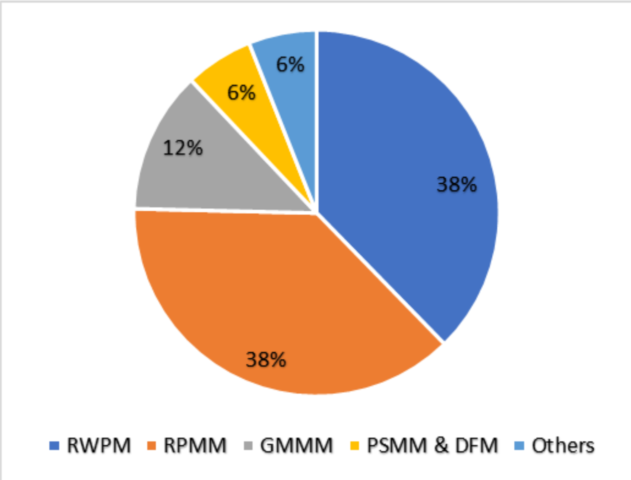

FIGURE 12. Percentage distribution of mobility models that implemented with Bio-Inspired Methods In FANET routing.

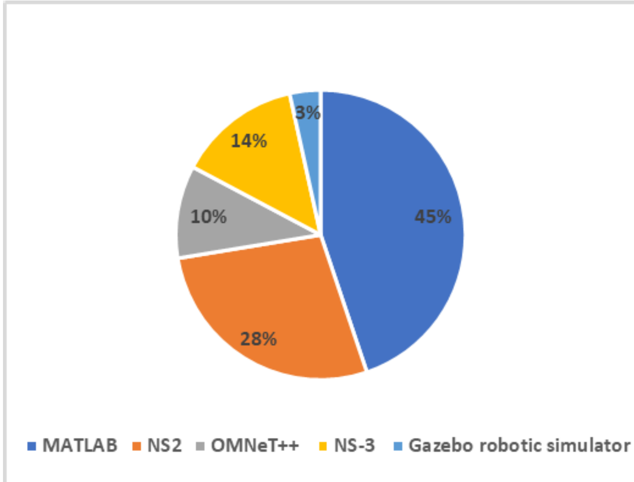

FIGURE 13. Percentage distribution of Simulators used to simulate BIA-based FANET routing.

outside the simulation field's bounds, the motion is forced to 180° in the other direction, thereby preventing it from getting too close to the edge of the simulation field. As this approach eliminates abrupt starts and pauses, it best suits applications like search and rescue operations.

iv) Particle Swarm Mobility Model (PSMM)

Mobile scenarios for FANETs are produced using the Particle Swarm Mobility Model (PSMM), which evolved from PSO [104]. The process for this model is split into two steps. In the first stage, the trajectory of a UAV node is roughly approximated by a set of waypoints separated at random intervals. The second stage keeps a distance between waypoints to guarantee collision-free UAV flying sessions. PSMM are more suited for surveillance and sensing systems.

v) Distributed Flocking Model (DFM)

A model called the Distributed Flocking Model (DFM) is suggested [105] using the Boids of Reynolds notions of cohesion, separation, and alignment. This model takes nodes' roles as leaders and followers to describe the mobility of a UAV network with a swarm of nodes. Followers must adjust their parameters to match the leader's flight qualities to maintain the nodes' connection.

Moreover, the experimental results from this review's analysis of mobility models aid in understanding the distribution of mobility models used in simulations throughout the deployment of FANET routing with BIA, as depicted in Fig. 12. RWPM and RPMM make up 38% of the mobility models used. In comparison, Gaussian Markov Models are used in 12%. While PSMM and DFM, each at 6%, were utilized in the other experiments. According to Fig. 12, RWPM and RPMM are the most frequently employed models.

d: SIMULATION TOOLS AND EVALUATION METRICS FOR BIO-INSPIRED FANET ROUTING

Setting up a real fanet environment for evaluating and analyzing the efficiency or output of an algorithm must be difficult. Hence simulators are the most conveniently used tool for assessing and helps to analyze the qos parameters of the routing algorithm in fanet. An analysis of simulation tools, that have been used for implementing Bia in fanet as well as its performance metrics helps to answer the research question RQ3. Table 10 Summarizes the simulators and their evaluated metrics. The metrics for evaluation considered in the non-clustering-based bio-inspired fanet algorithm are throughput, packet drop rate, end-to-end delay, and probability of successful delivery, while in clustering-based, energy consumption, stability or lifetime, and building time of cluster are evaluated.

