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Connectivity Guarantee Within UAV Cluster: A Graph Coalition Formation Game Approach

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ABSTRACT Unmanned Aerial Vehicle (UAV) clustering is promising for performing large-scale missions because of high mobility and easy deployment. However, the connectivity problems caused by the high mobility of UAVs and the interferences are mostly ignored in existing UAV mission executions. Rapid restoration of UAV network connectivity is essential for preventing communication disruption and improving the overall network performance. Thus, a graph coalition formation game that integrates the UAV time-varying topology graph with the coalition formation game is proposed to rapidly restore the connectivity of the UAV network in need. The method improves the utility of UAV clustering and ensures the network connectivity. Then, a graph coalition formation game algorithm based on the shortest path tree (SPT-GCF) rapidly forms an approximately optimal coalition structure. The simulation results show that the proposed approach increases the average utility of UAV clustering by 6.5% and 14.5% respectively when compared with the existing non-overlapping coalition formation game (NOCFG) and the coalition formation game without considering the cluster connectivity.

INDEX TERMS UAV cluster, connectivity, overlapping coalition formation game, graph coalition formation game.

I. INTRODUCTION

Unmanned Aerial Vehicles (UAVs) have been very popular in performing tasks in certain domains [1], [2], [3], such as natural disaster management [4], aerial reconnaissance [5], anti-terrorism arrest, and other civilian and military fields [6], [7]. Unlike a single UAV, UAV clusters can provide connectivity to other flying UAVs that can be linked to carry out missions individually or collaboratively. Thus, it is believed that UAV clustering can be more efficient than a single UAV when executing missions [8], [9]. However, such UAV clusters are hard to operate with existing methods due to a broad range of challenges, including interference mitigation [10], [11], reliable communication, and energy saving [12]. For further study, existing works relevant to the UAV clustering connection are to be reviewed next.

A. LITERATURE REVIEW

Many existing works have studied the deployment of UAVs that can be cluster-connected to enhance their operations [13]. However, loss and interruption of communication data between UAVs might be inevitable probably because of the high mobility of UAVs and the malicious interferences in the process of task execution [14], [15], [16]. Thus, the communication in multi-UAV networks must be routed in a way that the negative effect of UAVs' mobility and the malicious interferences can be minimized to reduce network delays, energy consumption, and disconnection. Since UAV nodes demand for fast and low energy consumption data dissemination, a well-established multi-UAV network connection could be capable of guaranteeing a high communication reliability [17], [18], [19], [20], [21]. In other words, connectivity recovery approaches that adapt to the UAV clustering are required to improve communication performance. Literature [22] provided the boundary of average outage probability and cluster density of UAV to eliminate interference, but with restricted influences due to the neglect of the dynamic uncertainty of UAV clusters.

To counter the direct link failure between UAVs in scenarios of dynamic disconnection, an ad hoc UAV network can be applied to temporarily restore connectivity. Unlike the static UAV assumptions in [22], the multi-hop transmission method of dynamic UAV networks has been studied in recent works [23], [24], [25]. Reference [23] modified a dynamic source routing protocol based on the ant colony algorithm to realize an efficient routing selection. Reference [24] proposed a novel multi-agent deep reinforcement learning-based algorithm, named multi-agent QMIX (MAQMIX), to tackle the challenges of dynamic networks and coordinate the trajectories among UAVs. Besides, alternating optimization and successive convex programming were adopted to obtain a locally optimal solution by designing the connection between UAVs and ground users as a multi-hop relay deployment problem [25], [26], [27], [28]. However, ad hoc UAV networks are featured by great node mobility, fast network topology variance, and complicated appliance situations, which have brought great challenges for the time-varying network connectivity assurance of UAVs.

The above said challenges induce a possible solution through network topology management. For instance, [29] presented a group-based topology control algorithm framework to solve the UAV connectivity and energy consumption problems. Moreover, [30] solved the time-varying formation control problem of UAVs by using the second-order integral characteristic. Despite of the above achievements, it is still challenging to determine the connectivity of a time-varying UAV network due to the intricate nature of time-varying network topology.

Graph theory is an important tool to analyze the characteristics of interconnected systems, including formation stability and control ability. It can analyze the connectivity of time-varying UAV networks well [31]. In [32], by applying graph theory and convex optimization to the UAVs connected, the UAV trajectories were optimized to minimize the UAV traveling time while ensuring that each UAV was always connected with at least one base station. Meanwhile, in [33], an SINR graph was constructed based on the channel gain maps and their loading factors in a cellular-connected UAV network. Then, the optimal UAV path was proceeded by leveraging the obtained SINR graph. However, though interesting, the cooperative communication through coordinated UAV clustering transmission was not considered, which was a prominent connectivity guarantee tool.

Coalition formation game (CFG) has been widely studied as a cooperative communication method for task implementation in UAV networks in [34], [35], [36], [37], [38], [39], [40] to improve the mission execution efficiency. For instance, [38] adopted an overlapping coalition formation game (OCFG) for UAV spectrum resource allocation and relay selection to increase the systems' capacity. Reference [40] proposed a group-buying coalition formation auction method that made sensors to form coalitions to bid for UAVs' service. Recently, the architecture design and performance optimization for UAV-enabled networks' connection have attracted much attention. In specific, a coalition game between UAVs and the Internet of Connected Vehicles (IoCVs) was designed to determine the option strategy of content distribution and extend the connectivity of the Internet of Things (IoT) [41]. The CFG and the distributed air-ground integrated deployment method [42] were studied to improve the data transmission efficiency while ensuring communication connection. In this case, the CFG has paved the way to ensure the connectivity of UAV clusters.

Nevertheless, the cooperation and connectivity of UAV clusters will still face following challenges: first, the communication performance of UAV clusters is unstable owing to wireless interference, leading to high transmission delays [43]; second, the dynamic network topology and the communication between UAVs may be invalid sometimes because of the high mobility of UAV clusters [8]; finally, without incentives, UAVs with energy capacities may be selfish and unwilling to assist the communication [44] with disconnected UAVs. Therefore, it is still a vital issue to design an effective mechanism to ensure connectivity between UAV clusters under a dynamic and interference environment.

B. CONTRIBUTIONS

Motivated by the above issues, a graph overlapping coalition formation game method is proposed. Firstly, areas with strong and weak communication connectivity are differentiated for UAV clusters according to whether an area is interfered, and the connectivity recovery of UAV clusters in different areas is analyzed. Secondly, a UAV can join in multiple coalitions and assist the transmission of multiple users at different time points to ensure the connectivity of UAV clusters. Thus, a graph connectivity metrics is proposed to reflect the connectivity values of clusters. In this way, the connectivity of the entire network can be achieved by forming a stable overlapping coalition structure to realize the effective cooperative transmission of UAV clusters. Thirdly, a trade-off optimization between network connectivity contribution, end-to-end transmission delay, and UAV energy consumption is designed as a coalition utility to encourage the formation of coalitions. Finally, a graph coalition formation game algorithm based on the shortest path tree (SPT-GCF) is proposed to rapidly form an approximate coalition structure. The main contributions of this paper are threefold:

- A novel mobility model that effectively analyzes connectivity guarantee problems under different interferences of UAV clusters. The communication scenario of a UAV cluster is divided into strong and weak connectivity areas according to whether an area is interfered. Different connectivity areas have different communication benefits.
- A graph coalition formation game method integrating graph connectivity metrics with coalition game theory is proposed for UAV cluster connectivity guarantee. Specifically, the time-varying network topology of UAV clustering is abstracted as a set of undirected graphs with continuous time slots, and UAVs forming a coalition based on the undirected graphs.
- An SPT-GCF algorithm is proposed to reduce communication delay and energy consumption while keeping the connectivity of UAV clusters, in which reward mechanisms are designed for different connectivity areas so that UAVs can be encouraged to form different coalitions to ensure connectivity.

