



RESEARCH ON UNMANNED CLUSTER RECONNECTION DECISION-MAKING METHOD CONSIDERING RESOURCE SUPPLEMENTATION

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Abstract

In recent years, with the widespread application, intelligence, and increasing complexity of task scenarios of unmanned cluster systems in various fields, the system capability of clusters has become increasingly dynamic and flexible. It is not only related to the state of individuals but also to the reconnection patterns of clusters. Consequently, the capability can be reversibly enhanced through structural adjustments or resource replenishment in the system. Therefore, addressing the issue of how to make decisions on resource replenishment methods to efficiently and reasonably utilize resources, and thereby ensuring the high reliability operation of unmanned clusters, this paper focuses on the unmanned aerial vehicle (UAV) cluster system in open environments. It analyzes the available states of unmanned clusters under conditions of no reconnection, reconnection, and resource replenishment, and proposes methods for decision optimization of cluster resource replenishment based on degree-preferred connections and particle swarm algorithm. This provides a systematic approach to solving the problems of replenishment, scale changes, and decision optimization of unmanned cluster resources.

Keywords: unmanned cluster system, performance evaluation, resource supplementation, connectivity decision

1. Introduction

The unmanned cluster system (UCS) refers to a holistic system in which multiple unmanned systems collaborate to accomplish complex tasks based on task allocation within a certain time and space. With the application of intelligence and the increasing complexity of task scenarios in UCS, the system typically dynamically supplements or replaces unmanned aerial vehicle (UAV) in case of task losses, and continuously withdraws and supplements UAVs according to task requirements. The system structure is thus open-ended, dynamically adjusting its composition and optimizing its structure according to task requirements to better adapt to new task demands. Therefore, in the process of UCS tasks, the system exhibits the characteristic of dynamic flexibility, which is influenced by factors such as the individual health status, impact, or interference, as well as the reconnection patterns of the cluster. Additionally, reversible recovery and enhancement can be achieved through resource replenishment. In this process, the reliability of tasks also dynamically changes, resulting in a high degree of uncertainty and instability. Efficient decision-making regarding resource replenishment is therefore crucial to ensure the high reliability operation of UCS.

This study considers health status as the inherent potential for performance. In the dynamic operation process, determining the optimal performance based on health status is an urgent problem in current cluster system state decision-making. Thus, it is necessary to first model unmanned clusters, assess their health status based on this model, and then conduct research on the application of health status. In previous studies, the modeling of UCS was based on their scale and emergence, with systematic analysis of individual properties of clusters. Common modeling methods include those based on complex networks and those based on multi-agent systems [1-4]. The assessment of UCS health status is based on the assessment of system and device health. In terms

of health status indicators at the level of single machine and device, the current research on index construction has been relatively mature, such as the health status system assessment of device based on rough set and genetic algorithm [5], or the Bayesian network information fusion of multiple health status factors [6]. However, compared with the health state of a single system, the research work on cluster health state is less. The application of health status in UCS is manifested in various ways, including redeploying communication connections, replacing damaged systems, restructuring organizational structures, and replenishing resources [7].

In terms of modeling for UCS, this paper refers to the complex network modeling method used by Kong et al. [8]. The UAVs in the system are considered as nodes, and the interactions between them are considered as connecting edges, forming a complex network. Additionally, based on the composition of UAV components, the multi-layer complex network is divided into communication, structural, and task layers. Based on the multi-layer complex network model of UCS and considering the specific applications in scenarios, a performance index system for UCS under resource replenishment is established, including structural topology performance, flow connectivity performance, and task efficiency. Specifically, structural topology performance refers to the weighted sum of the average degree K , average clustering coefficient C , and global efficiency CE of the structural layer network.

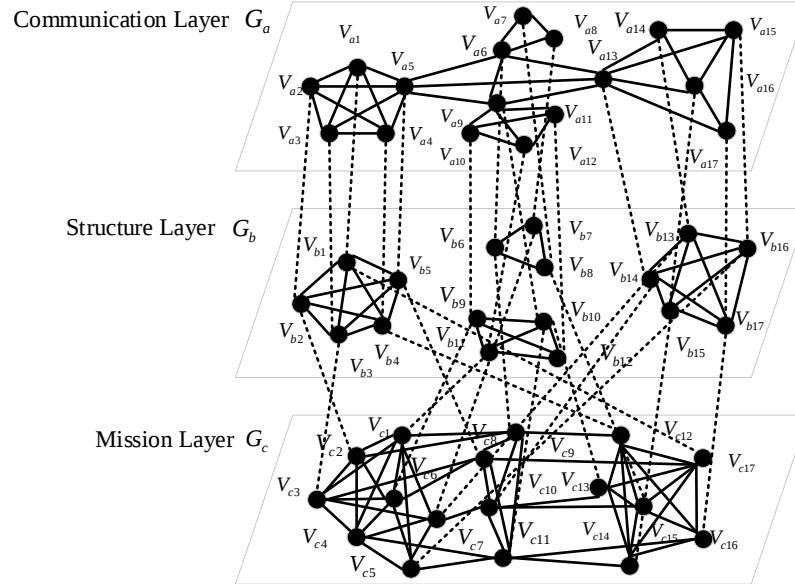


Figure 1 – Schematic diagram of the multi-layer complex network model of UCS.

Based on this, the study utilizes the concept of reliability entropy to establish health status indicators for structural topology performance, in order to measure the quality of performance. The health reachable states of the cluster are measured by the number of available states that can be formed under the current state, thus understanding the utilization efficiency of UCS. Subsequently, through the study of supplementary reconstruction rules and optimization methods, resource elastic replenishment decisions for UCS based on health status are realized.

