

Research Article

Connectivity of Drones in FANETs Using Biologically Inspired Dragonfly Algorithm (DA) through Machine Learning

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Received 10 October 2021; Revised 28 December 2021; Accepted 10 January 2022; Published 28 January 2022

Academic Editor: Zahid Khan

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Flying Ad hoc Network (FANET) presents various challenges during communication due to the dynamic nature of network and ever-changing topology. Owing to high mobility, it is difficult to ensure a well-connected network and link stability. Thus, flying nodes have a higher chance of becoming disconnected from the network. In order to overcome these discrepancies, this work provides a well-connected network, reducing the number of isolated nodes in FANETs utilizing the depth of machine learning by taking inspiration from biology. Every biological species is innately intelligent and has strong learning ability. Moreover, they can also learn from existing active events and can take decision based on previous experience. There may be some unusual events such as attack of predator or when it may become isolated from the rest of the community. This ability helps them to maintain connectivity and concentrate on target. In this work, we take inspiration from dragonflies, which provide novel swarming behaviors of dynamic swarming and static swarming. The nodes in FANETs learn from the dragonflies and use this learning to search for a neighbor, ensuring connectivity. Moreover, to avoid collision and establish larger coverage area, they employ separation and alignment. In case a drone is isolated, it strives to become part of the network using machine learning (ML) via the dragonfly algorithm (DA). The proposed scheme results in larger coverage area with reduced number of isolated drones. This improves the connectivity in FANETs adding to the network intelligence via learning through DA, allowing communication despite the complexity of mobility and dynamic network topology.

1. Introduction

UAV (unmanned aerial vehicle) is an aircraft without a human pilot onboard which is popularly known as flying drone. They are equipped with a variety of additional equipment such as cameras, global positioning systems (GPSs), GPS-guided missiles, navigation systems, and sensors. They have ultra-stable flight and can hover and perform

different acrobatics in the air. Their versatility is what truly makes them popular. Multiple drones are connected directly or through intermediate nodes in FANETs. These drones act as wireless relay in ad hoc networks, which provide coverage of wirelessly connected devices. Formation of small drones are now being introducing in military expeditions, civilian applications, disaster management, forest fire detection, agricultural management, border surveillance, and

telecommunications [1]. FANETs can be used as mobile radio stations or WLAN transmitters in regions lacking infrastructure [2–12].

Connectivity of a network is of utmost importance in critical fields involving uncertain flying driving units in FANETs. If a drone is destroyed by an enemy, it is important to offload data wirelessly to other neighboring drones. Therefore, FANETs can address predisaster and postdisaster calamity in real-time applications. Drones in the predisaster situation, collect the location information of all vulnerable zones and update that information periodically such as occurrence of disaster. This can measure the destroyed area for rescue operation. It can strengthen respond ability to the end user. Moreover, drones deployed on the postdisaster situation can help to establish necessary communication service. Application of FANETs in calamity situation is shown in Figure 1.

Previously, traditional approaches were adopted to analyze the performance of FANET to model the connectivity. The performances of the biological inspired algorithms are important development to capture the scalability and reliability patterns of wireless ad hoc networks. We therefore propose a machine-learning-based DA algorithm for connectivity of the drones in FANETs. Quick deployment of small flying drones is similar to dragonfly's behavior. Instead of food, the drones are searching for neighbors to enable wireless communication network. The choice of dragonfly technique comes into inspiration due to their light weight, rapid flying adjustment and finding neighbors within a communication range. They are able to maintain mobility, reduce isolation, and search for target consistently. Unpredictable FANETs scenario needs to organize crucial flight factors of altitude, speed, direction, etc. Organizing flying drones is a key challenge to establish a wireless network, and we attempt to make it possible through social inspiration behavior of dragonfly. To the best of our knowledge, the proposed work is the first solution for connectivity in the field of FANETs using machine learning. Our proposed scheme is valid for ad hoc applications and other wireless development technologies.

The rest of the paper is constructed as follows: Section 2 briefly explains the existing work. Section 3 presents the proposed working architecture of the dragonfly algorithm. The simulation results of the proposed work are presented in Section 4. Finally, the conclusion of this paper is presented in Section 5.

2. Related Work

FANETs are sparsely connected networks because of low density and high mobility of nodes. This causes fluctuation of link, loss of connectivity, and performance degradation. In He et al.'s study [13], the concepts of relay chain and relay tree are presented. When nodes are unable to establish connection with existing infrastructures on the ground, they can still communicate through other nodes. In Rautu et al.'s study [14], air-to-ground communication is investigated to overcome the loss of connectivity. The results showed that network stay connected when node replacement is performed. Optimal replacement of flying drone is a challenging task during flight missions. However, it is not feasible to replace the drones in an existing network.

Replacing a drone is not a simple task due to ever-changing location information.

In Zhao et al.'s study [15], emergency communication system is established with the help of UAVs which relies on the mesh network with the objective to ensure connectivity between ground station and UAV. Yu et al. [16] developed UAVNet framework and established flying wireless mesh network. These studies focused on infrastructure-based ad hoc networks which is not the case of pure ad hoc network and may influence the quality of communication due to interference and time delay. Oubbati et al.'s study [17], an algorithm that considers change in network topology was constructed with an assumption that UAVs have full knowledge of the location of devices. It is investigated that optimal movement of UAVs can improve the connectivity of ad hoc networks.

