Energy Efficient Task Cooperation for Multi-UAV Networks: A Coalition Formation Game Approach

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ABSTRACT In this paper, we study the multi-task cooperation problem for unmanned aerial vehicle (UAV) swarms, where the UAV energy consumption is taken into consideration during location scheduling and task implementation. One task may need the cooperation of several UAVs with specific capabilities. To avoid unreasonable task allocation, we quantify the mission properties of UAVs and task areas. We comprehensively consider the overlapping and complementary relationship of the UAV's task types, so that UAVs can form corresponding collective execution tasks according to the task attributes. Based on the coalition game theory, we model the distributed task assignment problem of UAVs as a coalition formation game (CFG). We propose a task allocation algorithm, and then prove that it can achieve the joint optimization of energy and task completion by decision-making of UAVs in finite iterations. With the equilibrium properties of coalition formation in UAV networks, we further optimize the position of UAVs to minimize the network energy consumption. Simulation results verify that the proposed method can reduce the flight loss with high task completion degree.

INDEX TERMS UAV swarm, task assignment, energy optimization, coalition formation game (CFG).

I. INTRODUCTION

A. BACKGROUND AND MOTIVATION

Nowadays, unmanned aerial vehicles (UAVs) have been employed to perform various tasks in many scenarios due to their flexible features, such as border patrol, reconnaissance, attack and enhanced communication [1]–[3]. Multiple UAVs can form UAV swarms to perform remote, large-scale and complex tasks [4]–[6]. Therefore, the task assignment of UAVs has attracted widespread attention in recent years [7]–[13].

In the existing work, UAVs were mainly used to perform specific tasks [7]–[10], where each task was assumed can be completed by one UAV, so that one-to-one task assignment strategies were developed for optimizing task execution efficiency. For example, the authors in [7] studied the task

assignment problem to maximize the mission throughput with constraints on the travel distances of UAVs. In [8], under the premise of maintaining connectivity among UAVs, the authors optimized the data transfer task sequence to minimize the task execution time. In [9], UAVs were assigned to perform data relay tasks for maintaining the connectivity of dynamic heterogeneous networks. In [10], the authors assigned multiple UAVs into one mission area to investigate forest fires fighting, where an auction-based algorithm was proposed to address the task assignment issue.

With the development of UAV technology, one UAV can be equipped with diverse devices that support multiple capabilities, such as data collection, ground reconnaissance, and audio monitoring at the same time. Therefore, the problem of multi-task assigned by multi-UAV was raised [11]–[13]. In [11], multiple UAVs with different capacities were assigned to performing tasks with heterogeneous requirements. In [12], the UAV can perform multiple tasks

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such as forward data as a relay and coverage of the task area. The authors assigned multiple UAVs to multiple tasks to improve task performance while ensuring communication. In [13], multiple UAVs were used to perform attack, reconnaissance and induced tasks. The authors proposed an adaptive-limitation penalty term based on the potential function. It can be seen that multiple UAVs with heterogeneous capabilities are able to accomplish the tasks more efficiently.

However, the task performing behavior of different UAVs was assumed independent in the above work [7]–[13], while the cooperative relationship between heterogeneous UAVs was not considered. In fact, one mission area may contain multiple types of tasks, and UAVs can perform multiple missions. To maximize the efficiency of task execution, on the one hand, different types of UAVs need to complement each other in the task execution process. On the other hand, the cooperation of the same type of UAVs is also needed to increase the speed of mission execution. Therefore, it is necessary to characterize and distinguish different types of task attributes, and then refine the task allocation planning according to the task execution capabilities of UAVs to improve the overall efficiency of task execution.

In addition, due to the flexible deployment characteristics, UAVs mainly improve task execution efficiency by adjusting their deployment locations [7]–[13], which is different from task assignment issues in traditional ground networks. However, the energy consumption caused by the flight propulsion in the process of optimizing task efficiency was always ignored in the existing work. Considering the importance of energy efficiency to the endurance of UAV swarms, we jointly improve the energy efficiency of task assignment planning by optimizing UAV flight and hovering time in this paper.

B. CONTRIBUTIONS

Therefore, we propose an energy-efficient task cooperation scheme for heterogeneous multi-UAV in view of cooperative task assignment and energy optimization of heterogeneous UAVs. Firstly, a task relationship model is proposed to quantify the task attribute of ground task areas, the capabilities of UAVs in terms of task types they can run, in order to define a general satisfaction function to quantify the task completion degree. Then, the energy consumption model is proposed to account for the energy loss during flight and hovering stages.

To achieve automatic and self-organizing task cooperation with energy constraints, we establish a distributed task assignment model for UAVs based on the coalition formation game (CFG) [14]–[17]. Aiming at characteristics of cooperation and complementary relationships among UAVs brought by location and mission attributes, we develop the coalition formation game with the peer effects among UAVs [18]–[20]. We propose the coalition formation algorithm based on cooperation rule, where coalition merge rules and coalition split rules are designed. Moreover, we prove the convergence of the algorithm based on the potential game theory [21]–[23]. The contributions of this paper are summarized as follows:

- We study the problem of UAV assignment in multi-UAV and multi-task scenario. The UAVs' task types, energy loss and the time of performing tasks are considered to improve the task completion degree in the task area while reducing the energy loss of UAVs.
- We define a quantitative amount for each type of task. The definition of task completion degree includes the task performing time and the implementation of all types of tasks in the task areas.
- The coalition formation game is applied to the task assignment scenario of UAVs, and a coalition formation algorithm based on cooperative rule is proposed. The overlapping and complementary relationships of UAVs' tasks are considered, which can reduce the energy loss of the UAVs and improve the task completion degree in the task area.
- With the equilibrium properties of coalition formation in UAV networks, we further optimize the position of UAVs within the task coverage to minimize the network energy consumption.

C. RELATED WORK

1) COALITION FORMATION GAME THEORY

This paper focuses on the problem of task cooperation and mutual influence among multiple UAVs. Because the game theory is an effective tool to solve the problem of resource optimization in distributed systems [24], [25], an appropriate coalition formation game was used in this paper to model the task assignment problem of UAVs.

Coalition formation game can accurately and completely describe the cooperative relationships among users in sharing networks. In [16], the authors proposed a context-aware group buying mechanism to reduce users' data costs based on the coalition formation game. In [26], coalition formation game theory is used to obtain a solution to a resource allocation problem for a team of UAVs prosecuting a target. In [27], the authors proposed a reputation-based mechanism for coalition formation aiming to complete the designated tasks with minimal resource utilization. In [28], the authors studied the data clustering scheme based on the coalition formation game to improve the data collection efficiency in UAV-enabled wireless sensor networks.

Based on the existing work, an appropriate coalition formation game with peer effects is developed in this paper to model the task assignment problem of UAVs.

2) ENERGY CONSUMPTION MODEL

The endurance and performance of UAV systems are fundamentally limited by the on-board energy, which is practically finite due to the aircraft's size and weight constraints [29]. Thus, energy consumption should be an important concern for UAV task cooperation [30].

In [31], The authors investigated an uplink power control problem for UAV-assisted wireless communications. The flying altitude, antenna bandwidth and location of UAVs, as well as allocated bandwidth of ground terminals were

TABLE 1. List of notations.