The rest of this paper is structured as follows. Section II describes the system model of the proposed solution. Sections III and IV respectively present a graph coalition formation game and a graph coalition formation algorithm based on the shortest path tree. Numerical results are analyzed in Section V and conclusions are drawn in Section VI.

II. SYSTEM MODEL

Fig. 1 depicts a scenario where a swarm of UAVs executes missions. Note that there are strong and weak-connectivity areas that divide the UAVs' flight ranges. Specifically, the UAV communication is interrupted in weak-connectivity areas while not in strong-connectivity areas. The total task execution time is divided into T equally spaced time slots, that is, $\mathcal{T} = \{1, 2, \ldots, t, \ldots, T\}$ represents continuous time slots. The set of UAVs at time t can be represented as $\mathcal{N}(t) = \{u_1, \ldots, u_k, \ldots, u_{N(t)}\}$ if N UAVs are distributed over the task area to perform the task at time t. In areas with strong connectivity, there is no malicious interference, that is, UAVs can communicate normally within the communication range. Otherwise, some UAVs in the cluster may be disconnected in areas with weak connectivity due to malicious interference.

To guarantee successful information transmission between UAVs in the weak-connectivity area, and considering the real-time network topology of UAV clustering, the graph coalition formation game is adopted to model the cooperation between UAVs, and game participants include all UAVs. Fig. 1 demonstrates the presence of malicious interference in the mission area leading to the failure of connectivity between some UAVs in clusters in the weak-connectivity

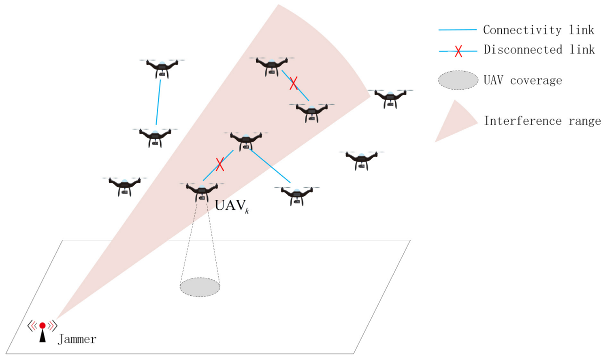


FIGURE 1. One illustrative UAV cluster task execution scenario.

area. Due to limited energy and communication capabilities of a single UAV, multiple UAVs are encouraged to form a coalition according to the real-time network topology to help those with connectivity failure to cooperatively recover their communication. UAVs only need to exchange their position information to complete the coalition formation process.

We propose a multi-stage dynamic graph coalition formation game, in which UAVs dynamically form different coalitions according to the network topology at different times to guarantee the connectivity of the entire network. The coalition structure at time t is defined as the set of UAVs containing part of the UAVs, i.e.,

$$\mathcal{S}(t) = \{S_1(t), \ldots, S_i(t), \ldots, S_n(t)\}, n \in \mathcal{N}, \tag{1}$$

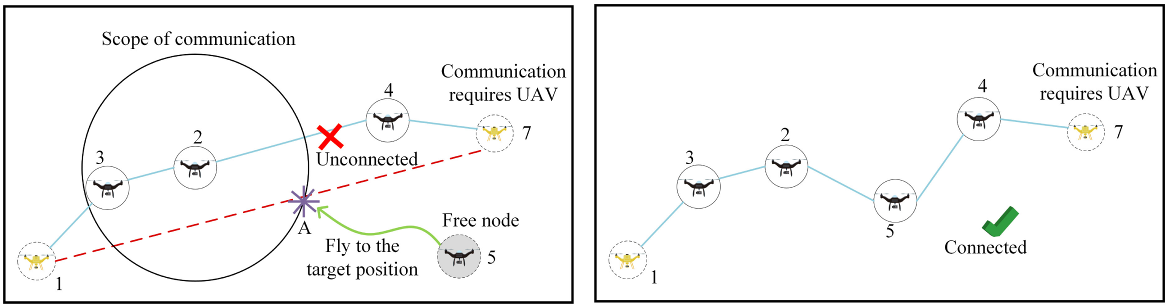
where n represents the number of UAV communication pairs that need to establish communication at time t. Without changing the network topology, the same UAV in the same time slot can join other coalitions to assist other communication pairs whose connectivity has failed to be resumed, i.e., $S_i(t) \bigcap S_i(t) \neq \varnothing, \exists i \neq i'$. The coalition formation at each moment can be divided into three stages: 1) Information sharing stage: a UAV cluster shares its own location information in real time to judge the connectivity of the network and build the initial network topology with connectivity information; 2) Initial coalition formation stage: the UAV cluster forms the initial coalition according to the initial network topology to solve the connectivity failure problem to speed up the final coalition formation; 3) Coalition adjustment stage: the UAV members in the initial coalition adjust their actions according to their own utility and coalition utility, and finally form a stable coalition structure to ensure the connectivity of the entire network.

A. UAV COMMUNICATION MODEL

Without loss of generality, this paper assumes that the communication between UAVs in the air is a free-space path loss model, then the channel gain between UAV nodes u_j and u_k at time t is

$$g_{j,k}(t) = \left(d_{j,k}(t)\right)^{-\alpha}, \tag{2}$$

where α represents the path loss index, $d_{j,k}(t)$ is the distance between UAV nodes u_j and u_k at time t. Given that the



(a) Free nodes find and fly to the target position when the UAV cluster is disconnected.

(b) UAV cluster connectivity recovery.

FIGURE 2. Schematic diagram of UAV dynamic connectivity restoration.

transmit power of UAV u_j at time t is $P_j(t)$, the signal-noise ratio (SNR) of the receiver of UAV u_k can be expressed as

$$\gamma_{j,k}(t) = \frac{P_j(t) g_{j,k}(t)}{\beta \cdot I_j(t) + \sigma^2}, \tag{3}$$

where $I_j(t)$ is the interference to the UAV u_k at time t; σ^2 is the Gaussian white noise variance; β is the indicator function to determine whether the transmitter UAV is located in the strong or weak-connectivity area, i.e.,

$$\beta = \begin{cases} 0, & u_j \text{ is located in the weak-connectivity area,} \\ 1, & u_j \text{ is located in the strong-connectivity area,} \end{cases} \tag{4}$$

$\beta = 0$ indicates that the UAV is located in the strong-connectivity area with no malicious interference; $\beta = 1$ indicates that the UAV is located in the weak-connectivity area with malicious interference.

Based on (3), we can obtain the transmission rate between UAV nodes u_j and u_k at time t, that is,

$$R_{j,k}(t) = B_{j,k}(t) \log_2 \big(1 + \gamma_{j,k}(t)\big), \tag{5}$$

where $B_{j,k}(t)$ is the transmission channel bandwidth between the UAV nodes u_j and u_k at time t. To guarantee the normal transmission between UAVs, the communication between neighboring UAVs should satisfy the condition that its SNR is greater than or equal to the SNR threshold, i.e., $\gamma_{j,k}(t) \geq \gamma_{\text{th}}$. Then, the one-hop communication range between UAVs can be expressed as

$$r_j(t) \leq \left(\frac{P_j(t)}{(\beta \cdot I_j(t) + \sigma^2)\gamma_{th}} \right)^{-\alpha}. \tag{6}$$

B. TRANSMISSION DELAY MODEL

Considering the limited communication range of UAVs, long distance communication between UAVs and that between UAVs with connectivity failure during task execution often require the cooperation of other UAVs and the multi-hop information transmission, which asks for low communication delay of the whole network to ensure the communication timeliness. Assuming that there is a coalition $S_i(t)$ in the network to help information transmission between UAV communication pairs that cannot communicate directly at time t, the information transmission delay in the coalition $S_i(t)$ at the time slot t can be expressed as

$$T_{S_i}(t) = \sum_{s,p \in S_i(t)} T_{s,p} = \sum_{s,p \in S_i(t)} \frac{F_i(t)}{R_{s,p}(t)}, \tag{7}$$

where, $T_{s,p}$ is the transmission delay between two adjacent nodes s, p of the coalition $S_i(t)$; $F_i(t)$ is the amount of data that needs to be transmitted between the communication pair i at the time slot t.

