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# Intelligent cluster routing scheme for flying ad hoc networks

Ali KHAN[1], Somaiya KHAN[2], Athar Shahzad FAZAL[1], Zhongshan ZHANG[2*] & Adnan Omer ABUASSBA[3]

[1]*School of Computer and Communication Engineering, University of Science and Technology Beijing, Beijing* 100083*, China;*
[2]*School of Information and Electronics, Beijing Institute of Technology, Beijing* 100081*, China;*
[3]*School of Information Technology, Arab Open University, Ramallah* 4375*, Palestine*

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**Abstract** Flying ad hoc networks are used for many critical tasks. The network formation for routing data becomes difficult because of the mobility of unmanned aerial vehicles (UAVs). To solve the communication issue, we propose an intelligent cluster routing scheme for flying ad hoc networks (CRSF). Cluster head (CH) selection in our proposed methodology is based on fitness, which is determined by the position and UAVs' residual energy. For the efficient management of UAV swarm, a cluster management mechanism is also proposed, inspired by moth flame optimization. In CRSF, for stable cluster maintenance, a CH re-selection mechanism is proposed in detail, which helps maintain the cluster for effective topology management. A routing mechanism for UAV communication is proposed for CRSF. The route selection for transmission of information is performed using the route identification function based on the Euclidean distance and residual energy. The performance of the proposed CRSF is evaluated and compared with the existing routing algorithms.

**Keywords** self-organized, unmanned aerial vehicles, UAV, clustering, routing, FANETs

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## 1 Introduction

With technological advancements in wireless communication [1, 2], 5G and beyond networks have laid the foundation for a new sub-branch of ad hoc networks known as flying ad hoc networks (FANETs) [3]. FANET typically comprises mobile unmanned aerial vehicles (UAVs) networked together to form a coalition for data transmission [4]. Its applications can be found in various civil and military domains [5]. Most common applications of FANET are delivery service [6], search and rescue operation [7], object tracking [8], border monitoring [9], hazardous site inspection [10], agricultural field inspection [11], emergency networks [12] etc. to name the few.

FANET has many advantages such as lower cost and minimum maintenance, increased scalability, and sustainability [13]. The dynamic topology of FANET makes it useful in performing various tasks with ease. As FANET has mobile and ad hoc nature, it challenges handling rapidly changing network topology, which degrades the network performance [14]. Designing such a routing mechanism is needed to provide a better solution for network topology formation and management for disruption-free data transmission in FANET.

Recently, several studies on routing in FANETs have been conducted. Lin et al. [15] proposed geographically based data routing that uses the Gauss-Markov model for UAV movement prediction. In their proposed protocol, the next-hop is selected for UAVs' mobility and the Euclidian distance. It provides stable routing but has high complexity. In [16], the authors used a hybrid approach of uni-casting and geo-casting routing for the robust and reliable predictive routing protocol. Their proposed method considers both trajectory and location information of UAVs for route selection. It provides stability but

* Corresponding author (email: zhangzs@bit.edu.cn)

incurs high routing overhead. Bellur et al. [17] proposed a routing mechanism, where the performance of topology broadcast based on reverse-path forwarding is improved by introducing a minimum cost path, which is a high-quality communication link. However, the proposed mechanism has high complexity. Alshabtat et al. [18] proposed a mechanism for reducing multipoint relays using optimized link state routing (OLSR) and directional OLSR where UAVs are equipped with directional antenna. DOLSR is used to transmit data when the distance to the destination is larger than the transmission distance of the antenna; otherwise, OLSR is used for transmission. It provides stable networking but has a moderate complexity. In [19], the authors proposed a routing protocol named predictive optimized link state routing (POLSR), which is based on the relative speed of the UAVs calculated from the GPS information. Location information is also used for the evaluation of the link quality. A UAV that has high link quality is selected for the next route. Another protocol proposed in [20], based on OLSR, is the mobility and load aware-optimized link state routing (ML-OLSR). ML-OLSR uses position and relative speed between the neighboring UAVs for routing. Both POLSR and ML-OLSR have stability in networking but incur high complexity.

Another type of routing involves the breaking down of networks into small groups known as clusters. The clustering helps solve dynamic topological changes in FANET where UAVs in a cluster exhibit swarming behavior to the cluster head (CH). In [21], the authors proposed a multilinear principal component analysis (MPCA)-clustering algorithm for UAVs that combine the link expiration time (LET) and dictionary structure prediction. The calculation of LET is based on the information of mobility and UAVs' locations. The UAV with the largest weight of neighbor UAVs is selected as CH. The MPCA offers prediction-aware routing and incurs high routing overhead. Shi et al. [22] proposed a weighted-based clustering mechanism, the cluster-based location-aided dynamic source routing (CBLADSR), where every UAV maintains a neighbor table used to select and communicate with CHs. The UAV with the highest energy and neighbors and low relative speed is considered a CH. A CBLADSR offers scalability to the UAV network and has a moderate complexity. A weighted centroid-clustering mechanism based on localization was proposed in [23], where the authors used fuzzy logic for position calculation of UAV using received signal strength indicator among two UAVs, and the CH selection occurs based on UAV's location. The proposed method provides good localization accuracy but has high complexity. Zafar et al. [24] proposed a multicluster-based algorithm for FANET. In the proposed method, the CH selection is based on the ID, which depends on the value link quality calculated by distance from the neighbor UAVs, SNR, and delays. The proposed method has low latency and moderate complexity.

Artificial intelligence (AI) has significantly improved the 5G era communication by solving network-related problems. AI allows systems and machines to perform with a level of intelligence similar to humans. AI techniques like deep learning have contributed tremendously to cognitive technology, which has brought new opportunities for AI in 5G communication networks [25]. Self-organizing network (SON) [26] has formed a new concept of network management that provides an intelligent method for the operation and maintenance of the network. The SON automatically performs network configuration, planning, and optimization without intervention from humans, reducing overall complexity, costs, and human-made faults. Another term, swarm intelligence (SI) [27] mechanism that depicts the characteristics of self-organization has got the attention of researchers in networking and communication. SI is the intelligent behavior exhibited by social individuals, for example, ant colony, birds flock, glowworm swarm, etc.

