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Mobility and Location-Aware Stable Clustering Scheme for UAV Networks

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ABSTRACT In Unmanned Aerial Vehicle (UAV) networks, mobility of the UAV and the corresponding network dynamics cause frequent network adaptation. One key challenge caused by this in Flying Ad-hoc Network (FANET) is how to maintain the link stability such that both the packet loss rate and network latency can be reduced. Clustering of UAVs could effectively improve the performance of large-scale UAV swarm. However, the use of conventional clustering schemes in dynamic and high mobility FANET will lead to more link outages. Besides, frequent updates of cluster structure would cause the instability of network topology and the increase of control overhead and latency. To solve this problem, we propose a location-based k-means UAV clustering algorithms by incorporating the mobility and relative location of the UAVs to enhance the performance and reliability of the UAV network with limited resource. The objective of the proposed Mobility and Location-aware Stable Clustering (MLSC) mechanism is to enhance the stability and accuracy of the network by reducing unnecessary overheads and network latency through incorporating several design factors with minimum resource constraints. Furthermore, we derive the relationship between the maximum coverage probability of Cluster Head (CH) and cluster size to find the optimal cluster size to minimize the network overhead. Our simulation results show that the proposed MLSC scheme significantly reduces the network overheads, and also improves packet delivery ratio and network latency as compared to the conventional clustering methods.

INDEX TERMS Unmanned aerial vehicles (UAVs), coverage probability, stable clustering, k-means clustering.

I. INTRODUCTION

The Unmanned aerial vehicles (UAVs), also known as drones are considered as the enablers of many emerging applications in telecommunications, goods delivery, and surveillance [1]. The rapid development of wireless technologies such as low cost Wi-Fi modules, micro-computer, Global Position System (GPS), and sensors enables small UAVs to be extensively used in broader range of applications. However, a number of UAVs often have to be grouped as a collaborative swarm in carrying out critical missions due to the limited resource and capability of each UAV. The deployment of a large number of drones could bring some challenges such as collisions and interference, and subsequently affects the seamless operation of a UAV swarm. For the effective collaboration and cooperation among multiple UAVs, inter-UAV communication is critical to form Flying Ad-hoc Network (FANET). Moreover, UAV networks need a highly accurate location information with smaller interaction intervals due to the high mobility pattern in a multi-UAV environment.

In a FANET, one critical challenge is the effective management of a large number of mobile UAVs and various static ground stations. In overcoming this challenge, an extensive set of mini networks can be formed in an intelligent swarm. The self-organized network formation is an example of the intelligent cluster formation, where the UAVs are self-organized to reconnect themselves after a disruption in connections. Effective management of FANET is also directly related to the flying speed of UAVs, which are usually application dependent. The mobility of FANET is higher than that of Vehicular Ad-hoc Networks (VANETs) and Mobile Ad-hoc Networks (MANETs) [2]. The UAVs are highly mobile, with the speeds of 30 to 460 km/h [3].

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The UAV mobility causes a significant impact on the link connectivity of UAV swarm networks. Effective management of UAV swarms and FANETs also relies on low latency communications. A wide variety of applications including surveillance, rescue operations, and disaster monitoring require minimal latency as the information needs to be transferred instantly. To control and minimize the communication latency, the concept of data prioritization has been developed. In addition, the priority-based routing protocol can be used to manage the Quality of Service (QoS) for various message types. Therefore, the implementation of the most suitable protocol is essential for minimizing the latency and improving the QoS of overall networks. In multi-UAV networks, the network may have several types of communication links such as UAV-UAV and UAV-to ground link. The failure of a single UAV will disrupt the network stability and QoS requirements. Hence, the key features of mobile networks are reliability and survivability through redundancy.

The peer to peer connections are formed among the UAV swarms to maintain the coordination and collaboration, which can be effectively achieved by clustering/grouping [4]. For the homogeneous small-scale FANET, a single grouping is the best choice; however, for multi-purpose heterogeneous networks, there is a need for multi-cluster network. In this scenario, the Cluster Head (CH) is responsible for the inter-cluster communication as well as down-link communication. In the clustering process, the mobile UAVs are relocated in the cluster, where the position of CH is vertically projected on the centroid of the cluster. In the clustering process, CH selection and cluster formation schemes are very important to maintain the overall cluster structure. The clustering scheme enhances the overall QoS performance of the network such as network stability, throughput, and battery life [5].

The technical challenges in UAV networks are optimal deployment of UAVs, energy limitations, path planning, interference management, and stable wireless links. The optimal UAVs deployment and finding stable wireless links have great impacts on the network reliability and lifetime. Moreover, the packet drop rate and network latency are also dependent on the link stability between UAVs. The packet forwarding in UAV networks relies on the routing mechanisms applied in the MANETs. However, due to the frequent topology changes, high mobility, and unstable wireless links make the MANET protocols unreliable in UAV networks. The main contribution of this paper is to propose a Mobility and Location-aware Stable Clustering (MLSC) scheme for randomly deployed UAVs network by incorporating the mobility and coverage probability. In this regard, we first present the coverage probability and the optimal number of CH UAVs can have to maximize the coverage area with the minimum transmit power in the given geographical area. Subsequently, we propose the k-means clustering mechanism to select stable CHs in optimal locations. Furthermore, we also present the cluster maintenance scheme with reference to the relative mobility and locations to enhance the stability of the cluster network.