C. UAV ENERGY CONSUMPTION MODEL

In the scenario considered in this paper, as shown in Fig. 2, when the static network cannot guarantee the connectivity of a UAV cluster, there will be free nodes, specifically, nodes that are not in other coalitions, that can fly to suitable locations to restore the failed connectivity between nodes. Considering that the communication between UAVs needs to be established to restore connectivity, the suitable node for the final flight of free UAVs is selected as the location where the straight-line distance between the disconnected nodes and the nodes in need of communication is the maximum one-hop communication range. As shown in Fig. 2(a), when UAV nodes u_2 and u_4 are disconnected, there will be a maximum communication range circle of free node u_5 by flying to node u_2 and the intersection point A of the line between the communication demand pair u_1 and u_7. In this way, as shown in Fig. 2(b), the communication between u_2 and u_4 is established so that the normal communication between u_1 and u_7 is ensured.

This paper ignores the communication energy consumption of UAVs because the energy consumption of UAV flight is much greater than the communication energy consumption in practice [45]. For rotorcraft UAV, the energy consumption model proposed in [45] is adopted in this paper. The energy consumption per flight distance of a UAV can be expressed as

$$\begin{aligned} E_0(V) &\triangleq \frac{P(V)}{V} \\ &= P_0 \left(\frac{1}{V} + \frac{3V}{U_{\text{tip}}^2} \right) + P_i \left(\sqrt{V^{-4} + \frac{1}{4v_0^4}} - \frac{1}{2v_0^2} \right)^{1/2} \\ &\quad + \frac{1}{2} d_0 \rho s A V^2, \end{aligned} \tag{8}$$

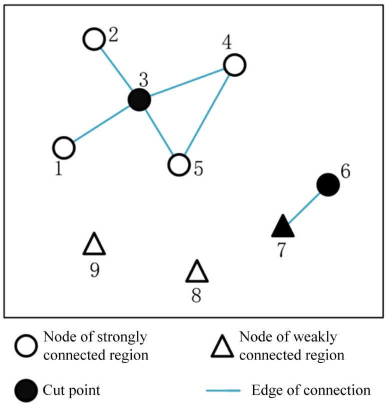


FIGURE 3. One illustrative topological graph of the network.

where V is the flying speed of the UAV; P_0 and P_i are two constants about the weight of UAV, rotor radius, air density and other environmental parameters; U_{tip} represents the tip velocity of the rotation; v_0 is the average rotor induction speed; d_0 represents airframe resistance ratio, ρ represents air resistance; s represents the fixation of the rotor; A represents the area of the rotor disk. Then the flight energy consumption of the UAV node u_j flying to the appropriate position at the time slot t is

$$E_{j,a}(t) = E_0(V) \cdot d_{j,a}, \tag{9}$$

where $d_{j,a}$ represents the distance between the UAV u_j and the appropriate location.

D. NETWORK TOPOLOGY CONNECTIVITY MODEL

The time-varying network topology of UAV clustering is represented as an undirected graph, namely, $G = \{G(1), \ldots, G(t), \ldots, G(T)\}, T \in \mathcal{T}$ with continuous time slots. Where $G(t) = (V(t), E(t))$ represents the network topology of UAV clustering at time slot t, and $V(t)$ represents the node set, namely, the UAV set in the network at time slot t; $E(t)$ represents the set of edges, that is, the set of communication links between UAVs in the network. Fig. 3 shows the topological graph of the network at time slot t, where the nodes in the task area are divided into strongly connected nodes (hollow circular nodes) and weakly connected nodes (triangular nodes), and the nodes within the one-hop communication range are connected by an undirected edge. Fig. 3 contains two connected subgraphs, where the black solid node is their cut point.

To enable the internal cooperation of a UAV cluster to guarantee the connectivity of the whole network, we express the connectivity contribution of the network topology in t time slots as K times the number of cut points $N(t)$ in the network. In addition, considering it is more difficult to guarantee the connectivity between UAVs in the weak connectivity areas, we set the connectivity contribution of the network in the weak connectivity area to $\mathcal{E}$ times that of the strong connectivity area. Then the connectivity contribution of the coalition $S_i(t)$ established at time slot t to guarantee the communication to i is

$$C_{S_i}(t) = \begin{cases} K \cdot N_{S_i}(t), & S_i \text{ serves strong connectivity areas}, \\ \varepsilon \cdot K \cdot N_{S_i}(t), & S_i \text{ serves weak connectivity areas}. \end{cases} \tag{10}$$

From the above analysis, it can be seen that the task execution efficiency of a UAV cluster is not only related to its internal connectivity, but also related to the communication delay between the UAVs and the flight energy consumption of the UAVs at time slot t. Therefore, the optimization objective in this paper is the trade-off optimization of connectivity between UAVs, transmission delay between UAVs, and energy consumption of UAVs. Then, the utility of the whole network at time t can be expressed as

$$U(t) = \sum_{S_i \in \mathcal{S}(t)} \left(w_1 \cdot C_{S_i}(t) - w_2 \cdot E_{S_i}(t) - w_3 T_{S_i}(t)\right), \tag{11}$$

where w_1, w_2, w_3 is the trade-off factor used to adjust the weight of the optimization index, and $w_1 + w_2 + w_3 = 1$.

Therefore, the optimization objective is to maximize the utility of the whole network, namely

$$\mathbf{P}: \max \sum_{t=1}^{T} U(t)$$
$$\text{s.t.} \quad P_{\min} \le P_j(t) \le P_{\max}, \forall t \in T, j \in \mathcal{N} \tag{12}$$
$$r_j(t) \le \left(\frac{P_j(t)}{\left(\beta \cdot I_j(t) + \sigma^2\right) \cdot \gamma_{th}}\right)^{-\alpha}, \forall t \in T, \tag{13}$$

where, (12) is the transmission power constraint of UAVs, and (13) is the communication range constraint between UAVs. Obviously, the optimization problem P is a typical NP-hard (Non-Deterministic Polynomial hard) problem, and the non-convexity of this problem makes it difficult to be solved efficiently by traditional optimization methods. Although the traditional centralized optimization tools can obtain high-quality approximate optimal solutions, they are not suitable for high-dynamic scenarios with rapid changes in network topology due to the extremely high computational complexity required. Hence, the optimization problem is modeled as a graph coalition formation game problem, and a graph coalition formation algorithm based on the shortest path tree is designed to make it converge to the equilibrium of the game quickly.

III. GRAPH COALITION FORMATION GAME

A. GRAPH COALITION FORMATION GAME MODEL

The traditional coalition formation game divides the set of players into several disjoint sets through the cooperation between users, and the players of the game pursue the maximization of their own interests. In this section, the time-varying network topology is used to characterize the potential game structure in the real environment, and the communication problem between multiple UAVs cooperating to recover the communication nodes with connectivity failure is constructed as a graph coalition formation game. In the constructed graph coalition formation game, the UAV cluster, as a participant of the game, acts as whether to establish communication with other nodes. According to the analysis in Section II, the payoff of a coalition $S_i(t)$ in time slots t is defined as the connectivity contribution of the connected subgraph brought by the coalition as

$$v^R_{S_i}(t) = C_{S_i}(t), \tag{14}$$

The cost of coalition $S_i(t)$ in time slot t is defined as the information transmission delay of the coalition and the flight energy loss of the UAVs within a certain flight distance in the coalition.

$$v^P_{S_i}(t) = w_2 \cdot E_{S_i}(t) + w_3 T_{S_i}(t). \tag{15}$$

Therefore, the value function of coalition $S_i(t)$ in time slot t is defined as the difference between revenue and cost, i.e.,

$$v_{S_i}(t) = w_1 \cdot C_{S_i}(t) - w_2 \cdot E_{S_i}(t) - w_3 T_{S_i}(t). \tag{16}$$

The value function of the coalition represents the revenue available to the whole coalition. In the graph coalition formation game with transferable utility, the gains obtained by the coalition can be distributed among the coalition members according to certain allocation rules. Combined with the network topology of the coalition, this paper adopts the allocation according to work criterion, that is, the utility of UAVs is allocated according to the degree of the vertices inside the coalition. Therefore, the utility of each UAV is

$$u_j(S_i) = \frac{L_{S_i}(j)}{\sum_L L_{S_i}(j)} \cdot \frac{v_{S_i}(t)}{|S_i|}, \tag{17}$$

where $L_{S_i}(j) = \frac{\deg(j)}{|V(S_i)|-1}$ is the degree centrality and $\deg(j) = |\{\{k, j\} \in E : k \in C_i\}|$ is the degree of the vertex.

