

Anti-Jamming Weighted Clustering Algorithm for UAV-Mounted Weapon Self-Organizing Network

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Abstract— Compared to traditional self-organizing networks, UAV-mounted weapon self-organizing networks are characterized by high node mobility, vulnerability to interference and attacks, extensive coverage, and large-scale network sizes. These factors complicate network management and the operation of routing protocols. Cluster-based topologies can be employed to optimize network management, reducing the impact of local topology changes on the entire network. To address the issue of cluster instability caused by the high mobility and interference susceptibility of UAV-mounted weapons, a anti-jamming weighted clustering algorithm(AJWCA) is proposed. The algorithm builds on existing weighted clustering approaches by incorporating an interference factor into the cluster head selection process. Additionally, a backup cluster head mechanism is introduced to mitigate cluster oscillations resulting from the failure of cluster head nodes in battlefield and emergency scenarios. The effectiveness of the proposed algorithm was validated through simulations. The results show that the algorithm effectively enables efficient clustering of network nodes and improves cluster head duration under interference conditions. Moreover, the method demonstrates rapid recovery capability in the event of node failures, making it well-suited for deployment in complex operational environments.

Keywords— UAV-Mounted Weapon, Network Topology, Clustering Method, Interference Factor, Backup Cluster Head

I. INTRODUCTION

Currently, UAV combat applications are becoming increasingly widespread and diverse, particularly with the advancement of technologies such as UAV platforms, communication technologies, payload detection, and precision-guided weapon systems. This has led to significant attention being given to UAV-mounted weapon systems, which are evolving toward micro precision-guided and precision strike capabilities [1]. As a result, establishing a reliable communication network for UAV-mounted weapon systems has become a critical area of research. UAV-mounted weapon networks are characterized by enhanced node mobility and highly dynamic changes in network topology [2, 3]. Additionally, to fully leverage the advantages of clustering, these networks typically involve a large number of nodes, with wider distribution and larger network scales. In real-world battlefield environments, it is also essential to address the issue of interference attacks on UAV-mounted weapon networks. Such interference attacks can affect a wide range of

nodes or links, leading to changes in network topology and, ultimately, reducing the stability of the network.

Considering the characteristics of UAV-mounted weapon networks, clustering strategies serve as an effective approach to enhance network performance. By partitioning the nodes into several clusters, each cluster can be viewed as a relatively stable sub-network [4]. Compared to a flat network structure, the clustered topology mitigates the impact of local topological changes on the overall network. During route calculation and generation, only a subset of nodes is involved, thereby reducing the routing and control overhead. Furthermore, the clustered structure facilitates efficient network management and control, thereby improving network stability [5]. In this structure, the UAV-mounted weapon system can achieve efficient deployment and stable communication.

Several research efforts have been dedicated to the clustering schemes for UAV system. In [6], the author proposes a adaptive enhanced weighted clustering algorithm, which improves the stability of cluster structure and the overall endurance of the UAVs. In [7], an improved weighted and location-based clustering (IWLC) scheme is proposed for FANET performance enhancement, under the constraints of network resources. In [8], an efficient clustering technique is proposed to handle routing and energy problems of Flying ad-hoc networks. The proposed scheme outclasses the existing state-of-the-art techniques in terms of energy consumption and cluster building time. In [9], A new weighted formula based on increasing reward index has been proposed for S-UAV clustering, which has lower total latency than other existing schemes. During mission execution, UAV-mounted weapon systems are vulnerable to external interference and attacks from adversaries. The aforementioned research lacks consideration of the anti-interference issue during the clustering process. Therefore, it is necessary to make corresponding improvements to the clustering algorithm to address the anti-interference challenge.

This paper proposes a anti-jamming weighted clustering algorithm(AJWCA) for UAV-mounted weapon self-organizing network. To address inter-cluster interference, the K-means++ clustering algorithm is employed to make the initial cluster centroids more dispersed, ensuring a more even

initial cluster distribution and reducing inter-cluster interference. To counter external interference, an interference factor is introduced into the cluster head election process. By weighting the selection factors for each cluster head, the algorithm computes the node weights within each cluster, selecting a primary cluster head and a backup cluster head to enhance topology stability.

