electronics

Article

Survivability Analysis of Unmanned Aerial Vehicle Network based on Dynamic Weighted Clustering Algorithm with Dual Cluster Heads

Yujing Zhang [1,2], Zhiqun Hu [1,2,*], Zhifei Wang [1,2], Xiangming Wen [1,2] and Zhaoming Lu [1,2]

[1] School of Information and Communication Engineering, Beijing University of Posts and Telecommunication, Beijing 100876, China; yujingzhang@bupt.edu.cn (Y.Z.); wxzf1995@bupt.edu.cn (Z.W.); xiangmw@bupt.edu.cn (X.W.); lzy0372@bupt.edu.cn (Z.L.)
[2] Beijing Laboratory of Advanced Information Networks, Beijing 100876, China
* Correspondence: huzhiqun@bupt.edu.cn

Abstract: The unmanned aerial vehicles (UAVs) network is vulnerable due to the high mobility and energy-constrained characteristics of UAVs. Nonetheless, as a UAV-based communication network, a stable network topology is crucial for efficient communication. To this end, in this paper, we propose a dynamic weighted clustering algorithm with dual cluster heads (DWCA-DCH) in this paper to deploy the UAV network. To trade off communication efficiency and lifetime, the selection of prime and backup cluster heads is designed by synthetically considering communication quality and remaining energy of the UAV. Furthermore, a survivability analysis method based on Markov process (SAM-MP) is constructed to analyze the survivability performance of the proposed UAV network based on DWCA-DCH when the UAV node suffers from energy exhausting or accidents. The simulation results show that the survivability and stability of the UAV cluster ad hoc network based on DWCA-DCH proposed in this paper is improved by about 35% compared with the single cluster head network.

Keywords: unmanned aerial vehicle; dual cluster head; dynamic clustering algorithm; survivability analysis

Citation: Zhang, Y.; Hu, Z.; Wang, Z.; Wen, X.; Lu, Z. Survivability Analysis of Unmanned Aerial Vehicle Network based on Dynamic Weighted Clustering Algorithm with Dual Cluster Heads. *Electronics* **2023**, *12*, 1743. https://doi.org/10.3390/electronics12071743

Academic Editors: Paul Mitchell and Maciej Ławryńczuk

Received: 14 February 2023
Revised: 23 March 2023
Accepted: 3 April 2023
Published: 6 April 2023

1. Introduction

Unmanned aerial vehicles (UAVs) have recently gained significant attention from researchers due to their various characteristics, including flexible deployment, line-of-sight communication, and strong scalability [1]. UAV communication can support high-speed data transmission, enhance better communication quality, and expand network coverage [2,3], and is an effective carrier for wide-area data acquisition [4]. Additionally, UAVs serve as effective carriers for wide-area data acquisition. UAV communication is extensively utilized in remote areas or after-disaster scenarios, e.g., emergency rescue, remote areas monitoring, industrial inspections, and other scenarios. In these scenarios, multi-UAV communication networks, commonly referred to as flying ad hoc networks (FANETs) [5], are utilized to enhance multi-tasking abilities and extend lifetimes through collaboration among UAVs. Various network topologies such as star, mesh, and cluster are applied to connect the multiple UAV nodes in FANETs [6]. UAVs have become increasingly important to support the resource starving applications of FANETs in 5G and beyond 5G mobile networks. Examples of use cases are after-disaster rescue, advanced mapping, and aerial photography, in which UAVs must satisfy the ever-increasing demands for mobile data communication and ubiquitous connectivity to different kinds of wireless devices [7]. FANETs have progressively advanced commencing from a solitary enormous measured UAV doing the allotted mission to a set of small-sized UAVs [8], owing to their nimbleness, maneuverability, and cost-effectiveness compared to larger UAVs. In FANETs, smaller UAVs are also more convenient to deploy and operate, especially when maintaining network connectivity requires a significant number of nodes. Table 1 displays the features of various types of UAVs.

Table 1. UAV classification [9].

Class	Weight	Altitude	Active Range
Very small	2–5 lb	<1000 ft	1–5 km
Small	5–20 lb	1000–5000 ft	10–100 km
Medium	100–1000 lb	10,000–15,000 ft	500–2000 km
Large	10,000–30,000 lb	20,000–40,000 ft	1000–5000 km
Tactical/combat	1000–20,000 lb	10,000–30,000 ft	500–2000 km

Owing to the expansion of network scale, clustering network topology has gained wide acceptance. The concept of clustering entails selecting nodes with requisite capabilities for data processing and transmission as cluster head nodes, while other nodes can register with the cluster head node and become members of the cluster. The cluster head nodes collaborate to form a connected virtual backbone network that ensures network topology and stability [10]. In [11], the authors proposed a weighted clustering algorithm (WCA), which takes into account the ideal degree, transmission power, mobility, and battery power of mobile network nodes. However, the proposed WCA algorithm is geared towards ad hoc networks with low node mobility and is not appropriate for high-mobility UAV networks.

The current research on UAV-based clustering algorithms [6,12–18] still has limitations in the following two aspects. Firstly, due to the high mobility of UAVs, frequent re-clustering is necessary, which leads to a decline in network performance. Secondly, limited energy supply in UAVs can cause energy loss during task execution and also the possibility of machine failure or other accidents. The interruption of cluster head nodes' service results in wastage of time and resources during the reselection of cluster heads and transmission of information required by cluster heads. Therefore, ensuring cluster stability in UAV networks is an urgent problem that needs to be addressed.

To solve the above problems, in this paper a dynamic weighted clustering algorithm with dual cluster heads (DWCA-DCH) is propopsed to deploy the UAV network and a survivability analysis method is provided to evaluate the network performance. The main contribution of this paper consists of the following aspects:

- We propose a DWCA-DCH to improve the network's stability and availability by selecting the prime cluster head (pCH) with higher communication quality and the backup cluster head (bCH) with higher stability. By introducing the dual cluster head mechanism, the bCH can take over the role of the pCH when the pCH fails to continue data transmission, thereby improving the system availability.
- Additionally, we propose the survivability analysis method based on Markov process (SAM-MP) to evaluate the survivability performance of the UAV cluster network and analyze the ability of the proposed UAV cluster network based on DWCA-DCH to complete the communication service when the system suffers from energy depletion, failure, or accidents.
- Simulation results demonstrate the effectiveness of the proposed algorithm in improving system availability and stability. The results also showcase the feasibility of the proposed SAM-MP for analyzing the survivability of the UAV network.

2. Related Work

Effective management and coordination of communication among UAVs is a critical aspect of UAV networks. Various standardization organizations have initiated standardization processes for UAV networks and FANETs. For instance, the IEEE 802.11 series includes multiple protocols and modes suitable for FANETs, such as IEEE 802.11s (mesh networking), IEEE 802.11p (vehicle communication), and IEEE 802.11ah (low power long distance communication). Additionally, ITU-R M.2171, 3GPP TR 36.777, and ISO/IEC 29180 discuss concepts, application scenarios, deployment and management issues, and safety requirements related to FANETs.

Different from a vehicular ad hoc network (VANET) or mobile ad hoc network (MANET), specific network topologies and operating mechanisms are required due to characteristics in the UAV network such as high mobility, frequent topology changes, unstable wireless links, and limited energy resources. Therefore, clustering algorithms in UAV networks need to be specially designed compared with other statistic or low mobility ad hoc networks.

The clustering algorithms in UAV networks have recently been widely discussed. For example, the authors in [12,13] provided overall investigations of the clustering algorithms in multi-UAV networks and compared them qualitatively. Aiming at the characteristic of high mobility, in [14], a mobility and location-aware stable clustering (MLSC) mechanism is proposed by incorporating the mobility and relative location of the UAVs to enhance the performance and reliability of the UAV network with limited resources. Additionally, Ref. [15] proposed a location-based k-means UAV clustering algorithm by incorporating the mobility and relative location of the UAVs to enhance the performance and reliability of the UAV network with limited resources. However, clustering algorithms in [14,15] mainly focused on the location and path of movement of the UAV, while the energy consumption of the UAV is not considered. To enhance the lifetime of the network, Ref. [16] proposed the energy aware link-based clustering (EALC) model based on the k-means algorithm for the selection of cluster heads. The node energy level and distance to neighbors are jointly considered when selecting cluster heads. EALC improved the cluster lifetime and reduced the overhead. In [17], a bio-inspired clustering scheme for FANETs (BICSF) is proposed based on a hybrid mechanism of glowworm swarm optimization (GSO) and krill herd (KH). UAVs' residual energy and luciferin levels are considered when electing cluster heads and a KH intelligent algorithm is utilized for cluster management. However, Refs. [16,17] are relatively vulnerable when UAV nodes are of high mobility. Ref. [18] proposed an energy balance and mobility prediction (EBMP) clustering algorithm which considered the balance of the energy consumption and stability of UAV nodes when selecting cluster heads, while the otherness of size of different clusters is not mentioned. Moreover, in [6], the authors proposed an energy-efficient swarm-intelligence-based clustering (SIC) algorithm based on particle swarm optimization (PSO), in which the particle fitness function was exploited for intercluster distance, intracluster distance, residual energy, and geographic location, therefore the network energy consumption was reduced and the network lifetime was extended.

