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EMASS: A Novel Energy, Safety and Mobility Aware-Based Clustering Algorithm for FANETs

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ABSTRACT The Unmanned Aerial Vehicles (UAVs), organized as a Flying Ad-hoc NETwork (FANET), are used to make effective remote monitoring in diverse applications. Due to their high mobility, their energy consumption is increasingly affected leading to reduced network stability and communication efficiency. The design of node clustering of a FANET needs to consider the number of UAVs in the vicinity (transmission range) in order to ensure an adaptive reliable routing. Novel clustering schemes have been employed to deal with the highly dynamic flying behavior of UAVs and to maintain network stability. In this context, a new clustering algorithm is proposed to address the fast mobility of UAVs and provide safe inter-UAV distance, stable communication and extended network lifetime. The main contributions of this paper are first to extend and improve important metrics used in two well-known algorithms in the literature namely: The Bio-Inspired Clustering Scheme for FANETs (BICSF) and the Energy Aware Link-based Clustering (EALC). Then, exploiting the improved metrics, an Energy and Mobility-aware Stable and Safe Clustering (EMASS) algorithm, built upon new schemes useful for ensuring stability and safety in FANETs, is proposed. The simulation results showed that the EMASS algorithm outperformed the BICSF and the EALC algorithms in terms of better cluster stability, guaranteed safety, higher packet deliverability, improved energy saving and lower delays.

INDEX TERMS Unmanned aerial vehicle (UAV), clustering algorithm, energy consumption, stability, mobility, safe-inter-UAV distance, Flying Ad-hoc NETwork (FANET).

I. INTRODUCTION

Nowadays, Unmanned Aerial vehicles (UAVs), also called drones, are progressively deployed in various applications and services [1], [2]. In addition, due to the rapid development of wireless technologies such as Global Position System (GPS) and cost-effective WIFI modules, the use of UAVs is doubled thanks to their continuous connectivity, resulting in networks of UAVs.

A Flying Ad hoc Networks (FANETs) is such kind of network that incorporates several UAVs flying in a coordinated fashion and collaborating in an ad-hoc manner [3]. It can be considered as a subset of the Mobile Ad-hoc network (MANET) [4] and Vehicular Ad-hoc Network (VANET) [5] composed by mobiles and vehicular devices and addressing the same peer-to-peer communication with difference that they are moving in the air. However, FANETs present various specific features and characteristics that make them different from MANETs and VANETs namely, higher mobility, deployment in squad formation, and fast and frequent network topology changes [6]. Consequently, these features do affect the stability of UAVs and makes the design of routing protocols quite challenging [7].

On the other hand, due to technical design limitations, UAVs present the handicap of limited battery energy that limits their computational power and constrains their flight time. Therefore, these resources have an impact on the network reliability and lifetime. Furthermore, the above handicaps should be well addressed to enable energy-efficient deployment that allows continuous and stable connectivity while minimizing routing overhead and maximizing throughput [8] thus, ensuring higher longevity, better reliability, and endurance.

With larger numbers of UAVs forming swarms, the task of coordination and exchange of messages becomes more complex. Indeed, in UAV swarms, member UAVs can't be spread

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over a large area due to their limited communication range. In addition, the communication between UAVs in a swarm tends to be intermittent due to rapid movement of UAVs in such networks. Furthermore, UAVs typically are constrained in terms of energy storage which renders them having limited air endurance. Hence, there is a need to address these challenges for UAV swarm architectures to make them suitable for several applications and missions.

In this context, UAV clustering is one of the methods that can be used to address the above challenges and alleviate the tasks of inter-UAV coordination and message exchange, if designed correctly and efficiently [9]–[11]. Consequently, UAV swarms may adopt a clustering structure to control flight formation for fast and stable communication. This will allow better scalability, efficient network management and improved overall performance of the FANET (in terms of higher throughput, lower end-to-end delay, balanced load and sustainable energy provisioning [12]).

Each cluster is composed of one elected Cluster Head (CH) and several Cluster Members (CMs). Only the CH is responsible for communication, first, with its (CMs) and, second, with peer CHs. One of these CHs will have the responsibility to communicate and relay data to a Ground Base Station (GBS) (a.k.a a sink) [13]. Developing a routing protocol ensuring reliable and stable connectivity is generally a complex task in UAV networks, mostly due to the high mobility of the flying drones, that usually results in fast and dynamic topology changes leading to frequent network partitions and random UAV spatial redistributions [12].

Unfortunately, the use of conventional clustering schemes for dynamic and high mobility network of drones will create more link disconnections. In addition, frequent updates of the cluster's structure will negatively affect the stability of network topology leading to excessive load control overhead and higher latency [14].

On the other hand, several recent proposed clustering mechanisms for FANETs rely on common parameters such as the average distance between nodes and the nodes degree in order to elect CHs and to ensure the communication between CMs in each cluster. Accordingly, the CH election is based on a sequential search to allow each node finding its nearest neighbors. Unfortunately, such technique can increase the probability of collision especially in the case of a dynamic network. In this context, in the present work, an average absolute distance between nodes is defined considering a proposed safe distance that should be calculated during the clustering process to avoid collision. In addition, in order to determine the correct number of clusters, it should have a stable structure. Thus, only the stable UAVs that are situated both in the same transmission range and in the safe zone are considered as stable neighbors and participate in the CH election procedure.

An Energy and Mobility-Aware Stable and Safe Clustering (EMASS) algorithm for FANETs is proposed to ensure load-balancing, energy-aware clustering, data forwarding and routing between UAVs that strives to maintain network stability and safety.

The rest of paper is organized as follows: section II reviews and discusses the previous clustering approaches in FANETs. Section III discusses the problem formulation and the main contributions of this work. Analytical modeling of the proposed algorithm is detailed in Section IV. Section V presents extensive analysis and proposed extensions of stability-related metrics and assumptions (proposed in two earlier algorithms in the literature) to ensure performance improvements. Section VI presents the proposed EMASS clustering algorithm. The EMASS algorithm's performance evaluation is detailed in section VII. Section VIII concludes the paper.

II. RELATED WORK

Despite the increasing interests in UAVs, their rapid mobility and highly dynamic network topology changes make network stability a difficult task. Thus, resulting in quick degradation of network performance and reliability [15]. In addition, controlling the network behavior and flight operation in such dynamic environment requires a deep understanding of the interaction between the motion and network functionalities. Accordingly, recent and relevant techniques and approaches have been proposed and developed to provide efficient FANET connectivity and better link stability such as Software Defined Networking FANET (SDN-FANET) [16] and newly proposed routing protocols and clustering algorithms as covered below.

Silva *et al.* [17] proposed a Software-defined networking (SDN) based Topology management for FANETs (STFANET). They explained the centralized SDN-based topology management algorithms to ensure the continuous communications between nodes. In addition, the authors described the role of the controller that is able to construct the routing table for each node based on the length of the links. Accordingly, the UAVs can be easily located that ensures the continuous connectivity of the network and a low packet loss ratio that can minimize the energy consumption and improve the network lifetime.

Xiong *et al.* [18] studied a distributed SDN architecture for UAV swarms. The proposed SDN framework uses Message Queuing Telemetry Transport (MQTT) protocol to exchange network conditions, QoS specifications, etc. Therefore, it allows adapting the FANET to frequent changes by eliminating the energy-exhausted UAV nodes and re-generating new RF links in case of their failure. Thus, considering link stability and efficient relay selection, the proposed work provides a reliable communication between UAV swarms in FANET that improves its expected lifetime.

Qi *et al.* [19] proposed a centralized Traffic-Differentiated cluster Routing (TDR) protocol for SDN-based FANET architecture. UAVs are grouped into clusters controlled by a stationary UAV. Having the positions, speeds and transmission range of UAVs, the controller is able to monitor their communications in the cluster and to predict their transmission reliability by considering their link availability and forwarding ability. The TDR aims to address the delay-sensitive and specific QoS requirements in each cluster.

Bertizzolo *et al.* [20] proposed a new Software Defined Radio (SDR)-based framework to supervise automatically the FANET in distributed environment. Taking into account the UAVs mobility, the authors aimed to design a distributed FANET self-optimizing and automated control. The authors presented real practical results using SDR-based UAV network platform prototypes, that indicate its high flexibility level and average throughput gain.