B. ANALYSIS OF NASH EQUILIBRIUM (NE)

Definition 1: For any UAV $k \in \mathcal{N}$ and two coalitions $S_1 \subseteq \mathcal{N}$ and $S_2 \subseteq \mathcal{N}$, the altruism criterion is defined as the following action

$$\begin{aligned} \mathcal{S}_1 \succ_j \mathcal{S}_2 \Leftrightarrow u_j(\mathcal{S}_1) &+ \sum_{k\in\mathcal{S}_1\backslash\{j\}} u_k(\mathcal{S}_1) \\ &+ \sum_{k\in\mathcal{S}_2\backslash\{j\}} u_k(\mathcal{S}_2\backslash\{j\}) \\ > u_j(\mathcal{S}_2) &+ \sum_{k\in\mathcal{S}_1\backslash\{j\}} u_k(\mathcal{S}_1\backslash\{j\}) \\ &+ \sum_{k\in\mathcal{S}_2\backslash\{j\}} u_k(\mathcal{S}_2). \end{aligned} \tag{18}$$

The preference relationship of altruistic criteria between coalition $\mathcal{S}_1$ and coalition $\mathcal{S}_2$ expressed in **Definition 1** is shown in Fig. 4. In this proposition, when UAV k joins a new coalition, that is, finds an access point in the new coalition to establish a communication edge between two points, the total utility of UAV k and the new coalition of UAV k leaving and joining is improved. According to the above analysis, the utility of UAVs is related to whether the nodes in the new coalition establish communication.

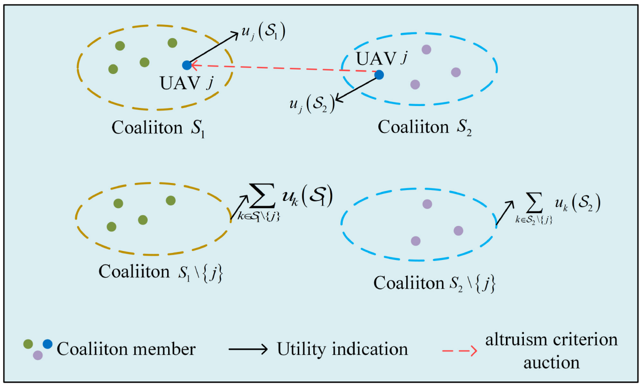


FIGURE 4. The schematic diagram of altruistic criterion.

Theorem 1: There is at least one stable coalition structure under the altruism criterion, and the optimal deconstruction of the utility maximization problem of the whole network is a stable coalition structure.

Proof: Refer to Appendix A. ∎

IV. ALGORITHM DESIGN FOR CONNECTED COALITION FORMATION

In this section, we'll focus on how to implement this ideal solution in a practical way. Due to the complexity of the problem under consideration, a real-time distributed method need to be proposed, which can form coalitions according to the time-varying network topology of the UAV cluster to ensure the connectivity of the network, because the topology of the UAV cluster changes rapidly during the task execution.

According to the analysis in Section III, the constructed graph coalition formation game has a stable coalition structure. The traditional method of solving the graph coalition formation game has a random selection strategy to obtain the local optimal Nash equilibrium solution, but the convergence speed of this method is slow and it is easy to converge to the poor quality of the local optimal solution. In this chapter, a graph coalition formation algorithm based on the shortest path tree is proposed, which can converge quickly and achieve better local optimal solution. The execution process of the algorithm is shown in Fig. 5. Fig. 5 shows the whole process from the broadcast phase to the connected coalition formation phase for a certain disconnected communication demand UAV in the UAV cluster. The whole algorithm process is divided into five process: 1) broadcast process. Unconnected UAVs with data transmission needs broadcast their communication needs and exchange their position information with other UAVs; 2) Initial alliance formation process. The shortest path tree initialization method is used to form the initial coalition structure will be found by us, and calculate the initial coalition connectivity and utility; 3) Excess action process. In this process, the non-essential members of the coalition, that is, the redundant members, and execute the withdrawal action of the coalition, so that

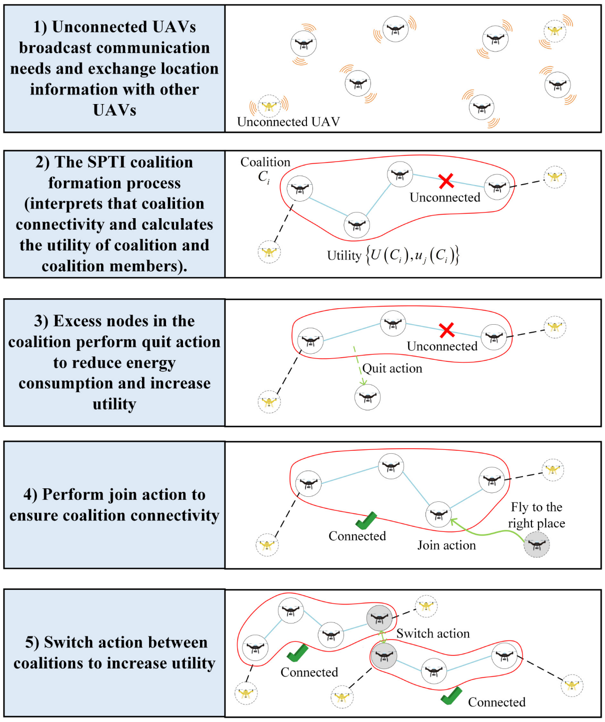


FIGURE 5. The execution process of the algorithm.

the structure of the coalition will not be too large and more drones can serve the areas in need; 4) Join action process. In this process, for the disconnected coalition, the free nodes will be found by us, which are not in any coalition at the current moment, and successively perform the action of joining the coalition until the coalition is connected. 5) Switch action process. The two coalitions in the connected state and the members of the two coalitions for the exchange action are randomly selected to obtain the coalition structure with a higher payoff.

The algorithm is executed by each UAV individually and is a distributed learning algorithm. Firstly, the shortest path tree based on Floyd algorithm is used to initialize the coalition formation and the utility of the initial coalition is calculated according to Equation (16). Then, the exit and join actions of the coalition are performed. In each iteration, the redundant nodes in the initial coalition and the free nodes outside the coalition are selected successively for policy update. The selected UAV will choose to quit and join the action in turn, and explore its utility value according to the result of the action. After that, the selected UAVs will compare their utility under the altruism criterion to decide whether to keep the original action or perform the new action. Through repeated iterations, it is known that convergence to the final stable coalition structure is achieved, in which neither UAV wants to deviate from the current mission choice.

Theorem 2: Under **Definition 1**, the proposed graph coalition formation algorithm based on the shortest path tree can converge to a stable coalition structure in a finite number of steps, that is, maximize the utility of the network.