Survivability refers to the ability of a system to remain alive or continue to exist while facing natural or man-made interference or disaster. Survivability has been utilized as an important indicator to evaluate the performance of the system in the ad hoc networks. For example, in [19] a Markov model was proposed to describe the node behavior for a power-aware wireless ad hoc network with DoS attack existing, where two energy consumption (high and low) levels were assumed. Ref. [20] presented a new survivability model based on correlated node behavior to study the global survivability of mobile ad hoc networks, which used a k-correlated survivability model to evaluate the impact of correlated node behavior particularly selfish, malicious, and failed nodes toward network resilience and survivability. Ref. [21] proposed a research method for survivability of wireless sensor networks based on tenacity. However, these works cannot apply to UAV networks directly due to the limited UAV energy and high mobility. Therefore, it is crucial to develop a survivability model which can apply to UAV networks.

3. System Model

The cluster-based UAV communication system is composed of UAVs, the ground base station (gBS) and the communication link between them. As shown in Figure 1, consider a network composed of N UAVs which are randomly distributed in a finite area with a constant height H. Each UAV is set to fly around the gBS following the circumference trace. During the movement process, all UAV nodes will be clustered according to their locations, mobility, channel conditions, and other factors. It is assumed that all UAV nodes obey the free space propagation model and the signal strength is only related to the propagation distance [22,23]. A pCH and a bCH are selected in each cluster. The cluster head is regarded as a service node, which constitutes the aerial backbone routing network. It is responsible for collecting information within the cluster, maintaining communication between clusters, and transmitting the collected information back to the gBS. In our model, the pCH collects the information in the cluster and backs up the information to the bCH. When the energy of the pCH is lower than the threshold or the pCH fails, the bCH can immediately replace the pCH to play the role of the cluster head. When both the pCH and the bCH are in a low power state (i.e., selfish state, see Section 5 for details), the bCH will enter the failure state as soon as possible and fly to the charging pile to charge, so as to restore the system to an available state as soon as possible.

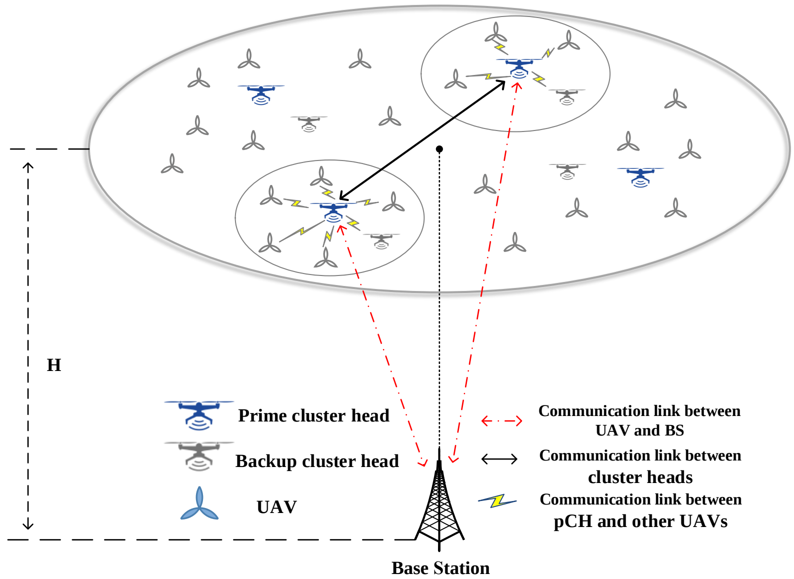


Figure 1. Cluster-based UAV communication system.

In this paper, we assume that all UAV nodes are divided into K clusters, and the set of all clusters in the UAV network is denoted by $\mathcal{C} = \{\mathcal{C}_i, i = 1, 2, \ldots, K\}$, $\mathcal{C}_i = \{\mathcal{C}_{ij}, j = 1, 2, \ldots, m_i\}$ denotes the cluster members of cluster i, where m_i is the size of cluster i, $\mathcal{C}_{ij}$ represents the jth member in cluster i. The set of pCH and bCH are respectively denoted by $\mathcal{P} = \{\mathcal{P}_i, i = 1, 2, \ldots, K\}$ and $\mathcal{B} = \{\mathcal{B}_i, i = 1, 2, \ldots, K\}$, in which $\mathcal{P}_i$ and $\mathcal{B}_i$ are the pCH and bCH of cluster i, respectively.

4. Dynamic Weighted Clustering Algorithm with Dual Cluster Heads

Dynamic weighted clustering algorithm with dual cluster heads is an improved UAV cluster clustering algorithm based on the WCA algorithm [11]. In the DWCA-DCH algorithm, considering the different functions of the two kinds of cluster heads, the function of the pCH is more focused on providing better communication conditions for the nodes in the cluster, while the bCH is more inclined to ensure longer standby time so that it can still provide services for the nodes in the cluster when the pCH is unavailable. Therefore, when selecting the pCH and the bCH, the weight coefficients of the same weight factor are different. After the initial cluster clustering is complete, dynamic maintenance for each cluster must be performed. Section 4.1 gives the weight factor of the DWCA-DCH algorithm; Section 4.3 introduces the detailed algorithm procedure.

4.1. Weight Factor

When selecting a cluster head, on the one hand, it is necessary to ensure that the number of cluster members is not too large or too small, resulting in low efficiency or a waste of resources. On the other hand, the cluster head needs not only to ensure good communication quality with the cluster members, but also to ensure the connection with the gBS. Therefore, degree, distance, and communication quality are introduced as weight factors. In addition, due to the characteristics of strong mobility and limited energy of a UAV, in order to avoid frequent replacement of cluster heads caused by this, the relative mobility and remaining service time of a UAV should be taken into account in the calculation of cluster head weight in addition to the size of the cluster, communication quality within cluster, and communication quality with gBS. Detailed weight factor calculations are shown below.

- Degree. If the cluster is too large, the load of the cluster head will be too high and the system efficiency will be degraded. If the clustering is too small, too few nodes in the cluster will result in resource waste. In order to realize balanced clustering, the concept of degree $\triangle_i$ is introduced to measure the difference between the number of neighbor nodes and the size of the ideal cluster, which is denoted by:

$$\triangle_i = |n_i - \delta| \tag{1}$$

  where δ is the ideal cluster size, n_i is the number of neighbor nodes of UAV i in set $\mathcal{U}$, $\mathcal{U}$ is the set of unclustered nodes during the initial clustering stage and the node set of the currently maintained cluster during the dynamic maintenance stage. n_i is expressed as $n_i = \sum_{i' \in \mathcal{U},\, i' \neq i} \{dist(i,i') < range\}$, where $dist(i,i')$ represents the distance between UAV i and i', $range$ represents the signal receiving distance of the UAV, which is the distance between the transmitter and the receiver when the receiving power is greater than the threshold. According to the free space propagation model, $range = \sqrt{\frac{P_T G_T G_R \lambda^2}{(4\pi)^2 L P_{th}}}$ [24], where P_T is the transmit power of the UAV, G_T and G_R are the antenna gains at the transmitter and the receiver, respectively. In addition, λ is the wavelength, L is the loss factor independent of propagation, and P_{th} is the threshold of receiving power.
- Distance. The signal intensity between two UAV nodes is affected by the distance between them [25]. When a node in a cluster is far away from the cluster head, the communication efficiency will be degraded due to signal attenuation. According to [25], air-to-air (A2A) channels obey line of sight (LoS) fading, and signal attenuation is proportional to the square of the distance. The distance factor D_i represents the sum of the distance between node i to all its neighbors, which can be expressed as:

$$D_i = \sum_{i' \in (N_i \cap \mathcal{U}),\, i' \neq i} ((X_i - X_{i'})^2 + (Y_i - Y_{i'})^2) \tag{2}$$

  where X_i and Y_i are the horizontal and vertical coordinates of UAV i, respectively. N_i is the set of neighbor nodes of UAV i.
- Communication quality. In order to ensure the communication connection between air network and gBS, the cluster head node needs to ensure good quality of the air-to-ground channel. The path loss factor PL_i is utilized for the air-to-ground path loss of node i, the lower the PL_i is, the better the communication is between the node i and the gBS. PL_i can be expressed as [26]

$$PL_i = \frac{A}{1 + a \cdot exp(-b \cdot arctan(\theta) - a)} + 10log(H^2 + d_i^2) + B \tag{3}$$

  where $A = \eta_{LoS} - \eta_{NLoS}$, $B = 20log(\frac{4\pi f}{c}) + \eta_{NLoS}$, η_{LoS} and η_{NLoS} are the excessive path loss of LoS condition or non-line-of-sight (NLoS) condition, while f is the frequency of the UAV, c is the speed of light, θ is the elevation angle satisfying $tan\theta = \frac{H}{d_i}$, d_i is the horizontal distance between UAV i and gBS, $d_i = \sqrt{(X_i - X_0)^2 + (Y_i - Y_0)^2}$, X_0 and Y_0 are the coordinates of gBS, and a and b are constants related to the communication environment.

