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Hybrid Self-Organized Clustering Scheme for Drone Based Cognitive Internet of Things

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ABSTRACT Network management by using a cognitive approach is an attractive solution for drone-based Internet of Things (IoT) environment to provide many modern facilities to IoT users. In this paper, we try to minimize the networking related issues for drone-based IoT by providing a self-organized cluster-based networking solution. We propose a Hybrid Self-organized Clustering Scheme (HSCS) for drone-based cognitive IoT which utilizes a hybrid mechanism of glowworm swarm optimization (GSO) and dragonfly algorithm (DA). The proposed scheme contains cluster formation and cluster head selection mechanism based on GSO. Furthermore, we propose an effective cluster member tracking methodology using the behavioral study of DA which ensures efficient cluster management. The cluster maintenance is performed by a mechanism to identify dead cluster member which improves the stability of the network. Further routing mechanism is proposed for HSCS in which next hop neighbor for data transmission is selected by using the route selection function which ensures efficient communication. The performance of HSCS is evaluated in terms of cluster building time, energy consumption, cluster lifetime, and the probability of delivery success with existed hybrid bio-inspired clustering algorithm.

INDEX TERMS Self-organization, clustering, Internet of Drones, routing.

I. INTRODUCTION

With the advancement of modern wireless communication technologies, Internet of Things (IoT) has become a widely used technology in the field of various intelligent services and applications. Over the years the increase in interconnectivity among various objects or things has generated huge amount of data. However these IoT applications still are not that intelligent for data perceiving and making decisions without the involvement of human cognition processing. Hence recently cognitive computing has gained interest by IoT researchers. The IoT having the cognitive ability is known as Cognitive IoT (CIoT) [1] which enables things or object to learn different data from connected devices, sensors, drones etc.

Unmanned Aerial Vehicles (UAVs) commonly known as drones have become an emerging technology with sensing, processing, storage and communication capabilities. They can be used in different industries such as intelligent transportation systems, smart cities [2]–[6] and internet of things (IoT) scenarios [1]. The deployment of swarm of drones for IoT services has become reality for various applications such as package delivery [7], public safety [8], search and rescue [9], tracking and surveillance [10]–[12]. These IoT enabled applications have paved the way for the new paradigm named as Internet of Drones (IoD) [13]. IoD can provide an ability to drone network to access users and drones via internet.

The characteristics of drones which are easy deployment and mobility, make drones useful for communication. As drones are mobile they can be used as information carriers that is forward the information to the distant destination. If the destination is not in direct communication range of the drone, the communication occurs via multiple hops [14]. The swarm of drones collaborate to form a network for forwarding the information to the destination [15]. Although survivability, scalability and reliability are the distinctive attributes of IoD but they bring more challenges in communication as well as networking of drones [16]. The high mobility of drones make

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the topology to change rapidly, resulting in communication problems. Self-organization based approach can be the solution for cognitive IoT [17], [18].

Recently there have been some researches for solving the communication problems through cluster based routing. Zang and Zang [19] proposed mobility prediction clustering algorithm (MPCA) for drone network, a combination of dictionary structure prediction and link expiration time (LET). LET between two drones is calculated by using location and mobility information of drones. The cluster head (CH) is elected on the basis of largest weight of neighboring drones and CH then broadcasts the CH announcement to the neighboring drone. The drone which receives several messages, considers CH with longer LET. Shi and Luo [20] proposed a weighted based mechanism of cluster based location aided dynamic source routing (CBLADSR). In CBLADSR the CH is elected on the basis of highest energy level, low relative speed and have a large number of neighboring drone. Every drone maintains neighbor table of all the neighbors for communication and CH election. The drone with highest weight factor among others becomes the CH.

In [21], the authors proposed a weighted centroid localization based clustering mechanism where the drone position is calculated using fuzzy logic. The CH is elected on the basis of the location, calculated by the RSSI between two drones. After the cluster formation, the distances for all drones are calculated by the received RSSI values. CH becomes responsible for the transmission of information from CMs to the distant base station. Another RSSI based hybrid clustering scheme is proposed by Okcu and Soturk [22] where a drone is considered as a mobile sink to collect data in WSN. The CH election is based on the residual energy and position of nodes near to the drone. The nodes which are not in the range of the drone are connected to CH via multiple hops. The sensor nodes continuously record the RSSI values from drone beacons which are considered for the clustering. The highest value of RSSI is considered for the CH election.

Yu *et el.* [23] proposed a bio-inspired mobility prediction clustering mechanism by combining the mobility factor of drones and foraging model of Physarum polycephalum to the drone network. For CH election, all droness calculate the value of neighboring drones. The drone with the highest probability becomes the CH and the rest of the drones become its cluster members (CMs). In [24] authors proposed a mechanism for efficient routing strategy in drone network by integrating the clustering features of WSNs and drone. Network is divided into multiple clusters and all the sensor nodes in the cluster are stationary and location aware. The drone knows the exact location information of all the CHs of the clusters. The moving drone collects the data from the CHs and route it based on Ant Colony Optimization (ACO). Bahloul *et al.* proposed a hybrid mechanism for communication among drones based on boid Reynolds and AODV protocol in [25]. Their proposed solution has three steps namely: AODV for reactive routing computation, Boids Reynolds method for connectivity and discovery of ground base station. Boid Reynolds method is a bio-inspired method of maintaining the formation of birds' flock or school of fish with three basic rules of separation, alignment and cohesion.

In [26] a bio-inspired clustering scheme for flying ad-hoc network (FANET) named as (BICSF) was proposed. BICSF uses hybrid approach of krill herd (KH) and glowworm swarm optimization (GSO). The CH election and cluster formation takes place on the basis of residual energy and luciferin value of the drone. A drone with better residual energy is elected as CH and rest of the drones become cluster members (CMs). The cluster management is performed by using the KH algorithm in which movement of drone is predicted and then genetic operators like crossover and mutation for optimal solution.

The research on cognitive IoT is still in initial stage. Although there are few approaches proposed using intelligent and self-organized networking for IoD but there are still some issues regarding efficient network management and self-adaptability of the network. The IoD needs to have cognition or intelligence element for self-organized based networking between the swarm of drones [27] that is IoD which will result in better network management and maintenance.