Chapter 2 of this thesis decomposes the various states of UCS, quantitatively analyzes the relationship between health status and performance, decomposes the degradation of individual machines and the connectivity of node connections, and clarifies the health reachable states of clusters under various reconnection modes. In Chapter 3, based on the above research, the study explores performance recovery decisions under resource replenishment, including the generation mode of preferred connections according to complex network preferences and the optimization method for resource replenishment. Chapter 4 validates the decision-making methods for UCS reconnection in the form of case studies, including scale decision-making methods for comprehensive resource replenishment performance and recovery costs, UCS resource replenishment methods based on preferred connections, and resource replenishment methods for optimal health status of UCS using particle swarm optimization algorithms. Finally, the conclusion section summarizes the methods proposed in this paper.

2. Analysis of UCS Availability Status Based on Health Status

The health status describes the maximum potential of the cluster under the current scale and structure. Ideally, through decision-making, the cluster's structure can reach its optimal state at every moment. However, in reality, due to constraints such as communication equipment limitations, task space restrictions, and resource consumption control, the structure of the cluster is always a certain gap from the ideal. Taking a 4-node cluster as an example, the relationship between the cluster's health status and performance is quantitatively analyzed.

Using the concept of entropy, the number of available states of the cluster represents its health status. For the established complex network model of the cluster, different network graphs/adjacency matrices represent different states of the system. Therefore, the state changes of UCS can be discretely represented. For example, in a 4-node connected network, there are a total of 64 states. Hence, the structural changes of the cluster during tasks can be viewed as the transformation among all available states. Disregarding node differences, nine state diagrams can be enumerated, as shown in Figure 2.

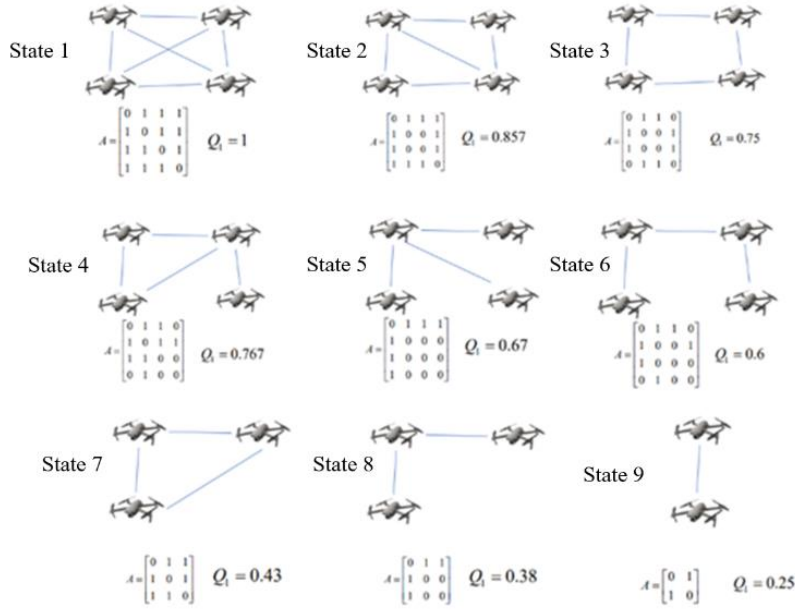


Figure 2 – Network states of 4-node UCS.

At each state, different performances are exhibited. The graph enumerates the adjacency matrix and structural topological performance Q_1 corresponding to each state. Based on the nine states, considering the single-machine performance degradation assumed to follow a Wiener process, the performance degradation curves of each state's Q_1 are depicted in Figure 3. Different scales of states are distinguished by different colors in the graph.

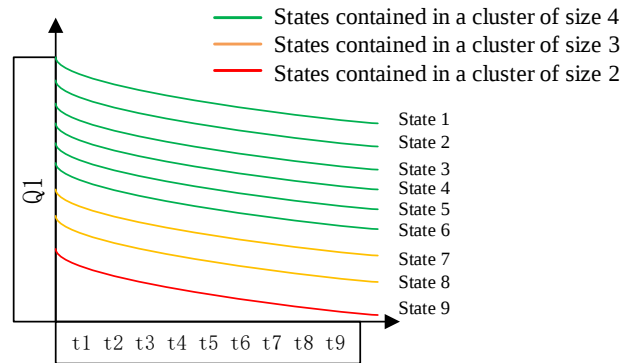


Figure 3 – Performance degradation curves for different states.

During the task process of UCS, it is influenced by both the degradation of individual machine performance and the network connectivity/disconnection caused by task conditions. Each time point corresponds to one of the states, and by identifying the state corresponding to each time point, the

performance change curve of UCS can be obtained. The task process of UCS can be seen as the continuous degradation of states and the process of transformation between states, thus decoupling the degradation of individual machines from network evolution.

From the example above, it is evident that the performance varies inconsistently between states, and state transitions are not simply unidirectional transfers. To analyze different scenarios' state transition patterns clearly, based on the level of autonomy of UCS intelligence, the autonomous recovery modes of the cluster are classified into three categories: no reconnection, reconnection, and resource replenishment.

2.1 Health Status of UCS in No-Reconnection Mode

In the no-reconnection mode, due to task consumption during task execution, machine failures and connection interruptions occur, leading to a monotonic performance decline and degradation of the cluster state. The state transition diagram is illustrated in Figure 4.