Recently, SI-based cluster routing mechanisms have also got attention from researchers. In [28], the authors proposed a bio-inspired mobility prediction clustering (BIMPC) based on the hybrid method that uses the mobility feature of UAVs and physarum polycephalum-foraging models. Every UAV calculates the probability of neighbor UAVs for the CH selection. The UAV with a higher probability is selected as CH. Another bio-inspired technique was proposed in [29] which uses ant colony optimization (ACO) for routing in FANET. The scheme is on the basic concept of ACO, where two types of routing mechanisms, reactive and proactive, are used for route selection and maintenance by forward and backward ants. Both BIMPC and ACO provide network stability but simultaneously have high complexity. In [30], a cluster routing mechanism was proposed that integrates the wireless sensor networks (WSN) and UAV. In the proposed method, the mobile UAV is used for data collection from CHs and, based on the ACO mechanism, routes the information. The UAV has information about the location of every stationary CH's in WSN. Their proposed mechanism is scalable for the network and has a moderate complexity. Ref. [31] proposed a hybrid scheme for UAV communication based on Boid Reynolds and ad hoc on-demand distance vector (AODV). The proposed method has the following steps: the computation of reactive routing is done by AODV and Boid Reynolds method for connectivity and discovery of ground base station. The bio-inspired method Boid Reynolds is the formation and maintenance of a school of fish or bird flock using three basic rules: cohesion, separation, and alignment. The proposed algorithm has the advantage of stable routing but also has high complexity. In [32], authors proposed the bio-inspired clustering scheme for FANETs (BICSF), which uses krill herd (KH) for cluster management and glowworm swarm optimization for cluster formation. CH is selected based on the fitness value, which depends on the luciferin value and residual energy of the UAV. The UAV with better fitness is chosen to be a CH. The proposed BICSF is efficient and stable in networking and has moderate complexity due to the cluster management mechanism using KH.

The main challenges of cluster routing research are selecting optimal CH and cluster management for efficient communication. The benefit of using a bio-inspired mechanism for self-organized networking is that it ensures stability, scalability, and maintenance. The reviewed mechanisms are not efficient in network management and incur high complexity, leading to higher energy consumption and lower throughput and cluster lifetime. The prime goal for cluster routing is to design such a self-organized networking mechanism that ensures network stability and incurs lower complexity and greater throughput to give a higher cluster lifetime. The lower the complexity of an algorithm, the lesser is the energy consumption, leading to a higher cluster lifetime and greater throughput. This paper focuses on network formation and management to achieve network stability to solve collaboration, cooperation, and communication problems among UAVs in FANET.

Based on the issues mentioned above on FANET, we propose an intelligent cluster routing mechanism for swarms of UAVs using the behavioral study of moths to have stable and efficient communication. The novel contributions of our work reviewed the routing schemes for UAV networks and concluded the benefits of using a bio-inspired mechanism for self-organized networking. As previously stated, the focus of our study is to propose an energy-efficient cluster routing mechanism that is less complex, provides stable networking, and yields higher throughput and cluster lifetime. Therefore, we propose a cluster routing scheme for FANET (CRSF) using moth flame optimization (MFO). The main stages of the proposed scheme are CH selection, cluster formation, cluster management, CH re-selection, and the routing mechanism in FANET. The CH selection in our proposed methodology, which is an important phase in the clustering algorithm, is based on fitness. A detailed mechanism for cluster formation is also proposed. For the efficient management of the UAV swarm, we propose cluster management inspired by the MFO. A mechanism for the next appropriate CH is also introduced for cluster maintenance. In CRSF, for cluster maintenance, a CH re-selection mechanism is proposed in detail, which helps maintain the cluster for effective topology management. We also propose a routing mechanism for UAV communication. The route selection for the transmission of information is performed using the route identification function (RIF).

The remaining paper is organized as follows: Section 2 has the system model. Section 3 explains the phases of CRSF in detail. Section 4 has the results and discussion, and Section 5 concludes our work.

## 2 System model

The system model for our proposed work consists of $N$ numbers of UAVs deployed for data transmission to a distant control center that can be related to any disaster or event as shown in Figure 1. A single UAV faces topology-related problems while performing critical tasks because of the limited resource capabilities of individual UAVs, sends some data to a destination that is not within direct range of the UAV. A practical solution to this problem is the formation of a UAV coalition for ad hoc information transmission through intermediate UAVs. A cluster-based network topology is formed to handle this $N$ number of UAVs, where a UAV with higher resource capability is selected as CH to take topology management and route selection for efficient data transmission. The other UAVs in the cluster become CM UAVs. In this study, we consider only the energy consumed in communication, and we use the first-order radio model as presented in [33] for energy consumption calculation. The notations are given in Table 1. Energy consumed in transmitting ($E_{Tx}$) and receiving ($E_{Rx}$) of $m$-bits is calculated by

$$E_T(m, d) = E_{Tx}(m, d) + E_{Rx}(m, d), \tag{1}$$

$$E_{Tx}(m, d) = E_{\mathrm{TRC}} \times m + E_A \times m \times d^2, \tag{2}$$

$$E_{Rx}(m, d) = E_{\mathrm{TRC}} \times m, \tag{3}$$

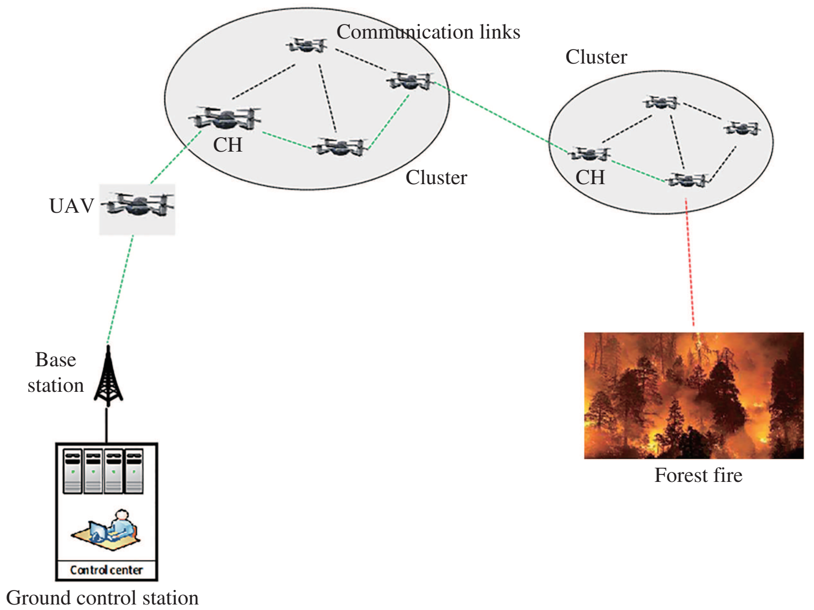



**Figure 1** (Color online) System model.

**Table 1** Notation

| Notation | Explanation | Notation | Explanation |
|---|---|---|---|
| $R_E(i)$ | Residual energy of $i$-th UAV | $\mathrm{CJ}_{\mathrm{message}}$ | Cluster joining message |
| $I_E(i)$ | Initial energy of $i$-th UAV | $\mathrm{CT}_{\mathrm{table}}$ | Cluster topology table |
| $C_E(i)$ | Current energy of $i$-th UAV | $\mathrm{TC}_{\mathrm{message}}$ | Topology configuration message |
| $H_M$ | Hello message | $C_{\mathrm{message}}$ | Confirmation message |
| $N_{\mathrm{table}}$ | Neighbor table | $D_{CH,CM}$ | Distance between CH UAV and CM UAV |
| NUAV | Number of neighboring UAV | CH UAV | Cluster head UAV |
| $T_{\mathrm{NUAV}}$ | Threshold number of neighboring UAV | CM UAV | Cluster member UAV |
| $\mathrm{CF}_{\mathrm{message}}$ | Cluster formation message | ED | Euclidean distance |