- Stability. Since UAVs have strong mobility, relative mobility is used to measure the stability of nodes in the cluster. The smaller the relative moving speed of a cluster head node and its neighbors is, the longer the cluster head node stays in the cluster, i.e., the stronger the stability of the cluster is. The stability factor is expressed as

$$M_i = \sum_{i' \in (N_i \cap \mathcal{U}),\ i' \neq i} (\omega_i - \omega_{i'})^2 \tag{4}$$

where ω_i and $\omega_{i'}$ are the angular velocity of UAV i and i', respectively. Since we assume that all UAVs fly at the same height and their flight trajectories are circles centered on the gBS, the difference of angular velocity between a UAVs nodes can be used to represent the relative position change between nodes, i.e., the stability within the cluster.

- Energy. The remaining energy of the UAV determines its remaining lifetime. The UAV that becomes the cluster head node needs to maintain as long of a lifetime as possible to maintain the intracluster communication. The energy factor is represented by the comsumed energy E_i, the lower E_i is, the longer the remaining lifetime of the node is. E_i is expressed as

$$E_i = E_{ini} - E_{rm} \tag{5}$$

where E_{ini} and E_{rm} represent the initial and remaining energy of the UAV, respectively.

4.2. Weight Calculation

According to the weighting factors given by Equations (1)–(5), the weighting function of node i when selecting pCH and bCH can be denoted by

$$W_i^p = w_1^p \cdot \triangle_i + w_2^p \cdot D_i + w_3^p \cdot PL_i + w_4^p \cdot M_i + w_5^p \cdot E_i \tag{6}$$

$$W_i^b = w_1^b \cdot \triangle_i + w_2^b \cdot D_i + w_3^b \cdot PL_i + w_4^b \cdot M_i + w_5^b \cdot E_i \tag{7}$$

where $w_1^k, w_2^k, w_3^k, w_4^k, w_5^k$ are the weighting coefficients, and $\sum_{i=1}^{5} w_i^k = 1$. Additionally, $k \in \{p, b\}$, where p and b denote the selection of pCH and bCH, respectively. Due to the different functions of pCH and bCH, the corresponding weight coefficients are different during the selection of cluster heads. It should be noted that the selection criterion of the pCH in this paper is higher service efficiency, therefore the value of weight coefficients w_1^p, w_2^p, and w_3^p which represent the serving quality are relatively large, while the criterion of selecting the bCH is higher stability, thus the value of w_4^b, w_5^b is larger. In other scenarios, the weight coefficients can be adjusted based on actual network requirements.

4.3. Algorithm Procedure

The detailed procedure of DWCA-DCH is shown in Algorithm 1. In the initialization stage, parameters are set such as the ideal cluster size, weighting coefficients, and the UAV energy threshold, etc. The UAV status array contains its coordinates, speed, energy, and so on. The set $\mathcal{U}$ includes all UAV nodes in the system initially. The set $\mathcal{C}$, $\mathcal{P}$, $\mathcal{B}$ are defined in Section 3, respectively. The DWCA-DCH algorithm determines cluster heads according to the weight of nodes in the initial clustering stage. First, the weight of each node is calculated according to Equation (6). In each cycle, the node with the lowest pCH weight in the node set that has not been clustered is appointed as the pCH of the cluster, and the unclustered neighbors of the selected pCH node are included in the cluster. Afterward, the selected pCH and its cluster member are removed from $\mathcal{U}$, until $\mathcal{U}$ is empty. At this point, all UAV nodes have been clustered. After the clustering, the node with the lowest bCH weight in each cluster is selected as the bCH according to Equation (7). In this way, the initial clustering of UAVs based on the DWCA-DCH algorithm is completed.

Algorithm 1 Dynamic Weighted Clustering Algorithm with Dual Cluster Heads

Initialization:
Setup parameters (ideal cluster size, weighting coefficients, UAV energy threshold, etc.)
Initialize the UAV state array (coordinates, velocity, energy) and the set of unclustered nodes $\mathcal{U}$
Seek for the set of unclusted neighbors of each node, define $\mathcal{J}_i, i = 1, 2, \ldots, N$ as the set of unclusted neighbor of node i ($\mathcal{J}_i = N_i \cap \mathcal{U}$)
Initial clustering stage:
while $\mathcal{U} \neq \phi$ **do**
  for all $i \in \mathcal{U}$ **do**
    Calculate W_i^p according to Equation (6)
  end for
  $\pi = \arg\min_{i \in \mathcal{U}} \{W_i\}$
  $\mathcal{P}_h \leftarrow \pi$
  $\mathcal{C}_h = \mathcal{P}_h \cup \mathcal{J}_\pi$
  $\mathcal{B}_h \leftarrow$ the node with the lowest W_i^b in the set $\mathcal{C}_h$
  $\mathcal{U} = \mathcal{U} \setminus \mathcal{C}_h$
  Update $\mathcal{J}$
end while
Dynamic adjustment stage:
Continue traversing all nodes (assume that the current traversing node is i, its cluster is $\mathcal{C}_r$, the pCH and bCH in $\mathcal{C}_r$ are $\mathcal{P}_r$ and $\mathcal{B}_r$, respectively.)
if The energy of node i $E_i < E_{th}$ or node i fails **then**
  if $i = \mathcal{P}_r$ **then**
    $\mathcal{P}_r \leftarrow \mathcal{B}_r$
    $\mathcal{U} \leftarrow \mathcal{C}_r$
    $\mathcal{B}_r \leftarrow$ reselected bCH after calculating W_i^b
  end if
  if $i = \mathcal{B}_r$ **then**
    $\mathcal{U} \leftarrow \mathcal{C}_r$
    $\mathcal{B}_r \leftarrow$ reselected bCH after calculating W_i^b
  end if
  $\mathcal{C}_r = \mathcal{C}_r \setminus i$
end if
if $dist(i, \mathcal{P}_r) > range$ **then**
  if $i = \mathcal{B}_r$ **then**
    $\mathcal{U} \leftarrow \mathcal{C}_r$
    $\mathcal{B}_r \leftarrow$ reselected bCH after calculating W_i^b
  end if
  $\mathcal{C}_r = \mathcal{C}_r \setminus i$
  $\mathcal{C}_q = \mathcal{C}_q \cup i$ (Assume that node i will join the cluster $\mathcal{C}_q$)
end if
$\mathcal{U} \leftarrow \mathcal{C}_r$
Calculate W_i^p
if W_i^p is less than $W_{\mathcal{P}_r}^p$ and stays there for a period of time **then**
  if $i = \mathcal{B}_r$ **then**
    $\mathcal{B}_r \leftarrow$ reselected bCH after calculating W_i^b
  end if
  $\mathcal{P}_r \leftarrow i$
end if
if Charging or maintenance of node i is complete **then**
  $\mathcal{C}_q = \mathcal{C}_q \cup i$ (Assume that node i will join the cluster $\mathcal{C}_q$)
end if

During the dynamic adjustment stage, all nodes are continuously traversed and the cluster is maintained. When the node loses energy or fails, it will fly away for charging or maintenance and update the nodes in the cluster. If the pCH fails, the bCH will replace the original pCH and select a new bCH. If the bCH fails, a new bCH will be selected. Since the bCH weight needs to be recalculated, $\mathcal{U}$ will be redefined as the set of all nodes in the cluster currently. If a node moves away from the cluster, the nodes in the cluster must be updated and a new cluster for the node must be selected. If the bCH moves away from the cluster, the bCH must be reselected. When the weight coefficient of the bCH/common node in a cluster is less than that of the pCH for a period of time, the pCH update is performed. When charging or maintenance of the UAV is complete, it will return and reselect a cluster.

5. Survivability Analysis

In order to evaluate the performance of a UAV network based on the dual cluster head mechanism proposed above, we propose a survivability analysis method based on the Markov process (SAM-MP) to analyze the survivability of the UAV network.

Since cluster head nodes are affected by various factors, the transition between their states is a random Markov process [19]. According to the availability and energy states of pCH and bCH, three states are introduced, namely cooperative state, selfish state, and failure state, to depict the UAV ad hoc network. The specific definitions are as follows:

- Cooperative state (C), where UAVs can complete data acquisition, processing, receiving, and transmitting normally.
- Selfish state (S), where the UAV's remaining energy is lower than the threshold E_{th}. In this case, the UAV only receives data and no longer transmits data. In addition, the UAV will fly to the charging pile.
- Failure state (F), when the energy of the UAV is exhausted or the UAV fails, it will enter into the failure state. In addition, the UAV is also in this state during charging or maintaining period.