Motivated by the above mentioned issues in IoD, we propose a hybrid self-organized clustering scheme for better cluster management and maintenance. The contributions of our paper are:

1) In this paper, we propose Hybrid Self-organized Clustering Scheme (HSCS) for IoD. Main phases of HSCS consists of cluster formation, cluster management and its maintenance along with communication between drones. The basic objective of this scheme is to effectively organize N numbers of drones into multi-swarm based network topology using self-organized mechanism for fire detection.
2) We propose cluster formation and CH selection methodology using Glowworm Swarm Optimization (GSO). A mechanism of swarm joining for isolated drone in HSCS is also proposed.
3) For better management of swarm based behavior of drones, we propose cluster management mechanism inspired from Dragonfly Algorithm (DA). CMs tracking methodology is also proposed by using the DA rules which help to manage the cluster topology more effectively.
4) In HSCS, the proposed cluster maintenance is performed by a mechanism to identify dead CM which improves the stability of a network.
5) A routing mechanism is also proposed for HSCS in which efficient route selection takes place using Route Selection Function (RSF).
6) The performance efficiency of our propose scheme is evaluated with the existing hybrid bio-inspired algorithm.

The rest of the paper is organized as follows; Section II consists of system model, Section III explains in detail about

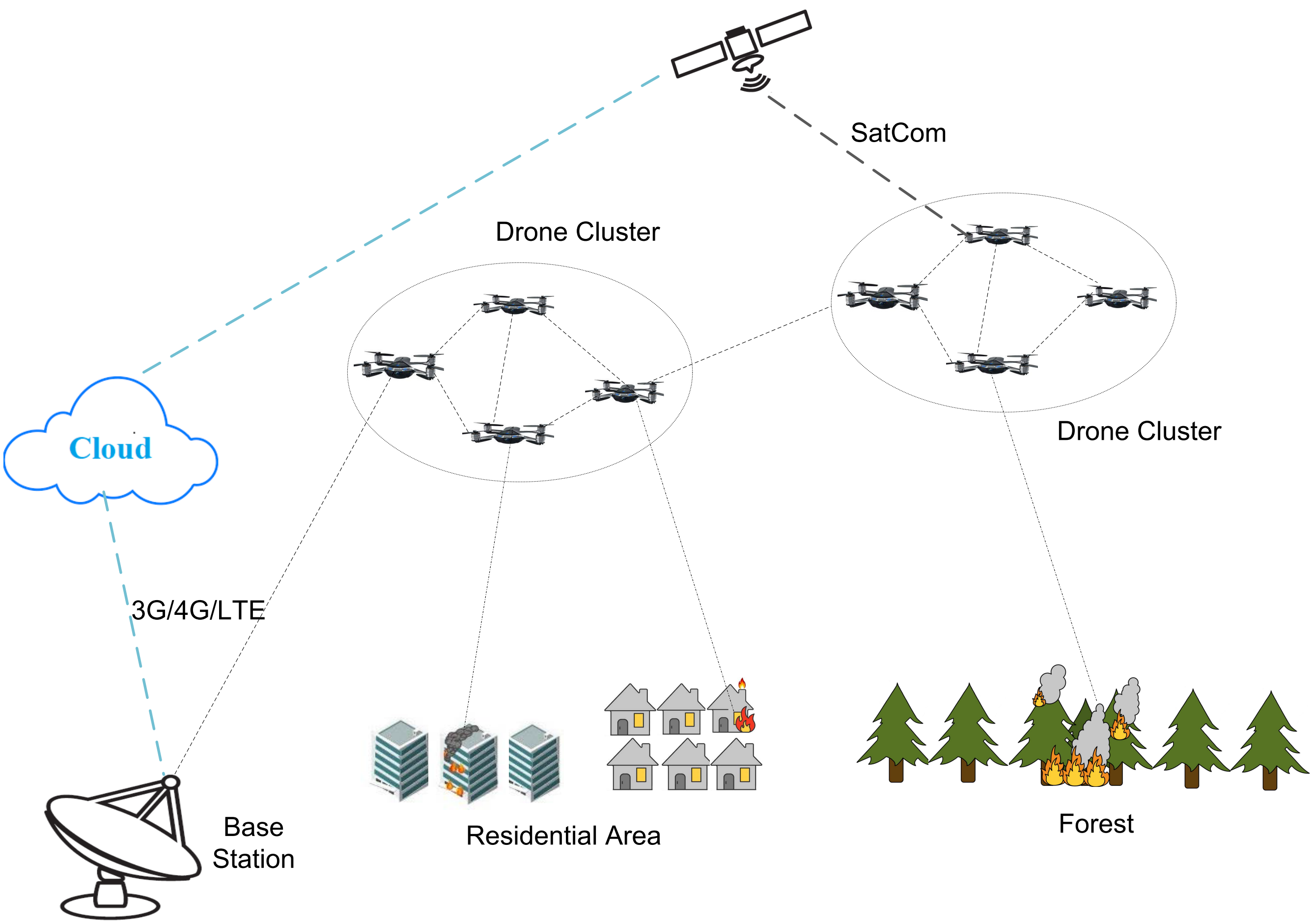

FIGURE 1. Fire detection using cluster based IoD network.

different phases of HSCS, Section IV evaluates the performance of our proposed HSCS and Section V concludes our paper.

II. SYSTEM MODEL

In this paper cluster based wireless networking model [26] is considered to handle swarm of drones which are performing an operation of fire detection as shown in figure 1. In our system model we have considered following assumptions. To handle swarms of drones we have taken a cluster based networking topology in which a drone is elected as a CH while other drones act as CMs. If a drone detect an event of fire, it can transmit that data packet to Base Station (BS) using the route selected by CH. We assume drone in an IoD network can access cloud facility using the satellite link if needed. Here the energy consumption for communication between drones depend upon receiving (E_{RX}) and transmitting (E_{TX}) of data packets.