The rest of this paper is organized as follows. Section II summarizes the related works and provides the literature review in the area of clustering schemes in UAV networks. In Section III, the proposed location and mobility aware clustering scheme is described in detail. In Section IV, the performance of the proposed scheme is evaluated via simulations. Section V, concludes the paper.

II. LITERATURE REVIEW

The clustering is an efficient network management scheme that can improve the overall performance of the ad-hoc UAVs network by dividing the complex network into the number of clusters. The clustering in UAV network provides several benefits such as reliability, scalability, fault tolerance, energy efficiency, latency minimization, coverage maximization, and stable connectivity. The literature of existing clustering algorithms are mainly classified into two categories [6]: (i) probabilistic clustering and (ii) deterministic clustering. The main objective of the probabilistic cluster algorithm is to find the best routing route by making the network lifetime longer. The probabilistic clustering algorithms can further be classified into three categories: (i) dynamic clustering, (ii) bio-inspired clustering, and (iii) hybrid clustering.

The UAV Routing Protocol (URP) [7] and UAV-based Linear Sensor Networks (ULSNs) [8] are examples of dynamic clustering algorithm. The URP and ULSN can effectively reduce the resource requirements of the network, and also improve the network lifetime. However, these algorithms are mainly designed for the Wireless Sensor Networks (WSNs) with the single UAV. In [9], the authors proposed the Energy-Aware Link-based Clustering (EALC) algorithm to address the problems related to the inefficient routing and UAV flight time. The author used a k-means algorithm to enhance the network lifetime by finding optimal cluster. Similarly, in [10] authors presented the Bio-Inspired Mobility Prediction Clustering (BIMPC) algorithm for the cluster formation and maintenance of large scale UAV networks. However, in both schemes, the authors did not consider the randomness and high mobility patterns of the UAVs. Moreover, the bio-inspired based Ant Colony-Bee Colony (AC-BC) scheme, Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Grey Wolf Optimization (GWO) are also used to perform the clustering in UAV networks [11], [12]. Nevertheless, these schemes did not consider the coverage probability and the optimal number of CH UAVs can have to maximize the coverage area with the minimum transmit power in the given geographical area.

To solve the issues related to the connectivity, coverage and energy consumption, the authors in [13] proposed the Received Signal Strength Indicator (RSSI) based Hybrid and Energy-Efficient Distributed (rHEED) based on HEED algorithm [6]. The rHEED scheme utilized the RSSI from the received from UAV, and also consider the residual energy of the node to elect the CH. This scheme provides the balanced and stable cluster. However, this scheme is proposed by considering a single UAV based WSN, and is not suitable for the UAV networks. The Ad-hoc On-Demand Distance Vector (AODV) protocol is also widely used in UAV networks. However, due to the dynamic link connections, it suffers from the network overhead and latency issues [14]. In [15], authors evaluated the performance of the Optimized Link State Routing (OLSR) protocol in UAV network comprising of ground stations and two UAVs, and conclude that the OLSR is unreliable in UAV networks due to the rapid topology changes.

In the case of the deterministic clustering algorithms, the CHs are elected based on the information exchanged by the neighboring UAVs. The common metrics used to elect the CHs are centrality, proximity, randomness, mobility, and residual energy. In [16], the authors present the scalable multiple target tracking system by applying Density-based Spatial Clustering Applications with Noise (DBSCAN) algorithm. The locations of the mobile target are estimated by using the extended Kalman filters. The main advantages of the proposed scheme are the path planner and optimal sensor manager to get the geolocations of targets within the cluster. The authors in [17] presented the Mobility Predication Clustering Algorithm (MPCA) based on the dictionary trie structure prediction algorithm and link expiration time mobility model. The proposed scheme is very useful to manage the stability of the network. However, due to the high mobile environment, the shape of the cluster structure changes rapidly, and a large amount of packet overhead will be introduced to maintain the stability of the cluster. The geographical-based routing protocol is presented in [18], and the authors considered mobility, direction, and velocity of UAVs to estimated the UAV link lifetime. Nevertheless, this work did not consider the coverage probability of UAV in a given geographical area. The work in [19] investigated the optimal movement and deployment area of the UAV to support the downlink wireless communications. However, the proposed scheme was limited to the single UAV and only considered for the downlink. In addition, the existing schemes did not consider the joint impact of the coverage probability and mobility of UAVs in cluster formation and maintenance mechanisms.