In Cicek et al.'s study [18], semicentralized framework is proposed to establish ad hoc communication between UAVs under the conserving centralized organization. In this research, movement planning and reliability are addressed with the structure of multiple groups. This requires a governing framework including control and motion planning. This can utilize the UAVs to play the role of gateway to connect the groups to the base station (BS) and communicate further. This framework presents improved performance as compared to purely centralized base framework. However, certain data transfer route through ground BS still exists which can cause network partition due to failure of BS. This failure can isolate a group of UAVs from the rest of the network. Popescu et al. [19] present the use of UAV as relay to support wireless sensor network and guaranteed the delivery of data generated by wireless nodes on the ground. As a feature of mobility, the significance of possible isolated drone is not studied in most research works. There is a need of intra-network connectivity for transmitting information with recently employed drone.

Many problems in networking can take inspiration from the biological world for its solution. Biological world demonstrates the algorithms which propose different models of networking behavior for optimal solutions. Unlike conventional networks, the study of swarm organizing helps to develop the idea from the natural world in the research field. There are several swarming techniques studied in which the researchers tried to figure out the principles of interaction between the individuals. The study that mimics the behavior of individuals and yields to social intelligence is called swarm intelligence (SI) [20]. It deals with the artificial implementation or simulation because there is no centralized unit to control and guide the individuals. The basic principles between some of them can easily simulate the social behavior of the entire population.

Ant colony optimization (ACO) is the first SI technique which simulates the social intelligence of ants [21]. Based on the natural ability of pheromone, each ant in this algorithm draws its own path from nest to food with the help of pheromone. Another popular SI model is particle swarm optimization (PSO) algorithm [22], which mimics the foraging and navigation behavior of flocking birds. It is based on three rules of interaction between birds:

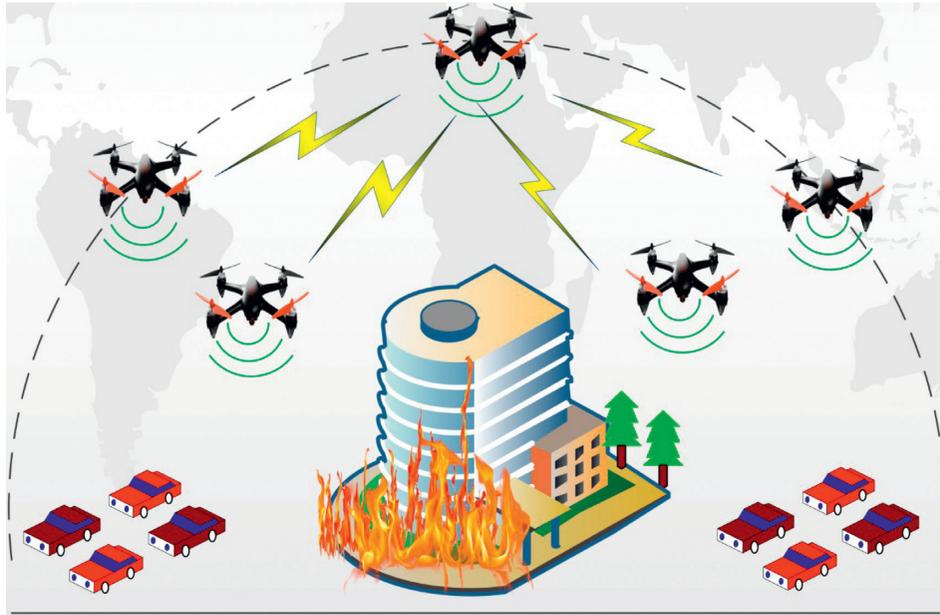


FIGURE 1: FANETs in calamity situation.

- (i) Fly and maintain their direction towards current direction
- (ii) Best food location obtained so far
- (iii) Best food swam found so far

These rules help each individual towards the optimal solution and swarm simultaneously. Artificial bee colony (ABC) is another recent and well-regarded SI-based algorithm [23], mimicking the social behavior of honey bees when foraging nectar. In this algorithm, bees are categorized in three different ways:

- (i) The employed bee
- (ii) Onlooker bee
- (iii) Scout bee

Implementations of PSO [24, 25], ABC [26, 27], and ACO [28, 29] have been applied in different problems to improve the existing algorithms. However these optimization techniques do not obtain static and dynamic swarming behaviors. DA is a recent development in swarm optimization which improved the diversity of solutions and caused exploration algorithms to become effective. The exploration and exploitation of DA are mainly determined by five primitive principles and significant research applications of DA in applied sciences have been conducted. For example, image processing [30–32], machine learning [33–35], wireless and network [36, 37], cooperative diversity [38, 39], etc. However, no study is discussed in literature for connectivity in ad hoc networks to simulate the individual and apply social intelligence of dragonfly swarming.