The energy consumed in transmitting data packet can be given as:

$$E_{TX} = \begin{cases} l * (E_{elc} + \in_s * d^2) & if\ d < d_0 \\ l * \left(E_{elc} + \in_l * d^4\right) & if\ d \geq d_0 \end{cases} \quad (1)$$

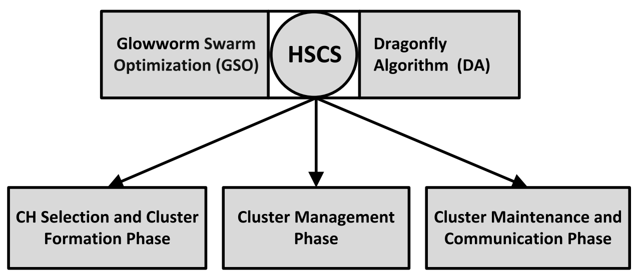

FIGURE 2. Illustration of HSCS with respect to phases.

E_{elc} is the energy dissipated by transmitter or receiver circuitry. l represents packet size, d is the distance between sender and receiver in meter while d_0 is a threshold distance. $\in_s$ *and* $\in_l$ represents energy consumed by amplifier during transmit of one bit at shorter and longer distance respectively.

The energy consumed in receiving data packet is given by:

$$E_{RX} = l * E_{elc} \quad (2)$$

III. PROPOSED SCHEME

For effective and adaptive cluster based networking solution for IoD, we propose a Hybrid Self-organized Clustering

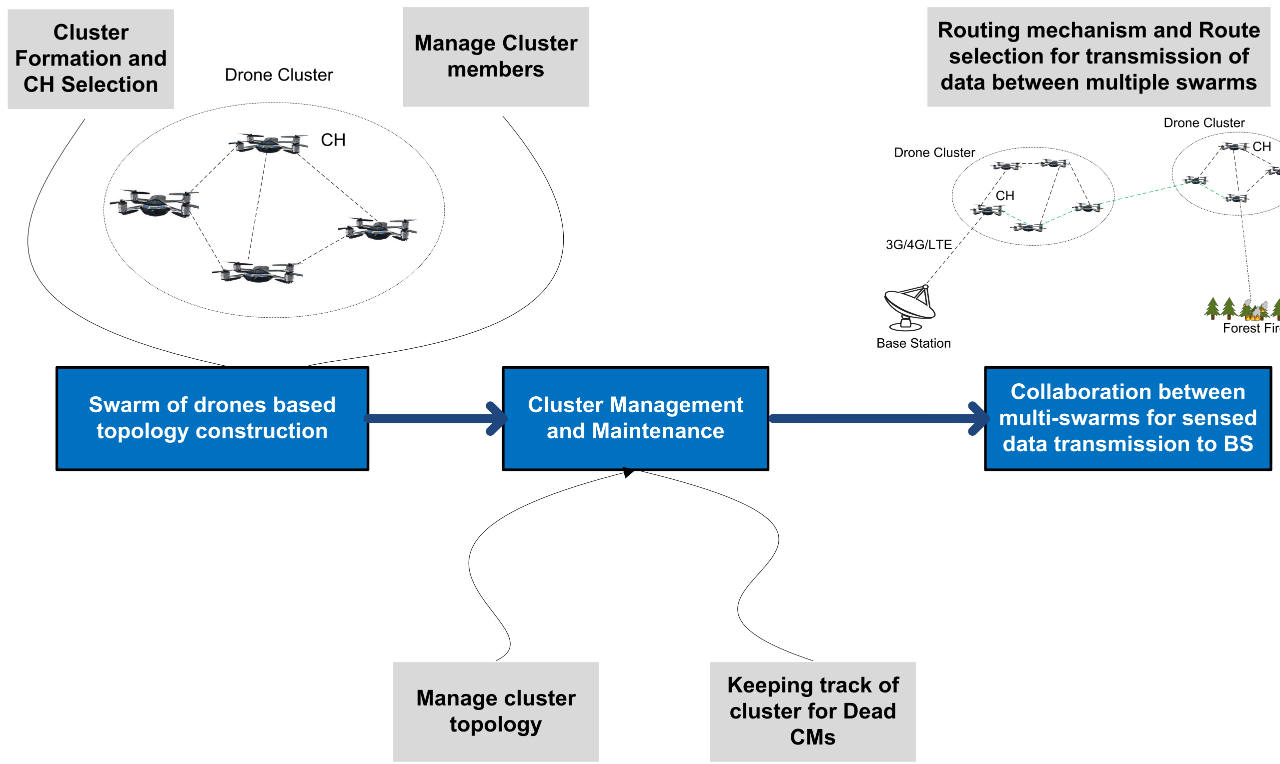

FIGURE 3. Framework of Proposed HSCS for cognitive IoT.

Scheme (HSCS) using GSO and DA which can provide an ability to manage swarm based network efficiently. HSCS consists of three phases as shown in figure 2. The CH selection and cluster formation phase is performed using GSO algorithm. Special cases for CH selection are considered based on connectivity with the BS along with the fitness comprising of residual energy and luciferin value which is calculated by the position of the drone. The drone with the highest fitness is selected as CH while rest of the drones become its CMs. The cluster management phase is inspired by DA which uses the position of the drones. The CH manages the cluster by updating the position of the drones and transmits the cluster topology table to its members. In cluster maintenance phase, the stability of a network is ensured by evaluating the status of every CM of a cluster. A routing mechanism is also proposed by using optimal route selection for transmission of sensed data to BS. The framework of HSCS is shown in figure 3.

Each phase of HSCS are explained in detail below:

A. CH SELECTION AND CLUSTER FORMATION PHASE

In our proposed scheme the drone is selected as CH on the basis of the connectivity with BS. The CH selection also takes into account the fitness of a drone which depends on residual energy and luciferin value.

In GSO algorithm [28] every glowworm has its own luciferin value and the local decision range which is neighborhood range. The luciferin value of a glowworm depends on the objective function and its position. Better the position of glowworm, brighter it is as compared to others and hence higher the luciferin value. The Luciferin value of glowworm is updated by the following equation:

$$L_i(t+1) = (1-\rho) L_i(t) + \gamma F(p_i(t)) \tag{3}$$

For each glowworm k, luciferin value is represented by $L_i(t)$, ρ is the luciferin decay constant which has range between [0, 1], luciferin enhancement fraction is given by γ and the objective function at position p_i is given by $F(p_i(t))$.