Algorithm 1: SPT-GCF Algorithm

Input: (x_i, y_i, z_i), $\mathcal{N}$, R_{max};
Initialization: $\mathcal{S}(t) = \{S_1(t), \ldots, S_k(t), \ldots, S_K(t)\}$, $t = 1$, $K = N$, $\mathcal{S}_k(t) = \{u_k\}$, $R = 0$;
loop $\forall n \in \mathcal{N}$
Broadcast requests to search for a possible coalition structure updates.
1) Take the source UAV and destination node as the initial coalition members, that is $\mathcal{S}_k^i(t) = \{u_s, u_d\}$.
2) Calculate the distance $d_s = \{d_{s,1}, \ldots, d_{s,n}\}$ between u_s and other UAVs.
3) Calculate the one-hop communication range $r_j(t)$ by equation (6).
while $d_{s,n} \geqslant r_j(t)$ **do**
Find the UAV u_s' closest to u_s;
$u_s = u_s'$;
$\mathcal{S}_k^i(t) = \{u_s, u_s', u_d\}$;
Repeat steps 2) and 3);
end while $S_k^i(t) = S_k^{(t)}$;
UAV $n \in S_k^i(t)$ makes the coalition action to search the optimal coalition structure solution.
4) Quiting action: UAV n leaves the current coalition $S_k(t)$ and as a free UAV node;
5) Joining action: Free UAV n leaves the current coalition $S_k(t)$ and joins another coalition $S_j(t)$;
6) Switching action: UAV $n \in S_k(t)$ and $p \in S_j(t)$ switch coalitions;
Calculate the utility $v_{S_k(t)}$ of the original coalition structure $S(t)$ by the equation (16);
Calculate the utility $\tilde{v}_{S_k(t)}$ of the changed coalition $\tilde{S}(t)$ structure by the equation (16);
if $\tilde{S}(t) \succ_n S(t)$ **then**
$S(t) = \tilde{S}(t)$;
else
$R = R + 1$;
end if
end loop
Return $\mathcal{S}(t)$;

Proof: Refer to Appendix B. ■

The time complexity of the graph coalition game formation algorithm based on the shortest path tree is further discussed. The algorithm complexity of UAV cluster connectivity maintenance is mainly determined by **Algorithm 1**. As shown in Table 1, the number of iterations of the proposed shortest path tree-based graph coalition formation algorithm is denoted by. Detailed analyses are given as follows.

1) In Step 1 (namely, coalition formation request and feedback), UAVs receive coalition formation requests from disconnected UAVs. Then, UAVs can respond to these requests based on their communication range constraint. The time complexity of this step is denoted by $\mathcal{O}(C_1 V)$, where C_1 is a constant decided by the duration of request and feedback.

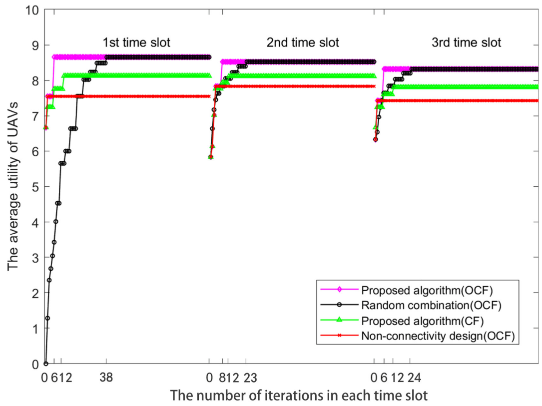


FIGURE 6. Convergence performance comparison.

TABLE 1. Time complexity analysis.

Algorithm Steps	Time Complexity
Step 1: coalition formation request and feedback	$\mathcal{O}(C_1 V)$
Step 2: shortest path initialization	$\mathcal{O}(N^3)$
Step 3: coalition structure exchange auctions	$\mathcal{O}(C_2 N)$
Step 4: utility comparison	$\mathcal{O}(C_3 N)$

2) In Step 2 (namely, shortest path initialization), the shortest path tree is searched in the undirected communication topology graph weighted by SPT algorithm. The time complexity of this step is denoted by $\mathcal{O}(N^3)$. This step makes the initialization action closer to the optimal solution to accelerate the convergence speed.

3) In Step 3 (namely, coalition structure exchange auctions), UAVs estimate the received utility over a time slot and decide to perform the exchange operation if proposed order is satisfied. In the worst scenario, each UAV attempts to make exchange operations with all other coalitions. So the complexity is decided by $\mathcal{O}(C_2N)$, where C_2 is a constant decided by the duration of estimation and decision.

4) In Step 4 (namely, utility comparison), UAVs make an exchange auction to obtain a new coalition structure. The duration of one comparison is denoted by C_3 and the complexity is calculated as $\mathcal{O}(C_3N)$.

To sum up, the time complexity of algorithm can be expressed as $\mathcal{O}(C_1V)+\mathcal{O}(N^3)+\mathcal{O}(C_2N)+\mathcal{O}(C_3N)$. Due to the cost of the coalition formation, UAVs will not form a very large coalition. Moreover, once the UAVs form a larger coalition, the number of exchange operation before converging to the stable coalition structure decreases since the feasible operating space reduces. Consequently, the complexity of exchange operations is affordable.

V. PERFORMANCE EVALUATION

In this section, The convergence behavior is the first to study, and then evaluate the performance of SPT-GCF algorithm. In the simulation, it is assumed that all UAVs fly at the same height, and the specific simulation parameter setting is shown in Table 2. In addition, the parameter settings related to the energy consumption of UAV flight mainly refer to the literature [46]. First, consider an initial network topology for UAV cluster task execution. Specifically, a 500m*500m plane is considered, and a total of 12 UAVs are randomly distributed in different areas in the mission area at any time.

TABLE 2. Parameter settings.

Parameter	Value
Amount of data transferred, $F_i, i \in \mathcal{M}$	$1 \sim 10$ Mbit
Transmission channel bandwidth, B	20MHz
Weight coefficient, w_1, w_2, w_3	$1/3$, $1/3$, $1/3$
Energy consumption factor of the UAV, P_j, P_0 [46]	5 W, 4 W
The flying speed of the UAV, V	$6 \sim 40$ m/s
Path loss exponent α_1 [36]	2
SNR threshold in strongly connected region γ_{s-th} [36]	-3 dB
SNR threshold in weakly connected region γ_{w-th} [36]	-2 dB
Gaussian white noise variance α [36]	-90dBm

A. CONVERGENCE PERFORMANCE

Fig. 6 shows the network convergence performance under the proposed algorithm, the traditional combinatorial optimization algorithm, the traditional non-overlapping coalition formation algorithm, and the traditional algorithm without considering connectivity. The specific simulation parameters set as shown in Table 2. The simulation results are obtained by 500 independent experiments and the expected value is obtained.

Fig. 6 shows the convergence behavior from stage 1 to stage 3 of the dynamic graph coalition formation game. From the three algorithms compared in the figure, it can be seen that the proposed SPT-GCF algorithm can converge to the optimal solution faster, which reflects the superiority of the graph coalition formation of the proposed algorithm.

B. CONNECTIVITY GUARANTEE PERFORMANCE

Fig. 7 shows the changing relationship of the average utility of UAVs across the network with the change of the number of UAVs. It can be seen from the Fig. 7 that when the number of UAVs increases, the average utility of UAVs rises first and then decreases. The rising utility stage reflects the advantage of cooperation between UAVs to guarantee communication connectivity, while the falling stage reflects the cost of cooperation. Because when the number of cooperative UAVs reaches a certain level, the total revenue of UAV cluster reaches saturation, so the cost of UAV will be dominated by too many UAVs. In addition, Figure 7 compares the average utility of UAVs under different algorithms, and it can be seen that the performance of the proposed SPT-GCF algorithm is better than other algorithms.