Symbols	Definitions
$\mathcal{M}$	Set of UAVs
$\mathcal{M}_u$	Set of UAVs heading to mission area u
$\mathcal{U}$	Set of task areas
$\mathcal{X}$	Set of task types
$\mathcal{X}_m$	Set of task types that UAV m can perform
l_x	Task amount of type x
δ_m	Decision of UAV m
h_{mu}	Channel gain from u to m
d_{mu}	Distance between m and task area u
R_{mu}	Transmission rate from task area to UAV
T_u	Time to perform task area u
D_u	Task satisfaction function of task area u
$\theta(x_i)$	Task completion degree of task x_i
V_{max}	Max speed of UAV
v_m	Speed of UAV m
P'_m, P''_m	Propulsion power of UAV
P_0	Blade profile power of UAV
P_i	Induced power in the hover state of UAV
$E^f_{mu}{}', E^f_{mu}{}''$	Flying energy loss of UAV
E^h_{mu}	Hovering energy loss of UAV

jointly optimized to achieve good performance in uplink sum power saving. In [32], the authors considered the jointly optimizing user association, power control, computation capacity allocation, and location planning in a mobile edge computing network with multiple UAVs to minimize the total power effectively. In [33], the authors formulated the energy minimization problem by jointly optimizing the UAV trajectory and communication time allocation among ground nodes. In [34], the author considered the problem of high-efficiency coverage deployment of UAVs and controlled the launch power of UAVs to achieve the purpose of energy conservation. In [35], an efficient algorithm was proposed for maximizing the UAV's energy efficiency with general constraints on the trajectory.

In this paper, we take the energy consumption of UAVs as part of the optimization in the process of the task assignment, which is important for the energy efficiency of task execution.

II. SYSTEM MODEL AND PROBLEM DESCRIPTION

A. SYSTEM MODEL

The relevant system parameters and physical meanings in this paper are summarized in Table 1.

1) NETWORK STRUCTURE

We consider UAV communication swarms consisting of M UAVs, which are randomly scattered in space. The set of UAVs is denoted by $\mathcal{M} = \{1, \ldots, m, \ldots, M\}$. Fig. 1 shows a simple example of the UAV task performing relationships. There is a control UAV used for the information sharing between UAVs. Each five-pointed star in the network represents a task area. The set of task area is $\mathcal{U} = \{1, \ldots, u, \ldots, U\}$. Each yellow box represents a type of task that needs to be performed. The set of task types is $\mathcal{X} = \{1, \ldots, x, \ldots, X\}$. Different numbers represent different tasks. The same tasks have different task amounts in different areas. The number in the white box represents the amounts of data for each type of task. $l_1, \ldots, l_x, \ldots, l_X$ are the task amount for each type of task. For example, task
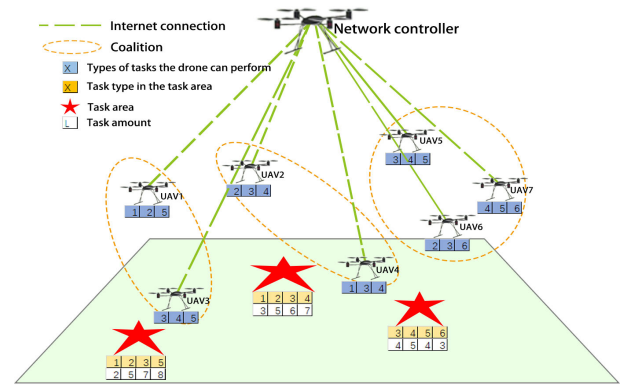

FIGURE 1. The task assignment model of multiple UAVs with various tasks.
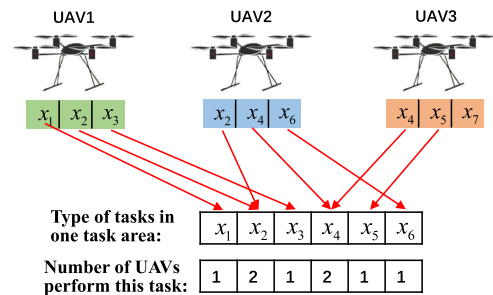

FIGURE 2. The example of cooperation relationship among UAVs.

types include information collection, audio collection, picture video capture and other tasks, while the task requirements can be audio data, information data and other task data. Here, we represent the task types and task amounts in numbers.

A single UAV can perform multiple types of tasks at the same time, such as collecting information while conducting reconnaissance. As shown in Fig. 1, each blue box represents a type of task that the UAV can perform. The set of executable task types of UAV m is denoted by $\mathcal{X}_m, \mathcal{X}_m \subseteq \mathcal{X}$, which is dependent on the equipped equipages types. Different UAVs work together in the mission area, the set of UAVs heading to mission area u is $\mathcal{M}_u, \mathcal{M}_u \subseteq \mathcal{M}$. Each task area has different task requirements, the type of tasks need to be performed in the task area u is $\mathcal{X}_u, \mathcal{X}_u \subseteq \mathcal{X}$. Each UAV chooses one task area to perform the tasks, the decision of UAV m is $\delta_m \in \mathcal{U} \cup \{0\}$, where 0 means the UAV does not participate in the tasks. u is the task area that the UAV m travels to perform the task.

2) TASK RELATIONSHIP

There are overlapping and complementary relationships between UAVs' task types. As the example shown in Fig. 2, there are six types of tasks $\mathcal{X}_u = \{x_1, x_2, x_3, x_4, x_5, x_6\}$, $x_1, x_2, x_3, x_4, x_5, x_6 \in \mathcal{X}$ that need to be performed in the task area u, the types of tasks that UAV m_1, m_2 can perform are $\mathcal{X}_{m_1} = \{x_1, x_2, x_3\}$, $\mathcal{X}_{m_2} = \{x_2, x_4, x_6\}$, respectively. If UAV1 and UAV2 cooperate to perform the tasks in the task area u, they will spend less time performing the overlapping task x_2.

UAVs need to select task areas that are compatible with their task execution capabilities to preferably perform tasks. When multiple UAVs perform tasks, UAVs in the task area wait for other UAVs in the mission area until they complete the mission and fly back together. We assume that the air-to-ground transmission are dominated by line-of-sight (LoS) links [36]. Thus, the channel power from UAV to task area follows the free-space path loss model as:

$$h_{mu} = \beta_0 d_{mu}^{-2} = \frac{\beta_0}{H^2 + x_{mu}^2 + y_{mu}^2}, \qquad (1)$$

where β_0 denotes the channel power at the reference distance one meter, whose value depends on the carrier frequency, antenna gain, etc. $d_{mu} = \sqrt{H^2 + x_{mu}^2 + y_{mu}^2}$ is the distance between m and task area u. We denote p_u as the transmission power by task area. Thus the transmission rate from task area to UAV in bits/second/Hz (bps/Hz) can be expressed as:

$$R_{mu} = \log_2\left(1 + \frac{p_u h_{mu}}{\sigma^2}\right) = \log_2\left(1 + \frac{p_u \gamma_0}{d_{mu}^2}\right), \qquad (2)$$

where σ^2 is the noise power, and $\gamma_0 \triangleq \beta_0/\sigma^2$. Thus, the time T_u of UAVs performing the tasks in the task area u can be defined as:

$$T_u = \max\left(\frac{l_i}{R_i}, \ldots, \frac{l_j}{R_j}, \ldots\right), \quad i, j \in \mathcal{X}_u, \qquad (3)$$

where R_i is the rate that UAVs perform the mission x_i in the task area u. The more UAVs with overlapping tasks in the same task area, the shorter the time the UAV performs the mission.