II. UAV-MOUNTED WEAPON SELF-ORGANIZING NETWORK CLUSTERING MODEL

A. Network topology model

Due to the high mobility of UAV-mounted weapons, a layered network structure is adopted to effectively reduce the overhead of routing control information and mitigate the impact of local topology changes on the entire network. The nodes in UAV-mounted weapons network are categorized into two roles through a clustering algorithm: cluster heads and cluster members, which together form a two-layer network, as shown in Figure 1. The cluster head is responsible for managing clusters, facilitating communication between different clusters, and communicating with external devices such as ground control centers. The cluster members can not directly communicate with nodes outside the cluster and must complete information collection and processing through cluster head forwarding.

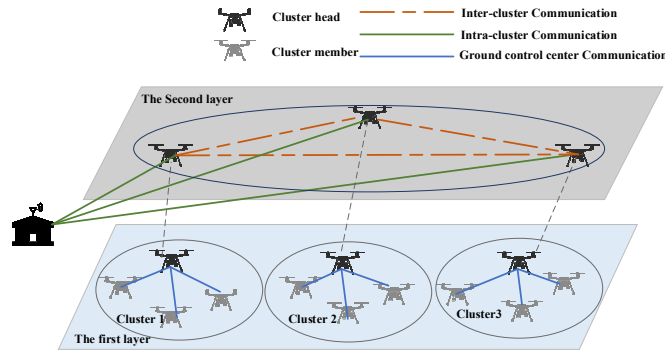


Figure 1. Network topology model

B. Clustering algorithm process

The clustering method for UAV-mounted weapons network usually includes clustering after network initialization, cluster head selection, network topology generation, and maintenance after clustering. The basic steps are shown in Figure 2.

1) Initialize cluster node information : All nodes within the network initiate mutual probing and exchange information, including the number of their neighboring nodes and their respective locations.

2) Divide nodes into different clusters : In the UAV-mounted weapons system, all nodes are assigned to distinct node regions based on the established partitioning rules, with each region representing a separate cluster.

3) Select cluster heads from each cluster : Within each partitioned cluster, the node that best meets the election requirements is selected as the cluster head through a specially

designed cluster head election algorithm. The remaining nodes within the cluster serve as member nodes, and a backup cluster head is chosen from among these member nodes.

4) Generate topological network : Building upon the pre-established clusters, along with the designated cluster head nodes and member nodes within each cluster, it is imperative to establish the connection relationships between intra-cluster and inter-cluster nodes.

5) Update and refactor cluster structure : After the initial clustering, ongoing maintenance and management of the clusters become imperative due to the continuous movement of the nodes. This dynamic nature of the environment requires the implementation of adaptive strategies to ensure the stability and effectiveness of the clustering structure over time.

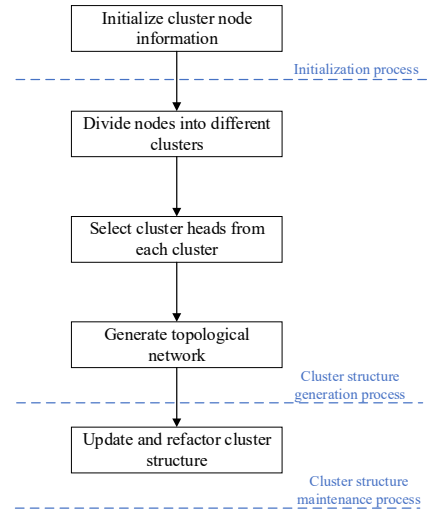


Figure 2. Clustering algorithm process

III. DESIGN OF ANTI-JAMMING WEIGHTED CLUSTERING ALGORITHM

A. Cluster formation

After network initialization, the UAV-mounted weapons cluster network is divided into regions by clustering algorithm, and each region is a cluster. In this section, the K-means++ algorithm is used to pre-cluster the network [10]. The algorithm considers the distance between the nodes when selecting the initial clustering center, which makes the initial centroids more dispersed so that the clusters are uniformly distributed and the inter-cluster interference is reduced. The basic steps of the K-means++ algorithm are as follows:

Step1: Randomly select a node in the network as the seed node, which is the clustering center.

Step2: Calculate the Euclidean distance between other nodes and this seed node.

Step3: Randomly select the node with larger distance from the seed node as the new seed node.

Step4: Repeat the steps of Step1~Step3 until K seed nodes are selected.