From the above related works, it is assumed that SDN can provide a central control of FANET dealing with the dynamic behavior of UAVs and their various locations, and their residual energy. Hence, SDN-FANET can provide flexibility to FANET management and safe UAVs connectivity.

Other recent research works focus on proposing new efficient routing protocols in the FANET context in order to improve the communication between UAVs and minimize the packet delivery loss. Consequently, this can ensure the FANET reliability and stability.

Cheriguene *et al.* [21] presented and detailed three multicast-based categories of swarm routing protocols such as the Bioinspired-based, geographical location-based, and multicast-based approaches. The authors focused on the last category and proposed a new Swarm Energy efficient Multicast Routing Protocol (SEMRP) aiming to ensure network reliability and scalability in order to improve its lifetime. In this context, an optimal multicast tree was built to transfer data from one UAV swarm member to another. Accordingly, two previous versions of the SEMRP protocol (SEMRP-v1 and SEMRP-v2) were revisited to minimize the energy consumption while finding the optimal route to the multicast destination nodes. Referring to the obtained results, SEMRP ensures efficient data forwarding between UAVs by increasing the Packet Delivery Ratio (PDR) and reducing the End-to-End delay (EED). Accordingly, a minimum transmission energy leading to improved network lifetime was achieved.

Bousbaa *et al.* [22] focused on swarm routing protocols and proposed the geocast-based routing protocol for a fleet of UAVs (GeoUAVs) used to manage a wildfire zone. The objective of this protocol was to transmit data to a group of UAVs localized in a specific geo-location. The results showed that the GeoUAVs protocol was able to disseminate data to destination nodes with a reduced average EED due to an accurate data transmission process. In addition, a high throughput and PDR were achieved for various network densities testifying the effectiveness of the protocol.

Different contributions based on clustering methods were proposed recently in the literature. Some cluster-based routing protocols have been proposed for UAV-based data gathering and forwarding in FANETs in order to remedy to frequent disconnections between UAVs.

In [12], Aadil *et al.*, presented the Energy Aware Link-based Clustering (EALC) algorithm for FANETs. The EALC aims to address two major problems in UAV routings such as short flight time and inefficient routing. To resolve both problems, the authors used a variant of K-means density clustering algorithm [23]. An optimal cluster enhances the cluster lifetime and reduces the routing overhead. In the process of CH selection, EALC uses the modified K-means density algorithm.

In [24], Khan *et al.* proposed a Bio-inspired Clustering Scheme for FANETs (BICSF) based on the use of Glowworm Swarm Optimization (GSO) [25] and Krill Heard (KH) [26] algorithms. The first one was implemented for cluster formation and CH election and the behavior study of KH was used for cluster maintenance. This scheme was evaluated with the Grey Wolf Optimization (GWO) and Ant Colony Optimization (ACO)-based clustering algorithms. Authors demonstrated that the proposed algorithm presents better results in terms of energy consumption, cluster lifetime, and cluster building time.

Kumar *et al.* [27] proposed a Quality of Service Provisioning framework for a UAV-assisted (QSPU) aerial ad-hoc network environment, focusing on reliable aerial communication. The UAV's aerial mobility and service parameters are modeled taking into consideration the highly dynamic aerial ad-hoc environments. UAV-centric mobility models are deployed to develop a complete aerial routing framework. The authors conducted a comparative performance evaluation to demonstrate the benefits of the proposed aerial communication framework.

Bhandari *et al.* [11] introduced a Mobility and Location-aware Stable Clustering (MLSC) mechanism in order to improve the drone network stability and efficiency taking into account the drones mobility level. Furthermore, the authors derive a relationship between the maximum coverage probability of CH and cluster size with the objective to find the optimal cluster size that minimizes network overhead. The obtained results demonstrated that the proposed mechanism provided a high Packet Delivery Ratio (PDR) with minimum network latency compared to conventional clustering methods.

Aftab *et al.* [28] suggested a Hybrid Self-organized Clustering Scheme (HSCS). They have exploited the GSO mechanism to create clusters and to select CHs. They have also tracked the behavior of cluster members by the use of the Dragonfly Algorithm (DA) in order to guarantee efficient cluster management. Furthermore, authors carried out an optimized drone route selection method to transmit data to the Base Station (BS). The results were compared with those obtained in [24] and demonstrated that HSCS outperformed peer protocols.

Aissa *et al.* [29] proposed a novel strategy for constructing fuzzy logic-based clustering algorithms useful for VANETs. The CH election was performed by taking into account the candidate nodes' relative speed and distance to other members of the cluster, using a fuzzy logic inference system. To ensure cluster stability, the authors have established an efficient cluster maintenance scheme by identifying the specific CHs or CMs leaving the cluster.

TABLE 1. EMASS performance positioning within FANET solutions/algorithm frameworks.

Solutions	References	QoS Parameters: Energy-Awareness	Network Lifetime	PDR	EED	Throughput	Nb. Leaving CH	Nb. Re-associations	Re-association Time	Other criteria: 3d Topology	Stability	Safety	Simulator
SDN-FANET	[16]	✓	✗	✓	✗	✗	✗	✗	✗	✓	✗	✗	OMNeT++
	[17]	✗	✗	✓	✓	✗	✗	✗	✗	✗	✓	✗	OMNet++
	[18]	✓	✗	✗	✓	✗	✗	✗	✗	✗	✓	✗	-
	[19]	✗	✗	✓	✓	✓	✗	✗	✗	✗	✗	✗	TinyOs
	[20]	✓	✗	✗	✗	✓	✗	✗	✗	✓	✗	✗	Real Practical
RP	[21]	✓	✗	✓	✓	✓	✗	✗	✗	✓	✗	✗	NS-2
	[22]	✗	✗	✓	✓	✓	✗	✗	✗	✓	✗	✗	NS-3
Clus Algo.	[12]	✓	✓	✓	✗	✗	✗	✗	✗	✓	✗	✗	Matlab
	[24]	✓	✓	✓	✗	✗	✗	✗	✗	✗	✓	✗	Matlab
	[28]	✓	✓	✓	✗	✗	✗	✗	✗	✗	✓	✗	Matlab
EMASS		✓	✓	✓	✓	✗	✓	✓	✓	✗	✓	✓	Matlab

Table 1 summarizes the main characteristics of the discussed solutions (SDN-FANET, Routing Protocols (RP) and Clustering Algorithms (Clus Algo.)) for FANET reliability.

Motivated by the efficient clustering solutions for FANETs that achieve low-energy consumption and improve the network lifetime, a new power-aware clustering algorithm is proposed and implemented. This algorithm considers UAV mobility, stability, and safety to provide stable and reliable routing and efficient data collection and forwarding.

III. PROBLEM FORMULATION AND CONTRIBUTION

The majority of the clustering schemes for FANETs, proposed in antecedent works, rely on a simple equation of neighborhood which takes into consideration only the value of the transmission range as a necessary and sufficient condition for two nodes to be neighbors. This assumption is correct for general cases related to Ad-Hoc, MANET and VANET networks. However, most of the time, for UAVs, this assumption is not efficient and consistent because the neighborhood exists only when a safe distance is ensured between UAVs.

In this context, some inefficiencies are found in some of the stability-related metrics and assumptions used in EALC [12] and BICSF [24] algorithms leading to inefficient cluster stability relying on inconsistent parameters. For instance, the clustering process in both algorithms is based on the use of the passive distance metric to select CHs. This distance does not consider the safety degree between nodes needed to reduce collision probability and increase network stability.

In the EALC, the node degree parameter (i.e., number of neighboring UAVs (N_i), for a node i situated in the same transmission range) was used as one of the main parameters in the fit function. This is not a consistent weight as it does not take into consideration the respective, relative positions of these neighboring nodes. Only stable neighbors situated at a safe distance from the current node must be taken into consideration to ensure safety and avoid the possibility of collision. Therefore, it is motivating to overcome this inefficiency and to consider UAVs at safe distance and belonging to the node's neighborhood set (N_i) to build relatively stable cluster structures.