According to Table. 9, the commonly used simulators are matlab, NS2, OMNET++, NS3, and gazebo robotic simulator. simulations of a majority of the algorithms in this review are done in matlab. the percentage distribution of simulator usage is given in Fig. 13.

e: CHALLENGES AND FUTURE SCOPE

Although FANET routing is a promising area for many applications, its routing with BIA techniques is still in the budding stage. Thus, BIA-based UAV routing has several issues that have not been fully addressed. Some of the key research challenges are discussed in the subsequent sections. In addition to providing an answer to RQ4, this section outlines its directions for future work.

1) Routing

Even though bia improves the efficiency of uav routing, hybrid bio-inspired algorithms prove to be more efficient than the former since they can nullify the disadvantage of one algorithm with the advantage of the other. hybrid algorithms can give better convergence than normal optimization algorithms, thereby reducing routing problems to a great extent. Researchers are concentrating on hybrid bia. Thus, the hybridization of bia with other optimization techniques is a major research topic.

Moreover, BIA clustering can reduce the challenges associated with data transmission in a multi-UAV environment. But mostly, the cluster heads during clustering are overburdened due to the maintenance of the cluster. This overhead is caused by an increase in dimensionality, rapid movement, and data transfer or data routing of UAV nodes. The quick movement of UAVs makes it challenging to organize clusters for routing. Therefore, another area of focus in research is the development of more effective BIA techniques to lessen the cluster head burden.

Furthermore, BIA plays an essential role in improving UAV routing performance. Understanding its shortcomings is equally important; it assists researchers in understanding how to improve the existing FANET routing algorithm based on BIA, which is discussed further below.

D. MATHEMATICAL MODEL FOR BIA-BASED APPLICATION

Researchers do not comprehensively understand the algorithms' actual functioning conditions from a conceptual viewpoint. Thus, a comprehensive mathematical model is also needed to fully comprehend BIA's operation in terms of many factors, including the rate of convergence, stability, and toughness. Iteratively reaching a fixed point is explained by fixed point theorems, which specific models attempt to support. However, for most BIA, the theorem's criteria might not be accurate [134]. Consequently, developing a common model for the mathematical analysis of BIA is a research issue.

E. TUNING BIA PARAMETERS

The tuning of BIA is achieved by setting some control parameters. It must be noted that the choice of the control parameters can have a remarkable influence on the global behavior of the algorithm, and this is often forgotten when claiming the good features of an algorithm over another [135].

Mathematical bases are available for fine-tuning single parameter algorithms like the quasi-Newton Method. However, BIA is generally tuned by trial and error or through parameter-based analysis, which depends on the algorithmic parameters. The optimal parameter values that fit the algorithm and ways to change, regulate, and modify those parameters to improve performance are still topics of discussion.

F. SCALABILITY OF BIA

There are several BIA applications with small to medium-sized problems including many parameters. However, whether the current methodologies can be scaled up during the high-end processing like high-performance computing, parallel computing, cloud computing, or IoT technologies is unclear. Scaling up the present algorithms, which work well for small-scale problems, to successfully handle large-scale, real-world situations is still an active research area.

1) MOBILITY MODEL

One of the critical factors in simulation is the mobility model. It imitates the real mobility patterns of UAV and helps to form a realistic simulation environment. The performance of FANET routing with BIA is crucially affected by the mobility models. FANET routing is usually simulated with MANET's mobility models, which causes an inaccurate simulation result, as the mobility pattern is imprecise. Mobility models aimed at FANETs are new and sparse. A more detailed simulation of UAV movements in a real-world environment will help to find an efficient mobility model [26]. These reasons urge for deep research on mobility models. Future study might focus on blending the best characteristics of existing mobility models and modifying random mobility to include improved features for an efficient routing.