Step5: Calculate the Euclidean distance between other nodes in the network and all seed nodes, and add them to the

nearest cluster to complete this round of cluster partitioning. At this point, the network is divided into different clusters.

Among them, K represents the number of clusters to be divided, which can be pre-set according to the needs of the scene or calculated based on the principle of throughput balancing.

B. Cluster Head Selection

Upon completing the initial clustering phase, the process transitions to the cluster head election phase. Within a clustered topology, the cluster head acts as a crucial hub for information exchange both among nodes within the cluster and between clusters, significantly enhancing the performance of UAV-mounted weapon system. Consequently, the selection of the cluster head is of paramount importance. The operation of UAV-mounted weapon system is often challenged by high mobility and vulnerability to external interference, resulting in frequent topological changes. To address these challenges and achieve improved topological stability, this study implements a backup cluster head mechanism and incorporates interference factors as a criterion for cluster head selection.

This article comprehensively considers the key factors affecting the network performance of UAV-mounted weapon systems and translates them into cluster head influence factors suitable for clustered topological structures, thereby completing the design of an optimal cluster head selection algorithm. The cluster head influence factors include: remaining energy factor, movement similarity factor, average distance factor, and external interference factor. The four factors are normalized to mitigate the effect of different scaling units.

1) Remaining energy factor : In a UAV-mounted weapon cluster network, the cluster head manages both intra-cluster data transmission and inter-cluster data forwarding, leading to significantly higher energy consumption for the cluster head compared to regular cluster members. Consequently, the initial remaining energy of the nodes must be considered in the cluster head selection process. Assuming all nodes in the ad hoc network have the same energy storage capacity, the remaining energy factor of candidate nodes is normalized as follows:

$$a_{E_i} = \frac{E_{ri}}{E_i} \quad (1)$$

where E_i represents the maximum energy of a node, and E_{ri} denotes the current residual energy of the node.

2) Movement Similarity Factor

In UAV-mounted weapon networks, the cluster head must maintain stable communication links with all cluster members. When the movement patterns of the cluster head and the cluster members are similar, the relative positional changes between them remain minimal, thus ensuring a stable connection. Similar movement trajectories reduce fluctuations in the distance between nodes, thereby minimizing communication interruptions caused by rapid changes in

distance or signal degradation. UAVs equipped with IMUs and GPS can acquire position and velocity information. This paper presents a method for calculating the relative mobility of nodes in a 3D coordinate system using velocity data. The movement states of the nodes within the cluster are shown in the Figure 3, with the velocity projection on the XY plane represented as:

$$v_i' = v_i \sin \alpha_i \quad (2)$$

$$v_j' = v_j \sin \alpha_j \quad (3)$$

The velocity difference between node i and j can be expressed as:

$$v_{ij-z} = v_i \cos \alpha_i - v_j \cos \alpha_j \quad (4)$$

$$\begin{aligned} v_{ij-x} &= v_i' \cos \theta_i - v_j' \cos \theta_j \\ &= v_i \sin \alpha_i \cos \theta_i - v_j \sin \alpha_j \cos \theta_j \end{aligned} \quad (5)$$

$$\begin{aligned} v_{ij-y} &= v_i' \sin \theta_i - v_j' \sin \theta_j \\ &= v_i \sin \alpha_i \sin \theta_i - v_j \sin \alpha_j \sin \theta_j \end{aligned} \quad (6)$$

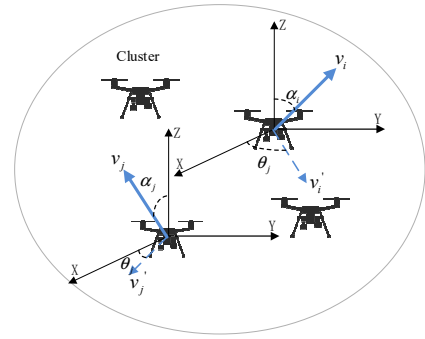


Figure 3. Movement states of the nodes within the cluster

The average speed difference between i and its neighbor nodes in the cluster can be calculated using the following equations:

$$\overline{v_{i-z}} = \frac{\sum_{j=1, j \neq i}^N v_i \cos \alpha_i - v_j \cos \alpha_j}{N-1} \quad (7)$$

$$\overline{v_{i-x}} = \frac{\sum_{j=1, j \neq i}^N v_i \sin \alpha_i \cos \theta_i - v_j \sin \alpha_j \cos \theta_j}{N-1} \quad (8)$$

$$\overline{v_{i-y}} = \frac{\sum_{j=1, j \neq i}^N v_i \sin \alpha_i \sin \theta_i - v_j \sin \alpha_j \sin \theta_j}{N-1} \quad (9)$$

$$\overline{v_i} = \sqrt{\overline{v_{i-x}}^2 + \overline{v_{i-y}}^2 + \overline{v_{i-z}}^2} \quad (10)$$

Where N represents the number of nodes within the cluster.