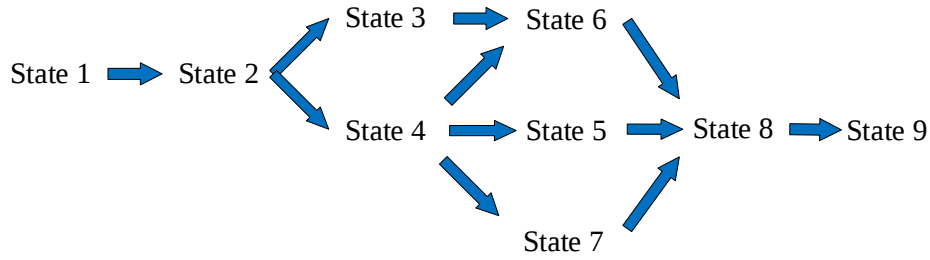


Figure 4 – State transition diagram in no-reconnection mode.

Due to the irreversibility of the no-reconnection mode in clusters, their states can only degrade. The number of available states shows a decreasing trend and cannot be restored. Therefore, the coverage range of health states also decreases unidirectionally with state transitions. If the performance of the cluster's actual operational state is as shown in the left figure of Figure 5, then the coverage range of health status can only include situations lower than the current performance state, as depicted in the right figure of Figure 5.

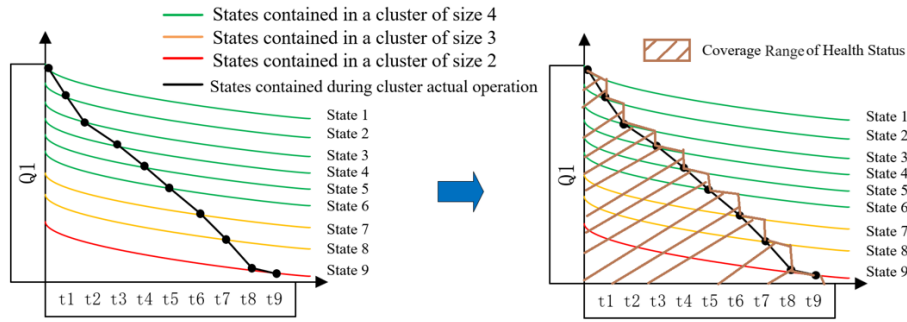


Figure 5 – UCS health status in no-reconnection mode.

2.2 Health Status of UCS in Reconnection Mode

In the reconnection mode, communication and task reconnection occur during the task execution process. The state transition diagram is shown in Figure 6.

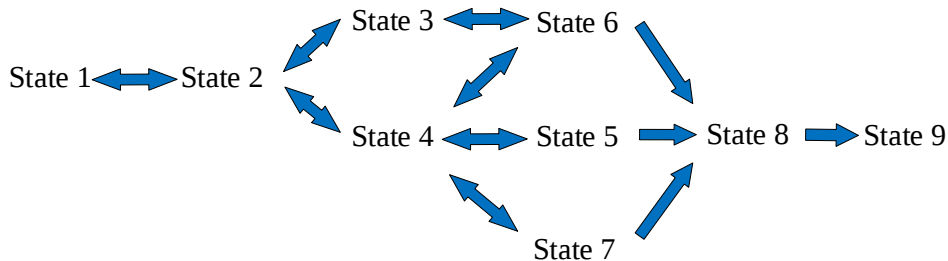


Figure 6 –State transition diagram in reconnection mode.

The performance not only decreases but also improves due to reconnection, allowing for state recovery. However, due to the inability to increase in scale, the number of available states for the

cluster can only vary within the corresponding scale state range. Its health status can only reach the maximum number of available states for the current cluster scale, as shown in Figure 7. The coverage range still exhibits a decreasing trend in its variation.

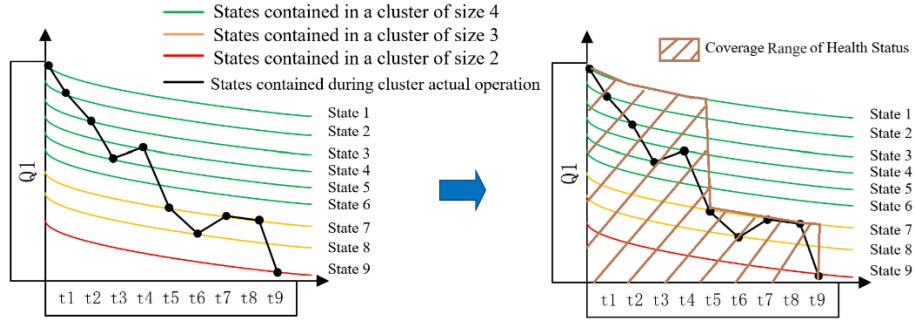


Figure 7 –UCS health status in reconnection mode.

2.3 Health Status of UCS in Resource Replenishment Mode

In the resource replenishment mode, the cluster receives resource replenishment during the task execution process, resulting in the recovery of cluster quantity. Therefore, due to both resource replenishment and reconnection, the health status of the cluster improves, and the state transitions occur in both directions, as illustrated in Figure 8.