Social behaviours of animals derived in Boids of Reynolds swarm intelligence introduced three primitive principles of separation, alignment, and cohesion [40]. Dragonfly algorithm [41] is an extension of Boids with the

novel objectives of static and dynamic swarming behavior of dragonflies. Therefore, no scientific procedures were made use of the objective that maintaining high-performance connectivity in FANETs. However, insufficient work cited to provide and maintain network connectivity. Moreover, literature has numerous SI algorithms for applied sciences; however, there is no study found to analyze the DA for FANETs. We summarize our contribution for this research and describe as follows:

- (i) Biological species are innately intelligent, and they have strong learning ability. Instead of searching for food as in biological species, the proposed learning-based approach supports the isolated drones to search for a neighbor to ensure connectivity.
- (ii) To construct a valid solution, our proposed work follows the nature-inspired flying principles of DA through machine learning.
- (iii) When a drone is isolated, it flies in a random flight termed as levy flight. This situation opts an important feature in learning contribution.
- (iv) Only isolated drone should go for levy flight to search for possible neighbor while learning helps them to become early finding of neighbors. The rest of the drones retain the mobility as per DA rules.
- (v) Learning supports the isolated drone to move to the direction experienced in its last isolation.
- (vi) Connectivity is a key challenge in dynamic topology network. However, when a drone is isolated during flight mission, it strives to become a part of the network.
- (vii) Maximum numbers of drones stay connected using DA to ensue connectivity in minimum number of iterations.

2.1. Machine Learning. Machine learning (ML) offers computer systems to learn with minimal human intervention and teach a machine how to learn and find better solution from practice. Basically, ML is an application of artificial intelligence (AI) and comprises on data analytics technique. This technique not only educates computer systems to do what comes naturally to human individuals but also biological species. This strategy permits computers to learn autonomously or assistance and adjust actions accordingly. Algorithms based on ML employing computational techniques to “learn” information directly without depending on a defined equation as a model. The learning process commence with different observations such as paradigm, direct behavior, experience, or command. Such actions have been learnt from regular practice. The iterative feature of ML is significant; however, as models are discovered to fresh data, they are intelligent to autonomously adjust. They learn from computations that have been done earlier and able to generate efficient and frequent judgments to improve accuracy.

3. The Proposed Dragonfly Algorithm (DA) Using Machine Learning

Dragonfly algorithm is an emerging SI algorithm which mimics the behavior of dragonflies. Logically, DA divides the search process into two phases, namely exploration phase and exploitation phase. Dragonflies get into small groups in exploitation phase which enable them to forage over different areas to find their food repeatedly, whereas they form a group of large number in exploration phase when migrating to a certain direction to one destination. The pentagon representation of the basic concept of DA consists of five primitive principles as shown in Figure 2. These are vital in finding the weights solution with the following classifications:

- (i) Separation
- (ii) Alignment
- (iii) Cohesion
- (iv) Attraction to food
- (v) Distraction from enemy

Due to natural leaning and intelligent decisions capability, our work assumes that the dragonflies in a swarm are similar to drone in a FANET. The search range of the dragonfly defines the communication range of drone with potential to allow accurate area marking and unambiguous identification of drones. Based on learning, the search agent feature of the dragonfly assists in identification of neighbors within the predefined range of each dragonfly. The quick deployment of drones inspired from DA and establishing small groups in static swarming may assist in situations to fly over disaster areas. Furthermore, subswarm or interaction of few drones within a network marks the presence of another subgroup in the existing network which aims the property of static swarming. Flying drones need to remain separated from each other in a defined range to avoid collision. Similarly, alignment in FANETs can control the flying speed and direction which ensures data transfer reliably. Finally, cohesion brings each drone to try to move to the center of swarm for the best position to achieve

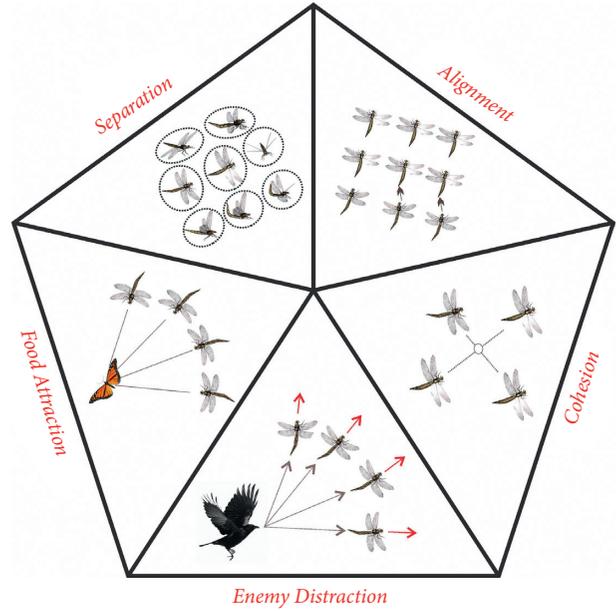


FIGURE 2: Primitive principles of DA.

better connectivity. Hence, DA is the only algorithm that fulfils the requirements to establish FANETs through ML and simultaneously search for neighbors to ensure connectivity.

3.1. System Model. Our system model details the features of dragonfly through ML in FANETs. This aims to provide efficient neighboring search solution and connectivity. Assuming similar mobility behavior of drones (i.e., speed and range), proper neighbor selection ensures the connectivity in a network. The drones are deployed randomly and connected within a fixed communication range “ R ” at the distance “ d ,” whereas each drone is equipped with ad hoc communication capability. Each drone tries to sustain connectivity within the vicinity; however, due to scarcity of network, some drones are isolated and listed outside the communication range of other drones as shown in Figure 3.