After normalization, the movement similarity factor a_{v_i} can be expressed as:

$$a_{v_i} = \frac{\overline{v_i}}{v_{\max}} = \frac{\sqrt{\overline{v_{i-x}}^2 + \overline{v_{i-y}}^2 + \overline{v_{i-z}}^2}}{v_{\max}} \quad (11)$$

Where $v_{\max}$ is the maximum movement speed of the node.

3) Average Distance Factor:

In a UAV-based weapon cluster network, the cluster head serves as the central node of each cluster, facilitating communication with other cluster heads or external nodes. The initial average distance between cluster members and the cluster head has a direct impact on communication delay and energy consumption. A closer cluster head can exchange data with intra-cluster nodes more quickly, avoiding long-distance communication and thereby improving network efficiency. Assuming that all nodes have the same transmission power and maximum communication range, the average distance factor for node can be normalized as follows:

$$a_{\overline{D}_i} = \frac{\sum_{j=1, j \neq i}^N \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2}}{(N-1)D_{\max}} \quad (12)$$

Where N represents the number of nodes within the cluster, $D_{\max}$ represents the maximum communication range of a node, (x_i, y_i, z_i) and (x_j, y_j, z_j) represent the 3D positional information of node i and j , respectively.

4) External Interference Factor

In real battlefield environments, hostile forces may attempt to disrupt our UAV-based weapon systems. These interferences can be broadly categorized into two types: energy-based interference and information-based interference. For energy-based interference, when the interference power is low, the communication quality between nodes degrades. However, when the interference power is high, it can completely disrupt the communication link between nodes. In contrast, information-based interference typically does not lead to the interruption of communication links but introduces erroneous data, resulting in a decline in communication quality, data transmission deviation, and consequently affecting data accuracy and communication efficiency.

When interference leads to a disruption in communication between nodes, the affected node cannot broadcast hello messages to other nodes or receive messages from them. As a result, it will not be able to participate in the clustering process or the cluster head competition. When interference only reduces communication quality, the degree of interference can be assessed by the packet error rate of hello messages periodically broadcast by each node, ensuring fairness across the network. Nodes with higher packet error rates indicate more severe interference and poorer communication quality.

The external interference factor a_{EPR_i} of the node i can be normalized through the packet error rate of its hello message, as shown in the following formula:

$$a_{EPR_i} = \frac{m}{M} \times 100\% \quad (13)$$

Where m represents the number of erroneous hello message packets received by the node i , and M represents

the total number of hello message packets received by the node i .

In summary, after determining the four cluster head selection factors, the clustering weight of a candidate cluster head node is calculated using a weighted method. The node with the lowest weight is elected as the cluster head. And the node with the second lowest weight is selected as the backup cluster head. The method for calculating the weight is as follows:

$$W_i = \varepsilon_1(1 - a_{E_i}) + \varepsilon_2 a_{\overline{D}_i} + \varepsilon_3 a_{EPR_i} + \varepsilon_4 a_{\overline{D}_i} \quad (14)$$

Where ε_1 , ε_2 , ε_3 and ε_4 are the weight coefficients for the four cluster head selection factors, and they must satisfy the condition $\varepsilon_1 + \varepsilon_2 + \varepsilon_3 + \varepsilon_4 = 1$. These coefficients can be dynamically chosen based on the network environment.

C. Network topology generation

After the completion of the above two phases, the network partitioning is finalized and cluster heads are selected. The next step is to generate the network topology. Cluster head nodes send out C-Clustering messages, and other nodes, upon receiving the clustering information from their cluster head, modify the Role flag in their Hello message to indicate that they are now cluster member nodes. They then send a C-Replay back to the cluster head, notifying it of their inclusion in the cluster. Once the cluster head receives the C-Replay, it updates the C-Clustering message with the new member information. This process continues until all nodes have joined their respective clusters, thereby completing the network topology construction. The message transmission process between the cluster head and cluster member nodes is shown in Figure 4.