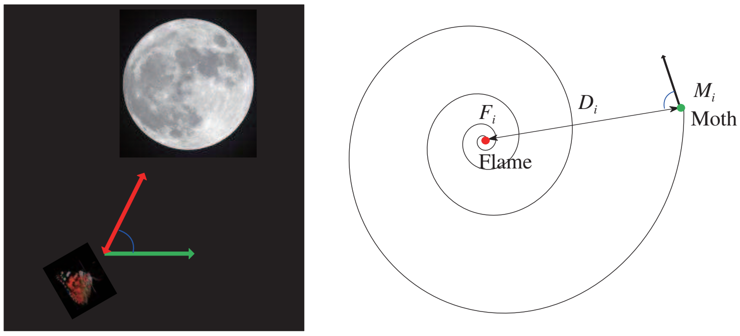
where $E_{\mathrm{TRC}}$ is energy dissipated in the running transmitter and receiver (50 nJ/bit). $E_A$ denotes the energy for the amplifier (10 pJ/bit/m$^2$), and $d$ represents the distance between receiver and transmitter.

The rest assumptions in our proposed work are as follows:

- All deployed UAVs have the same energy at the initial stage.
- Each UAV has the information of its position and accordingly updates it.
- Threshold value of UAVs $T_{\mathrm{NUAV}}$ in $N_{\mathrm{table}}$ is 3 to form a cluster. If there are just two UAVs, then it will have UAV-UAV communication.
- Based on its position, the UAV can join the cluster.
- All UAVs are given equal consideration for the CH selection.
- Every UAV broadcasts $H_M$ with constant time $T$.

## 3 Proposed methodology

In this section, we propose an intelligent CRSF using the behavioral study of MFO [34]. The objective of using MFO is due to the moths' transverse orientation (Figure 2(a)). In transverse orientation, moths fly keeping the fixed angle to the moon, which aids moths to travel long distances by maintaining the straight path and making MFO a better choice for position calculation. We propose a cluster routing scheme for efficient communication in FANET, which includes cluster formation, management, and routing mechanisms. The CH selection is based on the fitness, determined by UAV's position and residual energy. The UAV with the highest fitness is selected as CH to take responsibility for the whole cluster. For managing UAVs swarm, cluster management is inspired by the MFO. For stable cluster maintenance, a CH re-selection mechanism is proposed in detail, which helps maintain the cluster for effective topology




(a) (b)

**Figure 2** (Color online) Moth flame optimization mechanism. (a) Transverse orientation; (b) spiral flying path.

management. Then comes the communication part, which is based on the route selection mechanism. The details of our proposed method are described in the subsequent sub-sections.

### 3.1 Mathematical model of moth flame optimization

MFO, a population-based solution, is inspired by the navigation movement of the moths [34]. The mathematical model of MFO is described below.

The population of moths can be expressed as a set and represented in a matrix as

$$M = \begin{bmatrix} m_{1,1} & m_{1,2} & \cdots\cdots & m_{1,d} \\ m_{2,1} & m_{2,2} & \cdots\cdots & m_{2,d} \\ \vdots & \vdots & \cdots\cdots & \vdots \\ m_{n,1} & m_{n,2} & \cdots\cdots & m_{n,d} \end{bmatrix}, \tag{4}$$

where $n$ represents the number of moths and $d$ is the number of variables (dimension). The position vector of each moth is passed to the fitness function, which gives the fitness value of each corresponding moth, and the value can be stored in an array, which is given by

$$\mathrm{OM} = \left[\mathrm{OM}_1, \mathrm{OM}_2, \mathrm{OM}_3, \ldots, \mathrm{OM}_n\right]. \tag{5}$$

Similarly, there is another important component, which is the flame. Matrix $F$ and its corresponding fitness value are given by

$$F = \begin{bmatrix} F_{1,1} & F_{1,2} & \cdots\cdots & F_{1,d} \\ F_{2,1} & F_{2,2} & \cdots\cdots & F_{2,d} \\ \vdots & \vdots & \cdots\cdots & \vdots \\ F_{n,1} & F_{n,2} & \cdots\cdots & F_{n,d} \end{bmatrix}, \tag{6}$$

$$\mathrm{OF} = \left[\mathrm{OF}_1, \mathrm{OF}_2, \mathrm{OF}_3, \ldots, \mathrm{OF}_n\right]. \tag{7}$$

Here, note that moths are the search agent and flames are the optimal position. Moth moves toward the flame where it finds the best position, as shown in Figure 2(b).

MFO is a three tuple algorithm, which finds the global optimal solution for the given problem using the approximation function that is given by

$$\mathrm{MFO} = (I, P, T), \tag{8}$$

where $I$ function generates a random moths' population and the corresponding fitness values, $P$ function moves the moths toward the flame, and $T$ function checks the termination criterion and returns true or false according to the criterion.

This behavior of moths can be mathematically modeled, and their position to the flame is updated by

$$M_i = S(M_i, F_k), \tag{9}$$

where $M_i$ represents the $i$-th moth, the $k$-th flame is indicated by $F_k$, and $S$ shows the spiral function, which tells how moths will update their positions around the flames.

The logarithmic spiral function is given by the equation below for updating the MFO mechanism:

$$S(M_i, F_k) = D_i \cdot \mathrm{e}^{bt} \cdot \cos(2\pi t) + F_k, \tag{10}$$

where $D_i$ is the distance of the $i$-th moth from the $k$-th flame, $b$ (0.20) is a constant number for defining the spiral's shape, and $t$ represents a random number between $[-1, 1]$, which shows the movement of moth toward the flame. If $t = 1$, the moth is far away from the flame, and $t = -1$ shows that the moth is closest to the flame. $D$ is calculated by

$$D_i = |F_k - M_i|. \tag{11}$$

### 3.2 Cluster head selection

In this phase, the CH selection is based on the fitness evaluation, which depends on UAV's position and residual energy. The fitness of every UAV $i$ is calculated using (14). Each UAV sends the $H_M$ to its neighbor UAVs. To ensure every UAV in the neighbor receives the hello message within a defined time, a time $\tau$ (where $\tau < aT$ and $a > 1$) is set up. The UAV $i$ with the highest fitness is selected as CH.

The function for UAV's position can be calculated as

$$f_1 = M_i \leftarrow (9). \tag{12}$$

The function for UAV's residual energy can be calculated as

$$f_2 = R_E(i) = I_E(i) - C_E(i). \tag{13}$$

The fitness function for selecting the CH is calculated by the following equation:

$$\text{Fitness} = (w_1 \times f_1) + (w_2 \times f_2), \quad \text{where } w_1 + w_2 = 1. \tag{14}$$

The coefficients in (14), $w_1$ and $w_2$ are weights assigned to the parameters for evaluating the fitness of UAVs in CH selection. The corresponding weights $w_1$ and $w_2$ are fixed and equal, which is 0.5, so that the sum of weights should be 1. For the efficient performance of the clustering algorithm, residual energy and position are the two important parameters for the evaluation of UAV's fitness. The main reason for selecting equal weights for both factors is to give equal importance to the fitness evaluation. For example, we use a high value of $w_2$ as compared to $w_1$. In that case, the UAV with low residual energy but at a better position can be considered as having better fitness and is selected as CH since CH has the responsibility of managing the entire cluster, requiring more energy resources. So in this selection, the CH will quickly exhaust its energy resource and then frequently run the clustering algorithm, resulting in a lower cluster lifetime. Similarly, if $w_1$ has a higher value, then the node with no feasible position can be considered CH. Therefore, choosing equal weights for both parameters help in the selection of UAVs with much better fitness, thereby increasing the cluster lifetime and lowering energy consumption.