III. LOCATION AND MOBILITY AWARE CLUSTERING SCHEME

In this section, we describe the location and mobility aware clustering mechanism in detail. Firstly, we present the optimal deployment of CH UAVs to maximize the coverage probability. This model studies the relationship between the size of the cluster and maximum coverage probability in the network to find the optimal cluster size to minimize the number of transmissions. Secondly, we described the proposed distance based k-means clustering algorithm, and cluster maintenance scheme based on updated the relative location information by considering the speed, and transmission range of the UAVs.

A. EFFICIENT DEPLOYMENT OF CH UAVs

In this subsection, we investigate the optimal deployment of the CH UAVs in order to maximize the coverage area with the minimum transmit power. For the given target geographical area, the number of CH UAVs are equipped with the single antenna. The main objective of this scheme is to maximize the coverage performance by ensuring the coverage fields of UAVs do not overlap. The deployment model with a circular geographical area of radius R is shown in Fig. 1, where K CH UAVs must be deployed to provide the wireless coverage for the normal UAVs. The UAVs are assumed to have same transmit power. The CH UAVs' antenna gain can be approximated as [20]

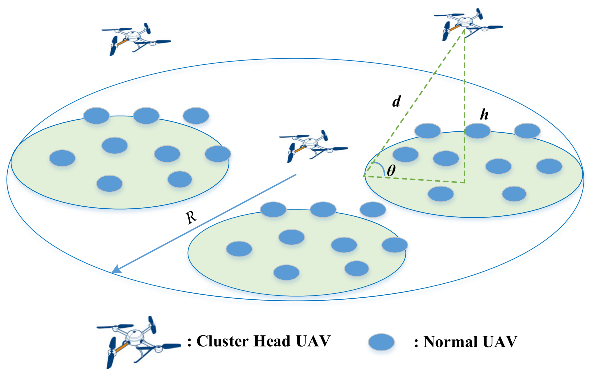

FIGURE 1. The optimal deployment of CH UAVs to maximize the coverage probability.

$$G = \begin{cases} G_{3\text{dB}}, & \frac{-\theta_B}{2} \le \varphi \le \frac{\theta_B}{2}, \\ g(\varphi), & \text{otherwise,} \end{cases} \tag{1}$$

where φ is the sector angle, $G_{3dB} \approx \frac{29000}{\theta_B^2}$ with θ_B in degrees is a main lobe gain, and $g(\varphi)$ is the antenna gain outside of the main lobe. The common approach for a channel modeling is to consider the Line-of-Sight (LoS) and Non-Line-of-Sight (NLoS) links between CH UAVs and normal UAVs. Each link has a distinct probability of occurrence which depends on the elevation angle, environment, and relative location of the CH UAVs and the normal UAVs. The shadowing and blockage loss for the NLoS links are higher as compared to the LoS Links. The received signal power at UAVs can be given as [21]

$$P_{r,j}(dB) = \begin{cases} P_t + G_{3\text{dB}} - L_{dB} - \psi_{\text{LoS}}, & \text{for LoS link,} \\ P_t + G_{3\text{dB}} - L_{dB} - \psi_{\text{NLoS}}, & \text{for NLoS link,} \end{cases} \tag{2}$$

where $P_{r,j}$ is the received signal power, P_t is the CH UAV's transmit power, and G_{3dB} is the antenna gain.

Also, the path loss L_{dB} is expressed as

$$L_{dB} = 10n\log\left(\frac{4\pi f_c d_j}{c}\right), \tag{3}$$

where f_c is the carrier frequency, c is the speed of light, d_j is the distance between CH UAV and normal UAVs, and $n \ge 2$ is the path exponent. Similarly, $\psi_{\text{LoS}} \sim N(\mu_{\text{LoS}}, \sigma^2_{\text{LoS}})$ and

$\psi_{\text{NLoS}} \sim N(\mu_{\text{NLoS}}, \sigma^2_{\text{NLoS}})$ are shadow fading with normal distribution in dB scale for LoS and NLoS links. The variance can be given as

$$\sigma_{\text{LoS}}(\theta_j) = k_1 \exp(-k_2\theta_j),$$
$$\sigma_{\text{NLoS}}(\theta_j) = g_1 \exp(-g_2\theta_j), \tag{4}$$

where $\theta_j = \sin^{-1}(h/d_j)$ is the elevation angle between CH-UAV and normal UAVs, k and g are constants, and depends on the environment.