Accordingly, the main purpose is of this work is to improve these proposed clustering approaches by implementing new parameters to assure stability and safety for efficient inter-UAVs communication in FANETs. Using these new parameter settings, a novel enhanced clustering algorithm, namely, the EMASS, is proposed and detailed in Section VI.

Figure 1 illustrates how the safe distance between UAVs should be respected in order to build safe and stable clusters.

IV. ALGORITHM ANALYTICAL MODEL

Firstly, an analytical model of the EMASS algorithm is developed. The UAV network is given as an undirected Euclidean graph $G = (V, E)$ for which V is a set of UAV nodes, and E represents the set of links of the graph G. r represents the transmission range between two nodes (u, v). For the sake of simplicity, it is assumed that r is the same for all UAVs (i.e., all UAVs using the same transmission hardware).

The set of edges E are defined, through the definition of node neighborhood, as: two nodes are considered neighbors if the distance between them is less than r. Hence, for any

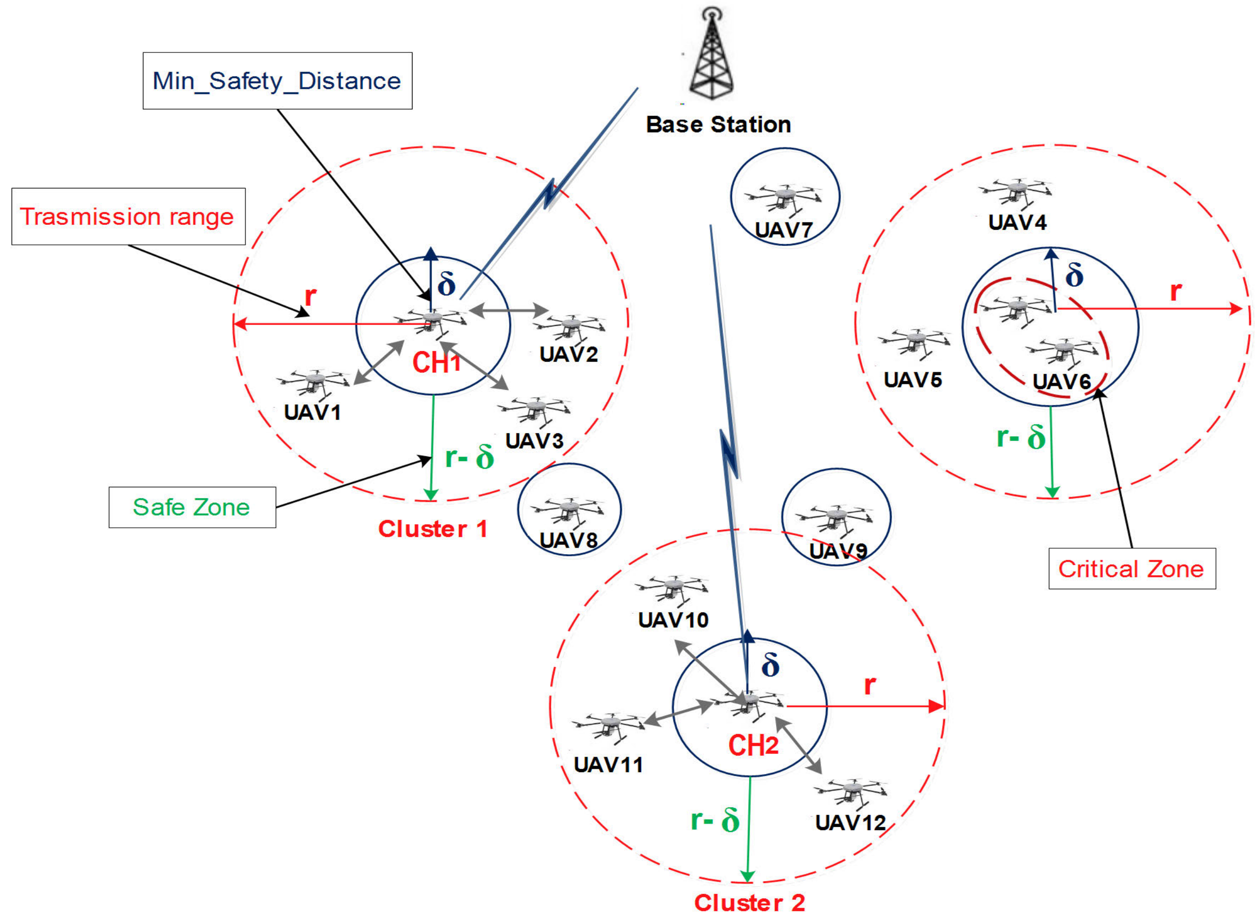


FIGURE 1. **General proposed idea for safe and stable FANET clustering.**

pair of nodes (u,v) ∈ V,

$$if\ dist(u, v) \leq r \quad then\ \{u, v\} \in E \tag{1}$$

On the other hand, the UAVs follow specific mobility patterns during their movement on the same altitude and dictated by the mission. Despite their dynamic behavior, a stable UAV network connectivity must be created to ensure an energy-efficient interconnection between UAV nodes resulting in a maximum coverage of the target monitored area and a maximum lifetime. The objective is to design a reliable clustering scheme ensuring a trade-off between the fast mobility of UAVs and the energy, safety, and stability requirements of any UAV system.

A. DEFINING THE HELLO PACKET STRUCTURE

In the suggested UAV system, to facilitate the inter-UAV communication and make it clearer, each node sends HELLO packets to its neighbors to inform them about its ID, velocity, position, and direction. In addition, once these packets are received by neighbors, the angles between their velocity vectors should be determined using their position information as in [30], [31].

State	UAV ID	Cluster ID	Velocity	Position	β_i	ξ_i	Direction
1	2	3	4	5	6	7	8

FIGURE 2. **Hello message structure of the embedded information.**

To keep things simple, it is assumed that all UAVs are heading in the same direction and consequently, this will guarantee a stable link connectivity with the respective cluster head each UAV is associated with.

The structure of the Hello packet is shown in Figure 2. For a given UAV, it is composed by the following information: UAV state, UAV ID ID_i, cluster ID CID_i (that is the cluster head ID), speed v_i, position (x_i,y_i) (given by GPS), Cluster Head selection index β_i, UAV behavior ξ_i and UAV flying direction.

The UAV state indicates its role in the cluster, either a *CH* or Cluster Member (*CM*). The UAV ID ID_i and cluster ID CID_i represent the UAV and the *CH* identifiers, respectively. The UAV velocity and position details its mobility information. The CH selection index β_i is calculated periodically by each UAV for CH election. The ξ_i parameter indicates the

UAV behavior, so that, it is set to 1 if the UAV expects to leave the system that excludes it from the election procedure and to 0 otherwise.

B. NETWORK CONNECTIVITY (NODAL DEGREE)

It is stated, in literature, that if the distance between two nodes is less than or equals to the transmission range r, they can be considered as two r-neighbors. This distance can be calculated using the position information enclosed in the broadcasted HELLO packet. Therefore, the set of r-neighbors of a node i, N_i can be expressed as follows:

$$N_i = \left\{ v_j, \, such \, that \, dis_{i,j} \leq r \right\} \tag{2}$$

where $dis_{i,j}$ is the average distance between UAV_i and UAV_j. In other words, the set N_i represents the neighborhood vicinity of a node i in terms of transmission range.

Accordingly, the total number of r-neighbors of each node i is defined as its nodal degree (nd_i) or the cardinality of the set N_i. It is calculated as follows:

$$nd_i = |N_i| \tag{3}$$

C. AVERAGE DISTANCE

Let (x_i, y_i, z_i) and (x_j, y_j, z_j) be the coordinate of the mobile nodes UAV_i and UAV_j in the coordinate system xyz, respectively. The absolute distance between the two UAVs is calculated as follows:

$$dis_{i,j} = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2 + (z_j - z_i)^2} \tag{4}$$

If a cluster contains N nodes, then the average absolute distance between all r-neighbors of a current UAV_i is obtained as follows:

$$ad_i = \frac{1}{N_i - 1} \sum_{j=1}^{N_i - 1} dis_{i,j} \tag{5}$$

V. PARAMETERS SETTING ANALYSIS AND ENHANCEMENT

In the fit function, elaborated in [24], some serious flaws affecting the accuracy and adequacy of the CH selection are found. The authors of [24] define a path detection function to select the best data communication path between UAVs. This function combined various parameters such as the UAVs' residual energy, the nodal degree and the distance between UAVs. This path detection function was expressed as follows:

$$Path \, Detection \, Function = \frac{w_1 * Residual \, energy}{(w_2 * N_i)(w_3 * distance)} \tag{6}$$

where w_1, w_2 and w_3 are the weights for the used parameters respectively and $w_1 + w_2 + w_3 = 1$. The authors noted that the energy-efficient path detection reduces energy consumption in the cluster and enhances FANET lifetime.