The maximum step size (Δ_{\max}) is defined for all the drones, and it is based on network dimension. This step size determines the mobility of the drone towards the partial network for joining or rejoining during flight operations. On the contrary, isolated drones are those drones that have no neighbors within their communication range. These drones need to survive and randomly search for possible neighbors by adopting levy flight. To become a part of a connected network, this can force the isolated drone to search for neighbors. Thus to recognize drone as isolated, ML supports the drone to opt efficient decision based on previous experience and obtain neighboring solution. Only those drones opt for random flights which have no neighbor. The rest of the drones retain the mobility as per DA rules.

Stability and control are much more complex for flying drones, which can move freely in three-dimensional space as compared to static or vehicular networks. At present, there is an increased need to establish a

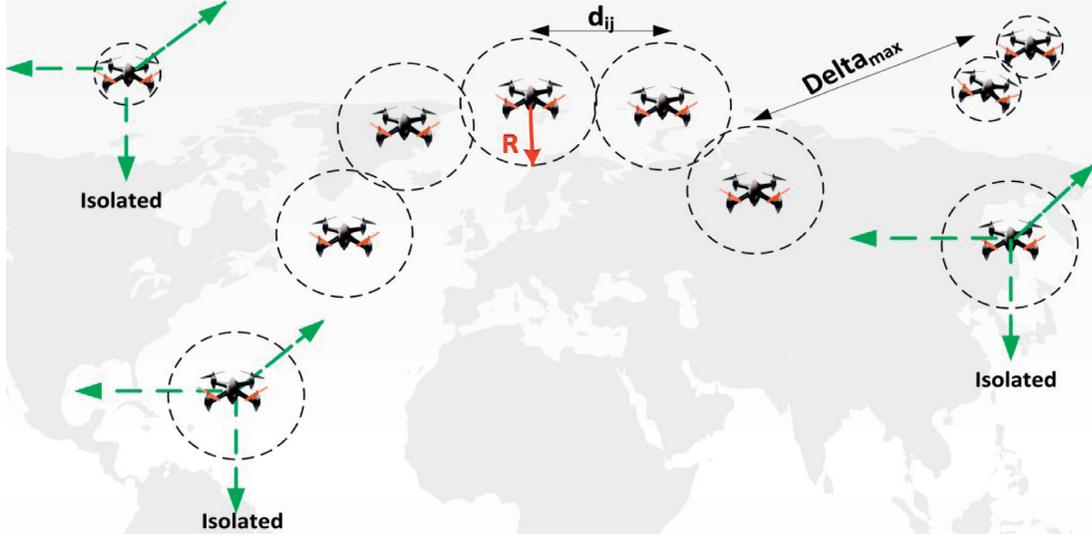


FIGURE 3: Schematic diagram of the system model.

mechanism which could define the collaborative steps among the uncertain movement of drones for its applicability in the FANETs.

3.2. Mathematical Model. This section details the mathematical modeling of proposed scheme. In this scheme, every drone can sense its communication range to determine any possible neighbor drones. The separation rule ensures to maintain a minimum distance between drones when they are closer to each other or to move towards a drone when located far away. The key separation among flying drones helps in avoiding collision by maintaining a minimum distance between the drones. Mathematically separation can be expressed as

$$S^i = - \sum_{j=1}^k p^i - p^j, \quad (1)$$

where S^i is the gap between the drones defined for i th drone, p^i is the current position of drone, and p^j is the position for j th point in the neighbor. The variable k is defined as the number of neighbors situated within the communication range of i th drone.

The i th drone moves with an average velocity which depends on the speed of other drones whether it is in searching mode or connecting mode. The flying movement of drones is matched in velocity to other nearby drones. This average velocity refers to the particles not exceeding in speed from other neighbors in a unit space. The tendency of an individual to match its velocity with neighboring drones can be mathematically calculated as

$$v^i = \frac{1}{k} \sum_{j=1}^k v^j, \quad (2)$$

where v^j is the velocity of j th neighbor for i th drone.

Every drone in FANETs obtaining the proposed architecture tends to move to the center of radius for the best position to achieve better results. In other words, the

cohesion step refers to the drone towards the center point of space that contains other drones close to its position. The tendency of an individual to move toward the center of mass of neighboring drones can be mathematically calculated as

$$C^i = \frac{1}{k} \sum_{j=1}^k (p^j - k p^i), \quad (3)$$

where p^i is the position of i th drone, k is the number of neighbourhood, and p^j shows the position of j th neighboring individual. Whenever a drone is isolated, it strives to move to find neighboring drone within the communication range to ensure connectivity. Let $d_{ij}(t)$ be the Euclidean distance at time t between position p^i and position p^j and is given as

$$d_{ij}(t) = \sqrt{(x^j - x^i)^2 + (y^j - y^i)^2}. \quad (4)$$

In view of the aforementioned mathematical model, the disciplinary instructions are assumed for drone operation in the flying zone. Thus, a newly linkedup drone in a swarm learns to follow these primitive rules to maintain the network connectivity and conserve its resources. As long as the drone is connected, cooperation among the drones would be sustainable which prolongs the network life.