Since the UAV nodes can supplement the network through charging or maintenance, the state transfer among the states of the single node is shown in Figure 2. The transition probabilities between states are respectively expressed as:

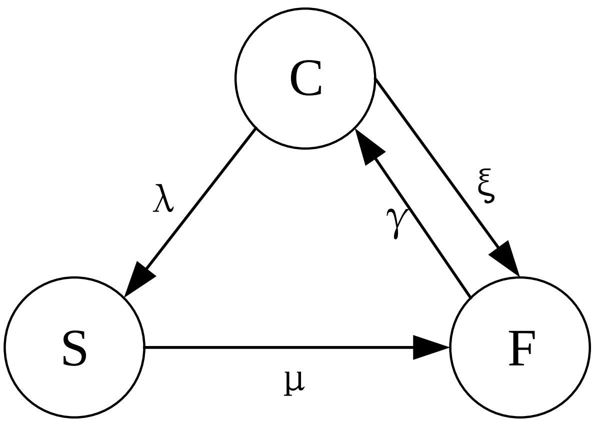


Figure 2. The state transfer among different states of a single node.

1. R(C, S) = λ, which denotes the transition probability of the node from state C to state S. The transition happens along with the natural energy consumption process of UAVs. Therefore, λ is related to the energy consumption rate of UAVs. Since the energy consumption of UAV communication is far less than that of its flight, only the flight energy consumption of a UAV is considered in this paper. The following is the calculation process.

Assuming that the lifetime of the UAV follows the Weibull distribution [27], whose probability density function is

$$f(t) = \frac{k}{\Lambda}(\frac{t}{\Lambda})^{k-1}e^{-(\frac{t}{\Lambda})^k},\ t \geq 0 \tag{8}$$

where Λ is the scale parameter. k is the shape parameter and $k > 0$, the value of k can be adjusted according to the requirements of the actual scenario. t is the random variable representing the lifetime of the UAV.

When the remaining UAV energy E_{rm} is less than the energy threshold E_{th}, the state of the node transfers from C to S, which follows:

$$E_{rm} = E_{ini} - E_i = E_{ini} - P \cdot t < E_{th} \tag{9}$$

where E_{ini} and E_i are the initial and consumed energy, respectively. P is the horizontal flying power of UAV. Accordingly, the lifetime of UAV can be denoted by

$$t > \frac{E_{ini} - E_{th}}{P} \tag{10}$$

where the horizontal flying power P is given by [28,29] as

$$P = P_p + P_I \tag{11}$$

where P_p is the parasitic power caused by the parasitic drag originating from the UAV's body friction from airlift drag, etc. It can be expressed as [29,30]

$$P_p = \frac{1}{2}\rho C_{D_0} S v^3 + \frac{\pi}{4} M \rho c_b C_{D_0} \omega^3 \beta^4 (1 + 3(\frac{v}{\omega\beta})^2) \tag{12}$$

where ρ is the air fluid density in $\mathrm{kg/m^3}$, C_{D_0} is the drag coefficient, S is the reference area (frontal area of the UAV-BS), M is the UAV rotor number, c_b is the blade chord, ω is the angular velocity, v represents the velocity in the horizontal direction, β is the radius of the rotor spinning disk in m.

P_I denotes the power for the lift generated by the wing to overcome the weight of the UAV-BS and the drag caused by the lift, and can be obtained by [28,29]

$$P_I = G\sqrt{\frac{\lambda' - v^2}{2}},\ \lambda' = \sqrt{v^4 + \frac{G}{\pi\rho\beta^2}},\ G = (W + w)g \tag{13}$$

where W is the frame weight of the UAV in kg, w is the battery and payload weight in kg, given the gravity g in $\mathrm{m/s^2}$.

Consequently, the transition probability of the UAV from state C to S is expressed as

$$\lambda = Pr(t > \frac{E_{ini} - E_{th}}{P}) = exp\{-(\frac{E_{ini} - E_{th}}{\Lambda P})^k\} \tag{14}$$

2. R(S, F) = μ, which denotes the transition probability of the node from state S to state F. There are two situations in this process: (1) the energy of the UAV is exhausted; (2) the UAV fails to provide services due to faults or other accidents.
3. R(F, C) = γ, which denotes the transition probability of the node from state F to state C. There are also two situations in this process: (1) the UAV finishes charging and restores to provide service; (2) the fault of the UAV is repaired.
4. R(C, F) = ξ, which denotes the transition probability of the node from state C to state F. The process takes into account situations where the UAV malfunctions or other accidents prevent it from continuing to provide service.

In order to analyze the survival performance of the network in DWCA-DCH, a parallel combination is carried out according to the single-node transition model. The initial state combination of the node is taken as the initial state of the network, and the state transition probability of the node is taken as the corresponding state transition probability of the network. Figure 3 shows the state transfer in the dual cluster head network, where S_0, S_1, S_2, S_3, S_4, S_5, and S_6 represent different dual cluster head combination states CC, SC, FC, SS, SF, FS, and FF, respectively. The first letter indicates the state of pCH, and the last letter indicates the bCH state.

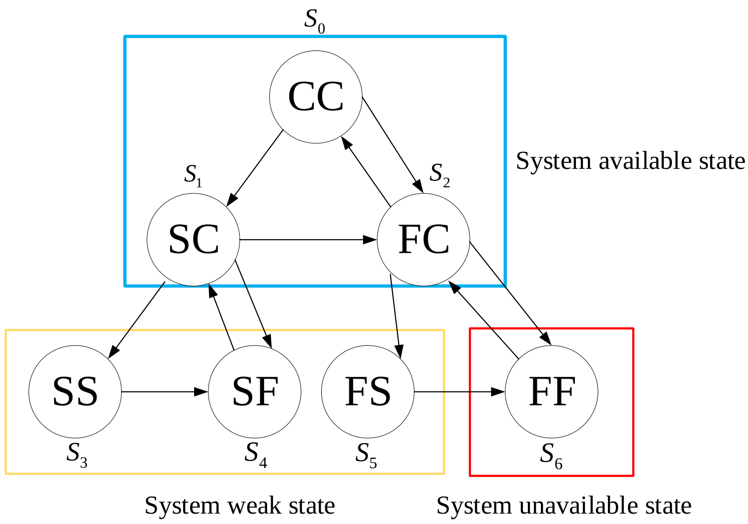


Figure 3. The state transfer among the dual cluster head network.

We denote P_0, P_1, P_2, P_3, P_4, P_5, and P_6 as steady-state probability of S_0, S_1, S_2, S_3, S_4, S_5, and S_6, respectively. According to the principle of equilibrium, the equilibrium equation set is given by:

$$\begin{aligned}
&S0:(\lambda_1+\xi_1)P_0=\gamma_1 P_2\\
&S1:(\lambda_2+\xi_2+\mu_1)P_1=\lambda_1 P_0+\gamma_2 P_4\\
&S2:(\gamma_1+\lambda_2+\xi_2)P_2=\mu_1 P_1+\xi_1 P_0+\gamma_2 P_6\\
&S3:\lambda_2 P_1=\mu_2 P_3\\
&S4:\mu_2 P_3+\xi_2 P_1=\gamma_2 P_4\\
&S5:\lambda_2 P_2=\mu_2 P_5\\
&S6:\mu_2 P_5+\xi_2 P_2=\gamma_2 P_6\\
&\sum_{i=0}^{6} P_i=1
\end{aligned} \tag{15}$$

where λ_1, μ_1, γ_1, and ξ_1 are the pCH state transition probability from C to S, S to F, F to C, and C to F, respectively. Similarly, λ_2, μ_2, γ_2, and ξ_2 are the corresponding transition probability of bCH. λ_1 and λ_2 can be deduced from Equations (8)–(14). The value of μ_1 consists of two parts: the probability resulting from energy consumption, which can be derived from Equations (8)–(14), and the probability resulting from UAV failure or other accidents in S state, denoted by ζ, which is set to a fixed value for pCH. Therefore, μ_1 can be calculated as

$$\mu_1 = exp\{-(\frac{E_{ini}-E_{th}}{\Lambda P})^k\}+\zeta \tag{16}$$

In contrast, μ_2 is assumed to be adjustable, considering that the bCH is required to reduce the dwell time at the S state and, thus, it can quickly return to the C state by flying to the charging pile after tranferring to the F state, which ensures the availability of the bCH. The influence of μ_2 on system performance is evaluated through simulation. Furthermore, γ and ξ represent the repairing rate and the failure rate, respectively, which are irrelevant to mobility and energy consumption. Therefore, we also assume them as adjustable parameters and they are evaluated through simulation.