In this context, the number of neighboring UAVs (N_i), for a node i, is not a consistent parameter as it does not take into consideration the safety distance these neighboring nodes are situated at. Therefore, only stable neighbors that are situated at a safe distance of the current node must be taken into consideration in N_i. Hence, in the proposed algorithm, the UAVs with safe neighborhood degree (N_i) are considered in order to build relatively stable and safe cluster structure.

A. CREATION OF A SAFE ZONE FOR COLLISION AVOIDANCE

As safety is usually a primary concern (not being considered in earlier works e.g., [[12], [24]]) for FANETs, then, to avoid collision between every pair UAV_i and UAV_j in the system, the inter-distance between all these pairs of nodes must satisfy the following inequation:

$$dis_{i,j} > \delta \tag{7}$$

where δ denotes the minimum safety distance between UAV_i and UAV_j which exists during all the flight to prevent any collision between them. It is worth mentioning that the safety distance δ must be much smaller than the transmission range r that is: $\delta \ll r$.

1) ASSUMPTIONS

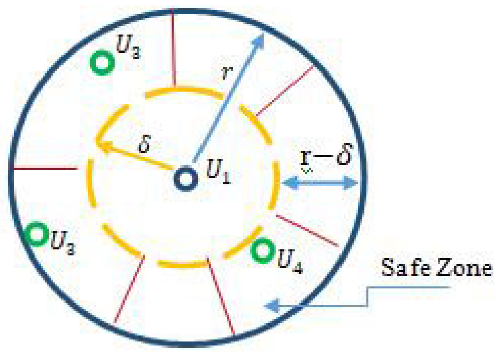
For the sake of simplicity, it is assumed that all the UAVs have the same forward velocity, and their flight is considered in a horizontal plane with x and y coordinates only (assuming stable flight condition). During the CH selection process, for all participating nodes, (7) will be used as a basis to discard nodes placed at a critical distance, from their list of neighbors N_i. This will result in decreasing overhead and time consumed on unnecessary calculations. Consequently, the neighborhood of nodes does not rely only on the existence of UAVs in the transmission range, but also on their position within a safe zone as well. Equations (2) and (7) are combined to obtain:

$$\delta < dis_{i,j} \leq r \tag{8}$$

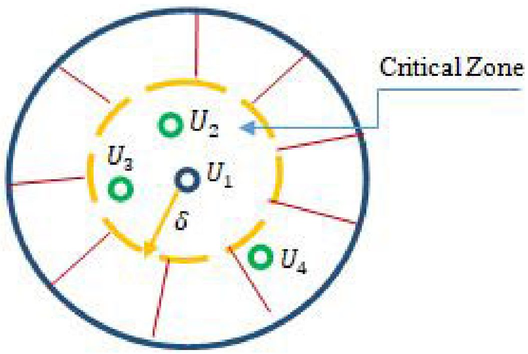
The interpretation of (8) is explained by Figure 3. In Figure 3(a), the inter-distance between U_1 and $\{U_2, U_3, U_4\}$ is bigger than δ and less than r. Consequently, U_1 is legible to participate in the CH selection process. However, in Figure 3(b), the inter-distance between U_1 and $\{U_2, U_3\}$ is less than r but it is also less than δ. Consequently, U_1 is not legible to participate in the CH selection process and it will be discarded as it is situated in a critical zone with the nodes $\{U_2, U_3\}$. Together, they form an unstable and unsafe neighborhood.

Furthermore, two incorporated disks, that define the safe regions of UAVs during the flight, are investigated. The first big disk with radius r (the transmission range) and the second small one with a radius δ. If there is an intersection with other UAVs'safe region, the nodes situated in the inner disk should be eliminated from the CH selection process.

It is clear that the information about the safe distance can improve the decision-making process with regards to the election of a stable CH. A CH, situated in a critical distance at a CM, cannot keep a stable neighborhood and consequently



(a) Safe Neighborhood: Refence node U_1 is situated at a safe distance from its neighbors $\{U_2, U_3, U_4\}$



(b) Unsafe Neighborhood: Refence node U_1 is situated at a critical distance from its neighbors $\{U_2, U_3\}$

FIGURE 3. **UAV system topology.**

cannot act as a stable neighbor and it will be discarded from the election process. In this context, (8) is used to eliminate unstable UAVs that are not allowed to be safe and stable neighbors.

It is noted that (8) guarantees that the stable and safe neighbors of a prospective *CH* node are situated on a disk with an area equals to $\Pi * (r - \delta)^2$ and where the *CH* constitutes the center of that disk. At the same time, (8) indicates that the unstable and unsafe neighbors of a prospective *CH* node, are situated on a disk with an area equals to $\Pi * \delta^2$.

Again, it can be shown that in (6), the parameter Distance represents the distance between the UAVs. However, it does not take into consideration the safety distance which should be respected by neighbor UAVs amongst themselves. Accordingly, the proposed work aims to correct this flaw, that was detected in BICSF [24] and in EALC [12], and thus introduces next, the proposed new distance parameter.

B. THE IMPROVED AVERAGE ABSOLUTE DISTANCE

The contribution is to select delegated *CH*s which are situated in a safe distance from their neighbors. Based on the above observation, the proposed safe distance $safed_{i,j}$ between UAV_i and UAV_j is presented as follows:

$$safed_{i,j} = \begin{cases} dis_{i,j}, & if\ dis_{i,j} \leq r\ and\ dis_{i,j} > \delta \\ r + \delta, & \text{otherwise} \end{cases} \tag{9}$$

Formula (9) penalizes UAV_j which does not respect the safe inter-UAV distance by setting its distance from UAV_i to $r + \delta$ in such a way to isolate it virtually from the rest of the neighbors of the UAV_i.

The newly proposed average absolute distance ψ_i between UAVs, that are directly connected to UAV_i, is then calculated as follows:

$$\psi_i = \frac{1}{nd_i - 1} \sum_{j=1}^{nd_{i-1}} safed_{i,j} \tag{10}$$

The smaller the value of ψ_i, the closer the position of the node to the center of its neighbors. It is to be noted that (10) is an improved version of the classical average absolute distance described in (5).

The authors of [12] proposed a fitness function to enable optimal *CH* selection that improves the clustering process resulting in reduction of network energy consumption and in extending cluster lifetime. Furthermore, they have set forward a condition that constrains the number of *CM*s to be the same for all clusters.

This constraint is not reasonable, due to the dynamic behavior of UAVs that modify their positions constantly, and randomly and hence update their set of neighbors as well.

Furthermore, it was stated in [12], that during the clustering process, each UAV determines the set of its neighbor nodes figuring in its transmission vicinity. Consequently, it calculates its fitness value using equation (11) and forwards it to its neighbors.

$$Fitness = \frac{w_1 * Energy_{res}}{(w_2 * avg_{dis})(w_3 * delta_{diff})} \tag{11}$$

Here, the $Energy_{res}$ is the UAV' s residual energy value, avg_{dis} represents the average distance between the UAV and its neighbor nodes and $delta_{diff}$ is the delta difference parameter. w_1, w_2 and w_3 are the above parameters respectively. The delta difference parameter, calculated using equation (12), is used to compare the node's degree with an ideal one to decide if it can be a cluster member or not.

$$delta_{diff} = \left| Ideal_{degree} - Node_{degree} \right| \tag{12}$$

Here, again, a serious flaw is shown, which is related to use of the parachuted value of the ideal degree $Ideal_{degree}$ proposed in [12]. Effectively, the authors claimed that the ideal number of nodes that a cluster head can manipulate is limited by the $Ideal_{degree}$ parameter used in (12). In addition, no rationale for computation is given for this parameter, as pointed out in [32] where they have criticized the used way that was initially proposed in [33]. It is estimated that the use of a predefined ideal degree value with no clear rationale will lead to the creation many cluster heads, which may result into an increase of energy consumption due to the increased communication overhead with the *CH*s and to an increased complexity of the cluster management.

