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A Coalition Formation Game Approach for Efficient Cooperative Multi-UAV Deployment

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Abstract: UAV cooperative control has been an important issue in UAV-assisted sensor network, thanks to the considerable benefit obtained from the cooperative mechanism of UAVs being applied as a flying base station. In coverage scenario, the tradeoff between coverage performance and transmission performance often makes deployment of UAVs fall into a dilemma, since both indexes are related to the distance between UAVs. To address this issue, UAV coverage and data transmission mechanism is analyzed in this paper, then an efficient multi-UAV cooperative deployment model is proposed. The problem is also modeled as a coalition formation game (CFG). The CFG with Pareto order is proved to have a stable partition. Then, an effective approach consisting of coverage deployment and coalition selection is designed, wherein UAVs can decide strategies cooperatively to achieve better coverage performance. Combining analysis of game approach, coalition selection and position deployment algorithm based on Pareto order (CSPDA-PO) is designed to execute coverage deployment and coalition selection. Finally, simulation results are shown to validate the proposed approach based on efficient multi-UAV cooperative deployment model.

Keywords: UAV-assisted sensor network; UAV cooperative coverage; coalition formation game; stable coalition partition; Nash equilibrium

1. Introduction

The past few decades have witnessed rapid development of application of unmanned aerial vehicles (UAVs), popularly known as drones. Given the characteristics of small volume, high mobility and low energy consumption, UAVs have been widely utilized in public, civil and military applications [1–3]. Especially with proper deployment and operation, UAVs can provide reliable and efficient wireless communication solutions for various real-world scenarios. Furthermore, UAVs can act like self-organizing sensor nodes, and efficiently carry out the pre-assigned tasks [4]. For instance, in public safety scenarios (earthquake, volcano, military attack, etc.), UAVs can be utilized as flying base stations, and replace damaged communication infrastructure and guarantee information dissemination for UAV-assisted sensor network [5,6].

Note that single UAV often fails to meet the need of complicated missions such as area coverage, communication connectivity and relay. To address this issue, large scale of UAVs is required to form groups (formations) to execute missions under different requirements. In [7], a multi-UAV cooperative model was presented to work out search and surveillance issues. Authors in [8] considered the information consensus under multi-UAVs communication noise, and constructed it as a signal to noise ratio model for UAVs cooperative target tracking. Authors in [9] proposed a cooperative detection model which consisted of target identification and time control.

Area UAV coverage problems were studied in [10–14]. Under the circumstance of cooperative multi-UAV coverage deployment, missions such as investigation, communication and mapping can be well accomplished. The most important part of the UAV area coverage problem is the evaluation of coverage ability. In [10], authors described ratio of coverage area and given area as the evaluation

of UAV coverage ability, which is one of the most common evaluations. Notably, characteristics of mobility and line-of-sight (LOS) enable UAVs to support terrestrial networks for information dissemination and connectivity enhancement [15–17]. Given the fact that the ground communication infrastructure will be destroyed during natural disasters, it is critical for UAVs to perform efficient coverage deployment and execute searching and rescue operations.

In the above scenarios, UAVs arrive at the designated location according to ground demand and perform coverage tasks such as data collection. Next the information (data, etc.) will be forwarded to the central UAV through the UAV-to-UAV link. Note that UAVs can carry limited energy, the energy consumed by information transmission must be minimized based on mission requirements. Therefore, data transmission mechanism should be well constructed in UAV communication. In general terms, as the transmitting distance grows, the energy consumption of UAVs will increase exponentially. To avoid high energy consumption, an effective technical solution is proposed in [18], utilizing some UAVs as relays. However, it remains challenging to deploy UAVs and design transmission mechanism due to the complex cooperative behaviors among UAVs.

Motivated by the design of the cooperative mechanism, with which authors significantly reduce the overhead of spectrum acquisition in [19,20], we adopt coalition formation game (CFG) to describe the relationships between UAVs. Unlike above studies, in our paper, coalition is constituted by considering coverage reward and corresponding energy cost among UAVs. The objective of CFG is to study the network coalition structure to optimize performance [21], which can be the basis for investigating cooperative behaviors of UAVs.

Research has been done to study CFG in UAV networks. Authors in [4] proposed a novel CFG model in data collection and transmission, where a certain amount of UAVs is sent to serve randomly located missions, collect data and transmit it to a central command through wireless communication. In [22], authors took the aerial back haul scheme among UAVs as the mechanism of network formation game, and proposed a model that utilizes UAVs as an on-demand flying network, where UAVs seek to form a multi-hop back haul network in the air. However, current research of CFG has focused on connectivity enhancement, data transmission improvement and routing, but without considering the trade-off between the coverage reward and energy consumed by transmitting and receiving in UAV network. In that situation, we jointly consider a communication coverage and data transmission scenario in the UAV-assisted sensor network, and propose an efficient cooperative UAV deployment model based on coalition formation. The key of coalition formation is to describe the relationships between coverage reward and energy consumption.