2) QUALITY OF SERVICE (QoS)

QoS requirements vary with respect to different applications that are implemented using FANET. The data from different applications of the networks has varying service requirements and performance constraints. Additionally, the dynamic behavior of nodes under various situations results in the data having a range of service needs and performance restrictions. Its demand, including those related to packet loss, jitter, latency, bandwidth, etc., must be assisted by protocols in FANET's routing, which is still under investigation by the researchers [12]. Developing a proper skeleton for assisting QoS is a tough task due to the decentralized and highly mobile nodes in FANET [23].

These factors highlight the necessity of using route optimization methods to identify the problems of fulfilling QoS requirements. When working with routing protocols, efficient optimization approaches decrease the latency, improve the packet delivery ratio, and consider the QoS characteristics [36]. Since each algorithm uses varied performance metrics, comparison of the algorithms' efficiency may not be fair and challenging to find most suitable metric for the comparison. Designing a typical frame work to compare the performance metrics of all algorithms fairly and rigorously can be a research problem.

3) SIMULATION

BIAs are mostly implemented with swarms of multi-UAVs in FANET. As FANET routing is used for a variety of applications, developing a generic simulation tool that supports most mobility models is a difficult task. Some tools, such as NS2, OPNET, etc., which are inevitable components of UAV routing [126], do not offer communication channel and 3D communication models. Enhancement of those tools can satisfy UAV requirements. For some algorithms, the authors developed simulators on their own that are application specific. Developing a standalone simulator for FANET will be beneficial to the researchers so that they can produce precise simulating results based on the various restrictions of UAVs.

4) LINK INTERRUPTION

Several layer protocols should be developed jointly to obtain the best tradeoff in dynamic multi-UAV applications. Doppler effect is another tough challenge in FANET [11]. With supersonic speed, UAVs are moving in some applications, leading to a frequency change of 10s of KHz per sec. During the positional difference between UAVs, the frequency shift may frequently change, causing signal processing challenges. The dynamicity will cause frequent changes in network topology [17]. Thus, a better algorithm is needed to control the topology that must be more fault tolerant, able to respond to changes such as node failures and addition of nodes in the network. Bio-inspired methods are a best option in applying with routing in FANET for minimizing link failure. This may be investigated further together with hybrid BIA.

5) SECURITY

Due to the open link between satellites and base stations, FANET transmission is susceptible to attacks like DoS, MITM, and eavesdropping [21]. With security criteria (availability, integrity, confidentiality, authenticity, non-repudiation, authorization and anonymity), it is possible to determine whether an Ad hoc network is secure. Due to FANET characteristics, Ad Hoc security solutions may not work. FANET must secure data and routing traffic. Control packets must be verified to validate message integrity and transmitter identification in wireless networks. To prevent traffic analysis and protect privacy, payload traffic secrecy is crucial. Active interference, idle eavesdropping, data corruption, exposing confidential information, message replay, message misuse, and denial of service may result from wireless connections between transmitter and receiver.

Some FANET security solutions are encryption, intrusion detection, reputation-based packet exchange, identity-based signcryption (a signature is established to check whether a drone/UAV is a true master/receiver or not), certificate-based encryption, certificateless signcryption Tag Key Encapsulation [14].

Secure UAV Ad hoc routing Protocol SUAP [10] does not give an effective way to handle the network's high mobility and frequent disconnections. However, it provides authentication, non-repudiation security, integrity, and extra protection against geographical leashes-based wormhole attacks to safeguard route finding. The security aspect of Position-Aware, Secure, and Efficient mesh Routing (PASER) has shown its effectiveness in very dynamic networks like FANETs. But in the experimental phase, control packets during discovery cause overhead and latency.

Since drones aren't always secure, the IoD must address various privacy and security problems [136]. The IoD uses lightweight protocols for encrypting and processing data, particularly with small, cheap devices. Malicious IoD drones may work together to track targets and reveal their identities. Drones or zone service providers (ZSPs) may not encrypt massive datasets like real-time video broadcasts. Drones or ZSPs may not be able to index or search encrypted data.