Moreover, as stated in [24], authors in [12] have used the classical equation (4) wrongly, by setting the inner summation up to N_i instead of up to N_{i-1} (counting the current node as well) to calculate the average distance. Therefore, in the present work, this issue is solved by proposing the use of equation (10) instead of (5) which results in collision avoidance due to the inclusion of equation (9) that computes the safe distance parameter $safed_{i,j}$. This reinforces the concern for safety assurance in clustering UAVs in a FANET context.

In [34], the authors considered node mobility and incorporated the safety degree Y_{ij} (given in (13), as they called it) into their routing metrics. The safety degree finds the closest nodes in terms of the distance d_t as follows:

$$Y_{ij} = \frac{r - d_t}{r} \tag{13}$$

where r is the communication range of a UAV, and d_t is the Euclidean distance between two nodes i and j. The higher Y_{ij} value, the closer nodes i and j are. Analyzing (13), it includes in its computation the nodes which are situated in a critical zone (as explained in Figure 3(b) where the nodes will be situated in the inner ring). Another contribution here consists in extending (13) to overcome this inefficiency. The d_t is substituted by the new calculated safe distance $safed_{i,j}$ and the calculation is restricted to the safe zone $(r-\delta)$ as depicted in Figure 3(a).

$$\begin{aligned} sd_{ij} &= \frac{(r-\delta) - safed_{i,j}}{r-\delta} = 1 - \frac{safed_{i,j}}{r-\delta} \\ &= 1 - \frac{1}{r-\delta} safed_{i,j} \end{aligned} \tag{14}$$

Now, the average safety degree is calculated for a UAV_i connected with its $(nd_i - 1)$ neighbors as λ_i:

$$\begin{aligned} \lambda_i &= \frac{1}{nd_i - 1} \sum_{j=1}^{nd_i - 1} sd_{i,j} = \frac{1}{nd_i - 1} \sum_{j=1}^{nd_i - 1} (1 - \frac{1}{r-\delta} safed_{i,j}) \\ &= \frac{nd_i - 1}{nd_i - 1} - \frac{1}{nd_i - 1} * \frac{1}{r-\delta} \sum_{j=1}^{nd_i - 1} safed_{i,j} \\ &= 1 - \frac{1}{(nd_i - 1)(r-\delta)} \sum_{j=1}^{nd_i - 1} safed_{i,j} \end{aligned}$$

Consequently, the average safety degree is deduced as follows:

$$\lambda_i = 1 - \frac{1}{(nd_i - 1)(r-\delta)} \sum_{j=1}^{nd_i - 1} safed_{i,j} \tag{15}$$

Next, a mobility-aware factor is defined to be used as indicator of cluster stability that incorporates UAVs' speed.

C. DESCRIPTION OF THE MOBILITY-AWARENESS FACTOR

The challenging mobility issue must be strongly investigated in FANETs due to the movement of UAVs causing continuous changes in network topology. As explained earlier, FANETs are characterized by higher mobility compared to MANETs or VANETs, and consequently by a higher topology unsteadiness that affects network connectivity and stability. Consequently, the respective speeds of the UAVs constitute one of the main factors of the stability level of a cluster [11]. Therefore, a measure of the node mobility, called, the mobility-awareness factor is proposed and is dealing more efficiently with network topology changes. This usually results in higher packet deliverability and overhead reduction. The reader will find that this concept of node mobility awareness wasn't considered neither in BICSF [24] nor in EALC [12], while it is found to be critical for FANETs.

In the following, for deriving the mobility-awareness factor, (16) is used to compute the relative speed between two nodes i and j and define their mobility.

$$t_i = \frac{|v_j - v_i|}{v_i} \tag{16}$$

where v_i, v_j present the UAV_i and UAV_j velocity, respectively. Then, the mobility-awareness factor is given by the following equation:

$$M_{i,j} = e^{1-t_i} \tag{17}$$

From (16) and (17), a lower value of the relative velocity implies a higher mobility-awareness that will provide more stability in the links between nodes. Thereafter, the average mobility-awareness factor between any CH and all its CMs is calculated as follows:

$$\sigma_i = \frac{1}{nd_i - 1} \sum_{j=1}^{nd_i - 1} M_{i,j} \tag{18}$$

D. RESIDUAL ENERGY

Efficient energy consumption in FANETs is a critical issue that should be considered during the selection of UAVs as CHs and the building of their routing path. To this end, the residual energy (denoted (E_R)) in each UAV should be monitored to decide whether it can be a candidate for a CH role. The idea is to discard UAVs with low residual energy from participating in the CH selection process.

1) RESIDUAL ENERGY COMPUTATION

The residual energy is usually computed as the initial energy level of the UAV minus the energy consumed since the start of operation. The total energy consumption for all UAVs of a cluster is regarded as an important indicator of clustering efficiency that should be minimized in order to enhance network lifetime.

In FANET, the energy is dissipated by the communication between UAVs (E_c), the energy consumed for flying the UAV (E_f), and the aggregated energy consumed by the sensors mounted on the UAV (E_s). The communication energy is due to the energy spent for packet transmission (E_{Tx}) and reception (E_{Rx}) and it represents the more consumed energy.

The total energy (E_T) is obtained as following [35]:

$$\begin{cases} E_T = E_c + E_f + E_s \\ E_c = E_{Tx} + E_{Rx} \\ E_{Tx} = E_{elec} * L + E_{amp} * L * dist^2 \\ E_{Rx} = E_{elec} * L \end{cases}$$

where E_{elec} designates the consumed energy during running the transmitter and receiver. E_{amp} denotes the energy for transmitter amplifier. L represents the number of bits per packet and *dist* represents the distance between the transmitter and receiver.

Hence the residual energy is computed as:

$$E_R = E_I - E_T \tag{19}$$

where E_R is the residual energy of a UAV, E_I represents the initial energy at the start of operation and E_T as the total energy consumed (i.e., dissipated).

Next, a fitness function, based on the above parameters, is implemented.

E. PROPOSED FITNESS FUNCTION

The contribution is to extend [12] and [24]. The values λ_i, E_R and σ_i are determined for each UAV_i and UAVs located in its transmission range. The fitness function β_i is calculated as following:

$$\beta_i = \frac{1}{w_1 \lambda_i} * \frac{w_2 E_{R,i}}{w_3 \sigma_i} \tag{20}$$

Here, w_1, w_2 and w_3 are the weighing factors for the used parameters, in a way that $w_1 + w_2 + w_3 = 1$. The node with the lowest fitness function will be chosen as a CH.

During the transmission of Hello packets between the UAVs in the network, each UAV_i can keep the list of all selection indexes β related to all nd_i of its neighboring UAVs. This list is denoted Ω_i and is defined as:

$$\Omega_i = \left\{ \beta_k | \, \forall k \in nd_i \right\} \tag{21}$$

The UAV with Id_i will be considered as a CH only if its fitness function β_i is the smallest one in Ω_i as expressed in (22).

$$CH = \left\{ Id_i | \, \beta(Id_i) \leq \min \{\Omega_i\} \right\} \tag{22}$$

F. STATEMENT ON EARLIER PARAMETERS IMPROVED IN THIS STUDY

The next table summarizes the improvements and extension of parameters used in BICSF and EALC algorithms that have been proposed in this paper.

VI. PROPOSED EMASS CLUSTERING ALGORITHM

In this section, the proposed Energy and Mobility Aware Stable and Safe Clustering (EMASS) algorithm is explained. The improved parameters addressed in the previous section are used with assigned weight factors to be applied depending on the system requirements.

The CH election algorithm considers a set of UAVs as a dominant set. This algorithm is executed either in parallel with the system activation or as soon as the previously selected set of CHs becomes unable to cover all the nodes.

The execution of this algorithm does not necessarily invoke the election of new CHs in case some nodes leave the cluster.

TABLE 2. Comparison of parameters improved by EMASS against BICSF, EALC.