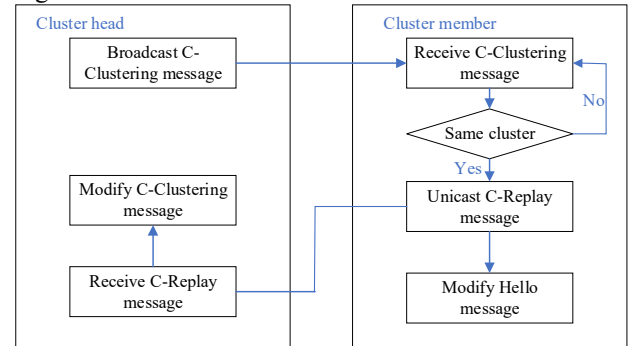


Figure 4. Message transmission process between cluster head and member

D. Dynamic Update and Maintenance of Cluster Structure

In real combat scenarios involving UAV-mounted weapon systems, cluster head nodes and cluster member nodes may suddenly go offline due to factors such as jamming attacks, equipment failure, battery depletion, or node mobility, which can lead to communication link disruptions. Therefore, dynamic updating and maintenance of the cluster structure are crucial to ensure network stability and efficient communication. The following provides a detailed explanation of the dynamic maintenance mechanisms for cluster member nodes and cluster head nodes:

1) Dynamic Update and Maintenance of Cluster Member Nodes

The cluster head node continuously monitors the connectivity of cluster member nodes by listening for Hello messages sent by them. If the cluster head fails to receive Hello messages from a specific cluster member node three consecutive times, it determines that the link with that node has been interrupted. The cluster head will then immediately update its internal data and remove the failed node from the current cluster's member list.

2) Dynamic Update and Maintenance of Cluster Head Nodes

The backup cluster head node continuously listens for Hello messages from the current cluster head node. If the backup cluster head fails to receive Hello messages from the cluster head node three times in a row, it assumes that the cluster head has become unavailable. At this point, the backup cluster head automatically takes over as the new cluster head and broadcasts a C-Clustering message to inform all original cluster members to rejoin the newly formed cluster structure. This process helps update the network topology of the cluster, ensuring continued operation and maintaining seamless connectivity within the network.

IV. EXPERIMENTS AND RESULTS

The experiments aim to evaluate the performance of the proposed anti-jamming weighted clustering scheme designed for UAV-mounted weapon self-organizing networks. In the simulation, the area is set to $1000 \times 1000 \times 1000$ m, with 30 nodes participating. The nodes move at speeds ranging between 20 and 30 m/s, and each node starts with an initial energy of 100 J. The maximum communication distance is capped at 200 m. Considering the significant impact of external interference and the average intra-cluster distance of the cluster head on the stability of network operations, the weight coefficients for cluster head selection were selected as $\varepsilon_1 = 0.2$, $\varepsilon_2 = 0.1$, $\varepsilon_3 = 0.3$ and $\varepsilon_4 = 0.4$.

A. Clustering Networking Function

The network is divided into five clusters based on the conditions of the system, following a two-step clustering process. First, the K-means++ algorithm is employed to partition the nodes into clusters based on their geographical locations. In the second step, a weighted algorithm is applied to select the cluster heads and backup cluster heads within each partition, ultimately forming the network topology. Figure 5 shows the initial distribution of nodes without clustering. Figure 6 illustrates the partitions formed after applying K-means++, considering the geographical locations of the nodes. As observed in Figure 6, the K-means++ algorithm effectively clusters the network nodes in a geographically balanced manner, minimizing interference between clusters. Figure 7 presents the resulting network topology after the selection of cluster heads and backup cluster heads. The selected cluster head nodes are 4, 14, 24, 2, and 18, while the backup cluster head nodes are 20, 21, 3, 28, and 12. By employing the proposed clustering algorithm, all

UAV-mounted weapon nodes are interconnected through the cluster head nodes within the clustered network structure, facilitating efficient deployment and ensuring stable communication.