The drone attaining at least one neighboring solution learns to update its positions by a couple of defined vectors, that is, velocity step vector (ΔQ^i) and position vector (Q^i) according to the following mathematical expressions:

$$\Delta Q^i(t+1) = sS^i + \hat{v}v^i + cC^i + fF^i + eE^i + w\Delta Q^i(t), \quad (5)$$

where $\Delta Q^i(t+1)$ is a step vector which is a movement of drone at the next time step $t+1$. The product sS^i shows separation weight and separation of i th individual respectively. Similarly, \hat{v} is velocity weight, v^i is the velocity of i th individual, c is cohesion weight, C^i is the cohesion of i th individual, f is food factor, F^i is the food source of i th individual, e is the attacker factor, E^i is the location of enemy of i th individual, w denotes the weight of inertia, and t is the

iteration number. The point of vector position is computed afterward by the step vector:

$$Q^i(t+1) = Q^i(t) + \Delta Q^i(t+1), \quad (6)$$

where $Q^i(t+1)$ is a position vector at next time $t+1$. The different explanative and exploratory natures can be obtained during flight such as separation, velocity, cohesion, food, and enemy attacker factors $s, \hat{v}, c, f,$ and e . Finally, the position of a drone having no neighboring solution updates its position using the following mathematical function:

$$Q^i(t+1) = Q^i(t) + \zeta Q^i(t), \quad (7)$$

where ζ is the levy flight and is calculated as follows [42]:

$$\zeta = 0.01 * \frac{r_1}{|r_2|^{(1/\beta)}} * \sigma, \quad (8)$$

where r_1 and r_2 denote the two random numbers in $[0, 1]$, β is assumed constant, and σ is computed as follows:

$$\sigma = \left(\frac{\Gamma(1+\beta)\sin(\pi\beta/2)}{\Gamma(1+\beta/2)2^{(\beta-1/2)\beta}} \right)^{(1/\beta)}, \quad (9)$$

where $\Gamma(x) = (x-1)!$. Solo flight reduces the lifetime of a drone and disrupts connectivity. This mathematical expression assists in learning the nearest neighbor when there is no neighbor and drone is isolated.

In order to ensure connectivity in a large area, every drone in FANET acts as relay for transfer of information to the other drones and/or base station. A link is established between nodes i and j such that $j \in k | d_{ij} < R$. As soon as these individuals are the members of a group, they maintain minimal separation and contribute to the connectivity of the entire network. If a drone is isolated, the connectivity is compromised for that particular region. Moreover, along with task-oriented sensors, drones are also equipped with GPS, radar mechanism, and height sensors. Frequent topology changes with drones leaving or joining the network is often another complex challenge in FANETs. This situation benefits from machine learning to accomplish communication in a highly dynamic topology network. In order to achieve maximum connected drones in entire flying network, we present a solution for connectivity problem. After performing primitive principles of natural species such as separation, alignment, and cohesion, it is now possible to achieve better communication path by maintaining link between drones so they can share data easily. Mathematical expression for improved path stability is given as follows:

$$\mu = \max(k_n), \quad (10)$$

where greater μ presents better connection opportunity. In the above discussion, it is established that drones do not remain isolated when following the devised strategy. Iteratively, isolated drones become a part of the swarm by using levy flight and cover larger area with maximum connectivity and minimize the isolated drones accordingly. In this learning scheme, the maximum number of flying drones stay connected in the network in minimum iteration and reduces

the isolated drones during flight. Hence, neighboring solution minimizes the isolated drones adaptively, which are preserved till the period of network communication.

The factor range index is taken into account when measuring the connectivity between drones. The connectivity decreases with increase in the distance and subsequently drone is not able to communicate with any of the other drones. Range index allows selection of appropriate drone for communication path stability. This can be modeled as follows:

$$\eta^i = \frac{\alpha^i}{\max_{v_j}(d_{ij}(t))}, \quad (11)$$

where η^i is the range index of i th individual that decreases with an increase in distance and α is a constant $0 < \alpha^i \leq 1$.

In order to determine the suitability of a drone for relaying as part of the swarm, a fitness function is considered which summarizes a single figure of merit. It shows a given design solution to achieve connectivity. The fitness is devised so that the number of isolated drones in the network is reduced and can be calculated as follows:

$$\lambda^i(t) = k^i(t) + \frac{\gamma^i(t)}{d_{iB}(t)}, \quad (12)$$

where λ^i is the fitness value of i th drone, k^i is the number of neighbors of i th drone at any given time t , γ^i is the remaining energy of i th flying drone, and $d_{iB}(t)$ is the distance of the i th drone from the BS at time t . The distance from BS is incorporated to accommodate the drones which may not have a neighbor but are within transmission range of BS. These drones are not isolated drones, rather these drones are a great option for relaying data of other flying drones to the BS.