In addition, there are complementary relationships between the task types of two UAVs. For a single UAV, the types of tasks it can perform are not sufficient to meet the task requirements of the task area. If the two UAVs form an effective coalition, they can perform the tasks in the mission area together. The types of tasks performed by two UAVs are far more than that of a single UAV. UAVs collaboratively perform the tasks that can greatly improve the task completion degree in the task area.

For the task area, we want the tasks to be fully executed. In the process of task assignment, UAVs should consider the complementary relationship between the types of tasks that the UAVs can perform. In addition to the overlapping tasks of the UAVs, each type of task in the task area should be executed, so we define the task completion degree. For the task area u, its task satisfaction function D_u is defined as:

$$D_u = \frac{1}{|\mathcal{X}_u|} \sum_{x_i \in \mathcal{X}_u} \theta(x_i), \qquad (4)$$

$$\theta(x_i) = \begin{cases} 1, & R_i \neq 0 \\ 0, & R_i = 0, \end{cases} \qquad (5)$$

where $|\cdot|$ represents the size of the set. x_i is one type of tasks $\mathcal{X}_u$ in the task area u. $\theta(x_i)$ is the completion degree of task x_i, and it is defined as whether there is a UAV that performs this type of task in the task area u. If there is a UAV performing
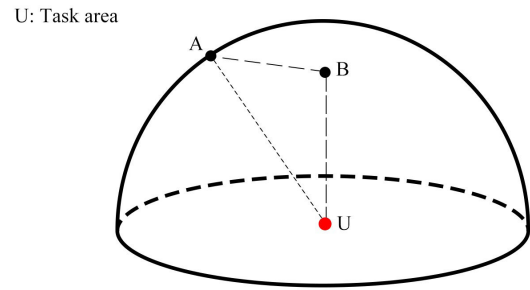

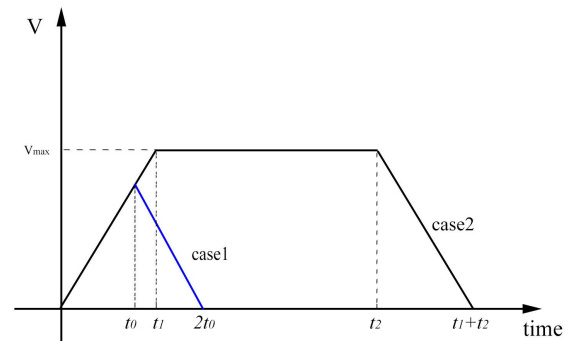**FIGURE 3.** Schematic diagram of UAV location deployment.

FIGURE 4. Different flight situations with influence of acceleration.

this type of task in the task area, the satisfaction level of this task type is 1. Otherwise, the satisfaction level of this task type is 0. D_u is the average of the task completion degree in task area u.

3) UAV FLIGHT HEIGHT AND POSITION ADJUSTMENT
It is assumed that different UAVs are assigned different flight heights, and each UAV is flying at its fixed altitude to ensure safety and mission execution. The impact of different heights is shown in Fig. 3. One UAV at point A can adjust their location on the AB line, where the hemisphere represents the coverage of the task area, and point U is the location of the task target. A is the farthest point where the UAV can perform this task, and point B is the closest one. BU line equals to the height of the UAV.

4) UAV ENERGY CONSUMPTION MODEL
UAVs incur flight energy losses when they fly to the task areas. There are also losses when UAVs hovering to perform tasks. Under these conditions, UAVs need to complete related tasks in the task area. We define the loss of UAVs performing the task as a certain energy loss. The effect of acceleration on the energy consumption of UAVs [37] is taken into consideration. As shown in Fig. 4, two acceleration situations were discussed as follow:

1) The hovering UAV increases the speed from zero to a specific V_1 speed less than $V_{\max}$ with the stable acceleration a during $[0, t_0]$, and then the UAV decreases the speed to zero with acceleration $-a$.

2) The UAV increases the speed from zero to max velocity $V_{\max}$ with the stable acceleration a during $[0, t_1]$, and then maintain the constant speed during $[t_1, t_2]$. Finally, the UAV

decreases its speed to zero with acceleration $-a$. The slope of the flight speed in Fig. 4 represents the acceleration a.

Both cases are affected by the distance between the UAV and the task area. If $d_{mu} < \frac{V_{\max}^2}{a}$, the UAV follows the case1 in the Fig. 4. If $d_{mu} > \frac{V_{\max}^2}{a}$, the UAV follows the case 2 in the Fig. 4.

The acceleration a will influence the time that UAVs fly to the task area. Thus, the energy loss of the UAV will be effected by the acceleration. According to [37] Appendix A, the propulsion power P'_m of the UAV with horizontal flight speed v_m can be given by:

$$P'_m = P_0 \left(1 + \frac{3v_m^2}{U_{tip}^2} \right)$$
$$+ P_i \varpi \left(\sqrt{\varpi^2 + \frac{\rho^2 A^2 v_m^4}{W^2}} - \frac{\rho A v_m^2}{W} \right)^{1/2}$$
$$+ \frac{1}{2} d_0 \rho s A v_m^3, \quad (6)$$

where W is the gravity of the UAV. ρ, A, d_0, s, U_{tip} are the aerodynamic and aircraft design related constant [31], [33]. P_0, P_i respectively indicate the blade profile power and the induced power in the hover state, and

$$\varpi \Leftrightarrow \frac{F}{W} = \left(1 + \frac{(\rho S_{FP} v_m^2 + 2 g_m a)^2}{4 W^2} \right)^{\frac{1}{2}}, \quad (7)$$

where S_{FP} is the fuselage equivalent flat plate area. g_m is the weight of UAV, and F is the rotor thrust. Moreover, the total energy consumption during $[0, t_1]$ with acceleration a can be expressed as [37]:

$$E_{mu}^{f'}$$
$$= \int_0^{t_1} \left[P_0 \left(1 + \frac{3}{U_{tip}} v_m^2 \right) \right.$$
$$+ P_i \sqrt{1 + \left(\frac{\rho S_{FP}}{2W} v_m^2 + \frac{g_m}{W} a v_m \right)^2}$$
$$\cdot \sqrt{\sqrt{1 + \left(\frac{\rho S_{FP}}{2W} v_m^2 + \frac{g_m}{W} a v_m \right)^2 + (\frac{\rho A}{W})^2 v_m^4} - \left(\frac{\rho A}{W} \right)^2 v_m^2}$$
$$\left. + \frac{1}{2} d_0 \rho s A v_m^3 \right] dt. \quad (8)$$

When the UAV speed reaches $V_{\max}$, the propulsion power P''_m of the UAV can be given by:

$$P''_m = P_0 \left(1 + \frac{3v_m^2}{U_{tip}^2} \right) + P_i \left(1 + (\frac{\rho S_{FP} v_m^2}{2W})^2 \right)^{\frac{1}{2}}$$
$$\cdot \sqrt{\sqrt{1 + (\frac{\rho S_{FP} v_m^2}{2W})^2 + (\frac{\rho A}{W})^2 v_m^4} - \frac{\rho A}{W} v_m^2}$$
$$+ \frac{1}{2} d_0 \rho s A v_m^3. \quad (9)$$

The total energy loss of UAV with speed $V_{\max}$ can be expressed as:

$$E_{mu}^{f''} = \int_{t_1}^{t_2} (P''_m) dt. \quad (10)$$

UAVs need to hover over mission area during the mission, the energy loss of the UAV cannot be ignored when they are hovering. The hovering energy loss E_{mu}^h of UAVs performing the task in the task area u can be defined as:

$$E_{mu}^h = P_h \times T_u, \quad (11)$$

when the UAV is hovering, UAV's power consumption is a constant P_h. As shown in (11), if UAVs in the same task area have more overlapping tasks, the time of UAVs performing the tasks will be shorter, this will reduce the hovering energy loss of UAVs.