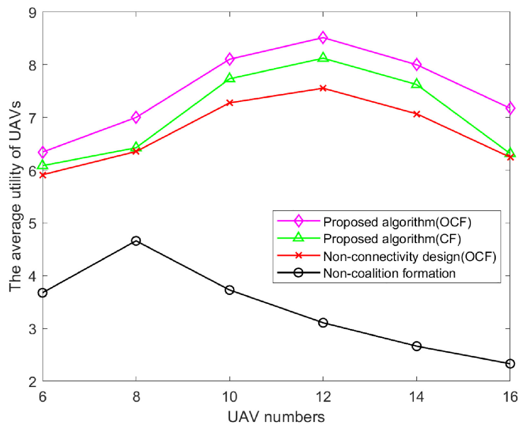


FIGURE 7. The average utility of UAVs versus the number of UAVs.

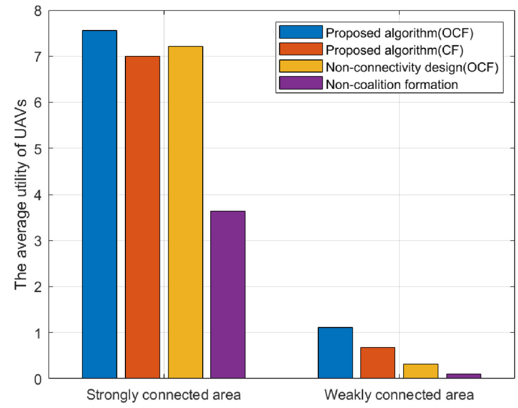


FIGURE 9. Comparison of average UAVs utility between strong and weak connectivity.

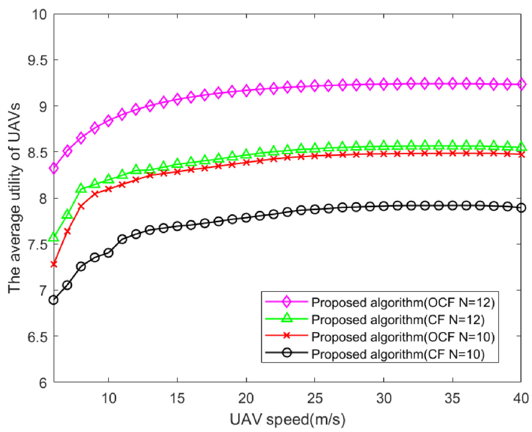


FIGURE 8. The average utility of UAVs versus the speed of UAVs.

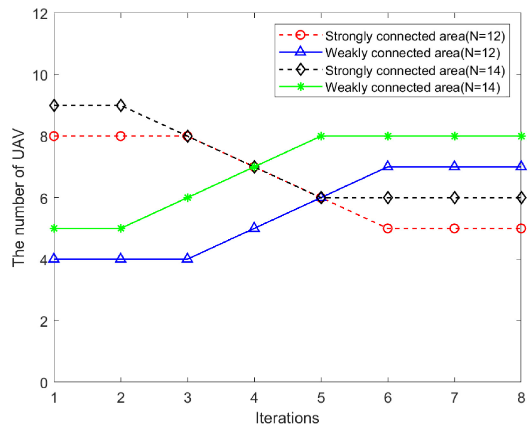


FIGURE 10. Variation of the number of UAVs in strong and weak connected areas.

C. IMPACT OF UAV SPEED ON PERFORMANCE

Fig. 8 represents the relationship between the average utility of UAVs in the network and the flying speed of UAVs when the number of UAVs in the network is 12 and 10. The Fig. 8 compares the average utility of UAVs under the overlapping graph coalition formation game and the non-overlapping coalition formation game. It can be seen that at the beginning, the average utility of UAVs increases with the increase of the flight speed of UAVs. However, when the flight speed of UAVs increases to 10m/s, the increase of its utility starts to become slow and gradually reaches the peak. The reason is that although the flight speed of UAV increases, the flight time of the same distance will be shortened, but at the same time, the flight energy consumption of UAV will be increased, so the average utility of UAV will not be improved all the time.

D. STRONG AND WEAK CONNECTIVITY PERFORMANCE

In addition, in order to better show the performance of the proposed algorithm in different connected regions, Fig. 9 shows the comparison of the average utility of UAVs in the strong and weak connected regions under different algorithms. The result is obtained by several independent simulation experiments and its expected value. From Fig. 9, it can be seen that the performance of the proposed algorithm is better than other algorithms in the strongly connected region and the weakly connected region. What's more, in the strongly connected area, our proposed method increases the average utility of the UAV by 6.5 %, while in the weakly connected area, our method increases the average utility of the UAV by 27 %. In addition, the advantage of the proposed algorithm for maintaining the connectivity of the whole network is more obvious in the weakly connected area.

Finally, as show in Fig. 10, the changing trend diagram of the number of UAVs in different connected areas is presented. It can be seen from the figure that in the strong and weak connected area where UAVs are evenly distributed, because UAVs in the weak connected area have greater communication demand and communication returns, UAVs originally belonging to the strong connected area gradually fly to the weak connected area to ensure the connectivity of the weak connected area.

VI. CONCLUSION

This paper studies the UAV clustering communication connectivity problem induced by interferences and high mobility of UAVs. The graph game is utilized to combine the strong-weak connectivity partition and the time-varying characteristic of the network topology. The time-varying network topology of UAV clustering is abstracted as a set of time-varying undirected graphs, and the connectivity benefits between UAVs are associated with the cut points of the undirected graphs. To improve the overall network performance, UAVs form an overlapping coalition to rapidly restore the network connectivity. The graph coalition formation game is leveraged to balance the connectivity benefits, communication delay and energy consumption of UAVs. Then, a graph coalition formation algorithm based on the shortest path tree is designed to realize the rapid coalition division of UAV clusters, and it is proved that the algorithm can converge to the stable coalition structure. The simulation results justify the competitiveness of our approach against the existing non-overlapping coalition formation game (NOCFG) and the coalition formation game without considering cluster connectivity by presenting respectively a 6.5% and a 14.5% increase of the average UAV clustering utility.

APPENDIX

A. PROOF OF THE FIRST THEOREM

Considering the local cooperation between UAVs, the utility function of UAV j is defined as

$$U_j\big(c_j, c_{-j}\big) = u_j\big(c_j, c_{-j}\big) + \sum_{k\in\mathcal{S}_{\text{original}}} u_k(c_k, c_{-k}) + \sum_{k\in\mathcal{S}_{c_j}} u_k(c_k, c_{-k}), \tag{19}$$

where S_{original} represents the coalition that the UAV j leaves and S_{c_j} represents the new coalition that the UAV j chooses to join. The potential energy function is defined as follows

$$\phi\big(c_j, c_{-j}\big) = \sum_{j\in N} u_j\big(c_j, c_{-j}\big). \tag{20}$$

If the UAV unilaterally changes its mission choice from c_j to $\bar{c}_j$, then the UAV ground utility function changes by

$$\begin{aligned} &U_j\big(\bar{c}_j, c_{-j}\big) - U_j\big(c_j, c_{-j}\big) \\ &= u_j\big(\bar{c}_j, c_{-j}\big) - u_j\big(c_j, c_{-j}\big) \\ &\quad + \sum_{k\in\mathcal{S}_{\text{oiginal}}} \big[u_k(c_k, \bar{c}_{-k}) - u_k(c_k, c_{-k})\big] \\ &\quad + \sum_{k\in\mathcal{S}_{c_j}} \big[u_k(c_k, \bar{c}_{-k}) - u_k(c_k, c_{-k})\big] \\ &\quad + \sum_{k\in\mathcal{S}_{c_j}} \big[u_k(c_k, \bar{c}_{-k}) - u_k(c_k, c_{-k})\big]. \end{aligned} \tag{21}$$