The pseudo code for the proposed solution is given in Algorithm 1. Considerable stages for the proposed scheme are detailed as follows: Lines 1 to 4 show the basic network initialization. Here, the number of drones is initialized with random deployment. Solution set for the drones is initialized in certain restricted boundaries. Furthermore, communication range for each drone remains the same, and step vector is initialized for necessary flight operation. Lines 5 to 12 show the computation and update stage. On the basis of initial deployment, each drone computes the position values and available neighboring solutions within an assigned communication range. Different weights such as $s, \hat{v}, c, f, e,$ and w are updated in this stage. Distances are calculated between the drones and BS. $S, v, C, F,$ and E are also computed in this stage. Thus drone should update the position values and neighbouring solution using first three primitive flight rules. In this course of action, each isolated drone learns to locate neighbors and update action of practice accordingly. Lines 13 to 22 show the proposed neighboring solution for isolated drones. If at least one neighbor is available within the drone vicinity, it should retain the flight as per DA principle. However, if there is no neighbor, it should go to opt learning and update their position using levy flight to search for possible neighbor. ML supports the isolated drone to move to the direction experienced in its last isolation. Hence, isolated drone count is reduced adaptively.

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Proposed DA algorithm using machine learning
(1) Initialize the random position of drones (flying nodes)
(2) Initialize the communication range and step size for all drone
(3) for iteration 1 to max
(4) Compute the position values of all the drones based on mobility
(5)         Determine the nodes in the communication range of each nodes
(6)         Determine learning stack to the isolated nodes
(7)         Compute the neighboring solution
(8) Compute the network parameters by Equations (1) to Equation (4)
(9)         Update the position values
(10)        Update the neighboring solution
(11)        Update learning solution
(12) if (a drone has at least one neighboring drone)
(13)    Learn velocity vector by Equation (5)
(14)    Learn position vector by Equation (6)
(15) else
(16) Declare the node as isolated
(17) Calculate the isolated drones
(18) Update position of isolated drone by flying randomly by Equation (7)
(19) Update the neighboring connectivity by Equation (8) to Equation (10)
(20) end if
(21) Check and correct the new positions by Equation (12)
(22) end for
(23) Determine average network connectivity based on the isolated node count

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ALGORITHM 1: Pseudo code for the proposed solution.

4. Simulation and Results

Simulations are conducted to evaluate the performance of the proposed scheme. In this section, the performance of the proposed scheme is tested using MATLAB simulator. This evaluation observes the effects of flight of drones, its connectivity and reduction of isolated drones using DA technique for machine learning. Basic set of parameters used for simulations are presented in Table 1.

Initial network deployment of nodes is shown in Figure 4. In this model, DA technique is implemented for learning in the proposed scheme. Network is initialized using DA principles such as random deployment of nodes, set the define parameters to maintain separation, velocity, and cohesion. Flight of the nodes experiences the course of actions during iterations, and they are based on learning. However, the wireless communication range for a node in a grid of 100 m^3 is set to 20 m for 10 homogeneous nodes. During flight, the network nodes detect their neighbors within 20 m communication range. There are six nodes shown isolated in an initial deployment of network, that is, 4, 5, 6, 7, 8, and 9. It can be seen that there is no neighbor within 20 m communication range for these nodes while rest of the nodes having at least one neighbor within their vicinity. If neighbor is found by a node, it will retain the mobility under DA principle; however, if there is no neighbor in the node vicinity, it will consider isolated and opt ML to flies in a levy flight. This can help the node to search for prospective neighbors. This search is repeated iteratively till a neighboring solution is found. If there is at least one neighboring solution for an isolated node, it will update its defined vectors of velocity step vector and position

TABLE 1: Simulation parameters.

Parameters	Values
Number of nodes	10
Network area	10 m^3
Node flight	Random
Channel type	Wireless channel
Communication range	20 m
Maximum iteration	25
Antenna model	Omni antenna
Upper bound	100
Lower bound	0

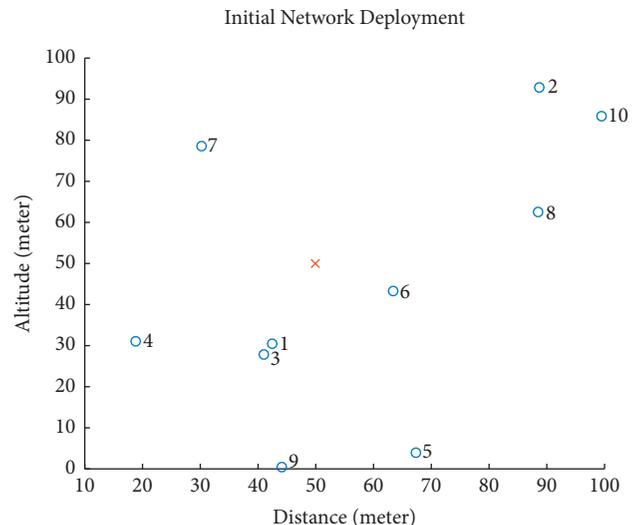


FIGURE 4: Initial network deployment.