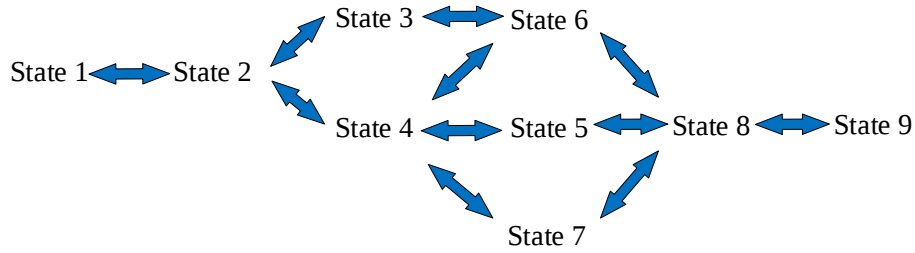


Figure 8 –State transition diagram in resource replenishment mode.

The cluster can achieve scale recovery under resource replenishment. Regarding the cluster's state, it can transition to various states, and its health status can reach the maximum number of available states for the current cluster scale. The coverage range can be expanded, as shown in Figure 9.

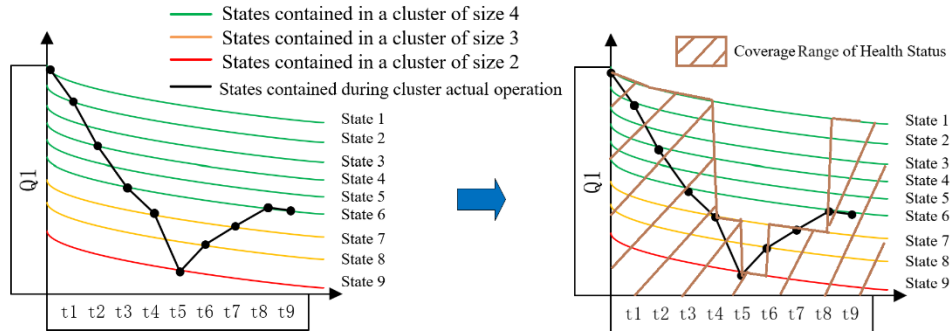


Figure 9 –UCS health status in resource replenishment mode.

Based on the coverage range of health states in different situations, the health state in no-reconnection mode is determined by the current state, and there is only a degradation situation in the state, resulting in a unidirectional narrowing of the coverage range. The cluster in reconnection mode can transition between states within the same scale, and its health status depends on the maximum number of available states for the current cluster scale, resulting in a unidirectional narrowing of the coverage range. The cluster in resource replenishment mode can transition to any state, and its health status coverage range follows the curve of the maximum number of available states for the cluster scale. Therefore, the recovery approach can be guided by the coverage range of health status.

3. Resource Replenishment Decision of UCS

3.1 Resource Replenishment Method Based on Preferential Attachment

Preferential attachment is an important concept in complex network theory. By formulating preferential attachment strategies, newly added nodes can connect to existing nodes with a certain probability. When applied to cluster networks, it can realize resource replenishment decisions. Therefore, the problem of resource elastic replenishment can be decomposed. First, the scale of resource introduction is determined, and then preferential attachment is used to make connection decisions.

3.1.1 Resource Replenishment Decision on Comprehensive Performance and Recovery Cost

Cluster in resource replenishment mode can reach every state. In order to find the optimal state under constraints, the performance improvement and resource requirements for different scales are first comprehensively measured. The performance gap between the performance curves of each state is different, and the cost of resources required to transition between states also varies. By using the concept of entropy, the state curves can be viewed as the process of state and energy transfer. On the one hand, entropy represents the directionality of energy transfer. A low-entropy system automatically transitions to a high-entropy system, while transforming a high-entropy system into a low-entropy system requires external work. In reliability studies, entropy represents the availability of a system. As a system transitions from its initial state to a degraded state, its entropy continuously increases, and the availability of its energy decreases, ultimately leading to failure. On the other hand, the process of entropy reduction requires energy consumption. The numerical value of entropy change represents the cost of state transition.

Based on Boltzmann entropy, the structural entropy of UCS is defined by the number of potential states that can form a topological structure of the cluster at its current scale and structure:

$$S = k \ln W = k \ln 2^{n_{\max}} \quad (1)$$

Where W represents the number of possible topological states that can be formed under the current cluster scale, and $n_{\max}$ represents the maximum number of edges that can be formed in the cluster under the current resources, $n_{\max} = C_n^2$.

From this, we can obtain the entropy difference between a cluster of size n and a cluster of size m as follows:

$$\Delta S = S_n - S_m = k \ln 2^{C_n^2} - k \ln 2^{C_m^2} = k \frac{C_n^2 - C_m^2}{\log_2 e} \quad (2)$$

For adjacent cluster sizes, i.e., when $m=n-1$, we have:

$$\Delta S = k \frac{C_n^2 - C_{n-1}^2}{\log_2 e} = \frac{k(n-1)}{\log_2 e} \quad (3)$$

In other words, the change in the entropy of the cluster health status varies with different scale changes, and the change in entropy is directly proportional to the cluster scale. That is, as the scale increases, the increase/decrease in the system's availability due to the increase/decrease in cluster size is greater, meaning more available states are provided. Therefore, when replenishing resources, the larger the cluster scale, the higher the cost of introducing the required resources.

When the cluster is at the same scale, the entropy of the cluster's health status remains the same. The potential number of state changes caused by different state transitions is also the same. For example, the entropy change when transitioning from state 3 to state 1 is the same as the entropy change when transitioning from state 5 to state 3, where Ω represents the number of states that can be formed under the structure of a particular state.

$$\Delta S_{31} = k \ln \Omega_3 - k \ln \Omega_1 = k \ln 2 \quad (4)$$

$$\Delta S_{53} = k \ln \Omega_5 - k \ln \Omega_3 = k \ln 2 \quad (5)$$

Therefore, the decision-making for cluster resource replenishment can be based on the combined

changes in health status entropy and performance caused by state transitions.