### 3.3 Cluster formation

For network stability and mitigation of congestion, the entire network is divided into clusters for better communication. The cluster formation process is shown in Figure 3(a). The cluster formation method (Algorithm 1) can be explained as follows.

(1) When UAV $i$ receives the $H_M$, it constructs an $N_{\text{table}}$ and sorts the entries of the other neighbor UAVs in descending order. The fitness is updated based on the latest $N_{\text{table}}$. The UAV $i$ also compares its fitness with others, and if UAV $i$ has the highest value, it declares itself as CH; otherwise, the UAV $i$ recognizes the UAV having the highest fitness as the best CH and waits for the $\text{CF}_{\text{message}}$. Every UAV independently runs the algorithm for CH selection of the proposed CRSF.

(2) The CH UAV transmits the $\text{CF}_{\text{message}}$ to the other UAVs in its $N_{\text{table}}$. When the UAVs receive the CH announcement, they recognize the CH.

(3) After receiving the $\text{CF}_{\text{message}}$ in a time period $\tau$, the UAV will send the $\text{CJ}_{\text{message}}$ to apply for joining the cluster.

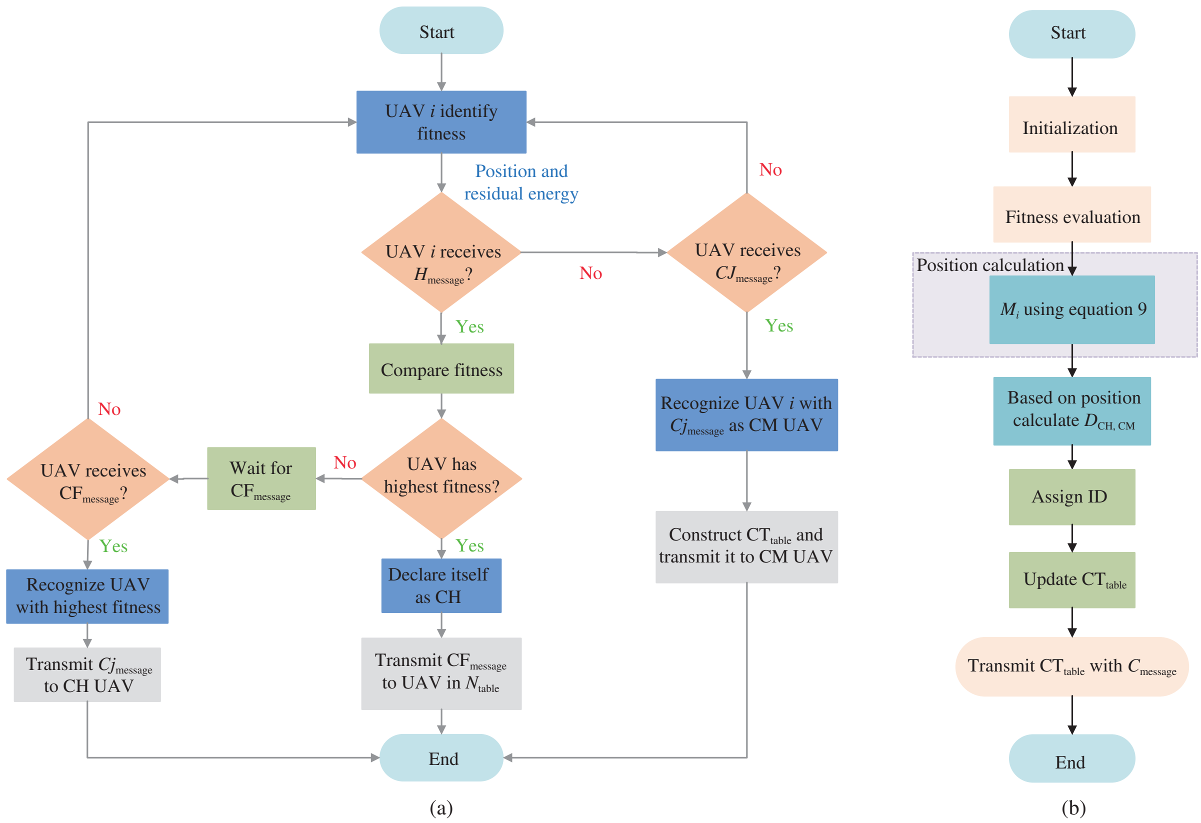



**Figure 3** (Color online) (a) Cluster routing scheme for flying ad hoc network cluster formation, (b) cluster routing scheme for flying ad hoc network cluster management.

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**Algorithm 1** CSRF cluster formation

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**Input:** $R_E(i)$, $M_i$;
**Output:** Formation of cluster;
**For** each UAV $i$ in a network ($i = 1, 2, 3, \ldots, N$);
**Calculate** Fitness; (using (14));
**Do** (Transmit Fitness with $H_M$);
  **While** (UAV $i$ receives $H_M$)
    **Construct** ($N_{\text{table}}$);
    **Compare** (Fitness);
    **Sort**($N_{\text{table}}$ entries in descending order);
  **Update**($N_{\text{table}}$ on every new $H_M$);
**While** (NUAV $\geqslant T_{\text{NUAV}}$);
    **Check** (Fitness information of UAV $i$ from $N_{\text{table}}$);
      **if** (UAV $i$ has highest Fitness);
        **Declare** (UAV $i$ as CH);
        **Transmit** ($\text{CF}_{\text{message}}$ to UAVs in $N_{\text{table}}$);
      **else**
        **Wait for** ($\text{CF}_{\text{message}}$);
  **if** (UAV $i$ receives $\text{CF}_{\text{message}}$);
    **Recognize** (UAV as CH);
    **Transmit** ($\text{CJ}_{\text{message}}$ to CH UAV);
  **While** (CH UAV receives $\text{CJ}_{\text{message}}$);
    **Recognize** (UAV $i$ as CM UAV);
    **Construct** ($\text{CT}_{\text{table}}$);
    **Transmit** ($\text{CT}_{\text{table}}$ to CM UAVs);
**end**

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(4) The CH UAV will send the $\text{CT}_{\text{table}}$ as an accepting announcement to the UAVs in the cluster. If UAV does not receive accepting announcement in a time period $\tau$, then the UAV removes the CH UAV from its $N_{\text{table}}$. However, when the UAV successfully becomes the CM UAV, it keeps the $\text{CT}_{\text{table}}$ to identify the cluster it belongs to.