Finally, the LoS probability is calculated as

$$P_{\text{LoS},j} = \alpha\left(\frac{180}{\pi}\theta_j - 15\right)^{\gamma}, \tag{5}$$

where α and γ are constant values reflecting the environment impact. Hence, the NLoS probability is given as [22], [23]

$$P_{\text{NLoS},j} = 1 - P_{\text{LoS},j}. \tag{6}$$

Our main goal is to provide the wireless coverage to the largest possible number of UAVs with minimum number of CH UAVs. The number of CH UAVs depends on the expected coverage in geographical area and the number of available normal UAVs. In this scenario, the number of normal UAVs is fixed to N and the number of CH UAVs is K. The main objective is to determine the optimal number of CH UAVs to achieve full coverage to N users. Let γ_{ij} is the signal to interference plus noise ratio (SINR) between UAVs i and j, and I_{ij} be an indicator of whether or not UAV i is connected to UAV j such that [24]:

$$I_{ij} = \begin{cases} 1 & \text{if } j = \arg\max\limits_{j \in \mathcal{M}} \gamma_{ij} \text{ and } \gamma_{ij} \geq \gamma_{\text{th}}, \\ 0 & \text{if otherwise.} \end{cases} \tag{7}$$

The problem can then be formulated as:

$$\min_{\mathcal{K}} \sum_{j\in\mathcal{K}} \sum_{i\in\mathcal{N}} I_{ij} \tag{8}$$
$$\text{s.t.} \quad \sum_{j\in\mathcal{K}} I_{ij} = 1, \quad \forall i \in \mathcal{N}, \tag{9}$$
$$\sum_{i\in\mathcal{N}} I_{ij} = N. \tag{10}$$

The first constraint ensures that every UAV is connected to only one CH and the second constraint ensures that all the UAVs are connected to CHs. This model ensures the optimal number of CH for a given number of UAVs in the field.

B. LOCATION BASED CLUSTER FORMATION

In this subsection, we present the clustering mechanism by using k-means clustering algorithm. Based on Section III-A analysis, we calculate the optimal number of a cluster for a given N number of UAVs in the field. The proposed scheme has two major steps; (i) elect K CHs from the set of N UAVs and divide into the K cluster with optimal size of the each cluster N_k as $N_k = \left[\frac{N}{K}\right]$, and (ii) formulate the backbone route to connect all the CHs to the sink (i.e., ground station). The UAV network can be modeled by $G = \langle U, D\rangle$, where U consists of the sink node u_0 and N UAVs. If the two UAVs are in communication range of each other, then there is a link between them. We assume that the sink/ground station has the full knowledge of the network topology. The sink is responsible for formulations of the clusters, elections of the CH for each cluster, and constructions of the backbone routing tree. The backbone routing tree connects all CHs and the sink.

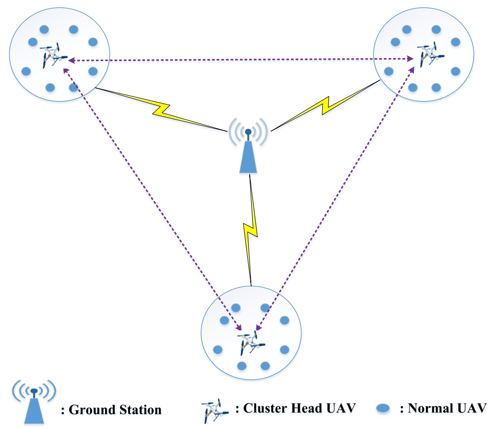

FIGURE 2. Location and mobility aware clustering in UAV networks. CHs are responsible to forward the packets to the ground station/sink.

Algorithm 1 Centralized Clustering Algorithm

Input: Number of cluster K for all $n \in N$
Output: CHs and corresponding cluster members CM_i
Start
Remaining UAVs ← All UAVs
while Remaining UAVs $(R_{UAVs})! = 0$ **do**
  Cluster the UAV network based on location using (11)-(13)
  CH_i ← UAV having minimum distances from other UAVs
  CM_i ← All UAVs in CH_i transmission range
  R_{UAVs} ← $R_{UAVs} - CMs$
end while
Return CH_i and CM_is
End

The centralized clustering algorithm is presented in Algorithm 1. The main objective of the k-means clustering algorithm is to perform the clustering of given N number of UAVs to K different clusters/groups. The important factors for the efficient clustering are to maximize the coverage probability and to determine the optimal size of the cluster. The size of the cluster affects the number of transmissions in the network. If the cluster size is large, the number of transmissions required to collect the data from member UAVs to the CH UAV will be very high and, thereby, affects the network performance. Similarly, if the cluster size is too small, the number of clusters will increase, and the data transmissions from all CH UAVs to the ground station will

Algorithm 2 Algorithm to Construct the Backbone Tree for Data Transmission From CHs to Sink

```
Input: Sink node u_0, set S of CHs, and distance D_CH between CHs
Output: List of edges A in MST to connect all CHs and the Sink node
Initialize: G_CH = ⟨U_CH, D_CH⟩
A ← ∅
for each vertex v ∈ V[U_CH] do
    MAKE-SET(v)
end for
Sort the edge nodes of D_CH into non decreasing order by locations
for each edge (u, v) ∈ E, taken in non decreasing order by minimum distance do
    if FIND-SET(u) ≠ FIND-SET(v) then
        A ← A ∪ (u, v)
        UNION (u, v)
    end if
end for
Return A
```

be very large. This, ultimately, leads to the degradation of the QoS performance of the network. From the theoretical analysis in the previous section, we can calculate the optimal number of CH UAVs for a given number of UAVs distributed in a field. To form the clusters, the CH UAVs are selected first, and Euclidian distance is calculated from each member UAV to all CH UAVs and finally, allocated to the nearest CH UAV. The main goal is to minimize the Euclidean distance of each member UAV to the closest CH UAV. The cost function to find the optimum μ_j can be defined as [25]

$$C_{n,j} = \sum_{n=1}^{N} \sum_{j=1}^{J} r_{n,j} ||x_n - \mu_j||^2, \tag{11}$$

where $r_{n,j}$ is defined as

$$r_{n,j} = \begin{cases} 1, & \text{if } j = \arg\min_i ||x_n - \mu_i||^2 \\ 0, & \text{otherwise.} \end{cases} \tag{12}$$