After that each glowworm i explores its neighboring region to check for the neighbors with highest luciferin value by applying the rule given below:

$$z \in N_i(t) \ \ iff \ \ D_{iz} < rd_i(t) \ \ and \ \ L_z(t) > L_i(t) \tag{4}$$

where z is the glowworm closest to glowworm i, $N_i(t)$ is the set of neighboring glowworm. D_{iz} represents the Euclidean distance, $rd_i(t)$ gives the local decision range of glowworm k and luciferin levels of glowworm z and i is represented by $L_z(t)$ and $L_i(t)$ respectively.

The best neighbor glowworm from the set of neighbors is selected by calculating the probabilities of every glowworm as:

$$Probability_{iz} = \frac{L_z(t) - L_i(t)}{\sum_{x \in N_k(t)} L_x(t) - L_i(t)} \tag{5}$$

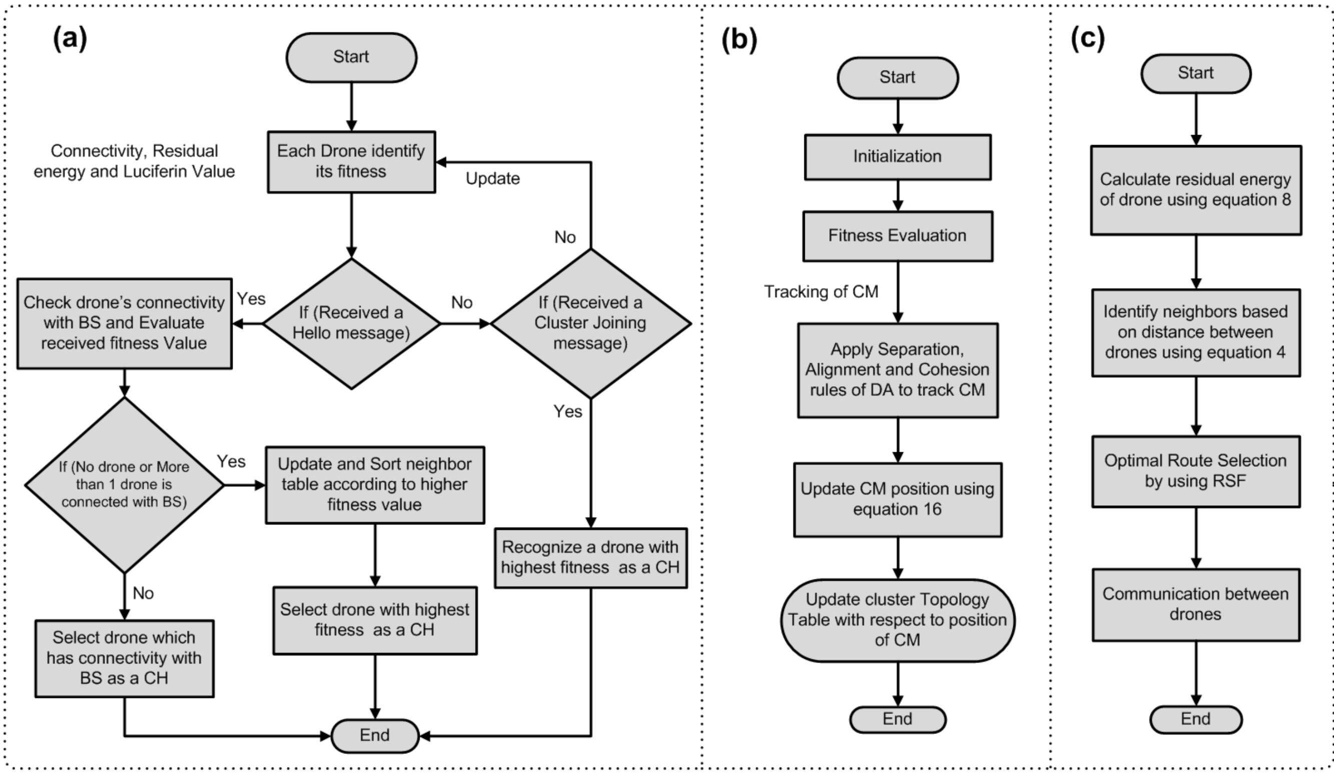

FIGURE 4. Working mechanism of HSCS: (a) CH Selection; (b) Cluster management; (c) Routing based on optimal route selection.

The position of glowworm is adjusted based on the selected best position of neighboring glowworm and calculated as follows:

$$p_i(t+1) = p_i(t) + s\frac{p_z(t) - p_i(t)}{Distance_{iz}} \tag{6}$$

where $s > 0$ is step size that a glowworm moves towards the other glowworm. The decision range $rd_i(t)$ is calculated by the following equation:

$$rd_i(t+1) = \min\{r_s \max[0, rd_i(t) + \beta(n_t - |N_i(t)|)]\} \tag{7}$$

where r_s is the radial sensor range constant, β is the model constant and n_t restricts the number of neighbors.

The residual energy of a drone is calculated by:

$$E_{res}(\mathrm{i}) = (E_I(i) - E_C(i)) \text{ where } \quad i = 1, 2, \ldots, N \tag{8}$$

Here $E_{res}(i)$ is the residual energy, $E_I(i)$ shows the initial energy of the $i-th$ drone and $E_C(i)$ represents current energy of the $i-th$ drone.

The CH selection and cluster formation mechanism of HSCS is explained in detail by using figure 4 (a) and Algorithm 1. CH selection takes place by considering 3 special cases which are given below:

1) CASE 1: A DRONE HAS CONNECTIVITY WITH THE BS

One of the criterion for a drone to be elected as a CH is its connectivity with BS. If only one drone in a swarm has a connectivity with BS, than this drone is eligible to be a CH. In this case it will declare itself as a CH and will transmit the cluster formation message to other drones. The rest of the drones will become its cluster member. The reason of this selection is because as the drone with direct connectivity with BS can quickly receive any special command or control packets for cluster as compare to other nearby drones which don't have direct connectivity with BS.

2) CASE 2: MORE THAN 1 DRONE HAS CONNECTIVITY WITH THE BS

To avoid rapid change in CH and for the stability of network if more than one drone is connected with the BS than the current CH evaluates the fitness based on drone's residual energy and luciferin value. In this case a CH will only change when the energy level of a current CH is in critical condition or it will lose its connectivity with BS. The drone with the highest fitness among other drones and having connectivity with the BS will be selected as CH.