B. PROBLEM DESCRIPTION

The choice of UAV $\delta_m(u)$ will affect the performance of networks. When a UAV make the decision, the set $\mathcal{M}_u$ will be influenced. This will affect the overlapping and complementary relationship of UAVs in the mission area, and task relationships will influence the energy loss of UAVs and the task completion degree of task areas. We aim to maximize the task completion while considering the flight loss of UAVs, the UAV group should accomplish the mission area task with minimum energy consumption.

When a UAV participates in a mission, this will bring the cost of flying energy. If the UAV does not participate in the mission, this will not bring energy loss, but the task completion degree in the task area will decrease. Here we discuss two optimization goals: task completion degree for all task areas and the flight energy loss of UAVs. When UAVs perform tasks in the relevant task area, the higher the task completion degree, the more types of tasks that UAVs need to perform. In order to perform all types of tasks, UAVs will cause a lot of energy loss. Therefore, in this paper, we consider the weighted relationship between the flight energy loss of the UAV and the mission completion degree in the task area. If a UAV can better complete the mission area task, then we think that the energy consumed by the UAV is worthwhile. The utility function $S_m(u)$ of UAVs performing the task area u is:

$$S_m(u) = \frac{D_u^2}{\alpha E_{mu}^h + \beta E_{mu}^f}, \quad (12)$$

where α, β are the weighting factor of flight energy, their roles are keeping the hovering energy loss and the flight energy loss in the same order of magnitude. E_{mu}^f is the total flight energy. The higher the task completion degree in the task area is, the higher the utility will be. Then, the optimization problem formula for the entire network is as follows:

$$\underset{\delta_m}{maximize} \sum_{m \in \mathcal{M}} S_m(\delta_m), \quad (13)$$

$$s.t. \quad \mathcal{X}_m \cap \mathcal{X}_{\delta_m} \neq \varnothing, \quad \delta_m \in \mathcal{U}, \quad (14)$$

$$|\mathcal{M}_{\delta_m}| \geq 1, \quad \delta_m \in \mathcal{U}, \quad (15)$$

$$|\delta_m| \leq 1, \quad (16)$$

where constraint (14) means UAV m travel to the task area which has the same type of tasks with it. The constraint (15) implies each task area requires at least one UAV to perform tasks. The constraint (16) ensures that each UAV can only perform tasks in one task area.

III. COALITION FORMATION GAME BASED ON TASK ASSIGNMENT MODEL

In this section, the problem of task assignment is modeled as a coalition formation game. The UAV group should perform all types of tasks as much as possible. We refer to the overlapping and complementary relationship of the UAV's mission types as the peer effect [18]–[20]. The explanation of the peer effect will be given in the following sections. We propose a coalition formation algorithm based on cooperation rule [16], and prove the existence of a stable solution. According to this algorithm, we get the suboptimal result of the UAV task assignment.

A. COALITION FORMATION GAME

The game model of UAVs task assignment problem is defined as $\mathcal{G} = \{\delta_m, \mathcal{M}, \mathcal{F}_m, S_m, r_u\}$, where δ_m is the UAV's decision. $\mathcal{M}$ is the set of UAVs' decision, S_m is the utility function of the UAV, it is defined in the (12). r_u is the utility function of the coalition u, which is defined as:

$$r_u(\mathcal{M}_u) = \sum_{m \in \mathcal{M}_u} S_m, \qquad (17)$$

where the utility of u is decided by the utilities of all UAVs it employed $\mathcal{M}_u$. A single UAV can perform tasks in one task area. One task area requires multiple UAVs to perform tasks. UAVs form a coalition near the task area to perform the related tasks, UAVs form different coalitions based on the type of task that they can perform. $\mathcal{F}_m = \{0, 1, \dots, u, \dots, U\}$ is the optional policy set for the UAV m, where 0 means the UAV is in an inactive state, UAV m does not participate in the execution of the task. A single UAV can only choose one coalition at one time, the coalition we study here is a non-overlapping coalition. The utility function of the coalition is the total utility of UAVs in the coalition.

1) PREFERENCE ORDER

For each UAV, it can join any coalition to perform tasks in any task area. For UAV m, $\succ_m$ is defined as a complete, reflexive, and transitive binary relation over the set of all feasible coalitions that UAV m can possibly form [16].

if $\mathcal{M}_{u_i} \succ_m \mathcal{M}_{u_j}$, UAV m prefers being a member of coalition $\mathcal{M}_{u_i}$ rather than coalition $\mathcal{M}_{u_j}$, the preference order can influence the convergence and final coalition structure.

In the coalition formation game, the preference order can guarantee the existence of coalition stability [15]. In addition to the preference order, there are many rules for coalition formation, and different rules lead to different coalition results. The Pareto order is the most commonly used in coalition formation.

2) PARETO ORDER

For an arbitrarily UAV m and two coalitions $\mathcal{M}_{u_i}, \mathcal{M}_{u_j}$, the Pareto order define that whether m joining or withdrawing from a coalition, the utility function of UAV m will not be harmed, and the utility of other users will not fall. In this article, it is the energy loss of the UAV will not increase and task completion degree will not decrease [16]. The Pareto order is defined as:

$$\mathcal{M}_{u_i} \succ_m \mathcal{M}_{u_j}$$
$$\Leftrightarrow r_{u_i}(\mathcal{M}_{u_i} \cup m) \geq r_{u_j}(\mathcal{M}_{u_j} \cup m) \wedge r_{u_i}(\mathcal{M}_{u_i} \cup m)$$
$$\geq r_{u_i}(\mathcal{M}_{u_i}) \wedge r_{u_j}(\mathcal{M}_{u_j} \cup m) \geq r_{u_j}(\mathcal{M}_{u_j})u_i,$$
$$u_j \in \mathcal{U}, m \in \mathcal{M} \backslash \mathcal{M}_{u_i} \cup \mathcal{M}_{u_j}, \mathcal{M}_{u_i}, \mathcal{M}_{u_i} \subseteq \mathcal{M}, \quad (18)$$

where $r_{u_i}(\mathcal{M}_{u_i} \cup m), r_{u_j}(\mathcal{M}_{u_j} \cup m)$ are the utility of the task area u_i, u_j after the UAV m join the coalition. $r_{u_i}(\mathcal{M}_{u_i})$ and $r_{u_j}(\mathcal{M}_{u_j})$ are the utility of the task area u_i and u_j before the UAV m join the coalition. The Pareto order is the commonly used criterion in CFG. In Pareto order, UAVs will never damage other UAVs' utility in the original and new coalition. The property ensures that the coalition profit will not decrease and the existence of the stable coalition partition. However, the UAV's profit is limited. In this paper, we improve a coalition formation algorithm based on the cooperation rule [16].