For the introduction of different scale clusters, assuming the current scale is n and m UAVs are introduced, the value function is as follows:

$$J(m) = aQ(n+m) - b(S(n+m) - S(n)) \quad (6)$$

By optimizing the value function, a decision on the introduction scale can be made by considering factors such as performance improvement and recovery cost limitations of the cluster. Furthermore, for the allocation of task types among m UAVs, assuming there are m_1 perception nodes, m_2 decision nodes, and m_3 execution nodes, with initial task node ratios of N_1 , N_2 , and N_3 respectively, we set the condition that m satisfies:

$$n_1 + m_1 : n_2 + m_2 : n_3 + m_3 = N_1 : N_2 : N_3 \quad (7)$$

The number of task nodes for each type can be calculated.

3.1.2 Preferential Attachment Mechanism in Complex Networks

Preferential Attachment is a probabilistic mechanism in complex networks that defines the probability of a newly generated node being connected to each existing node, with this probability often depending on node attributes. One commonly used approach is degree-based preferential attachment, where the probability of connecting to node i can be specified as follows:

$$\Pi(k_i) = \frac{k_i}{\sum_j k_j} \quad (8)$$

Where $\Pi(k_i)$ is the probability of a new node being connected to node i , and k_i represents the degree of node i , meaning that the probability of connecting to nodes with a higher degree value is also higher. Bianconi-Barabási proposed an adaptive model, also known as a scale-free model, where the probability of a new node's edge being connected to node i is:

$$\Pi(k_i) = \frac{\eta_i k_i}{\sum_j \eta_j k_j} \quad (9)$$

Where η_i represents the fitness of node i , and the randomly generated network connected according to this preference is a scale-free network.

3.1.3 Connection Decision Method Based on Preferential Attachment Rule

In the initial state of the cluster, nodes are connected to form a regular network. However, when it comes to resource replenishment, it is undesirable to have a degree-based power-law distribution, as it can lead to system vulnerability. Additionally, when the communication load of UCS becomes excessive, it puts high demands on its device performance, which can result in failures and decreased network connectivity. Therefore, during resource replenishment, the preferential attachment can be set opposite to the degree in order to achieve cluster uniformity. This can be represented by the following equation:

$$\Pi(k_i) = \frac{\eta_i \frac{1}{k_i}}{\sum_j \eta_j \frac{1}{k_j}} \quad (10)$$

That is, when a new node is present, there is a greater tendency to connect to nodes in the current network with lower degrees. Based on the principle of uniformity, the connection rule must satisfy: introducing the first edge of each node in turn, then introducing the second edge of each node, until reaching the end of the cycle.

The steps for setting up resource replenishment are as follows:

1) Based on the value function $J(m)$, it can be determined that introducing m UAVs is optimal. According to the preferential attachment rule, each node should be introduced in turn.

- 2) Introduce decision-class nodes, which are fully connected to other decision-class nodes.
- 3) Introduce perception-class nodes and determine the decision-class node with the minimum degree in the cluster network. If there are multiple decision-class nodes with the same degree, choose the closest one. If all decision nodes have reached the communication limit, then connect the remaining perception-class nodes within the formation that have the smallest degree.
- 4) When introducing execution-class nodes, determine the decision-class node with the minimum degree in the cluster network. If there are multiple decision-class nodes with the same degree, choose the closest one. If all decision nodes have reached the communication limit, then connect the remaining execution-class nodes within the formation that have the smallest degree.
- 5) Follow the order of looping through nodes first, and then looping through edges. Repeat the steps of connecting edges in 3) and 4) until all cluster nodes reach the communication capacity limit. After the loop is terminated, the network configuration with resources replenished can be obtained. The flowchart of the resource replenishment process under the cluster's preferential attachment rule is shown in Figure 10.

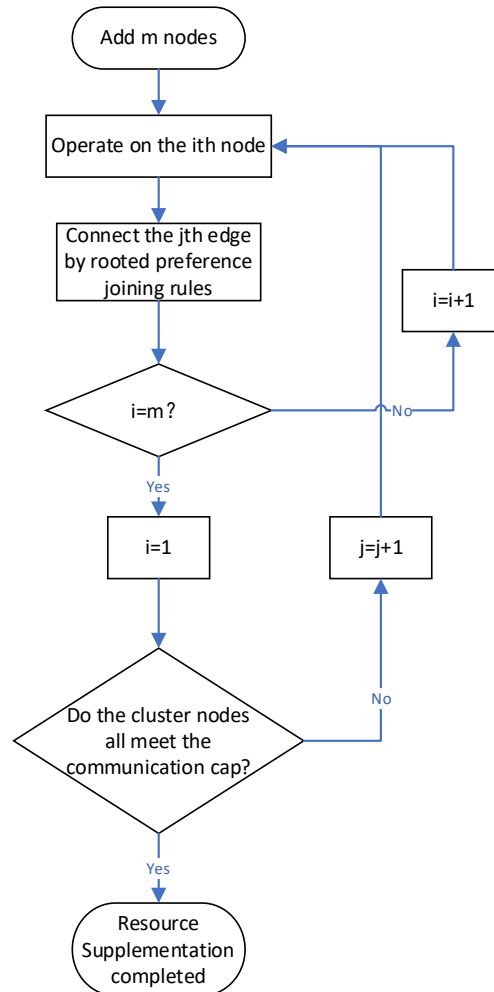


Figure 10 –Resource replenishment reconnection decisions based on preferential attachment rule.