3) WHEN THERE IS NO DIRECT CONNECTIVITY WITH THE BS

If there isn't any drone which has a direct connectivity with the BS then selection of CH will be based on fitness using energy level and current position. The drone with the highest fitness will be selected as a CH and the rest of the drones become its CMs.

Steps (1)-(21): In this algorithm, we consider that every drone calculates its fitness value. Fitness value is calculated based on residual energy, luciferin value by using equation

Algorithm 1 CH Selection and Cluster Formation Phase

For every drone in a network
Calculate Fitness using equation 8 and 3;
Do (Transmit Hello message with **Fitness**);
  While (Drone receives a Hello message)
    Check (connectivity with BS);
    Compare (**Fitness** with received **Fitness** of other drones);
    Construct (Neighbor Table with drone entries);
    Sort (Neighbor Table according to highest value of **Fitness**);
  Update (Neighbor Table with every new Hello message);
    if (1 drone has connectivity with BS)
    Declare (Itself a CH);
While (more than 1 drone has connectivity with BS || no drone has direct connectivity with BS in a cluster)
    Check (**Fitness** information of every drone from Neighbor table);
      if (drone has the highest **Fitness**)
        Transmit Cluster Formation message (CH claim);
        Declare (Itself a CH);
      else
        Wait for (Cluster Formation message);
        Consider (drone with highest **Fitness** as a CH);
        Transmit Cluster joining message (CH recognize);
end

8 and 3 respectively. After calculating fitness, every drone transmits a Hello message with its fitness value. When a drone receives the Hello message, it compares the received fitness value with its own. The drone constructs the Neighbor Table with drone entries and updates the Neighbor Table with every new Hello message and sort the table according to the highest fitness value. If a drone is connected with a BS then it declares itself as a CH. If more than one drone is connected with BS or no drone is connected with BS, the drone with highest fitness value transmits Cluster Formation message and declares itself a CH. If the fitness value of the drone is lower, it recognizes the drone with highest fitness value as CH and transmits Cluster joining message.

In a special scenario when a drone wants to join a cluster as a new member, it transmits a PING message. If a CM receives PING message, it forwards this message to its CH as a REQ message. A CH on receiving a REQ message will process the information of a new drone that wants to be a member of the cluster and updates the topology table based on new information and specific route of new member connectivity. A CH then transmits an ACK message to CM drone, after receiving ACK message, CM drone will forward that as a PONG message to a new drone and CH recognizes it as a newly joined CM. This message handshaking process is shown in figure 5.

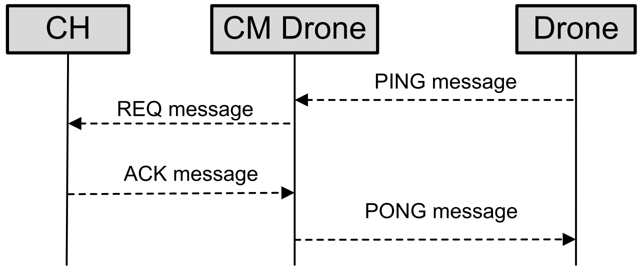

FIGURE 5. Swarm joining methodology for isolated drone in HSCS.

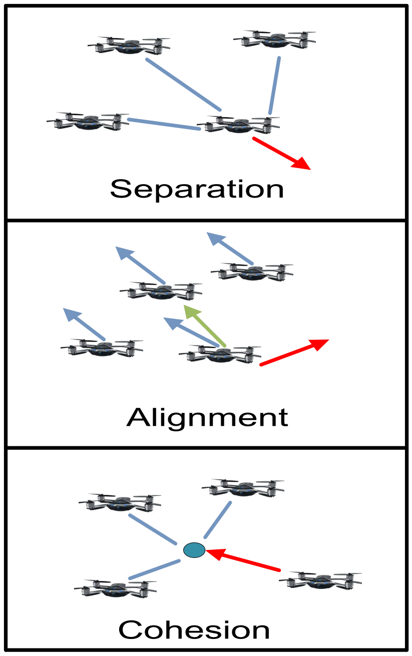

FIGURE 6. DA rules to track CMs in HSCS.

B. CLUSTER MANAGEMENT PHASE

The cluster management of HSCS comprises of tracking the CMs and managing the topology of cluster. To track CMs in HSCS, rules of DA are used as depicted in figure 6. The working mechanism of cluster management is shown in figure 4(b). In first step CH evaluates the fitness of each CM by calculating the residual energy level of each member drone. The position of each drone in a cluster is updated according to the movement based on separation, alignment and cohesion rules. Dragonflies have unique swarming behavior which comprises of hunting (static swarm) and migration (dynamic swarm). The static swarm has main characteristics as local movement and rapid changes in the flying route. In static swarm dragonflies hunt for the food while flying back and forth in a small group while in dynamic swarm, swarm of dragonflies move in one direction over a long distance. These swarming behavior are similar to the two phases of optimization using meta-heuristics namely exploration and exploitation respectively [29].

In DA, we consider three main factors for updating the position of dragonfly in swarms namely: separation, alignment and cohesion. The separation is the collision avoidance from each other in the neighbor range and is calculated as:

$$S_i = -\sum\nolimits_{k=1}^{N} X - X_k \tag{9}$$

where X is the current position, X_k represents the position of $k-th$ neighboring individual and number of neighbors is represented by N.

The alignment is when the individual matches the velocity of the other neighbors and is given by:

$$A_i = \frac{\sum_{k=1}^{N} V_k}{N} \tag{10}$$

where V_k represents the velocity of $k-th$ neighboring individual.

The cohesion is the tendency of individuals towards the center and is calculated as:

$$C_i = \frac{\sum_{k=1}^{N} X_k}{N} - X \tag{11}$$

The swarming behavior of dragonflies are the combination of these factors. For updating the position of dragonflies, two vectors namely step (ΔX) and position (X) are considered. The step vector shows the direction of movement for the dragonfly and is defined by:

$$\Delta X_{t+1} = (sS_i + aA_i + cC_i) + w\Delta X_t \tag{12}$$

where s, a and c are the separation, alignment and cohesion weights respectively while w represents the inertial weight and t shows current iteration.