According to Equation (15), the steady-state probability of each state can be obtained:

$$\begin{aligned}
P_1 &= \frac{\lambda_1}{\mu_1} P_0 \\
P_2 &= \frac{\lambda_1 + \xi_1}{\gamma_1} P_0 \\
P_3 &= \frac{\lambda_1 \lambda_2}{\mu_1 \mu_2} P_0 \\
P_4 &= \frac{\lambda_1(\lambda_2 + \xi_2)}{\mu_1 \gamma_2} P_0 \\
P_5 &= \frac{\lambda_2(\lambda_1 + \xi_1)}{\mu_2 \gamma_1} P_0 \\
P_6 &= \frac{(\lambda_1 + \xi_1)(\lambda_2 + \xi_2)}{\gamma_1 \gamma_2} P_0
\end{aligned} \tag{17}$$

$$[1 + \frac{\lambda_1}{\mu_1} + \frac{\lambda_1 + \xi_1}{\gamma_1} + \frac{\lambda_1 \lambda_2}{\mu_1 \mu_2} + \frac{\lambda_1(\lambda_2 + \xi_2)}{\mu_1 \gamma_2} + \frac{\lambda_2(\lambda_1 + \xi_1)}{\mu_2 \gamma_1} + \frac{(\lambda_1 + \xi_1)(\lambda_2 + \xi_2)}{\gamma_1 \gamma_2}] P_0 = 1$$

According to the ability of cluster heads to provide services for the system, the system survivability state can be divided into three conditions.

- System available state, which includes states S_0, S_1, and S_2. In this state, at least one of the pCH and the bCH are in the C state and can provide data gathering, receiving, processing, and transmitting services. In addition, when the pCH is in the C state and bCH is in the S or F state, the bCH should be reselected in time to guarantee the availability of the system. The corresponding probability P_{av} is expressed as

$$P_{av} = P_0 + P_1 + P_2 \tag{18}$$

- System weak state, which includes states S_3, S_4, and S_5. In this state, both the pCH and the bCH are not in the C state, but can still receive data. This state can be regarded as an emergency state of the system. In order to ensure that the system is restored to the available state, the cluster head node needs to be charged or maintained as soon as possible after the system enters the weak state to ensure normal service. When the bCH is in S state, the bCH will enter the F state as soon as possible and fly to the charging pile to charge, so as to restore the system to available as soon as possible. The corresponding probability P_{wk} is expressed as

$$P_{wk} = P_3 + P_4 + P_5 \tag{19}$$

- System unavailable state, which includes state S_6. In this state, pCH and bCH are all in state F and cannot provide service. The corresponding probability P_{unav} is expressed as

$$P_{unav} = P_6 \tag{20}$$

6. Applicability of DWCA-DCH in Post-Disaster Scenarios

The DWCA-DCH algorithm proposed solution can be utilized in emergency rescue operations such as natural disasters or accidents, because UAVs can provide timely and dependable communication services for rescue teams and victims on the ground. Post-disaster scenarios often involve large scale damage to infrastructure, high demand for emergency services, and unpredictable user mobility. In such circumstances, UAVs can play a vital role in providing network resilience and coverage extension by serving as aerial base stations or relays. However, UAVs face limitations such as limited energy, high mobility, and dynamic topology. The proposed DWCA-DCH can mitigate the aforementioned problems. The dual cluster head mechanism ensures network stability and survivability in the event of UAV failures or energy depletion. Additionally, the dynamic clustering algorithm can adapt to the high mobility and frequent topology changes of UAVs. Moreover, the Markov process-based survivability analysis method can evaluate the performance and reliability of the UAV network under different conditions and parameters.

An example of using DWCA-DCH in post-disaster scenarios is depicted as follows. Assume a disaster has occurred in a specific area and some ground users urgently require communication service. A group of UAVs is deployed to form a cluster ad hoc network based on DWCA-DCH. Each cluster comprises one prime cluster head, one backup cluster head, and several cluster members. The prime cluster head is responsible for communicating with ground users and other clusters, while the backup cluster head is ready to take over when required. According to the aforementioned criterion of cluster head selection, the selected pCH is required to ensure the post-disaster network services and, thus, higher values of w_1^p, w_2^p, and w_3^p are recommended. As for the selection of bCH, the values of w_4^b and w_5^b are larger in order to meet the requirement of network stability. The clusters are dynamically formed and updated based on the network status and user demands. Moreover, to further enhance the resilience of the system, it is recommended that the bCH in S state flies to the charging pile as soon as possible to restore the system to available more quickly. By utilizing the proposed SAM-MP, it is possible to derive optimal deployment strategies according to the system performance under different conditions, such as drone quantity and speed. Additionally, the proposed SAM-MP can provide guidance accordingly, such as improving fault repair rates and other related suggestions.

7. Simulation Results

In this section, we analyze the proposed algorithm and verify its performance according to the proposed survivability analysis method. We assume that the UAV nodes are randomly distributed in a square of 1km*1km, with a constant flying height of 50 m, while the gBS is located at the center of the area. The maximum velocity is 15 m/s. The flight path of the UAV is a circle centered on the gBS, and the η_{Los} and η_{NLoS} are 1.6 dB and 23 dB, respectively. The carrier frequency of the UAV is 2 GHz [31]. In this paper, the selection criterion for the pCH is higher service efficiency, and the selection criterion for the bCH is higher stability, therefore the values of $w_1^p, w_2^p, w_3^p, w_4^p, w_5^p$ are set as 0.4, 0.2, 0.2, 0.1, 0.1, and the values of $w_1^b, w_2^b, w_3^b, w_4^b$, and w_5^b are 0.1, 0.1, 0.1, 0.5, and 0.2, respectively. In other scenarios, the value of different weight coefficients can be adjusted according to actual network requirements. The rest of the parameters not mentioned are listed in Table 2.

Table 2. Parameter settings.

Notation	Value
The air fluid density $\rho/\mathrm{kg/m^3}$	1.2
UAV drag coefficient C_{D_0}	0.025
Reference area of the UAV $S/\mathrm{m^3}$	0.192
UAV rotor number M	4
UAV blade chord c_b/m	0.022
The radius of the rotor spinning disk β/m	0.25
The frame weight of UAV W/kg	2
The battery and payload weight of UAV w/kg	2
The gravity $g/\mathrm{m/s^2}$	9.8
Ideal cluster size δ	5
The scale parameter Λ	0.5
The shape parameter k	1
Signal receiving distance of UAV $range/\mathrm{m}$	300

Figure 4 shows the distribution and clustering results of the UAVs. The pCH nodes of the UAVs are represented by rhombuses, the bCH nodes are represented by hollow circles, and the nodes in the same cluster are shown in the same color.

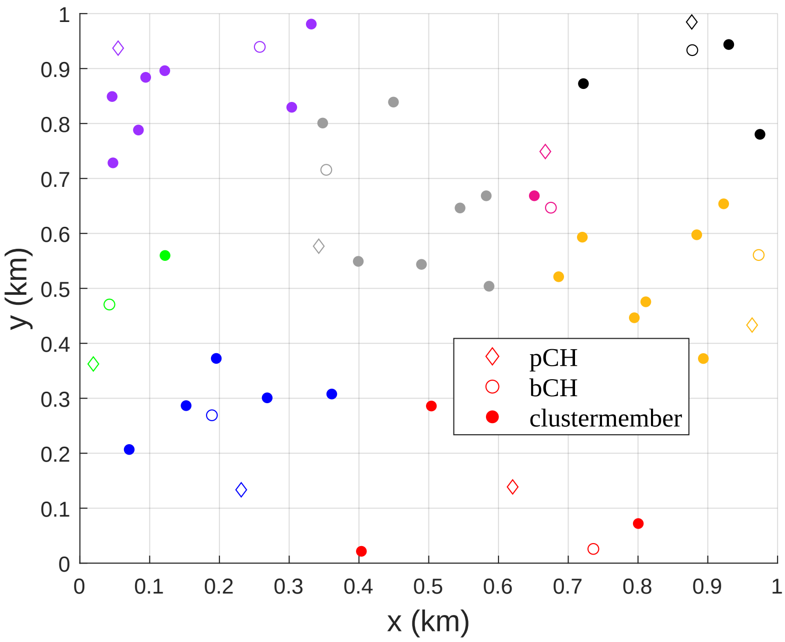
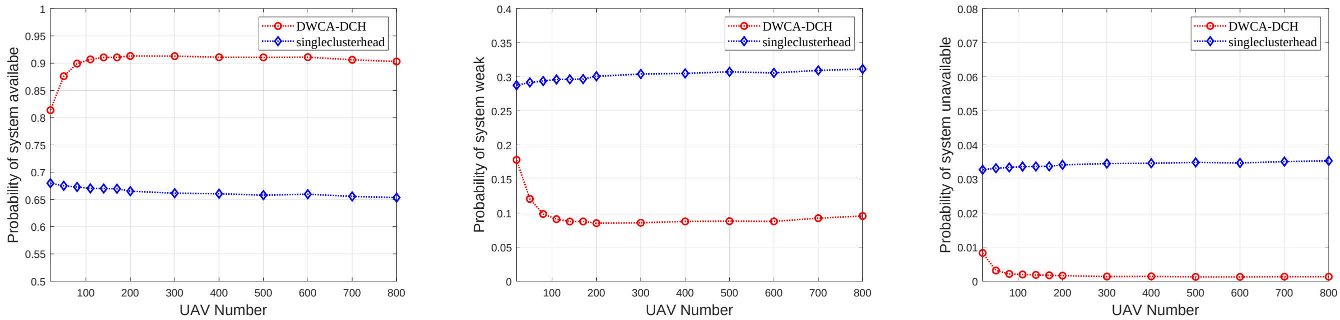


Figure 4. The distribution and clustering results of the UAVs. The nodes in the same cluster are shown in the same color. The label takes one of the clusters as example.