### 3.4 Cluster management

The cluster is managed using CH UAV, which keeps the topology updated as given by Algorithm 2 to maintain the swarming behavior of CM UAVs in the cluster. In MFO, the real search agents that move around the search space are moths, while flames are the moths' optimal position. Therefore, flames can be considered flags or pins dropped by moths while searching the search space. So each moth searches around a flame (flag) and updates it whenever it finds a better solution. By applying this procedure, a moth will not miss its best solution. The basic idea of using the MFO mechanism is to optimize the position, which is an important parameter for selecting CH. MFO is used due to the moths' transverse orientation where moths fly, keeping the fixed angle to the moon, which aids moths to travel long distances by maintaining the straight path, thus making MFO a better choice for the position calculation. Cluster management phase (Figure 3(b)) can be explained as follows.

(1) In the cluster management phase, the CH UAV receives $\mathrm{TC}_{\mathrm{message}}$ from CM UAVs, which has the position of CM UAVs. All the CM UAVs can exhibit swarming behavior concerning the CH UAV movement. The CH UAV updates and maintains the topology table of the cluster and sends it to the CM UAVs after a while. The CM UAVs keep the topology table updated for route selection while transmitting the information.

(2) Based on the position of the CM UAVs, the CH UAV calculates the Euclidean distance (ED) of the CM UAVs. The CH UAV then assigns an ID based on the calculated distance. The CM UAV, which has the shortest distance from the CH UAV, is assigned the lowest ID, and other UAVs' IDs increase, respectively, as per their distance.

(3) The CM UAV having the shortest distance from CH UAV and the lowest ID number (i.e., 1) will be considered for the next selected CH based on other fitness parameters.

The $D_{(\mathrm{CH,CM})}$ is calculated by

$$D_{(\mathrm{CH,\ CM})} = \mathrm{ED}(\mathrm{CH\,UAV}, \mathrm{CM\,UAV}). \tag{15}$$

**Algorithm 2** CSRF cluster management

**Input:** $M_i$;
**Output:** Update cluster topology;
Every UAV do;
**Transmit** ($\mathrm{TC}_{\mathrm{message}}$);
**While** (CH UAV receives $\mathrm{TC}_{\mathrm{message}}$);
  **Calculate** ($D_{\mathrm{CH,CM}}$ of CM UAV based on the position from $\mathrm{TC}_{\mathrm{message}}$);
    **Assign** (ID to the CM UAV based on calculated distance);
  **Update** ($M_i$ in $\mathrm{CT}_{\mathrm{table}}$);
  **Transmit** ($\mathrm{CT}_{\mathrm{table}}$ with $C_{\mathrm{message}}$);
**end**

### 3.5 Cluster head re-selection

The CH UAV is responsible for managing the cluster, making the energy consumption more in CH UAV than the CM UAVs. The responsibility of CH UAV is to maintain the cluster topology in a network and update the routing table at any instant. As UAVs are mobile, so over time, relative mobility between CM UAVs and CH UAV changes. This will result in the re-selection of CH in a cluster shown in Figure 4(a). The following are the conditions for the re-selection of CH to occur.

(1) When the CM UAVs after a long time $aT$ do not receive hello message from CH UAV, then the CH UAV is considered a dead UAV that is out of the network. At this moment, CM UAVs will remove the CH UAV and reselect a new UAV as CH.

(2) When the fitness value of the CH UAV becomes less than the fitness value of the CM UAVs, the CH re-selection occurs. The previous CH is no longer the CH, nor does it participate in the CH selection, but it only waits for the new CH announcement. According to the fitness values, the new CH modifies the cluster topology table, resulting in improved cluster efficiency.

(3) The re-selection of CH is based on the ID assigned to all the CM UAVs. The CM UAV with the lowest ID number (i.e., 1) will be considered for the next possible CH based on other fitness parameters.

### 3.6 Routing mechanism

Once the cluster is formed, a UAV can send data to a distant destination using a routing mechanism shown in Figure 4(b). For information routing, the most important part is the selection of the optimal

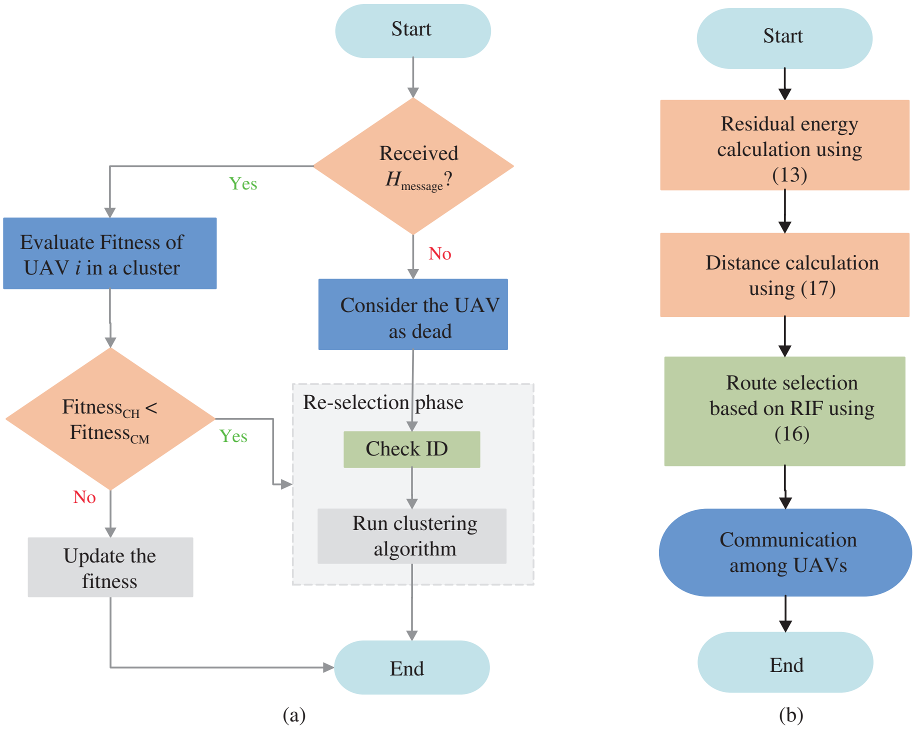


**Figure 4** (Color online) (a) Cluster head re-selection for cluster maintenance, (b) cluster routing scheme for flying ad hoc network routing mechanism

route. In this paper, the proposed routing mechanism uses RIF, multi-hop communication, to improve communication efficiency and reduce communication costs. For efficient route selection and load balancing in FANET, the next-hop UAV for routing of data is selected based on the Euclidian distance $D_{\rm UAV}$ between UAVs and residual energy $R_E$. The UAV with the shortest distance and highest residual energy is considered in the route. The following equation can calculate the RIF

$$\mathrm{RIF} = \frac{R_E}{D_{\rm UAV}}, \tag{16}$$

where $D_{\rm UAV}$ is calculated as

$$D_{\rm UAV} = D_{i,j} = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2}. \tag{17}$$

When any CM UAV needs to send some data to another UAV, it first checks whether that UAV is in the neighbor table. If the destination UAV exists in the $N_{\rm table}$, then CM UAV directly communicates with the destination UAV. Otherwise, the UAV sends the information to CH UAV, and the CH UAV then acts as a relay and handles the communication.