3.2 Optimal Resource Replenishment Method Based on UCS Health Status

The resource replenishment method based on preferential attachment takes the node degree of the cluster as the basis to reconnect, but does not consider the cluster's health status during the connection process. In order to fully explore the various states of the cluster during reconnection and delve deeper into the exploration of resource replenishment, this section solves for the optimal performance state to make decisions regarding cluster resource replenishment. By using performance as the objective function, we seek to find the optimal recovery configuration for the cluster, guiding the cluster's connection decisions during resource replenishment.

3.2.1 Principle Analysis of Particle Swarm Optimization Algorithm

The particle swarm optimization algorithm is a type of optimization algorithm that is inspired by the

foraging behavior of birds. Based on the concept of swarm intelligence, multiple particles are set, and each particle is initialized with parameters such as position and velocity. Each particle searches for its individual optimal value while the swarm collectively feedbacks the global optimal value. Based on the individual and global optimal values, each particle adjusts its position and velocity until the iteration ends. The overall process of the particle swarm optimization algorithm is as follows:

- 1) Initialize the particle swarm by setting the number of particles, their velocity and position, maximum velocity, maximum position, iteration times, and hyperparameters.
- 2) Evaluate the fitness of particles by calculating the fitness value of each particle based on the objective function.
- 3) Update the individual best values and the global optimal solution based on the fitness values.
- 4) Adjust the velocity and position of the particles based on the velocity update and position update formulas.

$$v_{id}^k = wv_{id}^{k-1} + c_1r_1(pbest_{id} - x_{id}^{k-1}) + c_2r_2(gbest_{id} - x_{id}^{k-1}) \quad (11)$$

$$x_{id}^k = x_{id}^{k-1} + v_{id}^{k-1} \quad (12)$$

- 5) Repeat steps 2 to 4 until the stopping conditions are met, such as reaching the preset maximum number of iterations or finding the optimal solution that meets the accuracy requirements.

Compared to other meta-heuristic algorithms, the particle swarm optimization method is simple to implement and can achieve excellent results when the conceptual factors of the problem are relatively well-developed. Therefore, for the decision-making on the resource replenishment method of UCS, a reasonable D-dimensional space and fitness function can be set to solve the problem.

3.2.2 Health Status Optimization Based on Particle Swarm Optimization Algorithm

The problem of optimizing the health status under resource supplementation in a clustered network is an NP-hard problem. The D-dimensional space of particles can be set as the number of edges that the node can connect to, and the position and velocity in the space are discretized. Each discrete point represents a configuration formed by the node, that is, a health status. Its velocity represents the direction of the position in the next step. The complexity of this problem is directly proportional to the exponential power of the possible addition of edges, assuming that the original configuration of the cluster remains unchanged. Considering the high time complexity of the overall problem when introducing m UAVs, the problem is processed step by step by adding each new node sequentially. However, the particle swarm optimization algorithm has the issue of falling into local optima. Therefore, perturbation settings are applied to the problem of optimizing the health status. The improved particle swarm optimization algorithm process is as follows:

- 1) Through scale decision-making, a resource supplement scale m is generated, and the initial particle swarm size is set to num . The position and velocity of each particle are randomly initialized, ensuring a uniform distribution within the number of nodes due to the independent performance of cluster connections. The position of the particle i is $x_i = (x_{i1}, x_{i2}, \dots, x_{iD})$, satisfying $0 \leq x_{ij} \leq num (j=1, 2, \dots, D)$. The velocity is $v_i = (v_{i1}, v_{i2}, \dots, v_{iD})$. Due to the limitation of communication capacity, constraints are imposed on the number of occurrences of each position coordinate. The initial hyperparameters w , c_1 , c_2 , and the number of iterations n are set accordingly.
- 2) Introduce the first node, calculate the fitness of each particle, update the individual best historical position $pbest$ and the global best historical position $gbest$ based on the fitness, and update the velocity and position of each particle according to the velocity and position update formula. Since the velocity direction only consists of three components: inertia, individual optimality, and global optimality, in order to prevent the algorithm from falling into local optimality, improvements are made to the particle swarm optimization algorithm by adding a reverse disturbance ε .

$$v_{id}^k = wv_{id}^{k-1} + c_1r_1(pbest_{id} - x_{id}^{k-1}) + c_2r_2(gbest_{id} - x_{id}^{k-1}) - \varepsilon \quad (13)$$

- 3) Repeat the above steps until the maximum number of iterations is reached or the termination

condition for reaching the optimal position is met. Then, the optimal health status under the current scale is found, and the optimization of the first point is completed. Update the entire network and repeat the above steps in sequence to find all remaining nodes. The entire process flowchart is shown in Figure 11.