ZSPs manage the IoD architecture; therefore, the control systems between them and drones are enticing targets for attackers that want to compromise the system [136]. Attackers might utilize DoS, spoofing, and data injection. Third-party inspection or auditing may be needed to identify these threats. Trusted computing systems can prohibit software and hardware alterations but may have significant latency or false alert rates.

UAVs are exposed to cyber-attacks. Profound research is needed to discover the existing attacks that cause security problems for FANET rather than suggesting any security methods [5].

IV. DISCUSSION

Flying ad hoc networks (FANETs) are networks of drones that may form autonomously and work together to accomplish complex tasks. FANETs serve a crucial role in managing the autonomous movement of drones and facilitating drone-to-everything (D2X) communications as the fundamental building element of the Internet-of-Drones (IoD). Internet-of-Drones (IoD) and its applications are accelerating due to the growth of drone-based technologies. In IoD, a large number of drones communicate with one another in a coordinated fashion to meet the goals of maintaining regulated airspace, coordinating drones, and delivering application-specific services [57].

Numerous literature reviews contribute groundwork in routing the UAV nodes in FANET. One of the areas of current research is the implementation of optimization techniques, particularly those inspired by natural processes with FANET. However, none of the reviews thoroughly analyses the method specified above. A systematic literature review is performed in this work, which aids in conducting a thorough analysis of the "bio-inspired method," a metaheuristic optimization technique used in FANET.

Research questions RQ1 through RQ5 are developed and answered adequately to reach the intended objective. Twelve features are discovered and discussed in this evaluation based on the RQ1 data analysis. Most publications focus on node mobility, power consumption, topology change, and node density. This fact implies that the attributes are receiving much scholarly attention. In the review of publications with bio-inspired optimization techniques, eight algorithms are developed using hybrid optimization methods, while the remaining algorithms are implemented using non-hybrid optimization methods. The facts mentioned above assist in answering RQ2, underlining the importance of research in this emerging field. Existing works have demonstrated their efficacy, and it is necessary to do extensive study to improve the performance of FANET routing with BIA and its hybrid algorithms in this regard. Thus, RQ2 helps identify the unexplored areas in the literature related to FANET that implement BIA for better routing.

The mobility models used to determine the motion and directions of UAVs were investigated as required by RQ3. RWPM and RPMM mobility models are the most commonly used models. It is simpler to design and analyze waypoints at random. Hence the model has most likely been widely utilized in simulations. In addition, the RWP model may not accurately represent many real-world scenarios.

Alternatively, complex mobility models, such as reference point group mobility (RPGM) models, can successfully replicate the motions of nodes in real-world settings, such as a battleground or rescue mission [136]. While PSMM and DFM are seldom adopted, GMMM was the next mobility paradigm to attract more attention.

Besides, the outcomes of RQ4 are the performance measurements and the data analysis of the simulation tools. The majority of the metaheuristic implementation work for FANET is performed in MATLAB. Next to it is NS2 [137], which is gaining popularity in research owing to its versatility, robustness, and extensive support base as an open source. Some algorithms utilize NS3 [138], an upgraded version of NS2 with a few additional capabilities. Furthermore, using end-to-end delay as the evaluation metric, the current study concentrates on bio-inspired clustering, with just a few studies addressing throughput, packet loss rate, and packet delivery ratio. MATLAB assesses performance using all provided mobility models, but the NS2 simulator only utilizes the RWPM model.

Finally, RQ5 makes an effort to draw attention to some of the important contemporary difficulties in the targeted field that involve routing, mobility model, QoS, simulation, and Link Interruption and security (related to FANET and IoD). Additionally, the research suggestions offered by this review will be helpful to future researchers that concentrate on the FANET routing technique based on BIA.