To minimize the cost function, first we have to take the derivative with respect to μ_j and set to zero, which gives

$$\mu_j = \frac{\sum_{n=1}^{N} r_{n,j} x_n}{\sum_{n=1}^{N} r_{n,j}}. \tag{13}$$

In addition, we also used the Minimum Spanning Tree (MST) algorithm [26], [27] to formulate the backbone route. The backbone tree construction mechanism is presented in Algorithm 2. The backbone route connects the all CHs and sink/ground station. A set S of CHs is obtained from the above clustering scheme, and we introduced a graph $G_{CH} = \langle U_{CH}, D_{CH} \rangle$, where U_{CH} consists of the sink node u_0 and set S of CHs. The distance D_{CH} is the shortest path between (CH_i, CH_j) in G. Then, we calculate the MST of the G_{CH}, and formulate the routing tree between all CHs and sink. In the auxiliary graph $G_{CH} = \langle U_{CH}, D_{CH} \rangle$, and each CH UAV in has an edge v to the each of the UAVs in its neighboring cluster. The distance of each edge (u, v) in E is taken in non decreasing order such that the total distance from the member UAVs in A to their nearest CH UAV is minimized. The computational complexity for k-means clustering is on the order of $O(K * N * I * D)$, where K is the number of clusters, N is the number of UAVs, I is the number of iteration, and D is the dimension or number of the attributes [28]. Similarly, the computational complexity of the MST algorithm is $O(ELogv)$, where E is the number of edges, and v is the vertices in the graph.

C. DISTRIBUTED UAV NETWORK IMPLEMENTATION

In this subsection, we present the distributed UAV network implementation of the proposed clustering algorithm scheme. We assumed that the UAV knows its speed and the geographical information. The location information and speed can be obtained from the attached GPS or by implementing the localization techniques. In addition, the sink knows the coverage area of the field, but does not know the location of the deployed UAVs.

The CH broadcasts an *advertisement* message to the UAVs in the cluster field to join the specified cluster. The *advertisement* message carries the information such as ID and location of CH, and the number of hop count. After receiving the *advertisement* message, the UAV updates the CH information if the hop count of the message is smaller than the pre-recorded value from same CH, and further broadcasts the message to its neighbor UAVs. After completion of CH advertisement, each UAV decides to join corresponding cluster based on the distance and number of hops to each CH.

The backbone route can be constructed in a distributed manner to connect all CH UAVs and the sink. The CHs can share their locations information by broadcasting the *advertisement* messages. The sink broadcast the central information to the UAVs through the respective CH. We used the distributed method of an approximate MST algorithm to construct the backbone network. For each CH, it elects the CH that has minimum number of hops from the set of CHs as its parent CH in the backbone route. After completing the backbone tree, each CH can have the information about neighbor CHs in the backbone tree.

D. CLUSTER MAINTENANCE

The cluster's stability rapidly degrades in a highly mobile environment. Hence, the relative speed S_k, defined for each UAV represents the good measure for the stability of a cluster. This metric can be evaluated as the average difference in velocities v between the CH UAV k and all N neighboring UAVs within its range, i.e. those belonging to the set Φ_k. Moreover, the value is normalized to be within the range of [0, 1]. The relative mobility can be expressed as [29]

$$S_k = \frac{\sum_{n=1}^{N} |v_k - v_n|}{N \cdot max\{\Omega_k\}}, \tag{14}$$

where the normalizing factor is the maximum value of the set Ω_k, and can be expressed as

$$\Omega_k = \{|v_k - v_n| \, |(v_k, v_n) > 0; \forall n \in \Phi_k\}. \tag{15}$$

Another metric which can be used to determine a stable CH UAV is relative position to its neighbors. A smaller normalized relative mean distance ∂_k indicates that the neighboring UAVs are closer to the potential CH UAV. Consequently, the mean relative distance ∂_k of UAV k is defined as

$$\partial_k = \frac{\sum_{n=1}^{N} \sqrt{[\Delta x_{k,n}]^2 + [\Delta y_{k,n}]^2 + [\Delta z_{k,n}]^2}}{N \cdot max\{Z_k\}}, \tag{16}$$

where the normalizing factor is the maximum value of the set Z_k, which is composed of all the Euclidean distances between UAVs.