3) COOPERATION RULE

For any UAV and two coalition, the cooperation rule is defined as follows:

$$\mathcal{M}_{u_i} \succ_m \mathcal{M}_{u_j} \Leftrightarrow r_{u_i}(\mathcal{M}_{u_i} \cup m) + r_{u_j}(\mathcal{M}_{u_j})$$
$$\geq r_{u_i}(\mathcal{M}_{u_i}) + r_{u_j}(\mathcal{M}_{u_j} \cup m). \quad (19)$$

The cooperation rule is defined as: if the total utility of the coalition after the UAV joins the coalition is higher than the total utility of the UAV before joining the coalition, then the UAV will stay in the new coalition. The cooperative rule is measured by the utility of the entire coalition. The choice of UAV m maximizes the optimization of the coalition rather than just its own optimization.

After discussing the cooperation rule for coalition formation, we talk about the actions of coalition members. The coalition changes the status by exchanging coalition members and coalition members withdraw from the current coalition.

4) UAV JOINS THE COALITION

When a UAV exits from a coalition or joins a coalition from the idle state, the effectiveness of all UAVs in the coalition will not decline, and the overall utility of the coalition can be improved, then the UAV will stay in the current coalition and perform the tasks in the current task area. That is:

$$m \cup \mathcal{M}_{u_i} \Leftrightarrow$$
$$\forall m \in \mathcal{M} \backslash \mathcal{M}_{u_i}, r_{u_i}(\mathcal{M}_{u_i} \cup m) \geq r_{u_i}(\mathcal{M}_{u_i}). \quad (20)$$

5) UAV EXITS THE COALITION

When a UAV leaves from a coalition, the other UAVs in the coalition will not be affected, and the overall effectiveness of

the coalition will not be affected, then the UAV will choose to withdraw from the coalition. That is:

$$\mathcal{M}_{u_i} \backslash m \Leftrightarrow r_{u_i}(\mathcal{M}_{u_i} \backslash m) \geq r_{u_i}(\mathcal{M}_{u_i}), \quad (21)$$

where $r_{u_i}(\mathcal{M}_{u_i} \backslash m)$ is the utility of the task area u_i after m exit from the coalition. When the UAV leaves the coalition, it can choose to join other coalitions or enter an inactive state. When the UAV withdraws from the current coalition and chooses to join other coalitions, this is the same as the UAV joins the coalition. The rules for UAV joins the new coalition are used to determine whether the UAV can stay in the new coalition.

The basic rules of coalition formation are constituted by the joining and exiting of the UAVs. When the UAV performs a task, it is affected by the companion UAV. There may be a transient drop in utility that interrupts the exchange action when a single UAV join or exit from the coalition. Therefore, we define the exchange rules of the coalition.

6) COALITION EXCHANGE ACTION

When a UAV exits from the current coalition to join other coalitions, if the total utility of the existing coalition is greater than the total utility of the coalition before the UAV's decision, that is, the utility of the UAV joining the new coalition is greater than the utility lost when the UAV exits from the previous coalition, then the exchange action will occur. This is:

$$\forall m \in \mathbf{M}_{u_i}, m \cup \mathbf{M}_{u_j} \Leftrightarrow r_{u_i}(\mathcal{M}_{u_i} \backslash m)$$
$$+ r_{u_j}(\mathcal{M}_{u_j} \cup m)$$
$$\geq r_{u_i}(\mathcal{M}_{u_i}) + r_{u_j}(\mathcal{M}_{u_j}). \quad (22)$$

B. ANALYSIS OF STABLE GAME SOLUTIONS

We give the definition of the stable solution of the coalition, if and only if all the UAVs follow the preferred order, each UAV can't improve its utility by leaving or joining a coalition. At this time, the coalition reaches a steady state. That is:

$$\forall m \in \mathcal{M} \backslash \mathcal{M}_{u_i}, r_{u_i}(\mathcal{M}_{u_i}) \geq r_{u_i}(\mathcal{M}_{u_i} \cup m). \quad (23)$$

When the members of the coalition cannot improve the effectiveness of the coalition by withdrawing and joining the coalition, the coalition converges to a stable state.

In this scenario, the total number of UAVs is limited, the number of task areas is certain, and the UAV's policy set is limited. Therefore, the combined state of all UAVs is also limited. The problem is to find the optimal solution of the combination in the finite state. According to the limitations of the Pareto order, the UAV will eventually reach a stable coalition structure among a variety of states. When the coalition reaches a stable state, if a UAV changes the coalition selection, and this brings better utility, it will converge to a stable state again.

Due to the limited conditions of the Pareto order, when a UAV makes the decision, this will cause a short-term utility decline, and the final combination state will be interrupted.

Therefore, we continue to discuss the cooperation rule and analyze the convergence of the cooperation rule.

1) STABILITY ANALYSIS OF COOPERATION RULE

Based on the proof of cooperation rule, we prove the existence of the stable coalition by introducing the existence of Nash equilibrium solution of the potential game theory [21].

Theorem 1 (Exact potential game [21]): If there exists a potential function φ, when a UAV changes its decision uni-laterally, the difference in the potential function and in its utility function is the same, the game is an exact potential game with potential function. The following equation exists for any strategy $\delta_m \in \mathcal{F}_m$ and $\delta'_m \in \mathcal{F}_m$ of any UAV $m \in \mathcal{M}$:

$$S_m(\delta_m, \delta_{-m}) - S_m(\delta'_m, \delta_{-m})$$
$$= \varphi(\delta_m, \delta_{-m}) - \varphi(\delta'_m, \delta_{-m}), \quad (24)$$

where $S_m(\delta_m, \delta_{-m})$ is the utility function of the UAV m when $m's$ decision is δ_m, δ_{-m} is the decisions of other UAVs. $S_m(\delta'_m, \delta_{-m})$ is the utility function of the UAV m when its decision is δ'_m.

The game model is called the exact potential game. We can see that in the exact potential game, the change of the utility function, and the change of the potential function caused by any UAV change strategy is the same.

Lemma 1: There is at least one pure strategy Nash equilibrium for the exact potential game [21].

Lemma 2: The global or local optimal solution of the potential function in an exact potential game is a Nash equilibrium.

Next, we give proof of the convergence of the cooperative rule. First, we define the potential function φ as:

$$\varphi(\delta_m, \delta_{-m}) = \sum_{u \in \mathcal{U}} r_u(\delta_m, \delta_{-m}), \quad (25)$$

where $r_u(\delta_m, \delta_{-m})$ is the utility function of coalition u, when m's decision is δ_m. Through the formula, we can see that the potential function is the sum of the utility of the whole network. When the coalition selection of the UAV m changes from δ_m to δ'_m, the change in the potential function at this time is:

$$\varphi(\delta_m, \delta_{-m}) - \varphi(\delta'_m, \delta_{-m})$$
$$= \sum_{u \in \mathcal{U}} r_u(\delta_m, \delta_{-m}) - \sum_{u \in \mathcal{U}} r_u(\delta'_m, \delta_{-m})$$
$$= [r_{u_i}(\mathcal{M}_{u_i} \backslash m) - r_{u_i}(\mathcal{M}_{u_i})]$$
$$+ [r_{u_j}(\mathcal{M}_{u_j} \cup m) - r_{u_j}(\mathcal{M}_{u_j})] + \sum_{k \in \mathcal{U} \backslash u_i, u_j} \Delta r_{u_k}, \quad (26)$$

where $u_i = \delta_m, u_j = \delta'_m, m \in \mathcal{M}_{u_i}$. Δr_{u_k} is the change of utility function for other coalitions, which are not related to the coalition that m joins and quits. Because the decision of m does not affect the UAVs of other coalition members, so $\Delta r_{u_k} = 0$, and the change in the potential function is:

$$\varphi(\delta_m, \delta_{-m}) - \varphi(\delta'_m, \delta_{-m})$$
$$= [r_{u_i}(\mathcal{M}_{u_i} \backslash m) - r_{u_i}(\mathcal{M}_{u_i})]$$
$$+ [r_{u_j}(\mathcal{M}_{u_j} \cup m) - r_{u_j}(\mathcal{M}_{u_j})]. \quad (27)$$