In Figures 5–9, the proposed DWCA-DCH algorithm is compared with the traditional single cluster head WCA clustering algorithm [32]. Figure 5 shows the change of the probability of each state of the system with the increase of the number of UAV nodes. As can be seen from the simulation results, when the number of UAV nodes increases gradually, the system available probability in the DWCA-DCH algorithm increases significantly at first, reaches the maximum when the number of nodes is 200, and then presents an overall stable and slightly decreasing trend. When the number of nodes in the UAV network is low, the robustness of the network is poor. As shown in Figure 5, the performance of the p/bCHs selected by the DWCA-DCH algorithm proposed in this paper is better, which can effectively improve the network survivability performance. When the number of nodes in the network gradually increases to 200, the clustering basically reaches stability, and the system availability probability also reaches the peak. After that, as the number of nodes increases, the network gradually expands, and the system efficiency decreases slightly, but it is basically stable. As a result, optimal performance can be achieved when 200 UAVs are deployed. Therefore, in the following simulation, the number of nodes is selected as 50, 100, and 200 for comparison. In the compared single cluster head algorithm, the available probability of the system decreases as the number of UAVs increases. In the DCWA-DCH algorithm, the performance keeps increasing until the number of nodes reaches 200. As shown in Table 3, the system availability probability in DWCA-DCH is about 35% higher than that in the single cluster head algorithm in average. Therefore, the proposed DCWA-DCH algorithm can effectively improve the system performance and is more suitable for the deployment of a large number of nodes.

Figure 6 illustrates the trend of survivability of the system as a function of the velocity of UAV nodes, and highlights the correlation between state probabilities and mobility and energy consumption parameters. As shown in Figure 6a, the system available probability decreases along with the increase in velocity in both the DCWA-DCH algorithm and the single cluster head algorithm. The increase in velocity caused the corresponding energy consumption enhancement of the UAV, which further caused the increase in λ. By comparison, the system available probability in DCWA-DCH algorithm outperforms that of the single cluster head algorithm, which demonstrates that the introduction of bCH enhances the resilience of a UAV network against the instability caused by mobility and energy consumption.

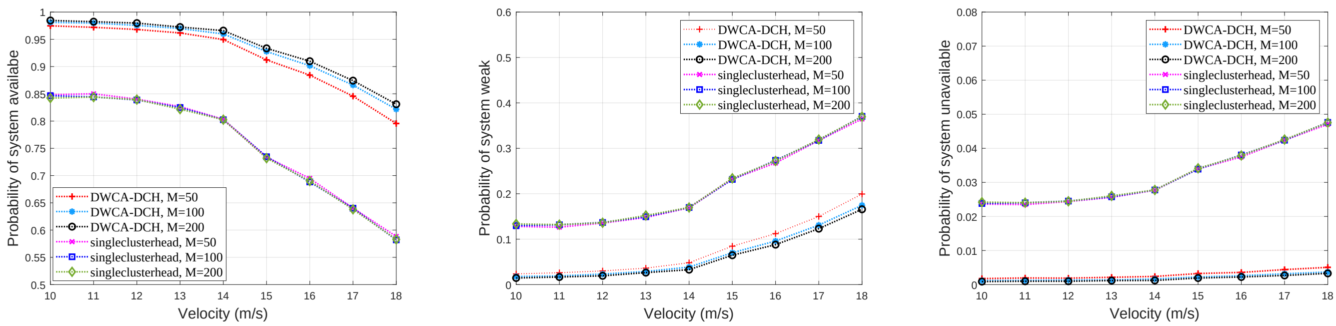


(**a**) System available state (**b**) System weak state (**c**) System unavailable state

Figure 5. The probability of each state of the system with the increase in the number of UAVs.

Table 3. Comparison of system available probability between DWCA-DCH and single cluster head algorithm.

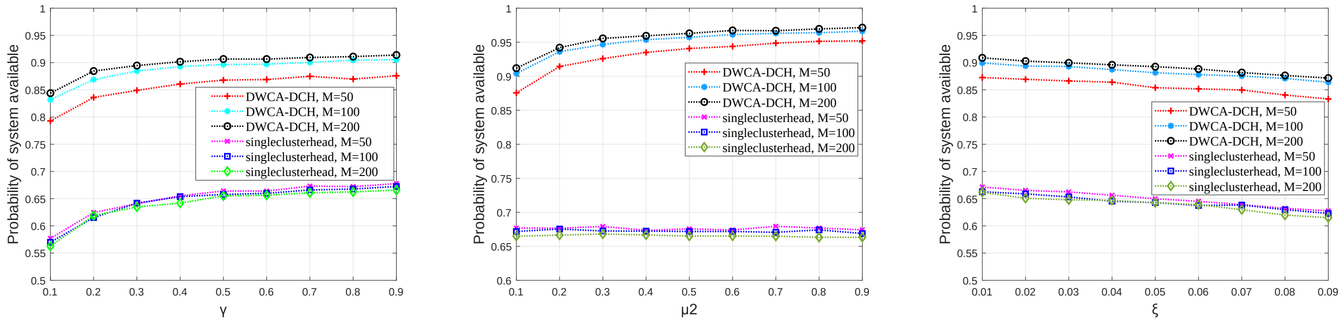
UAV Number	DWCA-DCH	Single Cluster Head	Improvement
20	0.8137	0.6797	19.7%
50	0.8761	0.6751	29.8%
80	0.8993	0.6728	33.7%
110	0.9069	0.6702	35.3%
140	0.9106	0.67	35.9%
170	0.9107	0.670	36.0%
200	0.9132	0.665	37.3%
300	0.9129	0.6614	38.0%
400	0.9109	0.6604	37.9%
500	0.9106	0.6578	38.4%
600	0.911	0.6596	38.1%
700	0.9062	0.6555	38.3%
800	0.903	0.6533	38.2%



(**a**) System available state (**b**) System weak state (**c**) System unavailable state

Figure 6. The probability of each state of the system with the increase in the velocity of UAVs.

Moreover, along with the increase in λ, the probability of UAV at S state increases. Hence, the system weak probability also increases along with the increase in velocity, which is shown in Figure 6b. Unlike the single cluster head algorithm, the system will transfer into the weak state only when both the pCH and the bCH are in S state or one is in S state and the other is in F state. Consequently, the system weak probability in DCWA-DCH is lower than that in the single cluster head algorithm, which demonstrates the robustness of the proposed DCWA-DCH. As system weak probability increases, system unavailable probability also increases under the same μ, which is shown in Figure 6c. The system unavailable probability in DCWA-DCH is also lower since the system will transfer into the unavailable state only when both the pCH and the bCH are in F state.



(**a**) Change γ (**b**) Change μ_2 (**c**) Change ξ

Figure 7. The variation trend of system available probability with different parameters.

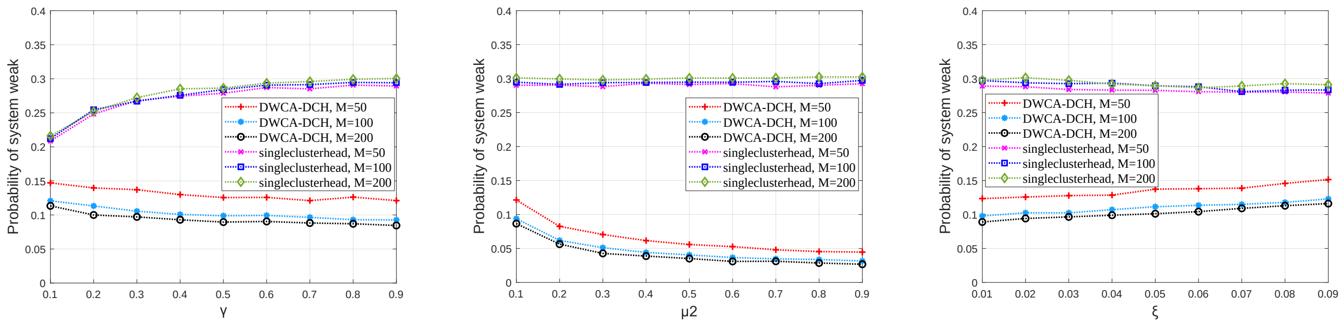
The variation trend of system available probability with different parameters is shown in Figure 7. As shown in Figure 7a–c, no matter how other parameters change, the DWCA-DCH algorithm outperforms the single cluster head algorithm in terms of the system available probability. As shown in Figure 7a, the system available probability of the single cluster head algorithm and the dual cluster head algorithm increases as γ increases (i.e., the probability of the UAV transferring from the F state to the C state increases). The system available probability of the dual cluster head algorithm is greater than that of the single cluster head algorithm. It shows that the dual cluster head algorithm increases the available probability of the system.