Similarly, the average distance between the ground station/sink and the inter-cluster UAVs can be expressed as

$$\mathcal{D}_k = \frac{\sum_{n=1}^{N} \sqrt{[\Delta x_{k,0}]^2 + [\Delta y_{k,0}]^2 + [\Delta z_{k,0}]^2}}{N \cdot max\{\varphi_k\}}, \tag{17}$$

where φ_k is composed of all the Euclidean distance between sink and inter-cluster UAVs.

Finally, the CH selection index is evaluated as the sum of the normalized values of the mean relative speed and distances as

$$\xi_k = S_k + \partial_k + \mathcal{D}_k, \tag{18}$$

which always fall in the range [0, 3]. Upon periodical exchange of the packets amongst all the UAVs in the cluster, the kth UAV can record a list of all CH selection indexes ξ belonging to every nth UAV in its neighbor's set Φ_k. The set of all ξ for every neighbor's set Φ_k can be defined as [29]

$$\Psi_k = \{\xi_n | \forall n \in \Phi_k\}. \tag{19}$$

To make the network stable and reliable, we have to maintain the cluster structure. The cluster maintenance and backup cluster election procedure is presented in Algorithm 3. The proactive backup cluster head CH_{bkp} scheme is introduced to fulfill the CH position, if current CH is resigned or away from the network. The choice of stable CH_{bkp} is assigned based on the selection index ξ. We also defined a set of all UAVs belong to the same cluster and CH as $\varnothing_i$. The CH keeps all the information of its CMs and knowledge of neighbours set Φ_k of every kth CM. The UAV k with ID ς_k will be elected CH if the selection index ξ_k is found to be smaller than ξ_n and can be expressed as

$$CH_{bkp} = \{\varsigma_k | \xi(\varsigma_k) \leq min\{\Psi_k\}\}. \tag{20}$$

Algorithm 3 Cluster Maintenance and Backup Cluster Head Selection

```
for each CH_i in ∅_i do
    CH_i assigns the CH^i_bkp using (20)
end for
if CH_i leaves network then
    CH_bkp ← CH_i
end if
if CH_i is in the coverage zone of another CH_j then
    if CH^i_bkp is not in coverage zone of another CH_j then
        CH_bkp ← CH_i
    else
        Merge cluster ∅_i and ∅_j
    end if
end if
if CM_i is not in coverage zone of CH_i then
    go to CH election Algorithm 1
end if
```

TABLE 1. Simulation parameters.

Parameters	Value
Simulation area	2000 m*2000 m*2000 m
Simulation round	2000
Number of ground station	1
Number of UAVs	20-140
MAC protocol and frequency	IEEE 802.11, 2.4 GHz
Transmission range	250-300 m
Traffic type	CBR
Packet size	20-500 kB
CBR rate	2 Mbps
UAV speed	10-30 m/s
Mobility model	Gauss-Markov mobility model

IV. PERFORMANCE ANALYSIS

In this section, we analyze and evaluate the performance of the proposed scheme by using the MATLAB software. The simulation parameters are presented in Table 1. We use IEEE 802.11 radio standard [30] operating in the 2.4 GHz frequency band for wireless communication. First, we determined the optimal number of CH to enhance the coverage probability, which also enhances the network performance by reducing the number of network overheads. Based on the analytic result, we perform the proposed MLSC scheme in the network. The deployed UAV network and the network after proposed clustering algorithm are shown in Fig. 3 and Fig. 4, respectively.

Figure 5 presents the impact of the CH UAVs on the coverage performance in various network sizes (i.e., no of UAVs) in the given deployment scenario. It is clearly shown that the coverage performance decreases as network size increases. There is a trade-off in deploying more CH UAVs to provide the optimal coverage. By increasing the CH UAVs (or the number of clusters), the coverage can be improved. However, by increasing the number of clusters, the

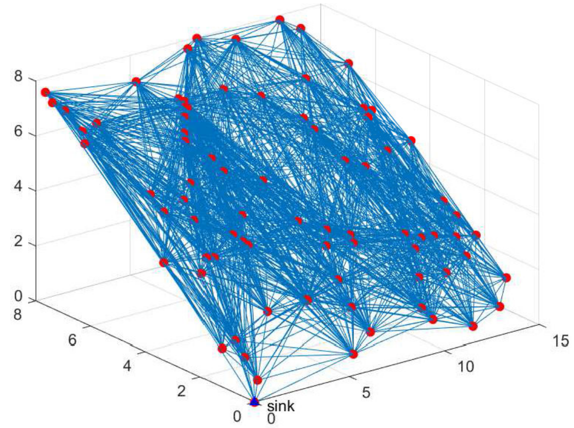

FIGURE 3. UAV node connectivity without clustering (Axis units are x100 meter). If all the UAVs trying to communicate with each other, then the network overhead will increase exponentially.