Second, we consider the impact of UAV's decision on the utility of the coalition:

$$
\begin{aligned}
S_m&(\delta_m, \delta_{-m}) - S_m(\delta'_m, \delta_{-m}) \\
&= \sum_{n \in \mathcal{M}_{u_i} \setminus m} S_n(\delta_m, \delta_{-m}) - \sum_{n \in \mathcal{M}_{u_i}} S_n(\delta'_m, \delta_{-m}) \\
&\quad + \sum_{n \in \mathcal{M}_{u_j} \cup m} S_n(\delta_m, \delta_{-m}) - \sum_{n \in \mathcal{M}_{u_j}} S_n(\delta'_m, \delta_{-m}) \\
&= [r_{u_i}(\mathcal{M}_{u_i} \setminus m) - r_{u_i}(\mathcal{M}_{u_i})] \\
&\quad + [r_{u_j}(\mathcal{M}_{u_j} \cup m) - r_{u_j}(\mathcal{M}_{u_j})] \\
&= \varphi(\delta_m, \delta_{-m}) - \varphi(\delta'_m, \delta_{-m}), \quad\quad (28)
\end{aligned}
$$

where $u_i = \delta_m$, $u_j = \delta'_m$, $m \in \mathcal{M}_{u_i}$. $S_n(\delta_m, \delta_{-m})$ is the utility of UAV n in the coalition. Through the change of potential function and lemma1, we conclude that there is at least one pure Nash equilibrium in the coalition game model. When no UAV can increase the utility of the entire network by unilaterally joining or leaving a coalition, the stable coalition state is achieved.

IV. COALITION FORMATION ALGORITHM BASED ON COOPERATION RULE DESIGN

In this section, we propose a coalition formation algorithm based on the cooperative rule, where the peer effect among UAVs during the coalition selection is analyzed.

A. PEER EFFECT OF THE COALITION

Different from the traditional coalition formation [14]–[16], which is not only based on conditions such as neighbor relations and location relations. In this paper, UAVs have the task complementarity relationship in addition to the overlapping task relationship. When a UAV join the coalition, the task relationships between UAVs will influence other UAVs' utility function. We define this influence between UAVs as the peer effect [18]–[20].

UAVs prefer to form coalition with UAVs who have more overlapping tasks. That is:

$$
\begin{aligned}
\{m_i\} \cup \{m_j\} &\succ_{m_i} \{m_i\} \cup \{m_k\} \\
&\Leftrightarrow |\mathcal{X}_{m_i} \cap \mathcal{X}_{m_j}| \\
&> |\mathcal{X}_{m_i} \cap \mathcal{X}_{m_k}|, \quad \forall m_i, m_j, m_k \in \mathcal{M}. \quad (29)
\end{aligned}
$$

The overlapping relationship will influence the hover time of both UAV m_i and m_j. In addition to the overlapping relationship, UAVs want to perform all types of tasks in the task area, so the complementary relationship also needs to be considered. For task area u, that is:

$$
\begin{aligned}
\{m_i\} \cup \{m_j\} &\succ_{m_i} \{m_i\} \cup \{m_k\} \Leftrightarrow \\
|\{\mathcal{X}_{m_i} \cup \mathcal{X}_{m_j}\} \cap \mathcal{X}_u| &> |\{\mathcal{X}_{m_i} \cup \mathcal{X}_{m_k}\} \cap \mathcal{X}_u|, \\
&\forall m_i, m_j, m_k \in \mathcal{M}. \quad (30)
\end{aligned}
$$

The complementary relationship will influence the task completion degree of the task area. For example, as shown in Fig. 5, UAV1 choice to perform the tasks. In order to save the task performing time, the UAV2 will join the coalition. The UAV2 has the same task types {1, 2} with UAV1.
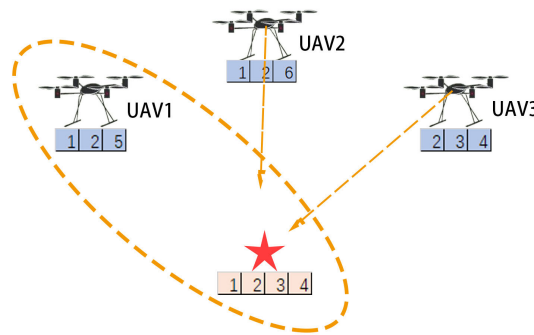

FIGURE 5. Peer effects in the coalition formation.

Affected by UAV2, UAV1 will spend a shorter time in performing the task. When UAV3 joins the coalition, the task types {3, 4} in the task area can be performed, the task completion degree of the task area will be affected by UAV3. The task relationships between UAVs can influence the utility function of the coalition, and the utility function will finally influence UAVs' decision. Peer effects among UAVs are considered in the task cooperation process.

B. ALGORITHM DESIGN

In section III, the definition of cooperation rule is given, as well as the stability is proved. When the UAV goes to the mission area to perform the tasks, each UAV sends its own location information and task information to the control UAV. The control UAV sends task assignment results to the UAV. When UAVs' decisions can improve the effectiveness of the entire network, the result of this decision will be retained. If the subsequent decision does not lead to a better result, then this decision is a stable solution. Considering the demand of the mission area, some UAVs may not have the types of tasks, which associated with the mission area. Forcing all UAVs to perform the task will increase the energy loss of the whole network. Therefore, we joined the exit mechanism of the UAV. In addition to performing the task, when the UAV makes a decision, it can choose to do nothing. The UAV is not involved in missions, we assume that the UAV in this state has no energy loss.

The mechanism of coalition formation algorithm based on cooperative rule mainly contains the following steps:

- UAVs share information of the mission area. Each UAV randomly selects a task area as its initial decision. Calculate the initial utility of the whole network.
- Random number of UAVs change their decisions. UAVs should complete the tasks in the mission area as much as possible, so UAVs select the task area, which has the same type of tasks with them. When a UAV join in a coalition, the coalition can make the decision whether to accept the new UAV. If the addition of this UAV can improve the utility of the coalition, then the UAV can stay in this coalition.
- When UAVs' joining and exiting can not lead to a better utility, UAVs are assigned to the best task area.

With the equilibrium properties of coalition formation in UAV networks, UAVs can optimize their positions within the

Algorithm 1 Coalition Formation Algorithm Based on Cooperative Rule

Input: location information of each UAV, task attribute information, location information of the task area, task type information of the task area, and task amount of each type of task in the task area.

Step1: Each UAV randomly selects the task area to be executed to generate the initial coalition selection, $\forall m \in \mathcal{M}, \forall u \in \mathcal{U}, \delta'_m = u$.

Step2: Each time a certain number of UAVs are randomly selected to change their choices, each UAV selects a task area with task relevance or does not participate in the execution of the task, $\forall m \in \mathcal{M}, m \cup \mathcal{M}_u, \mathcal{X}_m \cap \mathcal{X}_u \neq \emptyset$.