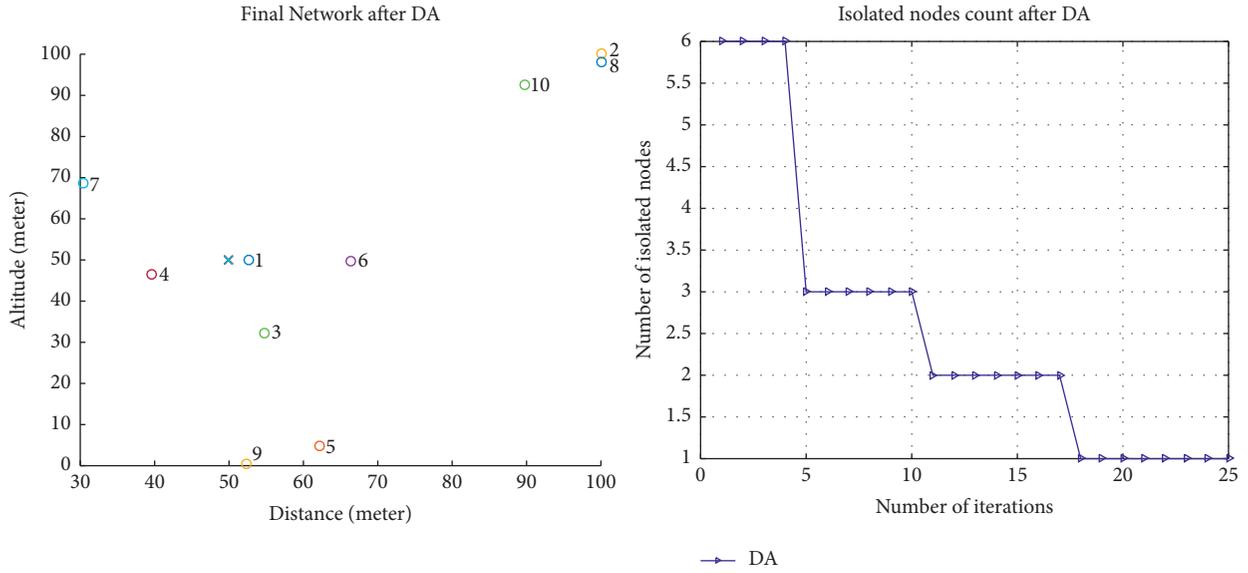


FIGURE 5: Final network after DA.

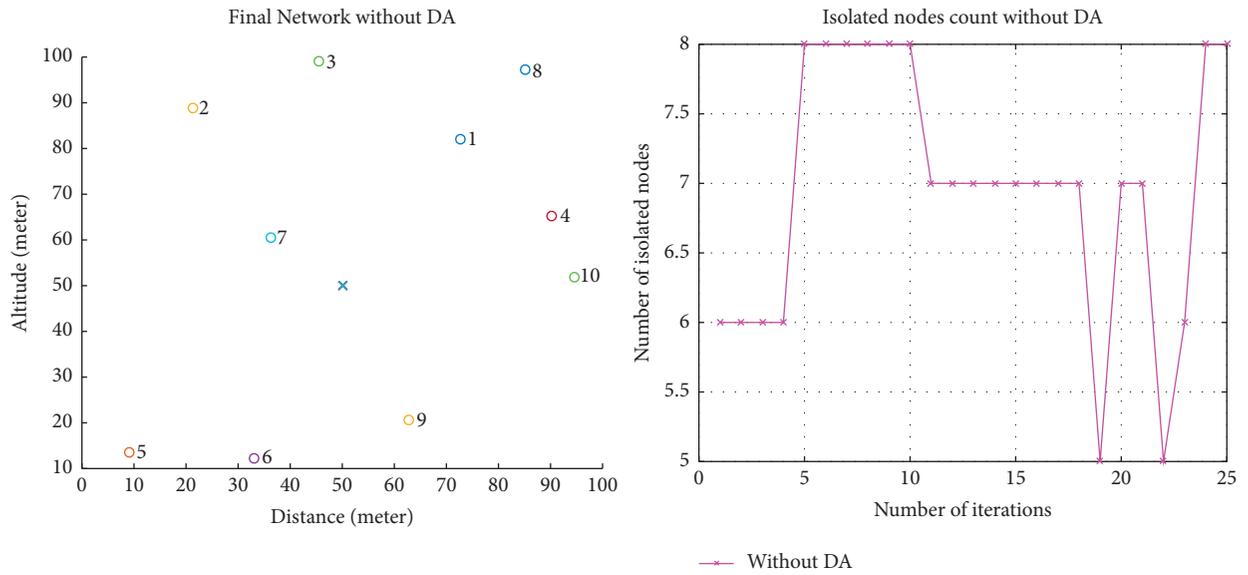


FIGURE 6: Final network without DA.

step vector according to Equations (5) and (6), respectively. Since the nodes are dynamic and gain experience due to repeatedly finding neighboring solutions. Such type of action helps the existing isolated node to learn for next term of isolation. This aims to update the node position efficiently in future course of actions. Those drones having no neighbor will have to update its position according to Equation (7).