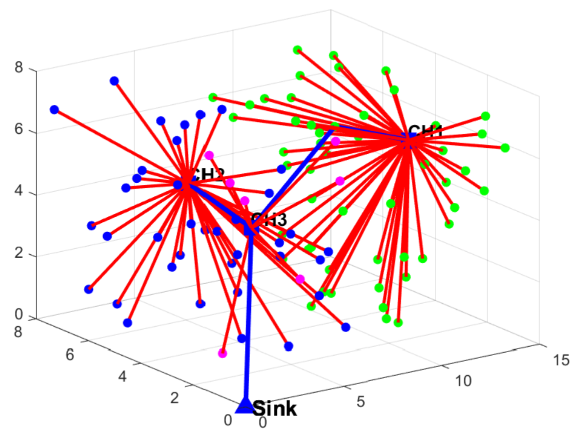

FIGURE 4. UAV network after clustering (Axis units are x100 meter). UAVs in each cluster transmit the packet to the CH. CHs are responsible to forward the packets to the ground station/sink.

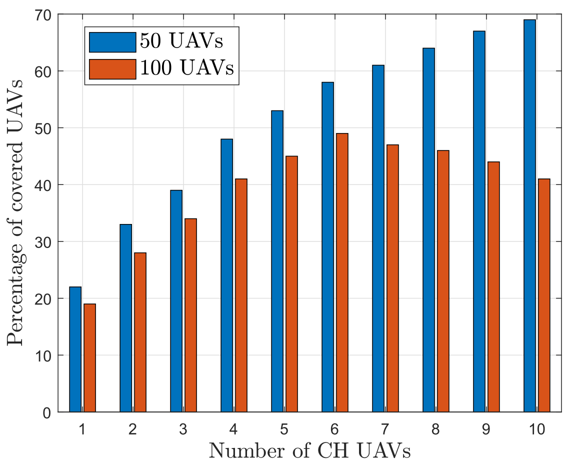

FIGURE 5. The impacts of a number of CHs on the coverage performance for various network size (i.e., for UAVs network size of 50 and 100).

aggregated interference increases which reduces the SINR value. For instance, the optimal number of CH UAVs for serving 100 UAVs is 6.

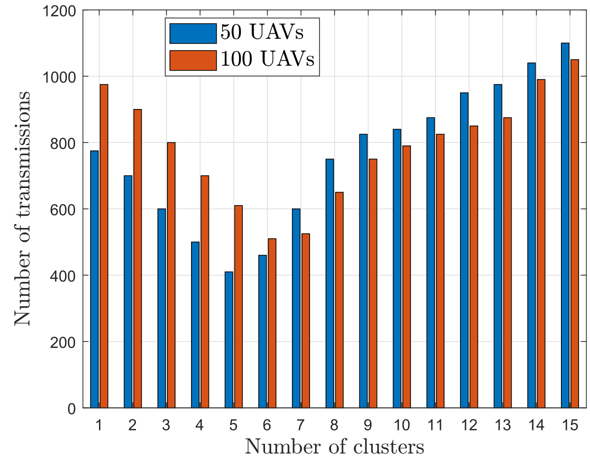

FIGURE 6. The impacts of a number of clusters on the data transmission for UAV networks of size 50 and 100.

Figure 6 represents the impact of the cluster size on the performance of the proposed scheme. The number of UAV is set 100 and 50, and the number of clusters K varies from 1 to 15. The main objective of the proposed scheme is to minimize the number of transmission in the cluster network, which is sum of the intra cluster transmission and the inter cluster transmission. From the Fig. 6, we can see that the number of transmissions decreases as the number of cluster increases until N_{ck} reaches certain value, afterwards increases of N_{ck} would lead to increase of transmissions.

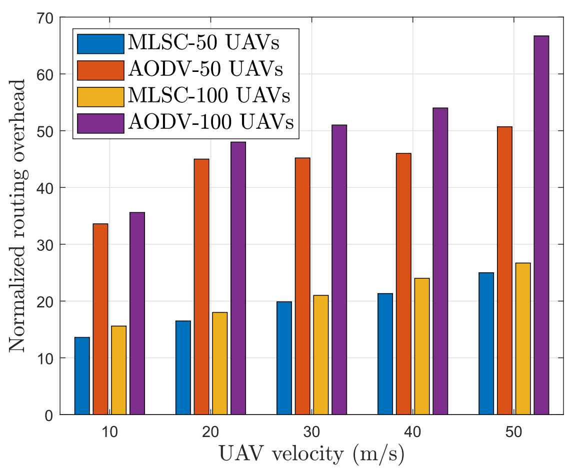

FIGURE 7. Performance comparison of the proposed MLSC scheme with conventional AODV protocol in terms of normalized routing overhead versus UAV velocity.