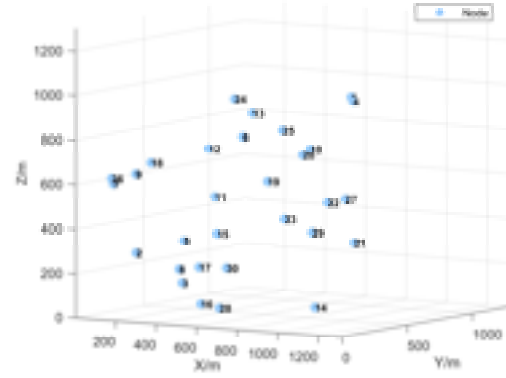


Figure 5. Initial node distribution

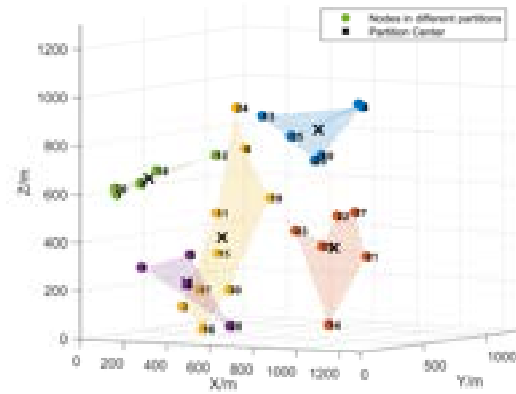


Figure 6. Network partitioning based on K-means++ algorithm

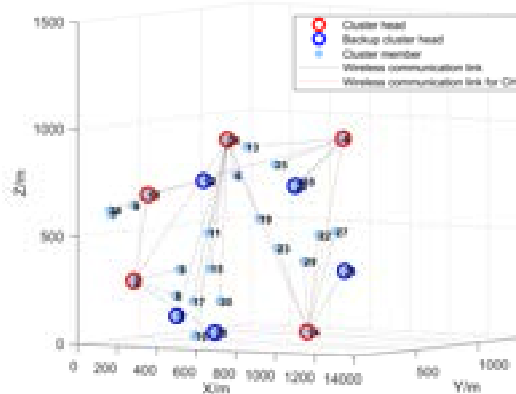


Figure 7. Final network topology based on clustering algorithm

B. Cluster Update and Maintenance Under Interference

After running the simulation for 3s, interference is simulated on cluster head node 24, causing its communication link to be disrupted. The process of cluster updating and maintenance is illustrated in Figure 8. Following the

disruption of node 24, the backup cluster head node 3 automatically assumes the role of the new cluster head, taking over the cluster and reorganizing other cluster members to join, thereby updating the network topology of cluster and ensuring normal operation and connectivity of the cluster.

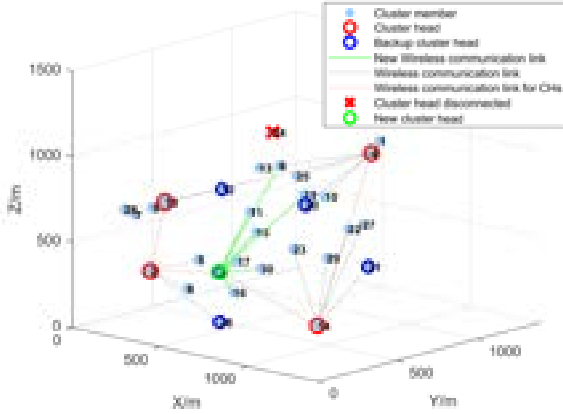


Figure 8. Cluster head replacement

After the simulation continues for another 5s, interference is simulated on cluster member node 10, causing its communication link to be disrupted. The process of cluster updating and maintenance is also shown in Figure 9. Following the disruption of node 10, cluster head node 4 removes the failed node from the current cluster's member list, completing the update of the network topology.