The CH UAV will prioritize routing to the UAVs that are near, i.e., have shorter distances because they will consume less energy for communication. The source UAV will send a route request (RREQ) to the CH UAV, which upon receiving, checks its $\mathrm{CT}_{\rm table}$ for the destination whether it exists in the cluster. If the destination exists in its cluster, the CH UAV will transmit route reply (RREP) to the source UAV after that route is established for communication, which provides a feasible path for transmission of data between the communicating UAVs.

There can be a scenario where the source and destination UAVs lie in different clusters; then, the communication takes place by inter-cluster communication mechanism. The inter-cluster communication occurs through CH UAVs, but there is a scenario when CH UAVs have no direct connection, then the communication occurs via gateway UAVs of a cluster. The gateway UAVs are connected, which is the only connection between two clusters. When a source UAV in cluster 1 needs to communicate with the destination UAV in cluster 2, the source UAV sends RREQ to the CH UAV, which will send RREQ to the CH UAV of cluster 2 via gateway UAVs. The CH UAV of the cluster will send RREP, which contains the shortest path based on the RIF. The CH UAVs will help in establishing the route between source

**Table 2** Simulation parameters

| Parameter | Value |
|---|---|
| Grid size | 1 km × 1 km and 2 km × 2 km |
| Number of UAVs | $15, 20, 25, 30, 35$ |
| Minimum distance between UAVs | 5 m |
| Mobility model | Reference point mobility model [35] |
| Simulation time | 120 s |
| Position exchange interval | 2 s |
| $w_1$ and $w_2$ | 0.5 and 0.5 |
| UAV's initial energy level | 80 Watt hour |
| Data packet | 512 bytes |
| Constant bit rate | 100 kbps |
| Receiver sensitivity | −90 dBm |
| Transmission range | Dynamic |
| Transmission frequency | 2.45 GHz |

and destination UAVs. After receiving RREP, the source UAV will transmit the information directly to the destination UAV. Due to frequent topology changes in FANET, it is important to validate the route for inter and intra-cluster communication. When a UAV detects a connectivity failure with neighboring UAVs, it transmits a route failure message to CH UAV. The CH UAV uses a failure management mechanism that uses information from the routing table to provide a substitute route for data packet transmission.

The selection of gateway UAV is based on the shortest distance from the other cluster's CH UAV. Based on this criterion, the gateway UAV is selected. If there is more than one UAV at the same distance as the CH UAV, then the selection occurs based on $R_E$ of those UAVs. The UAV with a higher $R_E$ will be considered gateway UAV while the other UAV will be considered standby gateway. This selection of the gateway UAV is continuously monitored because of the frequent changing topology of FANETs.

### 3.7 Computational complexity

Every UAV $i$ calculates the fitness for the CH evaluation, and there are $N$ UAVs in a network. To calculate the fitness, every UAV requires a constant time $t$. The total time for calculating the fitness for $N$ UAVs is given by $N \cdot t \in O(N)$. The formation of the cluster in our proposed mechanism depends on the position and residual energy. A better UAV position with a high value of residual energy will group to form a cluster. Based on the position, there can be three cases where nodes are very close to each other, moderately distributed, or extremely sparsely distributed. Then the complexity calculation for these cases can be given as follows.

(1) When the UAVs are very close to each other, it might end up making up a single cluster due to the fitness calculation and is given by $(O(N) \cdot 1) \in O(N)$.

(2) The second case is when the UAVs are moderately distributed; then, there can be $C$ clusters and is given by $(O(N) \cdot C) \in O(CN)$.

(3) The third case is when the UAVs are extremely sparsely distributed; then, the complexity is given by $(O(N) \cdot N) \in O(N^2)$.

The total computational complexity of our proposed CRSF is given by

$$C(\mathrm{CRSF}) = C(\mathrm{fitness\,function}) + C(\mathrm{position}).$$

For the first case, total complexity can be given as $(O(N) + O(N)) \in O(N)$, for the second case, the total complexity is $(O(N) + O(CN)) \in O(CN)$, and for the third case, the total complexity is calculated as $(O(N) + O(N^2)) \in O(N^2)$.

## 4 Results and discussion

In this section, we evaluate the performance of CRSF in terms of cluster lifetime, energy consumption, throughput, and packet delivery ratio (PDR) and compare with other schemes BICSF [32] and ACO [29]. The simulation environment is MATLAB. Table 2 [35] has the parameters for simulation setup.