When both the pCH and the bCH have low energy, the bCH will enter the F state as soon as possible and fly to the charging pile, so as to restore the system to available as soon as possible. Therefore, the impact of μ_2 is considered on the system survivability, i.e., the influence of the probability change of the bCH from the S state to the F state on the system survival probability. As shown in Figure 7b, the system available probability P_{av} increases along with the growth of μ_2, which is because the increase of μ_2 will prompt the bCH to transfer from the S state to the F state faster, and then recover to available faster. This indicates that increasing the transition rate of the bCH from the S state to the F state can make the dual cluster head system recover to available faster. In comparison, there is no μ_2 in the single cluster head algorithm, thus the blue line barely changes.

ξ represents the transition probability of the UAV from the C state to the F state, whose value is relatively low. Therefore, the variation range is set as 0.01–0.09 during simulation. In Figure 7c, it shows that the available probability of both the dual cluster head algorithm and the single cluster head algorithm decreases as ξ increases, but the available probability of the dual cluster head algorithm is greater than that of the single cluster head algorithm, which fully indicates that the introduction of the dual cluster head algorithm increases the availability of the system.

Figure 8a–c shows the variation trend of system weak probability with different parameters. The system weak probability of the dual cluster head algorithm is lower than that of the single cluster head algorithm. For DWCA-DCH, P_{wk} decreases as γ increases, showing that increasing the charging and maintaining rate will increase the rate at which the system exits the weak state (this is because the bCH will enter the F state as soon as possible when both the pCH and the bCH have low energy, and increasing γ will increase the rate that the bCH returns to C sate from F state), thus improving performance. As for the single cluster head algorithm, increasing γ can make the nodes in S state return to the

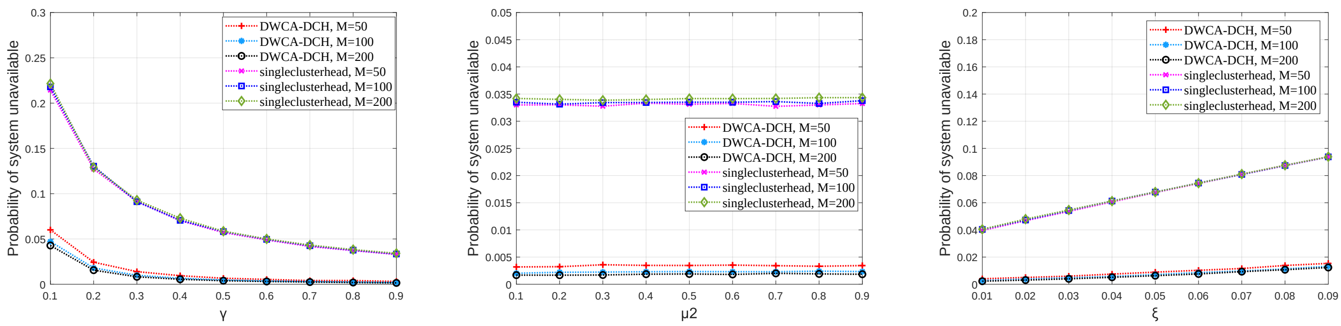
C state faster, which indirectly increases the probability of the node transferring to the S state. For the dual cluster head algorithm, P_{wk} decreases as μ_2 increases, indicating that increasing the transition rate of bCH from the S state to the F state can make the dual cluster head system recover to available faster. Since the single cluster head algorithm has no bCH, changing μ_2 has no effect on P_{wk}. In the dual cluster head algorithm, as ξ increases, P_{wk} increases, because it increases the probability that the system will move from SC to SF. For the single cluster head algorithm, increasing the probability that the node will move from C to F indirectly reduces the probability of node entering the S state, therefore with the increase in ξ, P_{wk} slightly decreases.



(**a**) Change γ (**b**) Change μ_2 (**c**) Change ξ

Figure 8. The variation trend of system weak probability with different parameters.

Figure 9a–c shows the variation trend of system unavailable probability with different parameters. It can be seen that the unavailable probability of the dual cluster head algorithm is much lower than that of the single cluster head algorithm. With the increase in the number of UAV nodes, P_{unav} gradually decreases in DWCA-DCH. P_{unav} decreases as γ increases. When μ_2 is increased, P_{unav} basically keeps steady. When ξ increases, P_{unav} increases significantly, while the curve of the dual cluster head is flatter, indicating that the proposed DWCA-DCH has better performance in improving system stability. Therefore, in the actual deployment, in order to reduce the probability of system unavailable, the fault maintaining and charging rate should be increased, and reasonable measures should be taken to reduce the fault rate of UAV.



(**a**) Change γ (**b**) Change μ_2 (**c**) Change ξ

Figure 9. The variation trend of system unavailable probability with different parameters.

Figure 10 shows the trend of system available probability of the proposed DWCA-DCH over time, and compares it with MLSC algorithm [14] and the single cluster head algorithm. It can be seen that as time goes on, in the proposed DWCA-DCH, the available probability of the system gradually declines and then rebounds, maintaining a stable trend on the whole. This is because as time goes on, the remaining energy of the p/bCH gradually decreases, and the movement of the UAVs causes the change of distance between each other, so that the system available probability gradually decreases. When a node more suitable to serve as pCH appears, the system will update the cluster head, so that the system available probability rebounds. Additionally, compared to MLSC, further improvement in system performance is achieved by promptly transitioning the UAV in the S state to the F state in order to fly to the charging pile, so as to restore the system to available as soon as possible. Consequently, as shown in Figure 10, the available probability in DWCA-DCH is higher than that in MLSC and the single cluster head algorithm. Furthermore, the available probability curves in the single cluster head algorithm and MLSC fluctuate (i.e., re-cluster) more frequently and with a greater amplitude. The overall available probability of the MLSC and the single cluster head algorithm gradually diminishes over time, and there may be sudden drops in its performance. It clearly illustrates that the system available probability of the DWCA-DCH algorithm is markedly superior to MLSC and the single cluster head algorithm, and it exhibits a more consistent trend.

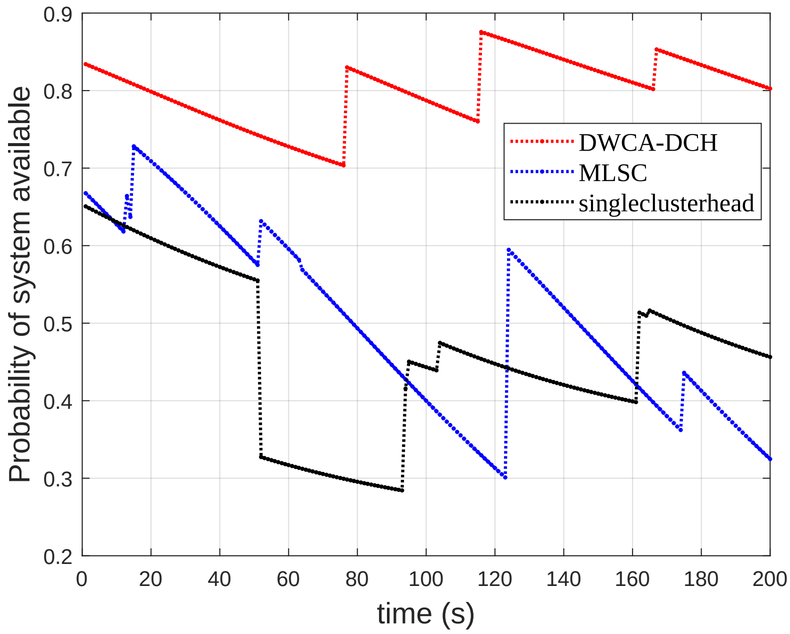


Figure 10. The variation trend of system of available probability as t increases compared with MLSC.

8. Conclusions

Aiming at the problems of high mobility and limited energy in UAV cluster ad hoc networks, a dynamic dual cluster head weight clustering algorithm is proposed. By jointly considering relevant weight factors, pCH and bCH are selected in each cluster. Meanwhile, the algorithm of cluster selection and dynamic cluster maintenance is given in detail. To evaluate the performance of the UAV network, we constructed a survivability analysis method based on Markov process to verify the survivability of the UAV network. The simulation results show that the DWCA-DCH can effectively improve the availability and stability of the UAV network. Furthermore, suggestions are given on the optimal deployment number of UAVs and network performance improvement schemes. Future research could focus on integrating artificial intelligence techniques such as machine learning and optimization algorithms to improve the performance of clustering algorithms. This could involve developing algorithms that can optimize the formation of clusters, the selection of cluster heads, and node localization, which would lead to longer cluster lifetimes and reduced energy consumption.