Algorithm	Comparative Parameters			
	Number of Neighbors	Distance / Average Distance	Delta Difference	Mobility Aware
BICSF [24]	✓	✓	✗	✗
EALC [12]	✗	✓	✓	✗
Corresponding Improved Parameters in the proposed algorithm				
Algorithm EMASS	Extended Nodal degree	Extended Average Distance	Extended Nodal degree and Average Safety Degree	✓

For instance, if a node decides to leave its cluster and moves to another one, the CH of the newly joined cluster will just need to update its member list without invoking the election algorithm again.

The EMASS algorithm is based on two main phases, namely, the CH election and the cluster maintenance procedures.

A. CH ELECTION ALGORITHM

As detailed in algorithm 1, CH election process aims to divide efficiently the network into a set of clusters. Each cluster is composed of an optimal node, elected as a leader or CH, and other cluster members. To determine the most appropriate CH the EMASS algorithm uses the utility function defined in The CH selection process, as detailed in (22). In addition, as mentioned above, only UAVs, that are moving in the same direction, are used.

B. BACKUP CH SELECTION

After the cluster building phase, a cluster maintenance procedure is performed to manage the possible changes in network configuration. Hence, it aims to maintain the stability and reliability of the network.

The backup CH selection is carried out when the CH is forced to relinquish its role. The procedure is used to determine the most appropriate cluster member to be elected as a new CH (that will be called backup CH (BCH)), without starting the CH selection algorithm again. The choice of the BCH must ensure the minimum CMs loss. In other words, the procedure of choosing the BCH should guarantee the minimum re-affiliation possible of the current CMs to other clusters, thus maintaining higher cluster stability.

The set of UAVs in the same cluster with their CH is denoted as C_i. The CH stores the information about all its CMs. A UAVi can be selected as a BCH if its index β_i is the next smaller index value in Ω.

$$BCH_i = \left\{ i | \, \beta_i \leq \min \{remainning\ CM_i \in C_i\} \right\} \tag{23}$$

Algorithm 1 Cluster Head Election

In the initial phase (No cluster is established in the system yet), each UAV node begins with an initial Free Node state,then broadcasts a Hello Message to all its neighbors containing its position, velocity and direction.

Begin

for *every* UAV_k *in the FANET System* **do**

  $(0 \leq k \leq (N-1))$

  /*Find the neighbors of UAV_k*/

  for *the* i^{th} *UAV* $(i \neq k)$ **do**

    $(0 \leq i \leq (N-2))$

    /*Neighborhood building step*/

    if $dis_{k,i} \leq r$ *and* $dis_{k,i} > \delta$ **then**

      neighbor$[UAV_k] \leftarrow UAV_i$

    end if

  end for

  for *each* $UAV_i \in neighbor[UAV_k]$ **do**

    $(1 \leq i \leq (nd_i - 1))$

    /*Fitness function computation*/

    - Calculate average safety degree and average mobility awareness factor using λ_i and σ_i

    $\lambda_i = 1 - \frac{1}{(nd_i-1)(r-\delta)} \sum_{j=1}^{nd_i-1} safed_{i,j}$

    $\sigma_i = \frac{1}{nd_i-1} \sum_{j=1}^{nd_i-1} M_{i,j}$

    - Compute the residual energy for each node i using (19)

    $E_{R,i} = E_{I,i} - E_{T,i}$

    - Compute the fitness function β_i using $E_{R,i}$, λ_i and σ_i

    $\beta_i = \frac{1}{w_1 \lambda_i} * \frac{w_2 \epsilon_i}{w_3 \sigma_i}$

    $\Omega_k \leftarrow \beta_i, UAV_i$

  end for

  - Sort Ω in increasing order

  - The UAV with the smallest β_i among its one-hop neighbors becomes the *CH*.

  - The *CH* sends an invitation message to its direct neighbors which turn into its *CM*s.

  - All the neighbors of the chosen cluster head are no longer allowed to participate in the election procedure and will be excluded from the set of available UAVs.

end for

/* The same procedure is repeated for all the remaining nodes. */

- Go to Cluster Maintenance (see algorithm 2)

End

C. CLUSTER MAINTENANCE

The maintenance phase, detailed in Algorithm 2, is used to account for any possible changes in the network topology that may occur such as a CH getting out of the network or a *CH* moving to join another cluster or a *CM* getting detached from its cluster or a new node being added to the network.

If a CH_i is no longer in the network, then the cluster maintenance procedure will cause the *BCH* to be the next *CH* of the cluster C_i. Accordingly, the corresponding *CM*s should stay in the same cluster, thus, avoiding *CH* re-election.

If the CH_i of a cluster C_i becomes in the transmission range of other *CH* and its *BCH* is still belonging to the cluster C_i, then, the *BCH* will be designated as the new CH_i without invoking the election process.

Another scenario can be revealed when both the CH_i and its *BCH* become within the transmission range of another CH. In this case, the two clusters will be combined into one cluster and the *CH* having more *CM*s will keep its role whereas the other one becomes a *CM*.

Finally, if a new node is added to the network, the *CH* election process should be executed again.

Algorithm 2 Cluster Maintenance and Backup Cluster Head Selection

Begin

for *each* CH_i **do**

  The BCH_i will be selected using (23)

end for

if CH_i *leaves the system* **then**

  $BCH_i \leftarrow CH_i$

end if

if CH_i *becomes in range of another* CH_j **then**

  if BCH_i *is not in range of* CH_j **then**

    $BCH_i \leftarrow CH_i$

  else

    Merge C_i and C_j

    Execute algorithm 1 (to select the new CH for the new merged cluster)

  end if

end if

if CM_i *is not in range of* CH_i *or new UAV joins the system* **then**

  Execute algorithm 1

end if

End

D. THE TIME COMPLEXITY OF CH ELECTION ALGORITHM

Algorithm 1 (cluster formation and CH election) is based on one external loop with $(N-1)$ iterations where N is the initial number of drones. This external loop contains two separate loops with $N-2$ iterations and $(nd_i - 1)$ iterations, respectively.

As $nd_i < N$, then time complexity of this algorithm is $O(N-1) \times O(N-2) \approx O(N^2)$.

The time complexity of Algorithm 2 (used for cluster maintenance) is $O(M)$, where M is the number of elected cluster heads. Algorithm 2 is called from Algorithm 1 outside the loops, which does not affect the time complexity of Algorithm 1.

Similarly, Algorithm 2 calls Algorithm 1 from outside its loop. Here, again, it does not affect its time complexity. Consequently, the overall complexity of the proposed EMASS

TABLE 3. Time complexities of the proposed algorithms in EMASS, BICSF and EALC.

Algorithms	Algo 1 (Cluster formation)	Algo 2 (cluster maintenance)	Overall Complexity
EMASS	$O(N^2)$	$O(m)n < N$	$O(N^2)$
EALC	$O(N^2)$	-	$O(N^2)$
BICSF	$O(N^2)$	$O(N(m+n)$	$O(N^2)$

algorithm is $O(N^2)$, which is similar to that of the EALC and the BICSF algorithms.

Table 3 summarizes the time complexities of the proposed algorithms in EMASS, BICSF and EALC. It is to be noted that the authors of the BICSF didn't provide any time complexity for their proposed algorithms. Consequently, the comparison is completed by providing the missing time complexities of the BICSF proposed algorithm.
where m is the number of UAVs in the cluster and n is the number of UAVs that are in the transmission vicinity of the CH.

The time complexity of the Algorithm 2 of the BICSF is more complex as its cluster maintenance procedure (called topology management in [24]) has one outer loop across all UAVs and two independent inner loops, one over all members of the cluster (m) and the second is over all the UAVs in each CH transmission vicinity (n). Thus, the complexity is evaluated as $O(N(m+n))$.

The overall time complexity is estimated as $O(N^2)$ under the condition that $m + n \ll N$. Still the computation time of Algorithm 2 is an additional overhead for the BICSF algorithm, as this result is reflected in the simulation results by the worst performance exhibited by BICSF in Figure 4 below.

It is to be noted that the authors of the EALC algorithm [12] did not address the cluster maintenance operations and consequently the simulation results pertaining to the EALC are subjective as compared to those of the EMASS and BICSF algorithms.