Loop in each unit time. A certain number of UAVs are randomly selected and their coalition selection is changed. Calculate the utility of the whole network.

    if

UAVs change decision can bring an improvement in utility, then keep current plan, and continue selecting a number of UAVs to change decisions. If $r_u(\mathcal{M}_u \cup m) < r_u(\mathcal{M}_u)$, then save (δ'_m, δ_{-m}).

    else Continue selecting a number of UAVs to change decisions, save (δ_m, δ_{-m}).

    end

Any UAVs change decision cannot bring an improvement in utility, then a set of stable solutions is obtained.

End Loop

Output: decision results of each UAV, final utility, task completion in each task area, and energy consumption across the network.

UAVs begin to perform the tasks in the task area.

---

mission coverage to obtain better energy-saving effects. The steps to adjust the position of the UAV are as Algorithm 2.

In the algorithm proposed in this article, the UAV's optional strategy set is the mission areas that have the same mission types with the UAV. UAV's selectable strategy set is limited, the number of UAVs is also limited. During the UAV selection process, the total effectiveness of the coalition will vary depending on the UAV's decision. UAV travel to the mission area, which has more relevant tasks with the UAV. UAVs with complementary relationships work together can increase the utility of the entire network. During finite iterations, when the network cannot get better utility by UAVs change their decisions, the UAV network reaches a stable result.

The complexity analysis of the proposed algorithm is further discussed [38]. We define the number of iterations for the coalition formation algorithm based on the cooperation rule as N_C. Each iteration of the algorithm needs to calculate the utility of the entire network, which includes flight energy loss caused by all UAVs and task completion degree of the task areas. Each task area needs to calculate the execution time of all types of tasks, the time complexity of this

Algorithm 2 A UAV Position Deployment Algorithm

Input: location information of each UAV, location information of the task area, UAVs' decisions.

Step1: Randomly choose a UAV m, calculate the utility of all coalitions at the current position, when coalitions converge to the steady state.

Step2: The selected UAV m moves on the shortest path with the task area in steps. Calculate the utility of the whole network under the current position of the UAV, if the utility of the whole network is improved, the UAV will stay in this position.

Step3: The UAV continues to move in steps until the UAV reach the coverage boundary of the task area or the utility of the whole network will not improved.

Output: UAVs' new state.

TABLE 2. Main notations and terminologies.

Notation	Physical meaning	Simulation value
A	Rotor disc area in m^2	0.503
U_{tip}	Tip speed of the rotor blade	120
S_{FP}	Fuselage equivalent flat plate area in m^2	0.0151
s	Rotor solidity	0.05
ρ	Air density in kg/m^3	1.225
d_0	Fuselage drag ratio	0.6
a	UAV's acceleration in m/s^2	5
V_{max}	UAV's max flight speed	20
W	UAV weight in Newton	20
g_m	UAV mass in kg	2

is $O(U \cdot X)$. The calculation of distance is included in each time, and its time complexity is $O(M^2)$. Finally, when calculating the global utility, the utility includes all the task areas, this is a constant, and its time complexity is $O(1)$. The algorithm also includes the judgment of whether a new coalition can be formed, its time complexity is $O(1)$. The final total time complexity C of this algorithm is:

$$C = N_c \left(O(U \cdot X) \cdot O\left(M^2\right) \cdot O(1) + O(1) \right). \quad (31)$$

V. SIMULATION RESULTS AND ANALYSIS
A. NETWORK SCENE SETTINGS
In this section, we will give the simulation results of the algorithm to verify its convergence and effectiveness. First, we set the aerodynamic parameters of the UAV. The parameter settings and physical meanings was given in reference [33], related notation settings and physical meanings are shown in Table 2. The simulation scene is set to a two-dimensional space of [0; 2000] [0; 2000] square meters, nodes in space are placed as UAVs to perform tasks. The position of the UAV is randomly generated every time. The types of tasks that the UAV can perform each time is also randomly generated. The network structure generated at one time is shown in Fig. 6, black dots represent UAVs, the red triangles are the mission areas for this time, and The circle indicates the coverage of the task area. We define the UAV's max flight speed as 20m / s. Each group of results is an average of 800 iterations.
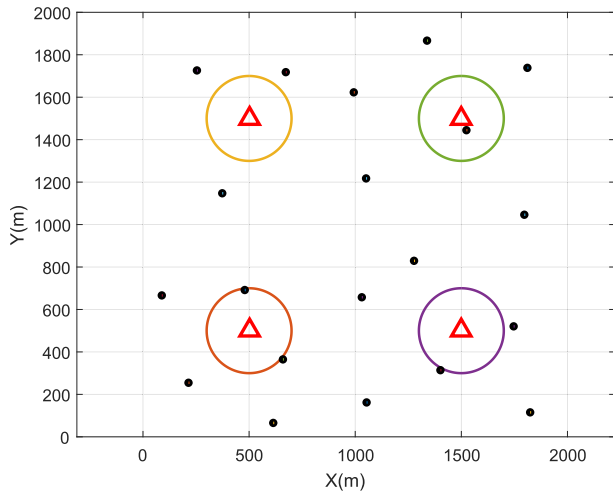
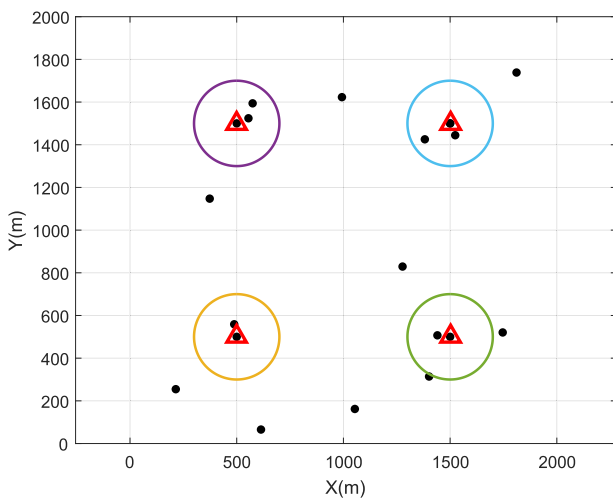**FIGURE 6.** The initial state of the UAV network.

FIGURE 8. CDF of algorithm based on the cooperation rule.

FIGURE 7. UAV network after convergence.
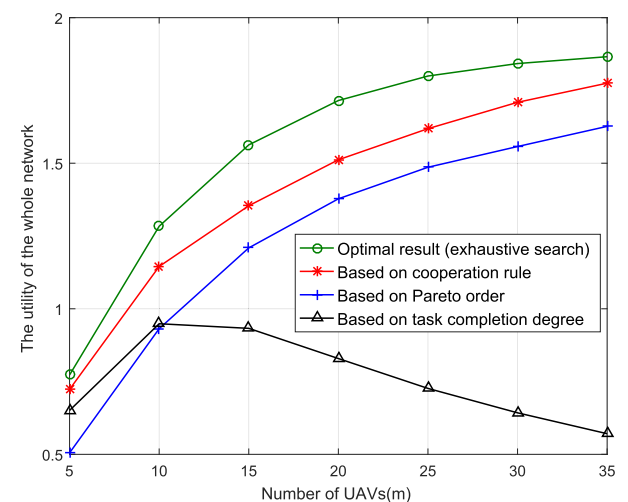
FIGURE 9. The total utility of the whole network various the number of UAVs.