V. CONCLUSION

A comprehensive, systematic literature review of FANET routing with BIA is presented in this paper. It aims to provide an insightful understanding of FANET routing characteristics and current research trends of FANET routing with various BIAs. Based on the SLR processes; 146 publications were selected as well as examined for this evaluation. These retrieved publications are subjected to extensive analysis. As a result, BIA and FANET routing protocols were organized into a taxonomy.

Furthermore, FANET's characteristics are analyzed, along with comparisons to other ad hoc networks. The existing UAV routing algorithms with BIA are thoroughly analyzed, and their strengths and weaknesses are compared. The mobility model plays a vital role in FANET routing. The mobility models used in the chosen SLR publications pertaining to BIA-implemented FANET routing have been analyzed statistically. Due to FANET's limitations in the implementation of real-world networks, simulators are frequently used to assess the QoS parameters of FANET algorithms. The challenges and potential future scope of this field have been outlined in this review paper. Since there has been an increase in recently published work, particularly with the implementation of BIA in UAV routing, the data analysis results in highlighting the significance of this field of study.

APPENDIX A

Abbreviations	Expansion.
ACO	Ant Colony Optimization.
AODV	Ad hoc On-Demand Distance Vector.
BAT-COOP	Bat algorithm using cooperation technique.
BCO	Bee Colony Optimization.
BFA	Bacteria Foraging Algorithm.
BIA	Bio-Inspired Algorithm.
CACONET	Clustering algorithm based on Ant Colony Optimization (ACO) for VANETs.
CLPSO	Comprehensive Learning Particle Swarm Optimizer.
DFM	Distributed Flocking Model.
dPSO-U	Distributed and dynamic PSO for UAV networks (dPSO-U).
DSDV	Destination-Sequenced Distance-Vector Routing.
DSR	Dynamic Source Routing protocol.
DTN	Delay Tolerant Networks (DTN).
EA	Evolutionary Algorithm.
ECRNET	Energy-aware Cluster-based Routing in FANETs.
FANET	Flying Ad hoc Network.
FFA	Fire Fly Algorithm.
FFOA	Fruit Fly Optimization Algorithm.
FSOA	Fish School Optimization Algorithm.
GA	Genetic Algorithm.
GCS	Ground Control Station.
GMMM	Gaussian Markov Mobility Model.
GPSR	Greedy Perimeter Stateless Routing.
GSA	Gravitational Search Algorithm.
GSO	Glowworm Swarm Optimization.
GW-COOP	Gray Wolf Algorithm using Cooperative Diversity Technique.
GWO	Gray Wolf Optimization Algorithm.
GWOCNET	Grey Wolf Optimization Based Clustering In Vehicular Ad hoc Networks.
GWPSO	Grey Wolf Particle Swarm Optimization.
HAP	High Altitude Platform.
HGSOFA	Hybrid Glowworm Swarm Optimization and Firefly Algorithm.
HGWO	Hybrid Gray Wolf Optimization.
iBAT-COOP	Improved BAT Algorithm using Cooperation technique.
IPSO	Improved Particle Swarm Optimization.
KHO	Krill Herd Optimization.
LAP	Low Altitude Platform.
LAR-3D	Location-Aided Routing.
MANET	Mobile Ad hoc Network.
MFO	Moth Flame Optimization.
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses.
PSMM	Particle Swarm Mobility Model.
PSO	Particle Swarm Optimization.
QoS	Quality of Service.
RDOAICRP	Red Deer Optimization Algorithm Inspired Clustering-based Routing Protocol.

RPGMM	Reference Point Group Mobility Model.
RQ	Research Questions.
RSoBIR	Recruiting Strategies over Bio-Inspired Routing.
RSoLSR	Recruiting Strategies over Link State Routing.
RWPM	Random Way Point Mobility Model.
SI	Swarm Intelligence.
SLPSO	Social Learning Particle Swarm Optimization.
SLR	Systematic Literature Review.
SSO	Sperm Swarm Optimization.
UAV	Unmanned Aerial Vehicle.
VANET	Vehicular Ad hoc Network.
WCMFO	Water Cycle Moth Flame Optimization.
WLAN	Wireless Local Area Network.
WOA	Whale Optimization Algorithm.

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