After the calculation of step vector, the position vector is calculated as follows:

$$X_{t+1} = X_t + \Delta X_{t+1} \tag{13}$$

For exploration of search space is done using random walk (Levy flight) and is calculated:

$$Levy\,(x) = 0.01 \times \frac{r_1 \times \sigma}{|r_2|^{\frac{1}{\beta}}} \tag{14}$$

where r_1 and r_2 are the random numbers ranges [0, 1], β shows the constant and σ is given by:

$$\sigma = \left(\frac{\Gamma(1+\beta) \times \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}} \right)^{1/\beta} \tag{15}$$

where $\Gamma\,(x) = (x-1)!$

The position of dragonfly can be updated by the following equation:

$$X_{t+1} = X_t + Levy(d) \times X_t \tag{16}$$

where d shows the dimension of position vector.

The CH manages the cluster by tracking the CMs and updates the topology table from the received position information of all the drones in a cluster as shown in Algorithm 2. Based on updates, each CM needs to follow the movement of the CH and adjusts its position accordingly to ensure swarm behavior. The DA rules of cohesion, separation and alignment will help to maintain a swarm behavior for CM according to the updates from CH.

Algorithm 2 Cluster Management Phase

```
1  For each drone i in a network where i = 1, 2, 3, ..., N
2  Update Position ← X_{t+1} (Equation 16)
3  Each drone i in a cluster do
4  Transmit (Topology Configuration message);
5  While (CH receive Topology Configuration message)
6      Calculate(position from topology configuration
              message);
7      Update (drone position in cluster topology table);
8      Transmit (confirmation message with cluster
              topology table);
9  end
```

Steps (1)-(9): This algorithm is proposed for the management of cluster topology. Each CM drone sends its position to the other CM drones in a Topology configuration message. The CH receives the topology configuration message and updates the CMs position in cluster topology table. After updating information of every CM, CH transmits it to all CMs in a cluster as a confirmation message so that all CMs ensure swarm behavior and adjust their new position according to movement of CH.

C. NETWORK MAINTENANCE AND COMMUNICATION PHASE

In HSCS, the stability of a network is ensured by evaluating the status of every CM of a cluster. A CH defines a threshold energy level for cluster which is predefined. The methodology of network maintenance is shown in figure 7. Residual energy level of each member drone is calculated by using equation 8. If the residual energy level of a member drone is less than the threshold energy level then in this case the drone is declared as dead member. CH will update the cluster topology table and transmit it to other member drones. If the residual energy level of a member drone is greater or equal to the threshold energy level then in this case stability of member nodes are further evaluated by checking the current position of CM using equation 16 and connectivity of CM based on neighborhood range using equation 7. By evaluating current position and connectivity determine either CM is within the range of cluster. If CM is not in the range of cluster, CH declares that CM a dead node. In this case CH will update the cluster topology table and transmit it to other member drones. If all CMs are in the range of a cluster this indicates all members are stable.

Routing mechanism for HSCS is illustrated in figure 4 (c).

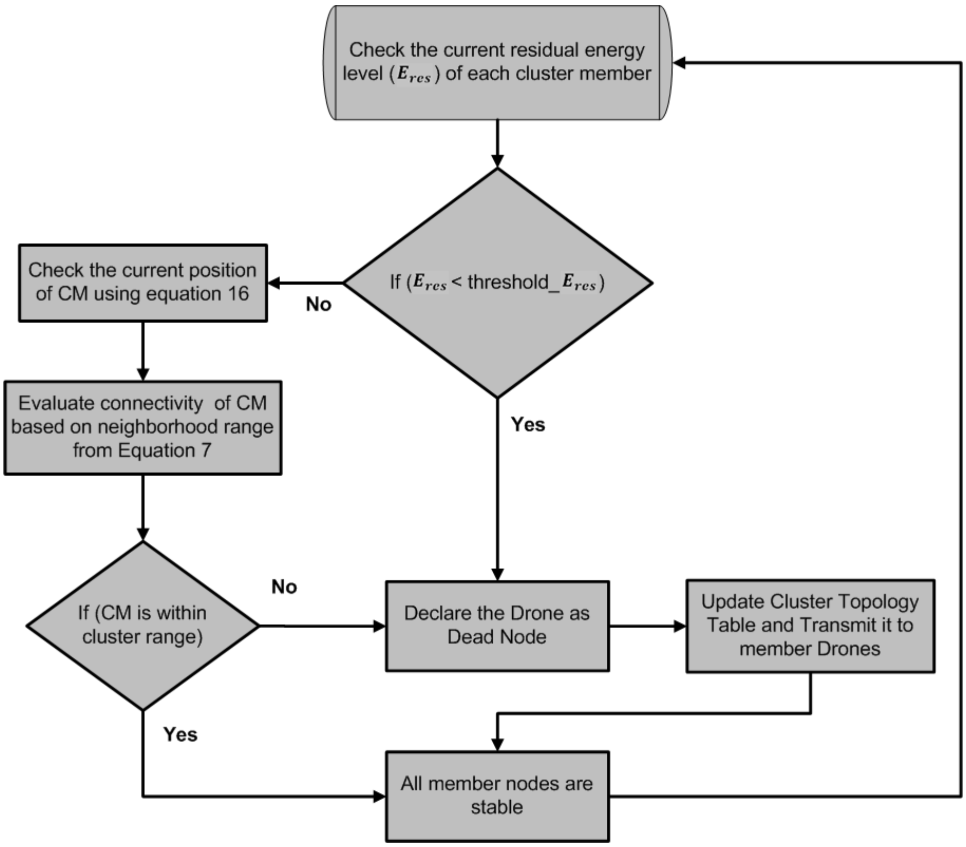

FIGURE 7. Cluster Maintenance to ensure network stability in HSCS.