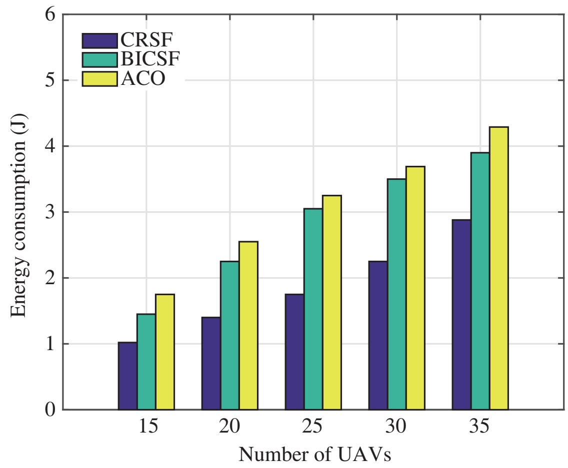


**Figure 5** (Color online) Number of UAVs vs. energy consumption (1 km×1 km).

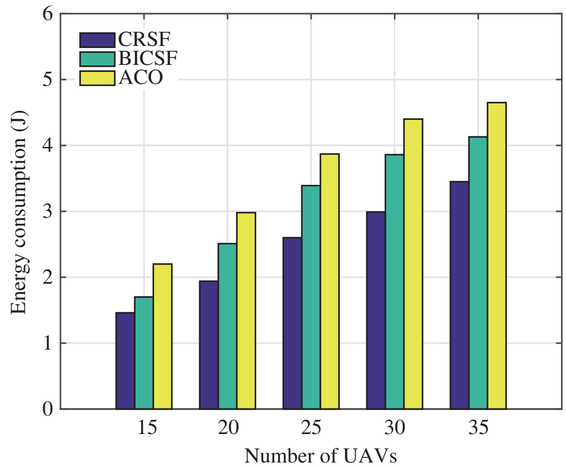


**Figure 6** (Color online) Number of UAVs vs. energy consumption (2 km×2 km).

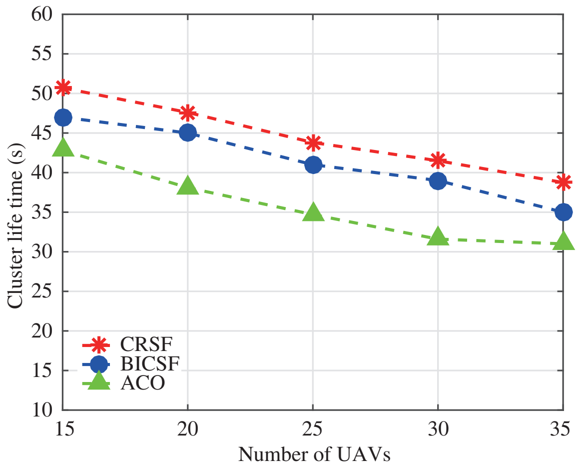


**Figure 7** (Color online) Number of UAVs vs. cluster lifetime (1 km×1 km).

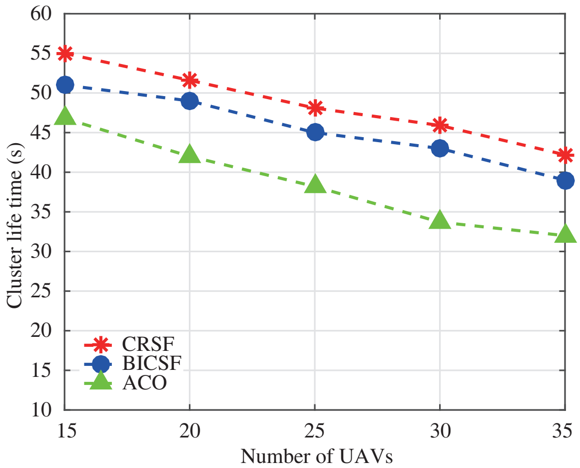


**Figure 8** (Color online) Number of UAVs vs. cluster lifetime (2 km×2 km).

**Energy consumption.** Figures 5 and 6 depict the energy consumption of the CRSF compared with ACO and BICSF. The results show that when new UAVs are inserted into the network, the processes involved in handling the UAVs in a network increase, which exhausts the energy resources of UAVs; therefore, energy consumption increases. Our CRSF shows better energy consumption compared to ACO and BICSF because of the efficient CH selection and maintenance mechanism.

**Cluster lifetime.** The duration when the cluster remains intact is from the cluster formation to disposition. From the results (Figures 7 and 8), note that the insertion of UAVs in the network degrades the network performance. As previously stated, the increase in the number of UAVs depletes the energy resources of UAVs, causing the clustering algorithm to be frequently executed, resulting in the degradation of cluster lifetime. A greater number of UAVs means the CH can manage more UAVs in a cluster, and the mobile nature of UAVs will result in connection breakages as the topology changes. This will exhaust the energy resources of CH due to the operations involved in cluster management. As the fitness of CH UAV gets lower than the earlier CM UAVs; then, the re-selection of CH occurs. The results show that CRSF has a better cluster lifetime than ACO and BICSF because the proposed CRSF has low complexity of clustering and an efficient route selection.

**Throughput.** The throughput of the network can be calculated by

$$\text{Throughput} = \frac{\text{Total number of packets received}}{\text{time}}. \tag{18}$$

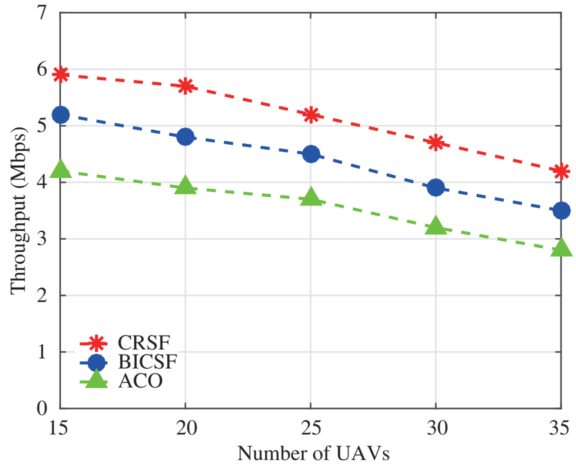


**Figure 9** (Color online) Number of UAVs vs. throughput (1 km×1 km).

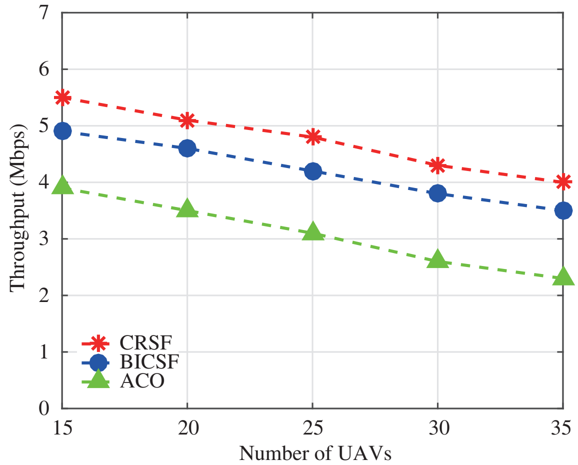


**Figure 10** (Color online) Number of UAVs vs. throughput (2 km×2 km).

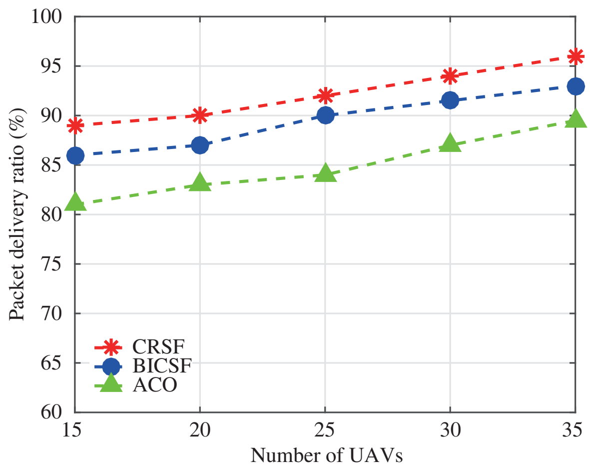


**Figure 11** (Color online) Number of UAVs vs. packet delivery ratio.

Figures 9 and 10 show that the throughput of CRSF is high compared to ACO and BICSF, which is due to the lesser load on CH UAV in the case of communication between neighboring UAVs. In communication between distant UAVs, CH UAV acts as a relay and takes charge of routing. As the number of UAVs increases, the time taken by the packets increases, resulting in a decrease in throughput. The greater the area, the greater the distance between UAVs, resulting in higher transmission time taken by the packets and lower throughput.

**Packet delivery ratio.** It is the successful delivery of data packets excluding failed data packets during transmission. Figure 11 compares PDR with the number of UAVs of our proposed CRSF to ACO and BICSF. The results show that CRSF has a higher PDR than the other routing schemes because of efficient route selection and better congestion handling. As more UAVs are added to the network, each UAV has more neighboring UAVs due to increased network density, resulting in more possible routes from source to destination, more data packets, and increased PDR.