As we can see in Fig. 7, the black dots in each circle represent the UAVs performing this task. When a UAV is far away from the mission area, if it can bring a high degree of completion to the task area, then we think that the energy loss of the UAV is worthwhile, and the UAV will move to the task area. Fig. 7 shows where UAVs will eventually perform these tasks.

B. ANALYSIS OF RESULTS

As shown in Fig. 8, we study the relationship between the convergence of the algorithm with the number of UAVs increases. Under different network topologies, we iterate the program 5000 times and get the CDF graph of the convergence result. When the number of UAVs is 10, in most cases, the program can reach convergence in about 400 iterations. With the number of UAVs grows to 20, UAVs need more iterations to reach convergence. In most cases, the program with 20 UAVs can reach convergence in about 800 iterations, and the program with 30 UAVs can reach convergence in about 1400 iterations. With the number of UAV increase, the program may need more iterations to reach a better result, but the network can quickly reach the convergence state.
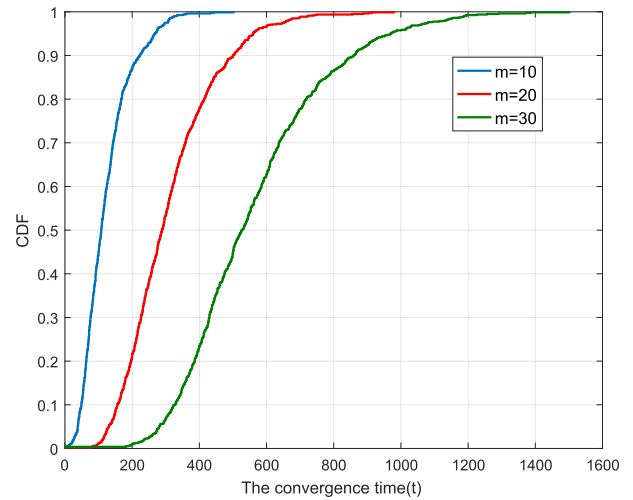
Next, we further analyze the performance of the algorithm. As shown in Fig. 9, we study the relationship between the utility of the entire network with the number of UAVs increases. In this simulation, we fixed the location of the task area, the task types of the task area, and the amount of each type of task. The coordinates of four task areas are (500,500), (500,1500), (1500,500), (1500,1500). The types of tasks need to be performed in four task areas and the amount of tasks for each type of task are [{2,4,5,7}, {3,4,1,5}], [{1,3,5,6}, {3,3,7,4}], [{1,3,4}, {4,3,4}], [{1,5,7}, {9,2,6}]. The number of UAVs ranges from 5 to 35. The positions of the UAVs are randomly generated each time. The types of tasks that the UAV can perform are randomly generated each time, and the result is an average of 800 times.

For distributed network scenarios, it is difficult to obtain the optimal result in theory. Compared with the optimal solution, the stable solution of the algorithm is more effective for the distributed system. We compared the performance of the proposed algorithm with the algorithm base on the exhaustive search. As shown in Fig. 9, with the number
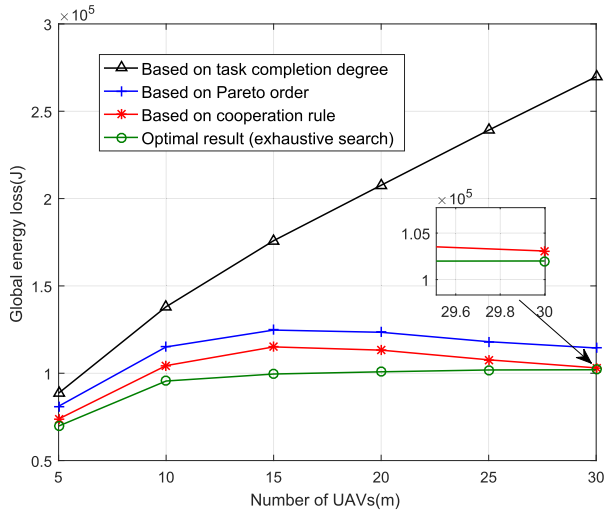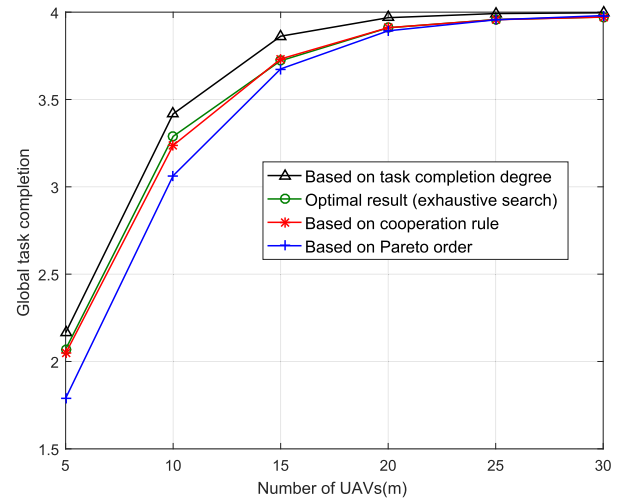
FIGURE 10. The change in the energy loss of the whole network various the number of UAVs.

FIGURE 11. The performance of task completion degree various the number of UAVs.

of UAVs increases, the global utility gradually increases. Increasing the number of UAV brings more kinds of combinations for UAVs. According to the proposed algorithm, UAVs can accurately find the most suitable task area to join, and can form the best coalition with overlapping and complementary tasks. Therefore, with the increase of UAVs, the result of the cooperation rule is closer to the optimal result.

Under the same algorithm environment, the algorithm based on the cooperation rule performs better than that of the Pareto order. The reason is that the Pareto order has more restrictions than the cooperation rule, which limits the performance. Moreover, with the number of UAV increases, the task planning algorithm without considering energy consumption will drive long-distance UAVs to perform tasks, which will increase the energy of the network. Thus, the algorithm based on task completion degree shows a downward trend in the utility of the network.

As shown in Fig. 10, the proposed algorithm performs better than the algorithm based on the Pareto order and task completion rule in terms of energy consumption control. With the number of UAV increases, in order to improve the task completion degree, the task planning algorithm will drive long-distance UAVs to perform tasks, which will increase the energy of the network. With the increasing number of UAVs, there are more UAV combinations to perform tasks, the result of the cooperation rule is closer to the optimal result.

As shown in Fig. 11, in terms of task completion degree, the proposed algorithm is very close to the optimal result. The algorithm proposed in this paper performs better than the algorithm based on the Pareto order. Under the premise of consuming more energy, the task completion degree of the task completion driven algorithm is slightly better than other algorithms, but compared with the overall performance, this improved effect is not obvious. Integrated the energy efficiency performance, it can be seen that the proposed algorithm is more reasonable.

VI. CONCLUSION

In this paper, we studied the multi-task cooperation problem for multiple UAVs. We modeled the task assignment problem of UAVs as a coalition formation process and proposed a task assignment algorithm. According to the analysis of the simulation results, the algorithm in this paper performed excellently in terms of task completion degree and flight energy loss. Assigning UAVs to various task areas by the proposed method can effectively reduce the UAV's flight loss and increase the task completion degree, it can achieve the best results of the whole network.

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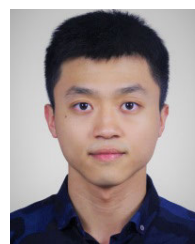
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