As in our case, multi-swarm network topology is deployed to sense an event of fire. When a drone detect an event of fire, it needs to send that data to BS. In a case when a drone is not in the range of BS, the coalition of multi-swarm will takes place for transmission of data to BS. The drone transmits data packet to the destination through multi hops via intermediate drones which will act as a relay. In HSCS, CH is responsible for transmitting the data to BS. For routing of data, selection of optimal route plays a vital role. In HSCS, efficient route selection takes place based on the Route Selection Function (RSF) which is calculated by CH as follows:

$$RSF = \frac{E_{res}}{(N_i)(D)} \tag{17}$$

RSF depends upon the value of residual energy (E_{res}) of a drone, number of neighboring drones (N_i) and distance between drones (D) as shown in equation 17. Each drone i explores its neighboring region to check for the neighbors with highest luciferin value using equation 4. The optimal route selection based on RSF will ensure efficient routing of data to BS along with fewer delays and less consumption of energy which ultimately improves overall network performance in HSCS.

TABLE 1. Simulation parameters.

Parameters	Values
Grid Size	1000 x 1000 m^2, 2000 x 2000 m^2 and 3000 x 3000 m^2
Number of drones	15, 20, 25, 30, 35
Minimum Distance Between drones	5 m
Mobility Model	Reference Point Mobility Model
Simulation Time	120s
Position Exchange interval	2s
Drone's Energy Level at Start Time	80 Watt Hour
Transmission Range	Dynamic
Transmission Frequency	2.45 GHz
Constant Bit Rate	100 kbps
Receiver Sensitivity	-90 dBm

IV. SIMULATION RESULTS AND DISCUSSION

The proposed scheme HSCS is evaluated on the basis of cluster building time, energy consumption, cluster lifetime and probability of delivery success and compared with BICSF [26]. The simulations are performed in MATLAB with varying grid size and number of drones in a network. Rest of the parameters are given in the table 1.

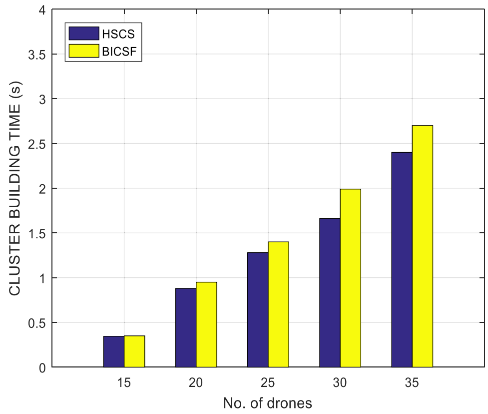

FIGURE 8. Cluster building time vs No. of drones.

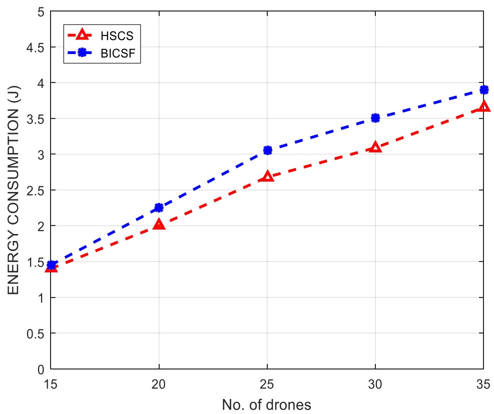

FIGURE 9. Energy Consumption vs No. of drones (Grid size 1000mx1000m).

A. CLUSTER BUILDING TIME

The time taken by the clustering algorithms in taking nodes with their corresponding fitness value as input and producing outputs which are the selection of CH and cluster member nodes is called cluster building time which also represents the computational complexity of that algorithm. As drones have low computational resources so higher cluster building will affect its performance. Higher cluster building time also increases the energy consumption and resulting in lower cluster lifetime. From the figure 8 it can be seen the insertion of more drones into the network results in higher cluster building time. The proposed HSCS outperforms BICSF as our proposed scheme takes less time in building a cluster. This lower cluster building time reduces the delay for optimal route selection resulting in energy saving during complex computations.

B. TOTAL ENERGY CONSUMPTION

The total energy consumption is the energy consumed by the algorithm for the whole network. There are three main mechanisms which consumes energy in drones, energy needed to operate drone, energy consumed by the sensors mounted on the drone and energy consumed in communication which is also the main source of energy consumption given by equations from [26]. From the figure 9 to 11 it can be seen that increasing the number of drones in the network

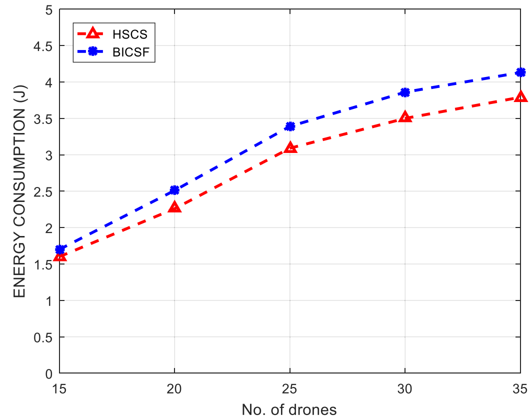

FIGURE 10. Energy Consumption vs No. of drones (Grid size 2000mx2000m).

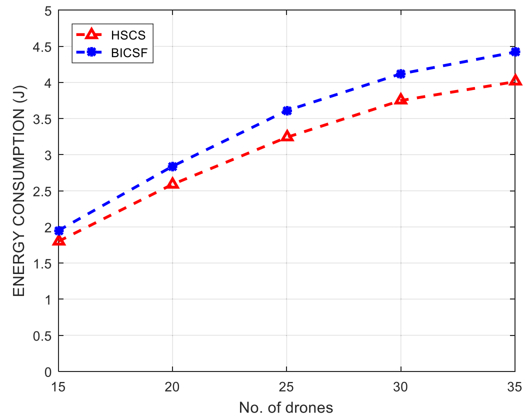

FIGURE 11. Energy Consumption vs No. of drones (Grid size 3000mx3000m).

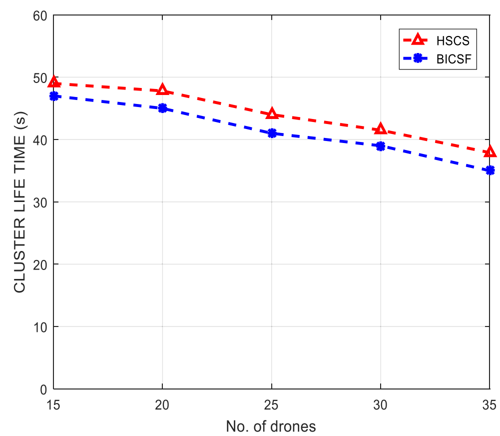

FIGURE 12. Cluster Lifetime vs No. of drones (Grid size 1000mx1000m).

consumes more energy. From the results it is clear that our HSCS performs better as compared to the other two clustering schemes. Lower energy consumption of our proposed scheme is because of the energy aware CH selection and cluster management.