VII. SIMULATION RESULTS AND ANALYSIS

The performance of the proposed EMASS is evaluated in comparison with the BICSF and the EALC algorithms, using the MATLAB based simulations. 100 simulations are ran with different random seeds to mitigate the randomness effects on the results for each point on the curves which is representing the average value obtained from the different runs. The simulation parameters are presented in Table 4.

While varying the number of UAVs, the cluster formation time and the energy consumption of the FANET (impacting the clusters' lifetime) are evaluated. Then, the packet delivery ratio and the average end-to-end delay metrics against the number of UAVs (i.e., the size of the FANET) are assessed. Moreover, the evaluation of the transmission range parameter's effect on the number of leaving cluster heads

TABLE 4. Simulation parameters.

	Parameters	Values
Simulation Scenario	Simulation Area	2000*2000 (m^2)
	Simulation Time	120 (seconds)
	UAVs Number	20,40,60,80,100,120,140
	Node energy level at start time	80 W/h
	Constant Bit Rate	100 kbps
	UAV moving speed	20 m/s-60 m/s
Routing	Mobility Model	Reference Point Mobility Model
	Propagation Model	Free space/ Line of Sight (LOS)
	Message size	200 bytes
	Transmission Frequency	2.4 GHZ
	PHY model	IEEE 802.11
	UAV Transmission Range	150-300m

(i.e., relinquishing their headship role), the number of UAVs' re-associating with other clusters, and to the required time for these re-associations is performed.

A. CLUSTER FORMATION TIME

The cluster formation time defines the time required by the clustering algorithm to select a CH and produce the associated UAV membership while varying the FANET size.

The result highlighted in Figure 4 depicts the cluster formation time required versus the number of UAVs. It is noted that the clustering algorithm's execution time increases with the increase of the cluster formation time, which in turn increases due to the insertion of more UAVs in the network. It is clear that the proposed EMASS algorithm outperforms the BICSF, and EALC algorithms in terms of shorter cluster formation timings.

The reduction in cluster formation time results in energy saving that would extend the network lifetime.

The BICSF was found to be the worst in cluster formation time due to its overall high time complexity.

B. EVALUATION OF THE ENERGY CONSUMPTION

Figure 5 illustrates the effect of the FANET size on energy consumption for the various algorithms considered. Thus, various number of UAVs is considered in the FANET and their corresponding energy consumption is computed.

It is evident, in Figure 5, that the proposed EMASS consumes less power compared with the other two clustering algorithms.

EMASS achieves this energy saving due to the implementation of the new strategy of creating BCHs that take over the task of CHs (when they leave, or when they join other clusters as CMs), thus, maintaining cluster stability and saving energy needed for new CH elections. Above that the EMASS ensures

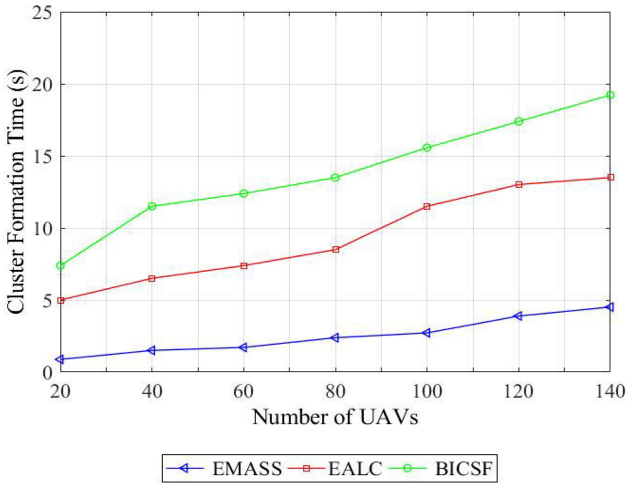


FIGURE 4. Cluster formation time required for different densities of UAVs.

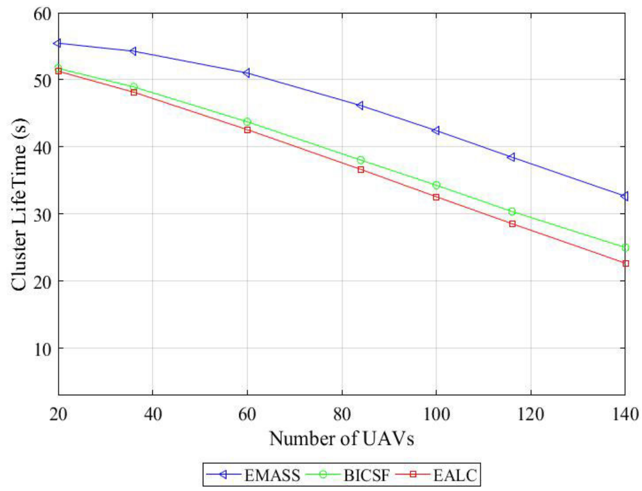


FIGURE 6. Cluster lifetime for different densities of UAVs.

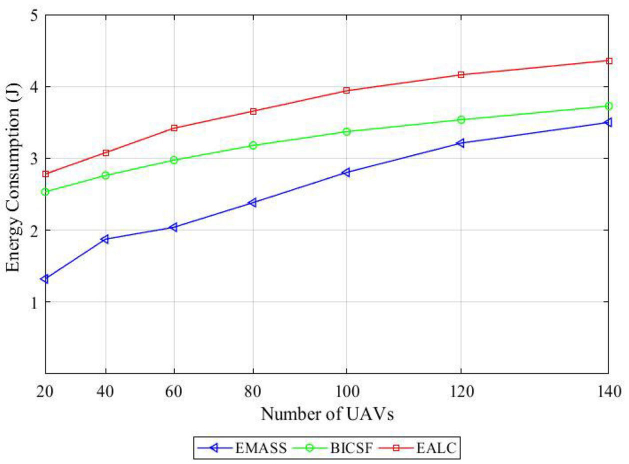


FIGURE 5. Energy consumption for different densities of UAVs.

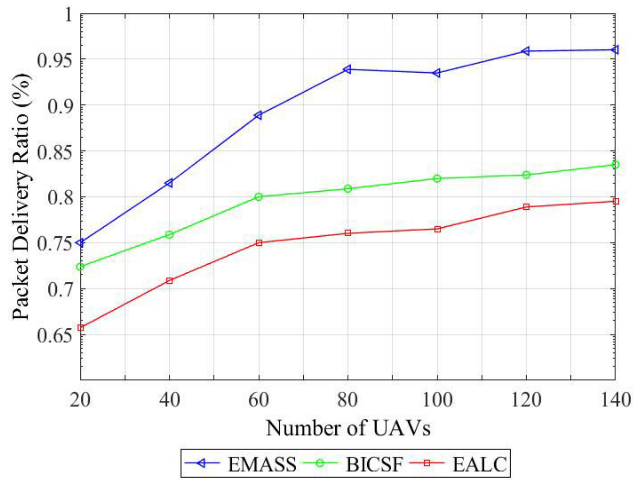


FIGURE 7. PDR for different densities of UAVs.

safety of the UAVs in flight, again safeguarding the FANET structure.

Figure 6 depicts the cluster lifetime metric against the FANET size. The cluster lifetime metric denotes the time that elapses from the CH election and cluster formation till the time a new CH is re-elected for any reason. This metric is a clear indicator of cluster stability. As shown in Figure 6, the average cluster lifetime declines with the increase of the number of UAVs.

It is again clear that EMASS, by focusing on enhancing the stability of CHs and BCHs, improves the cluster lifetime and keeps a steady structure of the FANET better than the other algorithms.

C. PACKET DELIVERABILITY EVALUATION

The Packet Delivery Ratio (PDR) evaluates the number of packets correctly transmitted from source nodes to their destination.

Figure 7 shows that the new algorithm achieves much higher PDR than the competing algorithms (achieving up to more than 95%) due to the adopted maintenance strategy that contributes to the overall network stability and thus allows more successful packet exchange between UAVs. Moreover, by increasing the number of UAVs, the network becomes more connected which guarantees more successful data packets delivery.