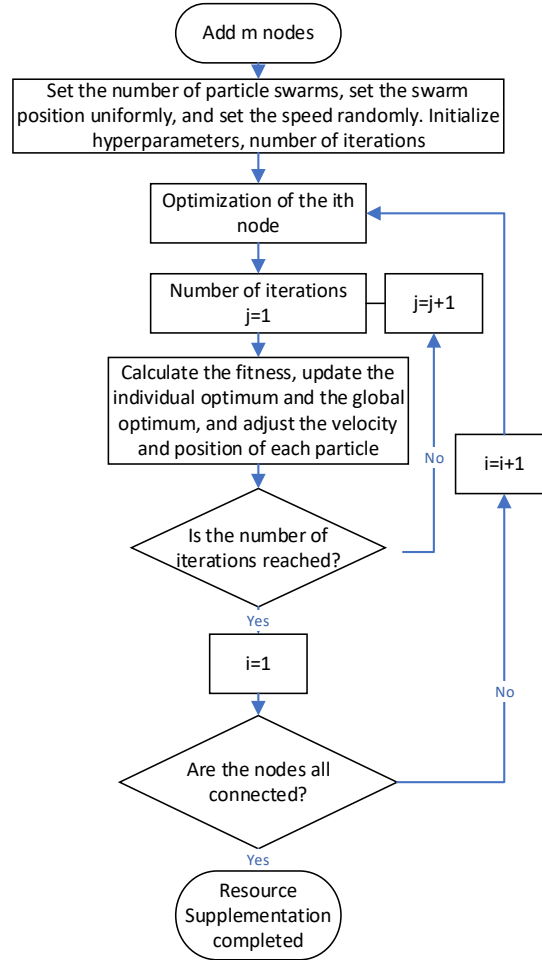


Figure 11 –Resource replenishment reconnection decisions based on particle swarm optimization algorithm.

4. Case Study

The background of this scenario task is the confrontation between UCSs. The UAVs are divided into three categories based on task types: perception, decision-making, and execution. Each node possesses a fixed initial stand-alone capability, and the task is to destroy 80 targets. When the task begins, the perception-type UCS conducts large-scale reconnaissance, and the reconnaissance radius is positively correlated with its stand-alone capability value. After cruising and detecting the targets, it provides the information to the decision-making-type UCS. After receiving the information, the decision-making-type UCS assigns the attack task to the corresponding execution-type UCS. Through information interaction, the execution-type UCS performs the corresponding strike task.

During the task, the main changes in UCS are as follows:

- 1) The UCS may be attacked by the targets, resulting in the destruction of UAVs, the corresponding nodes becoming ineffective, and the disconnection of their structure, communication, and task hierarchy connections.
- 2) After the communication network is damaged, the UCS reconnects the communication links through self-organization to maintain information interaction.
- 3) When the total number of UCS falls below a certain threshold, external resources are imported to the scene from the rear to respond with the current UCS and perform adaptive networking adjustment and restoration.

4.1 Verification of Reconnection Decision Method Considering Performance and Recovery

Cost

Based on the health status, the scale decision is made by solving the value function $J(m)$ to determine the scale of resource replenishment, and the number of perception, decision, and execution nodes m_1, m_2, m_3 is controlled proportionally. This section analyzes and verifies the method through a cluster resource replenishment case.

Assuming the initial size of the cluster is 120, with a ratio of 3:1:2 for perception, decision, and execution, and the cluster recovery mode is resource replenishment. After a series of tasks, the cluster size decreases, and the behavior of the cluster is simulated using NetLogo software.

The value function $J(m)$ varies with the number of resource replenishment m when the scale decreases to 98 (perception 54, decision 20, execution 24), 101 (perception 56, decision 20, execution 25), and 104 (perception 59, decision 20, execution 25) as shown in the figure below.

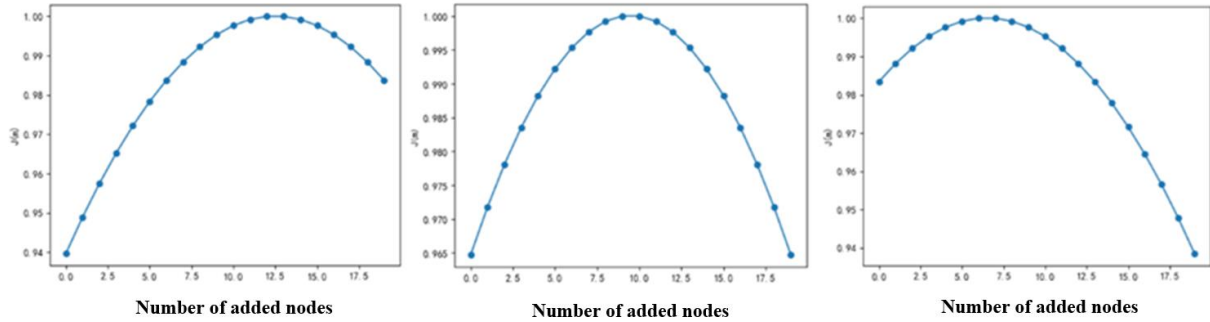


Figure 12 –The curve of $J(m)$ varying with m (left: the scale is 98; middle: the scale is 101; right: the scale is 104).

From the graph, it can be observed that $J(m)$ shows a trend of initial increase followed by decrease with m , reaching a maximum value at a certain point. When the scale is 98, 101, and 104, the introduction of the optimal scale and the corresponding task type proportions are 12 (perception 0, decision 0, execution 12), 9 (perception 0, decision 0, execution 9), and 6 (perception 0, decision 0, execution 6) respectively, all close to replenishing the resources to a scale of 110. In conclusion, under different initial scales, the curve of $J(m)$ increase with the increase in the number of nodes varies, but the optimal situation for cluster recovery is minimally affected by the change in the initial scale. Therefore, as the performance of resource replenishment for the cluster increases, the entropy of the health status decreases, leading to an increase in the cost of cluster resource replenishment. By setting a value function, a quantitative basis can be provided for making scale decisions for cluster resource replenishment, taking into account the comprehensive performance and recovery cost.