When the simulation begins, three important flight factors of separation, velocity, and cohesion are performed for sustainable network operation. To avoid collision, the distance between the nodes is maintained. They shall also match the velocity to its neighboring nodes and maintain cohesion among these nodes. All nodes which become a part of this disciplinary behavior create a group for future

cooperation. It is important that members of the group must be in the neighboring communication range. DA aims the group of nodes plays a key role in selecting a networking architecture for effective performance. As soon as a neighboring solution exists for a node, the network becomes connected. Furthermore, as explained, there are two important vectors of DA such as velocity step vector and position vector are incorporated to store and update position of those nodes having at least one neighboring node. They are now able to update their positions by adding the step vectors to the position vectors as given in Equation (6). Keep knowing the updated vectors of all nodes; this work enables us to simulate the next iteration based on the existing node position as well as the learning performs levy

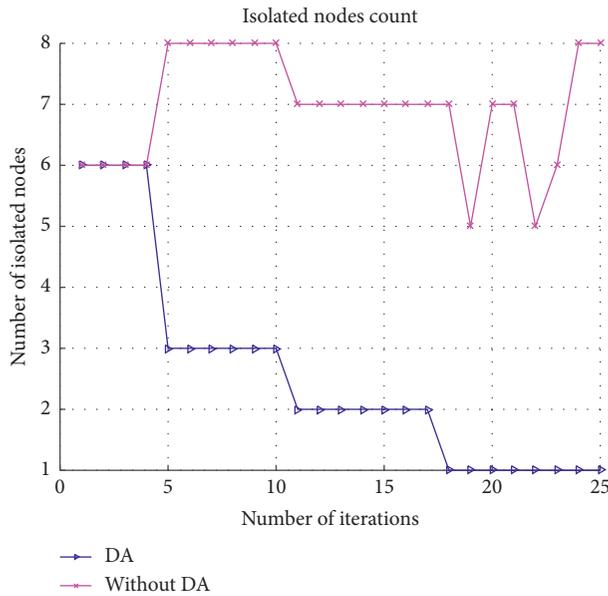


FIGURE 7: Comparison result with and without DA.

flight of nodes who is finding the solo flying in an entire network. Thus, a node in a dynamic topology network may be isolated and reduce network efficiency especially in high mobility FANETs.

Graphical representation of isolated nodes count after DA results the significance of DA through ML. The result of the final network after DA is shown in Figure 5. Although there are six nodes isolated in initial deployment, they become a part of cooperative nodes. This reduces the isolated node count significantly. It can be seen that after the completion of course of iterations, only one node is isolated, that is, Node 7. This improvement is achieved due to DA technique as well as previous experiences of isolated nodes during action of isolation using ML. Moreover, all the other nodes have one or more than one neighbors and consider connected to each other and/or BS. Hence maximum number of nodes stay connected using DA to ensue connectivity in minimum number of iterations. Based on learning-based finding neighbors, this scheme works to reduce the time, provides the best finding neighboring solution, maintains node's connectivity, and updates the flying positing of the drone. This scheme reduces the spatial complexities of possible isolated drones.

Significance of DA algorithm for proposed scheme is compared without DA algorithm. The result of isolated count without DA is shown in Figure 6. This view results the importance of DA algorithm for dynamic network. As mentioned earlier that there are six nodes isolated at the start of network deployment. The plot of isolated node count without DA shows that isolated node counts are not sufficiently reduced as compared to DA. Higher number of node isolated during course of iterations and found no learning and discipline to force an isolated node to become a part of cooperative nodes. Consequently, only Node 4 and Node 10, which is lying exist within the vicinity of each other, while the rest of the nodes are isolated. The significance of DA can be gauged

from its implementation and comparison. This challenging problem of FANET is overcome by inspiring the biological nature of DA and especially the learning-based levy flight.

Significance of DA for ML is clearly viewed in the comparison result of isolated node count with and without DA which is shown in Figure 7. Simulations are performed iteratively and results are obtained for isolated node count. Now it can be clearly seen that isolated nodes count started with six isolated nodes for both the schemes. However, after course of iterations, DA reduced the isolated nodes in best way due to learning. Consequently, it overcomes the connectivity problem of FANETs by reducing the isolated nodes which improves the communication area. On the contrary, without DA scheme where there is no learning exists, maximum nodes stay isolated which reduces the network performance. Hence, neighboring solution minimizes the isolated nodes adaptively, which are preserved till the period of network communication.

5. Conclusion

In this paper, we have attempted to design a well-connected FANET via biological inspired learning. The rapid mobility of drones leads to drone isolation in FANETs which is a main challenge for FANETs. We present a scheme to minimize the number of isolated drones. This scheme is based on biologically inspired technique of DA using the depth of machine learning. Thus, connectivity is achieved by choosing the primitive principles of DA and ML. The preference to DA especially for FANETs is due to the novel SI behavior of dragonflies namely static swarming and dynamic swarming. Social behavior of DA is investigated in this paper, and an ML-based solution is proposed to find the efficient neighboring solution of the drones isolated during the flight mission. In this scheme, maximum number of flying drones stay connected in the network by effective learning in minimum iterations and reduces the isolated drones during flight. Hence, neighboring solution minimizes the isolated drones adaptively, which are preserved till the period of network communication. Furthermore, adopting the concept of biological step walk for neighbor searching overcomes the energy issue in the FANETs. We propose a fitness function for drones situated within the communication range which assists in the proposed learning scheme. Simulation results show that our proposed fitness function maximizes the network stability period, improves connectivity for routing, and updates the flying positioning of drones. Thus the proposed scheme benefits from the intelligence of machine learning and strategic learning of dragonfly to reduce energy consumption and ensure network connectivity.

Data Availability

Data of simulation code are available and provided in the supplementary materials in attachment separately.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

This work was supported by the Hubei Natural Science Foundation under grant 2021CFB156.

Supplementary Materials

The supplementary material contains only simulation code of the proposed methodology assisted to generate results as mentioned in this paper. . (*Supplementary Materials*)

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