## 5 Conclusion

In this study, we reviewed routing schemes for UAV networks and concluded with the benefits of using the bio-inspired mechanism for self-organized networking. We proposed an intelligent CRSF to solve communication issues. The CH selected in our proposed methodology is based on fitness, which is determined by UAV's position and residual energy. A cluster management mechanism inspired by MFO is proposed for the efficient management of UAV swarms. We propose cluster management using MFO to manage the swarm behavior of UAVs. In CRSF, for stable cluster maintenance, a CH re-selection mechanism is proposed in detail, which helps maintain the cluster for effective topology management. A routing mechanism for UAV communication is proposed. The route selection for the transmission of information is performed using RIF based on the ED and residual energy. The performance of the proposed CRSF is evaluated and compared with the existing routing algorithms. The results show that the proposed CRSF has less complexity and has better performance than the other bio-inspired mechanisms based on the considered benchmarks.

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**References**

1 Rong B, Zhang Z, Zhao X, et al. Robust superimposed training designs for MIMO relaying systems under general power constraints. IEEE Access, 2019, 7: 80404–80420
2 Du C, Zhang Z, Wang X, et al. Optimal duplex mode selection for D2D-aided underlaying cellular networks. IEEE Trans Veh Technol, 2020, 69: 3119–3134
3 Naqvi S A R, Hassan S A, Pervaiz H, et al. Drone-aided communication as a key enabler for 5G and resilient public safety networks. IEEE Commun Mag, 2018, 56: 36–42
4 Bekmezci I, Sahingoz O K, Temel S. Flying ad-hoc networks (FANETs): a survey. Ad Hoc Netw, 2013, 11: 1254–1270
5 Luo S X, Zhang Z S, Wang S, et al. Network for hypersonic UCAV swarms. Sci China Inf Sci, 2020, 63: 140311
6 Schneider D. Air traffic control for delivery drones. IEEE Spectr, 2017, 54: 32–33
7 Manathara J G, Sujit P B, Beard R W. Multiple UAV coalitions for a search and prosecute mission. J Intell Robot Syst, 2011, 62: 125–158
8 Qu Y H, Zhang F, Wu X W, et al. Cooperative geometric localization for a ground target based on the relative distances by multiple UAVs. Sci China Inf Sci, 2019, 62: 010204
9 Sun Z, Wang P, Vuran M C, et al. BorderSense: border patrol through advanced wireless sensor networks. Ad Hoc Netw, 2011, 9: 468–477
10 Maza I, Caballero F, Capitán J, et al. Experimental results in multi-UAV coordination for disaster management and civil security applications. J Intell Robot Syst, 2011, 61: 563–585
11 Xiang H, Tian L. Development of a low-cost agricultural remote sensing system based on an autonomous unmanned aerial vehicle (UAV). Biosyst Eng, 2011, 108: 174–190
12 Zhao N, Lu W, Sheng M, et al. UAV-assisted emergency networks in disasters. IEEE Wirel Commun, 2019, 26: 45–51
13 Jawhar I, Mohamed N, Al-Jaroodi J, et al. Communication and networking of UAV-based systems: classification and associated architectures. J Netw Comput Appl, 2017, 84: 93–108
14 Zeng Y, Zhang R, Lim T J. Wireless communications with unmanned aerial vehicles: opportunities and challenges. IEEE Commun Mag, 2016, 54: 36–42
15 Lin L, Sun Q, Li J, et al. A novel geographic position mobility oriented routing strategy for UAVs. J Comput Inf Syst, 2012, 8: 709–716
16 Gankhuyag G, Shrestha A P, Yoo S J. Robust and reliable predictive routing strategy for flying ad-hoc networks. IEEE Access, 2017, 5: 643–654
17 Bellur B R, Lewis M G, Templin F L. An ad-hoc network for teams of autonomous vehicles. In: Proceedings of the 1st Annual Symposium Autonomic Intelligence Network System, Los Angeles, 2002. 1–6
18 Alshabtat A, Dang L. Low latency routing algorithm for unmanned aerial vehicles ad-hoc networks. World Acad Sci Eng Technol, 2011, 5: 705–711
19 Rosati S, Krużelecki K, Traynard L, et al. Speed-aware routing for UAV ad-hoc networks. In: Proceedings of IEEE Globecom Workshops (GC Wkshps), 2013. 1367–1373
20 Zheng Y, Wang Y, Li Z, et al. A mobility and load aware OLSR routing protocol for UAV mobile ad-hoc networks. In: Proceedings of International Conference on Information and Communications Technologies (ICT 2014), 2014. 1–7
21 Zang C, Zang S. Mobility prediction clustering algorithm for UAV networking. In: Proceedings of the GLOBECOM Workshops (GC Wkshps), Houston, 2011. 1158–1161
22 Shi N, Luo X. A novel cluster-based location-aided routing protocol for UAV fleet networks. Int J Digital Content Tech, 2012, 6: 376–383
23 Khelifi F, Bradai A, Singh K, et al. Localization and energy-efficient data routing for unmanned aerial vehicles: fuzzy-logic-based approach. IEEE Commun Mag, 2018, 56: 129–133
24 Zafar W, Khan B M. A reliable, delay bounded and less complex communication protocol for multicluster FANETs. Digital Commun Netw, 2017, 3: 30–38
25 You X H, Zhang C, Tan X S, et al. AI for 5G: research directions and paradigms. Sci China Inf Sci, 2019, 62: 021301
26 Zhang Z, Long K, Wang J. Self-organization paradigms and optimization approaches for cognitive radio technologies: a survey. IEEE Wirel Commun, 2013, 20: 36–42
27 Zhang Z S, Long K P, Wang J P, et al. On swarm intelligence inspired self-organized networking: its bionic mechanisms, designing principles and optimization approaches. IEEE Commun Surv Tut, 2014, 16: 513–537

28 Yu Y, Ru L, Fang K. Bio-inspired mobility prediction clustering algorithm for ad hoc UAV networks. Eng Lett, 2016, 24: 83–92

29 Maistrenko V A, Alexey L V. Experimental estimate of using the ant colony optimization algorithm to solve the routing problem in FANET. In: Proceedings of International Siberian Conference on Control and Communications (SIBCON), 2016. 1–10

30 Yang J, Wang X, Li Z, et al. Path planning of unmanned aerial vehicles for farmland information monitoring based on WSN. In: Proceedings of the 12th World Congrress Intelligence Control Automat (WCICA), 2016. 2834–2838

31 Bahloul N E H, Boudjit S, Abdennebi M, et al. A flocking-based on demand routing protocol for unmanned aerial vehicles. J Comput Sci Technol, 2018, 33: 263–276

32 Khan A, Aftab F, Zhang Z. BICSF: bio-inspired clustering scheme for FANETs. IEEE Access, 2019, 7: 31446–31456

33 Khan A, Aftab F, Zhang Z. Self-organization based clustering scheme for FANETs using Glowworm Swarm Optimization. Phys Commun, 2019, 36: 100769

34 Mirjalili S. Moth-flame optimization algorithm: a novel nature-inspired heuristic paradigm. Knowledge-Based Syst, 2015, 89: 228–249

35 Roy R R. Reference point group mobility. In: Handbook of Mobile Ad Hoc Networks for Mobility Models. Boston: Springer, 2011. 637–670