4.2 Validation of Reconnection Decision Method Based on Preferential Attachment

Based on the scale decision results, this section verifies the resource replenishment decision with a replenishment scale of 12 when the scale is 98. The reconnection decisions are made using both the nearest connection and preferential attachment methods. A comparison of the cluster performance curves between the nearest connection method and the preferential attachment method is conducted to analyze the effectiveness of the preferential attachment method. The following figure shows the cluster structure at the start of recovery, after the nearest connection is completed, and after the preferential attachment is completed.

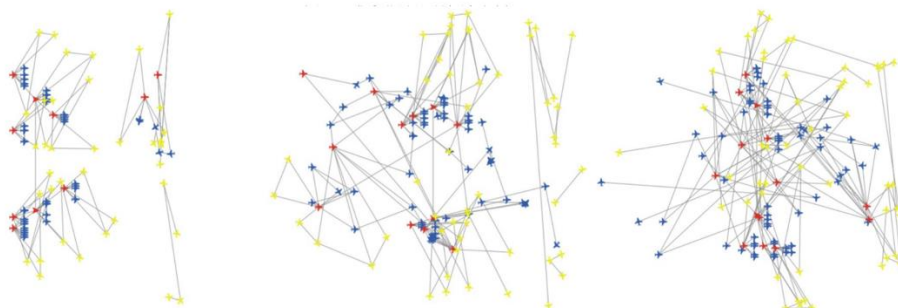


Figure 13 –Cluster structure at the beginning of recovery(left); Cluster structure with resource

replenishment based on nearest connection(middle); Cluster structure with resource replenishment based on preferential attachment (right).

It can be concluded that the topology structure of the cluster under the two recovery modes is different. Under the condition that the cluster is supplemented with the same scale, the performance recovery curves of the two decision-making modes are shown in Figure 14.

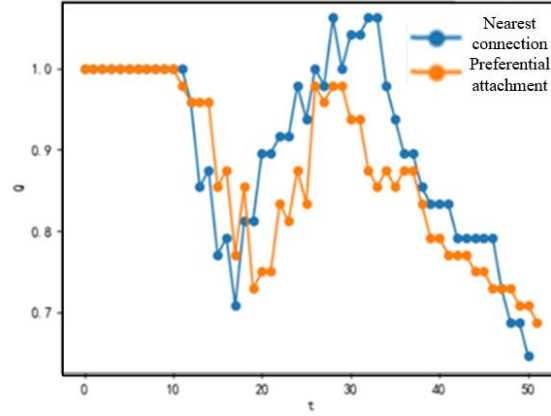


Figure 14 –Performance recovery curves of nearest connection and preferential attachment.

From the figure, it can be seen that the performance recovery achieved by preferential attachment reaches a better state. It also demonstrates a certain advantage in terms of recovery speed. This indicates that during the state transition process, compared to the nearest connection method, the cluster's preferential attachment mode can more rapidly and accurately find the optimal state.

Furthermore, utilizing the particle swarm optimization algorithm to optimize the performance of UCS, and comparing it with the other two connection methods, the cluster performance results are as shown in the following figure:

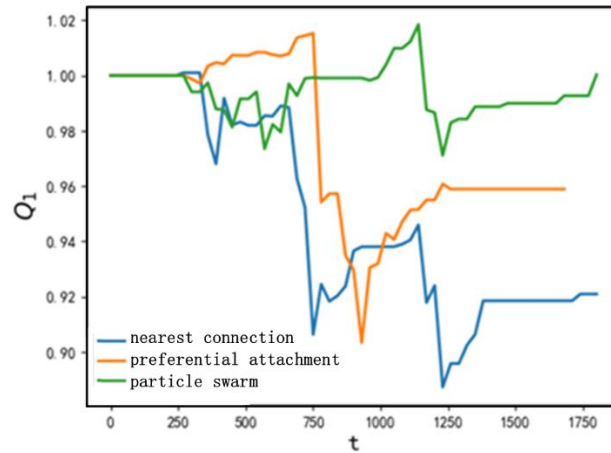


Figure 15 –Performance change curves for the three methods.

It can be observed that both the preferential attachment-based and particle swarm optimization-based methods can effectively improve performance. The performance improvement achieved through particle swarm optimization is significant as it directly seeks the optimal healthy state for the current scale, allowing the cluster to exhibit better resilience. However, it should be noted that the particle swarm optimization method requires time to find the optimal solution, making it less suitable for situations where the cluster needs to respond continuously. The preferential attachment-based method, although it has more limited improvement effects, performs better compared to the nearest connection approach, indicating that the preferential attachment of cluster vulnerabilities is effective. Therefore, in practical applications, preferential attachment-based and particle swarm optimization-based methods can both lead to effective improvements in the cluster. The choice of optimization method can be made based on the requirements of solution time and performance improvement magnitude.

5. Conclusion

This paper conducts an analysis of the coverage range of UCS health status in an open environment, and proposes a cluster resource supplement method based on preferential attachment and particle swarm optimization methods, and finally verifies the theory through an example. The main conclusions are as follows:(1) Through the analysis of available states under different scenarios, including no-reconnection, reconnection, and resource replenishment, it is found that the resource replenishment mode achieves the largest coverage range of the cluster's health status, indicating that this mode can achieve optimal health state for the cluster. (2) A method is proposed to optimize the decision-making process for cluster resource replenishment using degree-based preferential attachment and particle swarm algorithm. The feasibility of the reconnection decision-making model is demonstrated through case studies, and decision-making choices under different circumstances are provided.

The research findings of this paper provide a scientific and systematic solution to the problem of elastic resource replenishment in UCS in open environments. It offers more targeted approaches to address the issues of resource replenishment and decision optimization in UCS.

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