On the other hand, since the UAV unilaterally changes its mission selection, the change of the terrain energy function is as

$$\begin{aligned} &\phi\big(\bar{c}_j, c_{-j}\big) - \phi\big(c_j, c_{-j}\big) \\ &= u_j\big(\bar{c}_j, c_{-j}\big) - u_j\big(c_j, c_{-j}\big) \\ &\quad + \sum_{k\in\mathcal{S}_{c_j}} \big[u_k(c_k, \bar{c}_{-k}) - u_k(c_k, c_{-k})\big] \\ &\quad + \sum_{k\in\mathcal{S}_{\bar{c}_j}} \big[u_k(c_k, \bar{c}_{-k}) - u_k(c_k, c_{-k})\big] \\ &\quad + \sum_{k\in\mathcal{S}_{\text{original}}} \big[u_k(c_k, \bar{c}_{-k}) - u_k(c_k, c_{-k})\big] \\ &\quad + \sum_{k\in\mathcal{D}_j, k\neq j} \big[u_k(c_k, \bar{c}_{-k}) - u_k(c_k, c_{-k})\big], \end{aligned} \tag{22}$$

Where $\mathcal{D}_j = \{\mathcal{N}\backslash\mathcal{S}_{c_j}\backslash\mathcal{S}_{\bar{c}_j}\}$, $X\backslash Y$ represents the deletion of the set y from the set X. Since UAV h unilaterally changes its mission choice, it will only affect the coalition where UAV j leaves and joins, namely S_{c_j} and $S_{\bar{c}_j}$. Therefore, the following equation holds

$$u_k(c_k, \bar{c}_{-k}) - u_k(c_k, c_{-k}) = 0, \forall k \in \mathcal{D}_j, k \neq j. \tag{23}$$

According to the above analysis, we have

$$\begin{aligned} &\phi\big(\bar{c}_j, c_{-j}\big) - \phi\big(c_j, c_{-j}\big) \\ &= u_j\big(\bar{c}_j, c_{-j}\big) - u_j\big(c_j, c_{-j}\big) \\ &\quad + \sum_{k\in\mathcal{S}_{c_j}} \big[u_k(c_k, \bar{c}_{-k}) - u_k(c_k, c_{-k})\big] \\ &\quad + \sum_{k\in\mathcal{S}_{\bar{c}_j}} \big[u_k(c_k, \bar{c}_{-k}) - u_k(c_k, c_{-k})\big] \\ &\quad + \sum_{k\in\mathcal{S}_{\text{original}}} \big[u_k(c_k, \bar{c}_{-k}) - u_k(c_k, c_{-k})\big]. \end{aligned} \tag{24}$$

According to equations (22) and (25), the following equation holds

$$\phi\big(\bar{c}_j, c_{-j}\big) - \phi\big(c_j, c_{-j}\big) = U_j\big(\bar{c}_j, c_{-j}\big) - U_j\big(c_j, c_{-j}\big). \tag{25}$$

As can be seen from the above equation, since any UAV j independently changes its mission selection, the variation of ground utility function is the same as that of potential energy function. Therefore, the constructed graph coalition formation game is an exact potential energy game and there is at least one pure strategy Nash equilibrium. No drones, therefore, can choose by unilaterally changing its mission to improve their effectiveness. Since the constructed potential function is exactly equal to the utility of the whole network, it can be concluded that maximizing the potential function is equivalent to maximizing the utility of the task of the whole network. Based on this, **Theorem 1** is proved.

B. PROOF OF THE SECOND THEOREM

According to **Definition 1**, under the altruism criterion, the UAV selected in each iteration will choose the action that makes its utility increase. Therefore, when UAV j join a new coalition, the total utility of UAV j and UAVs leaving and joining the coalition increases. According to **Theorem 1**, the change of utility function and potential function caused by any UAV individually changing its mission choice are the same. Therefore, an increase in the utility function of the selected UAV in each iteration also implies an increase in the potential energy function. At the same time, due to the limited number of UAVs and energy, the potential energy function has an upper bound. Due to the boundability of the potential function, there is a finite improvement path so that the proposed SPT-GCF algorithm will converge to the maximum of the potential function within a finite number of iterations. Therefore, the algorithm can converge to the stable coalition structure in a finite number of steps, and this point is the maximum value of the utility of the whole network. Therefore, **Theorem 2** is proved.

REFERENCES

[1] H. Nawaz, H. M. Ali, and A. A. Laghari, "UAV communication networks issues: A review," *Arch. Comput. Methods Eng.*, vol. 28, no. 3, pp. 1349–1369, 2021.

[2] C. T. Nguyen et al., "Transfer learning for future wireless networks: A comprehensive survey," 2021, *arXiv:2102.07572*.

[3] M. Hua, L. Yang, C. Li, Q. Wu, and A. L. Swindlehurst, "Throughput maximization for UAV-aided backscatter communication networks," *IEEE Trans. Commun.*, vol. 68, no. 2, pp. 1254–1270, Feb. 2020.

[4] T. Do-Duy, L. D. Nguyen, T. Q. Duong, S. R. Khosravirad, and H. Claussen, "Joint optimisation of real-time deployment and resource allocation for UAV-aided disaster emergency communications," *IEEE J. Sel. Areas Commun.*, vol. 39, no. 11, pp. 3411–3424, Nov. 2021.

[5] P. Stodola, J. Drozd, K. Šilinger, J. Hodickỳ, and D. Procházka, "Collective perception using UAVs: Autonomous aerial reconnaissance in a complex urban environment," *Sensors*, vol. 20, no. 10, p. 2926, 2020.

[6] J. Gu, T. Su, Q. Wang, X. Du, and M. Guizani, "Multiple moving targets surveillance based on a cooperative network for multi-UAV," *IEEE Commun. Mag.*, vol. 56, no. 4, pp. 82–89, 2018.

[7] G. Jang et al., "Cost-effective unmanned aerial vehicle (UAV) platform for field plant breeding application," *Remote Sens.*, vol. 12, no. 6, p. 998, 2020.

[8] L. Gupta, R. Jain, and G. Vaszkun, "Survey of important issues in UAV communication networks," *IEEE Commun. Surveys Tuts.*, vol. 18, no. 2, pp. 1123–1152, 2nd Quart., 2016.

[9] V. Sridhar and A. Manikas, "Target tracking with a flexible UAV cluster array," in *Proc. IEEE Globecom Workshops (GC Wkshps)*, 2016, pp. 1–6.

[10] N. Qi et al., "Two birds with one stone: Simultaneous jamming and eavesdropping with the bayesian-stackelberg game," *IEEE Trans. Commun.*, vol. 69, no. 12, pp. 8013–8027, 2021.

[11] N. Qi et al., "A learning-based spectrum access stackelberg game: Friendly jammer-assisted communication confrontation," *IEEE Trans. Veh. Technol.*, vol. 70, no. 1, pp. 700–713, Jan. 2021.

[12] H. Wang, J. Wang, J. Chen, Y. Gong, and G. Ding, "Network-connected UAV communications: Potentials and challenges," *China Commun.*, vol. 15, no. 12, pp. 111–121, 2018.

[13] D. Mishra and E. Natalizio, "A survey on cellular-connected UAVs: Design challenges, enabling 5G/B5G innovations, and experimental advancements," *Comput. Netw.*, vol. 182, Dec. 2020, Art. no. 107451.

[14] X. Fu, P. Feng, B. Li, and X. Gao, "A two-layer task assignment algorithm for UAV swarm based on feature weight clustering," *Int. J. Aerosp. Eng.*, vol. 10, pp. 1–12, Nov. 2019.

[15] B. Li, Z. Fei, and Y. Zhang, "UAV communications for 5G and beyond: Recent advances and future trends," *IEEE Internet Things J.*, vol. 6, no. 2, pp. 2241–2263, Apr. 2019.

[16] Z. Zhang et al., "6G wireless networks: Vision, requirements, architecture, and key technologies," *IEEE Veh. Technol. Mag.*, vol. 14, no. 3, pp. 28–41, Sep. 2019.