Figure 7 depicts the normalized routing overhead for various UAV velocities. The mobility of UAV causes high route request rate and increases the control packet overhead. The control packet overhead surpasses the data rate, and also enhances the packet drop and network latency. The normalized routing overhead of proposed MLSC and AODV increases with increased UAV velocity in both cases. The routing overhead in AODV is very high as compared to the proposed MLSC scheme because a large amount of time is required to find a path in the high-speed networks. Besides, the AODV floods a route request (RREQ) messages to find a valid path to transmit the data. The RREQ flooding causes unnecessary network overhead that degrades the overall network performance such as packet delivery ratio and network latency. However, the proposed scheme shows comparatively lower normalized routing overhead due to the distributed network formation, where only CH node is involved in the route discovery procedure.

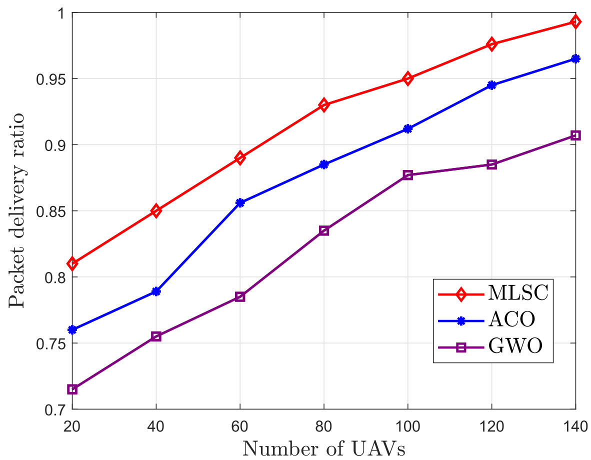

FIGURE 8. Performance comparison of the MLSC scheme with conventional ACO and GWO interms of the packet delivery ratio versus number of UAVs.

Figure 8 presents the performance comparison of the proposed MLSC scheme with conventional ACO and GWO algorithms in terms of packet delivery ratio (PDR) by varying the number of UAVs. The PDR is defined as the number of packets successfully received by the destination/sink node to the number of packets generated by the source nodes. From the Fig. 8, it is observed that the PDR in all three cases increases with the number of UAVs. However, due to the optimal CH selection algorithm and stable root selection method in the MLSC scheme, the PDR is relatively higher than the conventional ACO and GWO scheme. The proposed scheme clearly illustrates the effectiveness by delivering more than 95 percent of the generated packets to the sink. This also demonstrates that the proposed scheme effectively selects a stable CH and backup CH to maintain the stable cluster structure as compared to the other algorithms.

Figure 9 shows the end to end delay comparison of the MLSC scheme with conventional methods by varying the number of UAVs. It is observed that the average delay increases with the number of UAVs. Each UAV in the network begins to experience packet drops and congestion problems due to a large number of UAVs. Subsequently, the link connection of routing route disconnects frequently due to the mobility of UAVs. Moreover, due to the employed optimal CH and route selection scheme, the average end to end delay of the proposed MLSC scheme is lowest as compared to the conventional ACO and GWO scheme. In the proposed

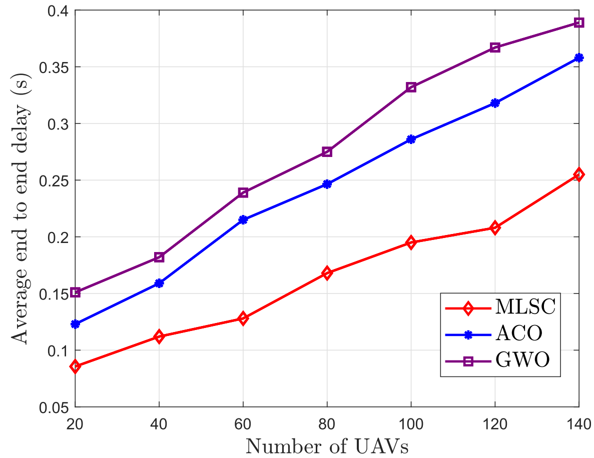

FIGURE 9. Performance comparison of the MLSC scheme with conventional ACO and GWO in terms of average end to end delay versus number of UAVs.

scheme, UAVs transmit the data to their CH, which is located in the optimal position. The packets are collected to CHs by the shortest path routing. Afterwards, the collected packets are forwarded to the sink using a stable backbone tree.

V. CONCLUSIONS

Due to the dynamic topology and high mobility of the UAVs, the conventional protocols which are designed for the stable network are not suitable for UAV networks. The conventional methods will lead to network instability and also increase the network overhead. In this paper, we proposed a location-based distributed clustering algorithm to enhance the performance and reliability of the UAV networks within resource constraints. The number of UAVs are organized into the clusters. Within the cluster, the data are collected to the CH, and forwarded to the sink/ground station following the backbone tree. We first present an analytical model to find the coverage probability of CH and the optimal number of CHs that enhances the network coverage and minimizes the number of transmissions. Then, we propose the clustering algorithm based on the results from the analytical model. With the help of the simulation results, it has been shown that the proposed scheme substantially improves the network overhead in comparison to the conventional AODV. Moreover, the significant performance is achieved in terms of PDR and average end to end delay as compared to the conventional ACO and GWO schemes.

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