Author Contributions: Conceptualization, Y.Z.; methodology, Y.Z. and Z.H.; validation, Y.Z., Z.H. and Z.W.; investigation, Y.Z.; writing—original draft preparation, Y.Z., Z.H. and Z.W.; writing—review and editing, Y.Z., Z.H., Z.W., X.W. and Z.L.; supervision, Y.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by National Natural Science Foundation of China (No. 61901163) and Beijing Natural Science Foundation (No. L192034).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

DWCA-DCH	Dynamic weighted clustering algorithm with dual cluster heads
SAM-MP	Survivability analysis method based on Markov process
UAV	Unmanned aerial vehicle
FANETs	Flying ad hoc network
WCA	Weighted clustering algorithm
MLSC	Mobility and location-aware stable clustering
SIC	Swarm intelligence-based clustering
PSO	Particle swarm optimization
pCH	Prime cluster head
bCH	Backup cluster head
gBS	Ground base station
A2A	Air-to-air
LoS	Line of sight
NLoS	Non-line-of-sight
C	Cooperative state
S	Selfish state
F	Failure state
AI	Artificial intelligence

References

1. Li, B.; Fei, Z.; Zhang, Y. Uav communications for 5g and beyond: Recent advances and future trends. *IEEE Internet Things J.* **2018**, *6*, 2241–2263. [CrossRef]
2. Bor-Yaliniz, I.; Yanikomeroglu, H. The new frontier in ran heterogeneity: Multi-tier drone-cells. *IEEE Commun. Mag. Artic. News Events Interest Commun. Eng.* **2016**, *54*, 48–55. [CrossRef]
3. Merwaday, A.; Tuncer, A.; Kumbhar, A.; Guvenc, I. Improved throughput coverage in natural disasters: Unmanned aerial base stations for public-safety communications. *IEEE Veh. Technol. Mag.* **2016**, *11*, 53–60. [CrossRef]
4. Dong, M.; Ota, K.; Lin, M.; Tang, Z.; Du, S.; Zhu, H. Uav-assisted data gathering in wireless sensor networks. *J. Supercomput.* **2014**, *70*, 1142–1155. [CrossRef]
5. Bekmezci, I.; Sahingoz, O.K.; Temel, S. Flying ad-hoc networks (fanets): A survey. *Ad. Hoc. Netw.* **2013**, *11*, 1254–1270. [CrossRef]
6. Arafat, M.Y.; Moh, S. Localization and clustering based on swarm intelligence in uav networks for emergency communications. *IEEE Internet Things J.* **2019**, *6*, 8958–8976. [CrossRef]
7. Khan, M.F.; Yau, K.L.A.; Ling, M.H.; Imran, M.A.; Chong, Y.W. An Intelligent Cluster-Based Routing Scheme in 5G Flying Ad Hoc Networks. *Appl. Sci.* **2022**, *12*, 3665. [CrossRef]
8. Srivastava, A.; Prakash, J. Future FANET with application and enabling techniques: Anatomization and sustainability issues. *Comput. Sci. Rev.* **2021**, *39*, 100359. [CrossRef]
9. Sadraey, M. Unmanned Aircraft Design: A Review of Fundamentals. *Synth. Lect. Mech. Eng.* **2017**, *1*, 193.
10. Joa-Ng, M.; Lu, I.T. A peer-to-peer zone-based two-level link state routing for mobile ad hoc networks. *IEEE J. Sel. Areas Commun.* **1999**, *17*, 1415–1425. [CrossRef]
11. Chatterjee, M.; Das, S.K.; Turgut, D. Wca: A weighted clustering algorithm for mobile ad hoc networks. *Clust. Comput.* **2002**, *5*, 193–204. [CrossRef]
12. Arafat, M.Y.; Moh, S. A survey on cluster-based routing protocols for unmanned aerial vehicle networks. *IEEE Access* **2018**, *7*, 498–516. [CrossRef]
13. Xia, X.; Yan, Y.; Li, Z.; Meng, D.; Xia, L.; Chen, C. A survey of UAV clustering algorithm. In Proceedings of the 2022 24th International Conference on Advanced Communication Technology (ICACT), Pyeongchang, Republic of Korea, 13–16 February 2022; pp. 191–196.

14. Bhandari, S.; Wang, X.; Lee, R. Mobility and location-aware stable clustering scheme for uav networks. *IEEE Access* **2020**, *8*, 106364–106372. [CrossRef]
15. Kovalenko, V.; Alzaghir, A.; Volkov, A.; Muthanna, A.; Koucheryavy, A. Clustering algorithms for uav placement in 5G and beyond networks. In Proceedings of the 2020 12th International Congress on Ultra Modern Telecommunications and Control Systems and Workshops (ICUMT), Brno, Czech Republic, 5–7 October 2020.
16. Aadil, F.; Raza, A.; Khan, M.F.; Maqsood, M.; Mehmood, I.; Rho, S. Energy aware cluster based routing in flying ad-hoc networks. *Sensors* **2018**, *18*, 1413. [CrossRef]
17. Khan, A.; Aftab, F.; Zhang, Z. BICSF: Bio-Inspired Clustering Scheme for FANETs. *IEEE Access* **2019**, *7*, 31446–31456. [CrossRef]
18. Fang, K.; Ru, L.; Yu, Y.; Jia, X.; Liu, S. An energy balance and mobility prediction clustering algorithm for large-scale UAV ad hoc networks. *Eng. Rev.* **2019**, *39*, 1–10. [CrossRef]
19. Yi, Z.; Dohi, T.; Okamura, H. Survivability modeling and analysis for a power-aware wireless ad hoc network. In Proceedings of the 2012 IV International Congress on Ultra Modern Telecommunications and Control Systems, St. Petersburg, Russia, 3–5 October 2012.
20. Halim, A.; Ahmad, R.; Noh, Z. Survivability Modeling and Analysis of Mobile Ad Hoc Network with Correlated Node Behavior. *Procedia Eng.* **2013**, *53*, 435–440.
21. Yu, J.; Yu, Z.; Ding, M.; Ye, W. Research on the Tenacity Survivability of Wireless Sensor Networks. *J. Ambient Intell. Humaniz. Comput.* **2020**, *11*, 3535–3544. [CrossRef]
22. Su, W.; Lee, S.J.; Gerla, M. Mobility prediction and routing in ad hoc wireless networks. *Int. J. Netw. Manag.* **2001**, *11*, 3–30. [CrossRef]
23. Zonoozi, M.M.; Dassanayake, P. User mobility modeling and characterization of mobility patterns. *IEEE J. Sel. Areas Commun.* **1997**, *15*, 1239–1252. [CrossRef]
24. Rappaport, T.S. *Wireless Communications: Principles and Practice*; Prentice Hall PTR: Hoboken, NJ, USA, 1996.
25. Yan, C.; Fu, L.; Zhang, J.; Wang, J. A comprehensive survey on uav communication channel modeling. *IEEE Access* **2019**, *7*, 107769–107792. [CrossRef]
26. Al-Hourani, A.; Kandeepan, S.; Lardner, S. Optimal lap altitude for maximum coverage. *IEEE Wirel. Commun. Lett.* **2014**, *3*, 569–572. [CrossRef]
27. Li, Y.; Li, S.; Ding, Q.; Wang, C. Research on reliability of ad hoc network communication in uavs formations. In Proceedings of the 2019 IEEE 6th International Symposium on Electromagnetic Compatibility (ISEMC), Barcelona, Spain, 2–6 September 2019.
28. Zeng, Y.; Zhang, R. Energy-efficient uav communication with trajectory optimization. *IEEE Trans. Wirel. Commun.* **2017**, *16*, 3747–3760. [CrossRef]
29. Mozaffari, M.; Saad, W.; Bennis, M.; Debbah, M. Mobile unmanned aerial vehicles (uavs) for energy-efficient internet of things communications. *IEEE Trans. Wirel. Commun.* **2017**, *16*, 7574–7589. [CrossRef]
30. Leishman, J.G. *Principles of Helicopter Aerodynamics with cd Extra*; Cambridge University Press: Cambridge, UK, 2006; pp. 159–191.
31. Yaliniz, R.; El-Keyi, A.; Yanikomeroglu, H. Efficient 3-d placement of an aerial base station in next generation cellular networks. In Proceedings of the 2016 IEEE International Conference on Communications (ICC), Kuala Lumpur, Malaysia, 22–27 May 2016.
32. Sun, Y.; Mi, Z.; Wang, H.; Lu, F.; Zhao, N. Adaptive enhanced weighted clustering algorithm for uav swarm. In Proceedings of the 2020 IEEE 20th International Conference on Communication Technology (ICCT), Nanning, China, 28–31 October 2020.