[17] K. Hazra, V. K. Shah, S. Roy, S. Deep, S. Saha, and S. Nandi, "Exploring biological robustness for reliable multi-UAV networks," *IEEE Trans. Netw. Service Manag.*, vol. 18, no. 3, pp. 2776–2788, Sep. 2021.

[18] M. R. Silva et al. "Performance evaluation of multi-UAV network applied to scanning rocket impact area," *Sensors*, vol. 19, no. 22, p. 4895, 2019.

[19] P. Yang, Y. Xiao, M. Xiao, and S. Li, "6G wireless communications: Vision and potential techniques," *IEEE Netw.*, vol. 33, no. 4, pp. 70–75, Jul./Aug. 2019.

[20] N. Qi, M. Wang, W.-J. Wang, T. A. Tsiftsis, R. Yao, and G. Yang, "Energy efficient full-duplex UAV relaying networks under load-carry-and-delivery scheme," *IEEE Access*, vol. 8, pp. 74349–74358, 2020.

[21] M. Hua, Y. Wang, C. Li, Y. Huang, and L. Yang, "Energy-efficient optimization for UAV-aided cellular offloading," *IEEE Wireless Commun. Lett.*, vol. 8, no. 3, pp. 769–772, Jun. 2019.

[22] X. Yuan, Z. Feng, W. Ni, Z. Wei, R. P. Liu, and C. Xu, "Connectivity of UAV swarms in 3D spherical spaces under (un)intentional ground interference," *IEEE Trans. Veh. Technol.*, vol. 69, no. 8, pp. 8792–8804, Aug. 2020.

[23] Y. Yu, L. Ru, W. Chi, Y. Liu, Q. Yu, and K. Fang, "Ant colony optimization based polymorphism-aware routing algorithm for ad hoc UAV network," *Multimedia Tools Appl.*, vol. 75, no. 22, pp. 14451–14476, 2016.

[24] R. Ding, J. Chen, W. Wu, J. Liu, F. Gao, and X. Shen, "Packet routing in dynamic multi-hop UAV relay network: A multi-agent learning approach," *IEEE Trans. Veh. Technol.*, vol. 71, no. 9, pp. 10059–10072, Sep. 2022.

[25] P. Li and J. Xu, "Placement optimization for UAV-enabled wireless networks with multi-hop backhauls," *J. Commun. Inf. Netw.*, vol. 3, no. 4, pp. 64–73, 2018.

[26] R. Yao, Y. Lu, T. Mekkawy, F. Xu, and X. Zuo, "Joint optimization of beamforming and power allocation for DAJ-based untrusted relay networks," *ETRI J.*, vol. 40, no. 6, pp. 714–725, 2018.

[27] T. Mekkawy, R. Yao, N. Qi, and Y. Lu, "Secure relay selection for two way amplify-and-forward untrusted relaying networks," *IEEE Trans. Veh. Technol.*, vol. 67, no. 12, pp. 11979–11987, Dec. 2018.

[28] B. Ji, Y. Li, S. Chen, C. Han, C. Li, and H. Wen, "Secrecy outage analysis of UAV assisted relay and antenna selection for cognitive network under nakagami-$\{m\}$ channel," *IEEE Trans. Cogn. Commun. Netw.*, vol. 6, no. 3, pp. 904–914, Sep. 2020.

[29] D. S. Lakew, U. Sáad, N.-N. Dao, W. Na, and S. Cho, "Routing in flying Ad hoc networks: A comprehensive survey," *IEEE Commun. Surveys Tuts.*, vol. 22, no. 2, pp. 1071–1120, 2nd Quart., 2020.

[30] Z. Ma, J. Qi, M. Wang, C. Wu, J. Guo, and S. Yuan, "Time-varying formation tracking control for multi-UAV systems with directed graph and communication delays," in *Proc. 40th Chin. Control Conf. (CCC)*, 2021, pp. 5436–5441.

[31] H. T. Do, et al., "Formation control algorithms for multiple-UAVs: A comprehensive survey," *EAI Endorsed Trans. Ind. Netw. Intell. Syst.*, vol. 8, no. 27, p. e3, 2021.

[32] S. Zhang and R. Zhang, "Trajectory design for cellular-connected UAV under outage duration constraint," in *Proc. IEEE Int. Conf. Commun. (ICC)*, 2019, pp. 1–6.

[33] S. Zhang and R. Zhang, "Radio map-based 3D path planning for cellular-connected UAV," *IEEE Trans. Wireless Commun.*, vol. 20, no. 3, pp. 1975–1989, Mar. 2021.

[34] T. Fang, J. Chen, and Y. Zhang, "Content-aware multi-subtask offloading: A coalition formation game-theoretic approach," *IEEE Commun. Lett.*, vol. 25, no. 8, pp. 2664–2668, Aug. 2021.

[35] W. Saad, Z. Han, M. Debbah, and A. Hjorungnes, "A distributed coalition formation framework for fair user cooperation in wireless networks," *IEEE Trans. Wireless Commun.*, vol. 8, no. 9, pp. 4580–4593, Sep. 2009.

[36] J. Chen et al., "Joint task assignment and spectrum allocation in heterogeneous UAV communication networks: A coalition formation game-theoretic approach," *IEEE Trans. Wireless Commun.*, vol. 20, no. 1, pp. 440–452, Jan. 2021.

[37] N. Qi, Z. Huang, F. Zhou, Q. Shi, Q. Wu, and M. Xiao, "A task-driven sequential overlapping coalition formation game for resource allocation in heterogeneous UAV networks," *IEEE Trans. Mobile Comput.*, early access, Apr. 12, 2022, doi: 10.1109/TMC.2022.3165965.

[38] Y. Zhao, Y. Li, D. Wu, and N. Ge, "Overlapping coalition formation game for resource allocation in network coding aided D2D communications," *IEEE Trans. Mobile Comput.*, vol. 16, no. 12, pp. 3459–3472, Dec. 2017.

[39] H. Luan et al., "Energy efficient task cooperation for multi-UAV networks: A coalition formation game approach," *IEEE Access*, vol. 8, pp. 149372–149384, 2020.

[40] N. Qi, Z. Huang, W. Sun, S. Jin, and X. Su, "Coalitional formation-based group-buying for UAV-enabled data collection: An auction game approach," *IEEE Trans. Mobile Comput.*, early access, Oct. 3, 2022, doi: 10.1109/TMC.2022.3211447.
[41] Z. Su, M. Dai, Q. Xu, R. Li, and H. Zhang, "UAV enabled content distribution for Internet of Connected Vehicles in 5G heterogeneous networks," *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 8, pp. 5091–5102, Aug. 2021.
[42] X. Yu et al., "Air–ground integrated deployment for UAV-enabled mobile edge computing: A hierarchical game approach," *IET Commun.*, vol. 14, no. 15, pp. 2491–2499, 2020.
[43] V. Sharma, M. Bennis, and R. Kumar, "UAV-assisted heterogeneous networks for capacity enhancement," *IEEE Commun. Lett.*, vol. 20, no. 6, pp. 1207–1210, Jun. 2016.
[44] C. A. Kerrache, A. Lakas, N. Lagraa, and E. Barka, "UAV-assisted technique for the detection of malicious and selfish nodes in vanets," *Veh. Commun.*, vol. 11, pp. 1–11, Jan. 2018.
[45] W. Saad, Z. Han, T. Basar, M. Debbah, and A. Hjorungnes, "Hedonic coalition formation for distributed task allocation among wireless agents," *IEEE Trans. Mobile Comput.*, vol. 10, no. 9, pp. 1327–1344, Sep. 2011.
[46] Y. Zeng, J. Xu, and R. Zhang, "Energy minimization for wireless communication with rotary-wing UAV," *IEEE Trans. Wireless Commun.*, vol. 18, no. 4, pp. 2329–2345, Apr. 2019.

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