C. CLUSTER LIFETIME

The cluster life time which is the total time for the cluster from its formation to disposition. When the clustering

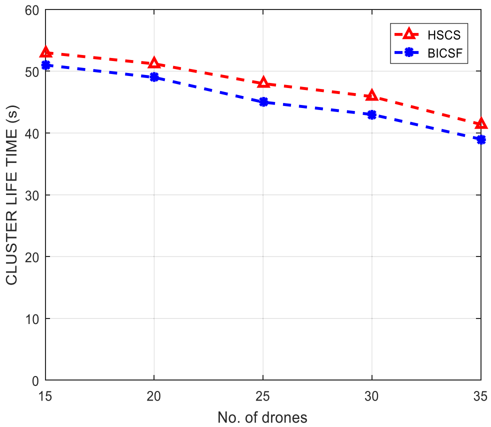

FIGURE 13. Cluster lifetime vs No. of drones (Grid size 2000mx2000m).

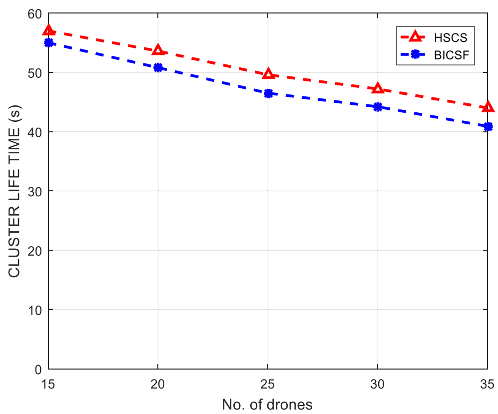

FIGURE 14. Cluster lifetime vs No. of drones (Grid size 3000mx3000m).

algorithm executes, the drone with the fittest value of fitness is elected as CH. The fitness value of drone gradually decreases over time due to different operations and when the value falls below threshold, the CH selection process takes place again. Shorter cluster lifetime shows that the clustering algorithm has to be executed repeatedly, increasing the communication as well as computational overheads in the network. It can be noted from the figure 12 to 14 that our HSCS algorithm performs better than BICSF. It can also be seen from results that the cluster lifetime decreases when more drones are introduced to the network. This is due to the fact that as there are more members in a cluster, it causes the topology to change more frequently.

D. CLUSTER LIFETIME VS ENERGY CONSUMPTION VS NO. OF DRONES

The figure 15 shows how cluster lifetime at z-axis, energy consumption at y-axis and no. of drones at x-axis have an effect on each other. The cluster lifetime depends on the number of drones and cluster building time. It can be noted from the figure the proposed HSCS has better results as compared to BICSF. As no. of drones increases in a network, the cluster building time increases which increases the energy consumption and as a result the cluster lifetime decreases. In other words when more drones are inserted into the network, the energy consumption increases because of the

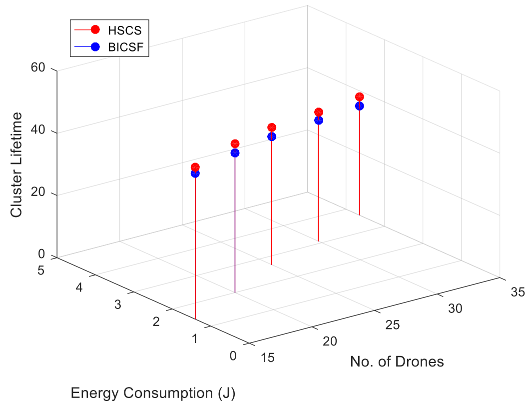

FIGURE 15. Cluster Lifetime vs Energy consumption vs No. of drones.

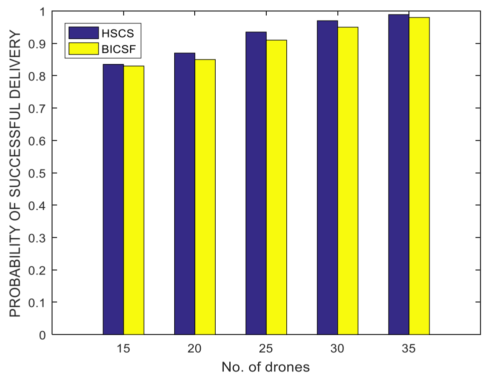

FIGURE 16. Probability of successful delivery vs No. of drones.

different operations by the resource constraint drones. Due to this degradation in resources, the clustering algorithm has to be executed more often resulting in decreasing the cluster lifetime.

E. PROBABILITY OF SUCCESSFUL DELIVERY

Probability of successful delivery is how successfully the packets are delivered at all intermediary nodes on the basis of the average hop count per packet. From the figure 16 it can be seen HSCS outperforms BICSF. With the increase of number of drones in a network, the network density increases and hence probability of successful delivery increases. This is due to the fact that with insertion of more drones in a network the packet drop ratio decreases.

V. CONCLUSION

In this paper, we proposed a cognitive networking solution by keeping in mind the main limitations of drone based IoT which are constraint resources and changing topology. We proposed an optimized topology management scheme for multi-swarm drone network deployed for fire detection. In our proposed scheme cluster formation and CH selection takes place by considering connectivity of drone with BS along with the fitness which depends on the residual energy and luciferin value (from GSO algorithm). A mechanism of swarm joining for isolated drone in HSCS is also considered. We also proposed efficient cluster management algorithm using position from DA rules which ensures swarm behavior in a cluster and alignment of CMs with respect to CH. Routing mechanism is also proposed for HSCS in which data transmission to BS takes place using optimal route selection method to ensure efficient communication. The simulation results of our proposed HSCS is compared with existing hybrid bio-inspired clustering algorithm BICSF. The results illustrate that proposed HSCS has better performance as compared to BICSF in terms of different evaluation metrics considered for performance evaluation.

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