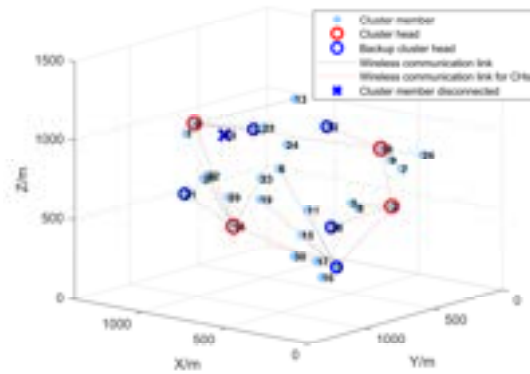


Figure 9. Cluster member disconnected

C. Cluster Head Duration Under Interference

The average cluster head duration can intuitively reflect the performance of the cluster head selection algorithm. The longer the cluster head duration time, the higher the stability of the selected cluster head. The cluster head duration of the AJWCA algorithm was simulated under varying interference power conditions and compared with the WCA algorithm. As shown in the Figure 10, the AJWCA algorithm achieves a longer overall cluster head duration than the WCA algorithm as interference power increases, indicating that the cluster heads selected by AJWCA have stronger anti-interference capabilities and greater stability.

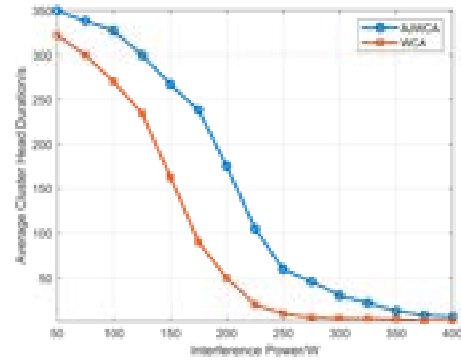


Figure 10. Average cluster head duration of AJWCA and WCA

V. CONCLUSIONS

To address the challenges of high mobility, interference, and large-scale coverage in UAV-mounted weapon networks, this paper proposes an anti-jamming weighted clustering algorithm (AJWCA). The algorithm uses K-means++ for balanced clustering, incorporates an interference factor, and introduces backup cluster heads for enhanced stability. Simulations demonstrate improved recovery, scalability, and adaptability, making AJWCA suitable for complex environments.

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REFERENCES

- [1] Skorobogatov G. Multiple UAV systems: a survey[J]. Unmanned Systems, 2020, 08(02):149-169.
- [2] X. Chen, J. Tang and S. Lao. Review of unmanned aerial vehicle swarm communication architectures and routing protocols[J]. Applied Sciences., 2020, 10(10): 3661.
- [3] B. Alzahrani, O. S. Oubbati, A. Barnawi, M. Atiquzzaman and D. Alghazzawi. UAV assistance paradigm: State-of-the-art in applications and challenges[J]. Journal of Network and Computer Applications, 2020,166: 102706.
- [4] M. Gheisari et al. A Survey on Clustering Algorithms in Wireless Sensor Networks: Challenges, Research, and Trends[C]. 2020 International Computer Symposium (ICS), Tainan, Taiwan, 2020, pp. 294-299.
- [5] F. Aadil, W. Ahsan, Z. U. Rehman, P. A. Shah, S. Rho, and I. Mehmood. Clustering algorithm for internet of vehicles (IoV) based on dragonfly optimizer[J]. The Journal of Supercomputing, 2018, 74: 4542-4567.
- [6] Y. Sun, Z. Mi, H. Wang, F. Lu and N. Zhao. Adaptive Enhanced Weighted Clustering Algorithm for UAV Swarm[C]. 2020 IEEE 20th International Conference on Communication Technology (ICCT), Nanning, China, 2020, pp. 709-714
- [7] Yang X, Yu T, Chen Z, Yang J, Hu J, Wu Y. An Improved Weighted and Location-Based Clustering Scheme for Flying Ad Hoc Networks[J]. Sensors. 2022; 22(9): 3236.
- [8] Raza, Ali and Khan, Muhammad Fahad and Maqsood, Muazzam and Haider, Bilal and Aadil, Farhan. Adaptive k-means clustering for Flying Ad-hoc Networks[J]. KSII Transactions on Internet and Information Systems, 2020, 14(6): 2670-2685.
- [9] G. Khayat, C. X. Mavromoustakis, A. Pitsillides, J. M. Batalla, E. K. Markakis and G. Mastorakis. On the Weighted Cluster S-UAV Scheme Using Latency-Oriented Trust. IEEE Access, 2023, 11: 56310-56323.

- [10] Arthur D. Vassilvitskii S. K-Means++: The Advantages of Careful Seeding[C]. 18th Annual ACM-SIAM Symposium on Discrete Algorithms, New York, USA, 2007, pp. 1027-1035.



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