D. END-TO-END DELAY (EED) EVALUATION

The effect of high mobility and of higher density of UAVs results into congestion situations that may imply packet drops. Accordingly, packets will spend higher average times to reach their destinations and thus incur higher end-to-end delays (EED).

As shown in Figure 8, the average EED of EMASS scheme is much lower than the ones obtained with the BICSF and EALC algorithms. This may be attributed to the proposed average safety degree and the average safe distance

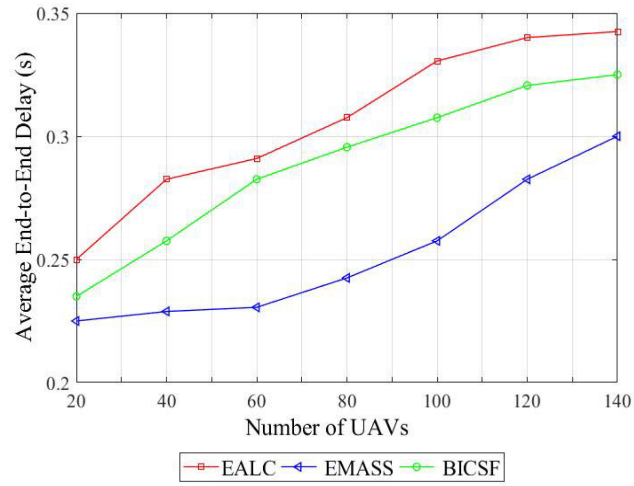


FIGURE 8. Average EED for different densities of UAVs.

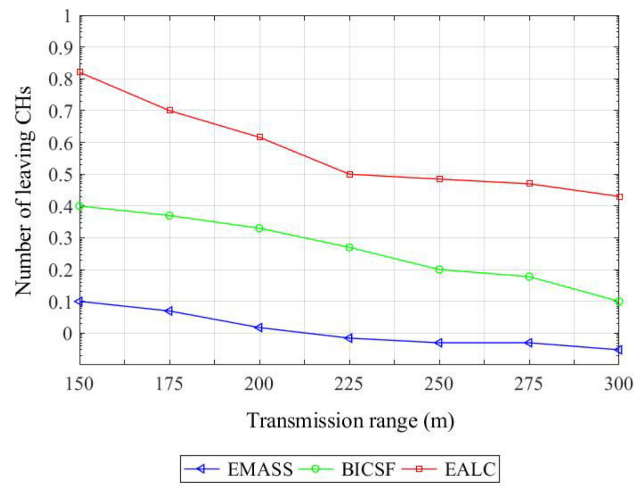


FIGURE 9. Number of CHs leaving the cluster vs transmission range.

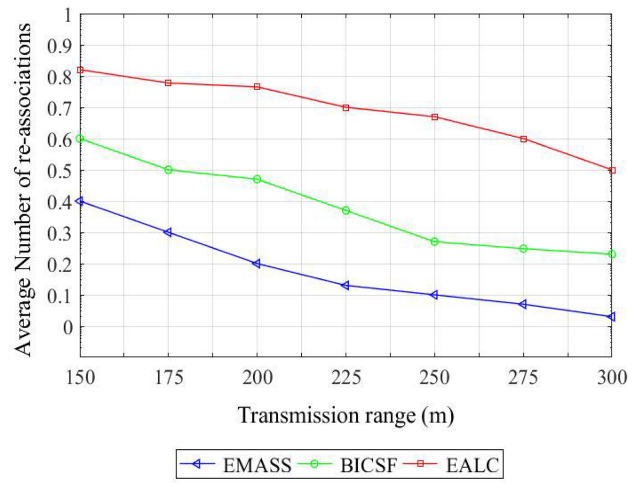


FIGURE 10. Average number of cluster re-associations vs transmission range.

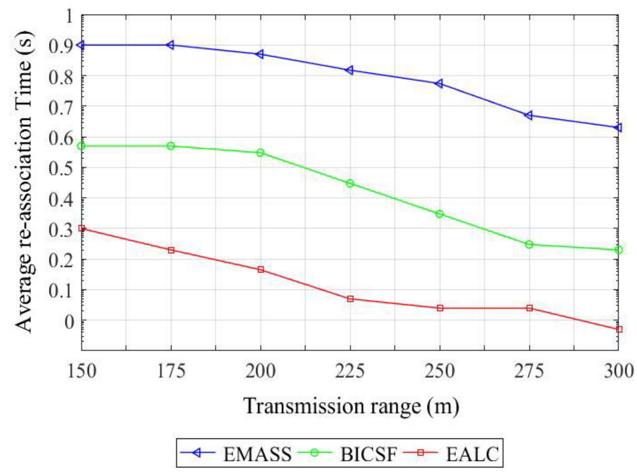


FIGURE 11. Average re-association time vs transmission range.

parameters that maintain safe distances between the UAVs and thus contributes to having less packet collisions and thus reducing EEDs. Moreover, it is noted that the EMASS is producing more stable clusters also contributes to lowering EEDs.

E. EFFECT OF THE TRANSMISSION RANGE ON THE NUMBER OF LEAVING CHs

During the simulations, CHs can leave the cluster for any reason (as specified above). Accordingly, the CH election process may be executed to associate detached CMs to another CH. This number of leaving CHs metric affects the cluster stability level.

Figure 9 illustrates the fact that the number of leaving CHs declines with higher communication range as it translates into higher probabilities of having better connected UAVs in the clusters and consequently, bigger cluster sizes and less CHs.

Again, the EMASS algorithm outperforms its peers exhibiting higher cluster stability. This may be attributed the newly proposed fitness function index β_i used for CH election.

F. EFFECT OF THE TRANSMISSION RANGE ON UAVS REASSOCIATION

In this experiment, the number and associated time-duration of reassociations (disconnecting from a cluster and joining another), that occur as a function of the transmission range, are evaluated. These are defined as the average number of times that UAVs re-associate (i.e., join) with other clusters, and the time required for this reassociation to occur. Therefore, the reassociation rate expresses an indication of cluster stability.

The simulation results in Figures 10 and 11 depict the average number and time of re-associations versus the transmission range for the three algorithms. As the transmission range increases, the average number and the probability of re-association time is reduced.

Again, the EMASS algorithm outperforms the other algorithms due to the use of the BCH role that reduces the number of UAVs getting detached from their cluster. This is because the selection of the BCH is done on the basis of being the node that is the most highly connected to the CMs of the cluster after the CH. This fact is conveyed thru a high value of λ_i in the fitness function equation (20).

Furthermore, although the effect of the Hello messages exchange was found to affect the average re-association time as a function of the transmission range (Figure 11), the overall effect of the higher overhead of the hello messages exchange was found to be beneficial for all the other metrics as seen from Figure 6 thru 10, thus, increasing the Cluster lifetime and PDR and lowering the EED and reducing the number of CHs leaving the cluster and the number of cluster re-associations.

VIII. CONCLUSION

Flying Ad-hoc Networks (FANETs) have demonstrated their unique role for ensuring accurate and rapid tasks in various sectors using autonomous and efficient UAVs. However, a large number of UAVs flying in formation and their dynamic behavior present serious issues that can reduce the FANET stability and reliability. For that reason, UAV clustering is investigated in the literature as an efficient solution to decrease FANETs' energy consumption, maintain their stable topologies and extend their lifetimes.

Conventional clustering schemes in high mobility of UAVs do not perform efficiently in terms of network latency and stability. Therefore, in this paper, a FANET clustering algorithm, that strives to ensure network stability and improve its power efficiency, is proposed. Hence, the novel Energy and Mobility-Aware Stable and Safe Clustering (EMASS) mechanism focuses on improving the overall network stability and safety by employing enhanced parameters related to mobility and safety distance awareness thus contributing to better cluster stability and higher energy saving.

The simulation results testified to the clear superiority of the EMASS algorithm over the BICSF and the EALC algorithms in terms of better cluster stability, higher packet deliverability, improved energy saving and lower delays.

The proposed work has been compared with two recent and much referenced approaches that are most closely related to the new contribution. As future perspective, it is interesting to compare the obtained results with other recent works as well. In addition, we believe that proposing a new SDN-based framework to control the obtained FANET clusters, using the proposed EMASS algorithm, may enhance the network energy consumption, stability, safety and may increase its lifetime.

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