The main contribution in this paper can be summarized as follows:

- An efficient cooperative multi-UAV deployment model based on coalition formation is proposed, describing trade-off between the coverage reward and energy consumption in UAV-assisted network. Coverage utility function is characterized as a reference for coalition formation to accurately depict the transmission model.
- Through game analysis, we prove that the stable state solution of the system model exists. The proposed approach can achieve at least one stable coverage deployment and coalition formation scheme to maximize the coverage utility of the entire UAV network.
- Coalition selection and position deployment algorithm based on Pareto order (CSPDA-PO) is designed to perform coalition selection and position deployment. CSPDA-PO algorithm can be able to achieve the stable state of our system model. Meanwhile, convergence of the proposed algorithm is also shown in the simulation.

Note that authors in [7] [23] did some works that are relevant to our work, especially in constructing the UAV coverage model, including evaluation of coverage ability and deployment mechanism. The main differences can be summed up to: (i) The UAV deployment is not only concerned with the coverage ability, but also the coalition formation under the comprehensive coverage reward and energy consumption. (ii) Energy consumption model for transmitting and receiving through RF

signals is introduced into coalition formation mechanism, which is associated with coverage reward under current deployment.

The rest of the paper is organized as follows. Section 2 shows the system model of multi-UAV cooperative deployment and problem formulation. In Section 3, a coalition formation game approach for system model is analyzed, and learning algorithm is designed to converge the proposed problem to the stable state. Simulation results and analysis are presented in section 4. Finally, the concluding remarks are given in section 5.

2. System Model and Problem Formulation

We consider a UAV-assisted sensor network employing N distributed UAVs and one central control UAV, where UAV groups perform reconnaissance and data collection tasks under disaster scenarios. UAVs communicate with each other through radio frequency (RF) signals of wireless sensors. The sensor devices are equipped on UAV's fuselage. Sensor devices have limited battery power and data processing capabilities. They can also acquire the location of other sensor nodes (UAV). The UAV groups need to collect data information by covering the ground. Here, UAV's coverage capability is determined by observation thresholds. Then, the data traffic collected by distributed UAVs is sent to the central UAV for processing. Due to the huge energy consumption caused by long distance transmission, it requires to form groups and utilize some UAVs sensor nodes as relays to carry out data transmission.

For the cooperative multi-UAV deployment example showed in Fig. 1, there are seven UAVs performing coverage mission and uploading the collected information data to the upper central UAV. Due to the limited energy of sensor devices, UAVs need to form groups to cooperate. In this case, some UAVs are used as relays to optimize the energy consumption of data transmission. In particular, the high transmission energy consumption between UAVs that are too far apart (such as UAV 1 and UAV 7) prevents the formation of the grand coalition. Therefore, it makes sense to consider the coalition formation by optimizing the coverage utility of the UAV network.

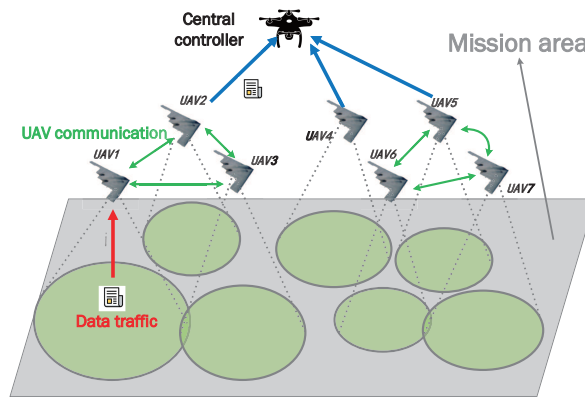


Figure 1. A diagram of UAV coverage in a mission area.

To facilitate computation, we discretize the continuous area $I \in \mathbb{R}^2$, which is uniformly meshed and divided into cells, and each cell i 's width is l_w and is identified by the position of its center $g_i^* = \{x_i, y_i, h_i\}$. Denote the number of available coalitions as M , $1 \leq M \leq N$, and the set of UAVs as \mathcal{N} , i.e., $\mathcal{N} = \{1, 2, \dots, N\}$, and the set of available coalition as \mathcal{M} , i.e., $\mathcal{M} = \{1, 2, \dots, M\}$. The serial number of the central UAV is set to 0. For each $n \in \mathcal{N}$, let c_n denotes UAV n 's coalition selections, $g_n = \{x_n, y_n, h_n\}$ denotes UAV n 's three-dimensional position. Hence, the UAV n 's state is defined as $s_n = \{g_n, c_n\}$. For each $m \in \mathcal{M}$, let CO_m denotes the set of UAVs which select coalition m for data transmission, i.e., $CO_m = \{n \in \mathcal{N} : c_n = m\}$. Besides, the central UAV's position is denoted as $g_0 = \{x^*, y^*, h^*, h^* > h\}$.

For each $i \in I$, suppose $\sigma(i)$ is the importance (traffic, etc) of mission cell i , and is denoted by the form of normalized density function. For simplicity, we set U_{ζ} as the reward for UAV set ζ completing the coverage of mission area I successfully, which is given as follows [1]:

$$U_{\zeta} = \int_I h(\min_{n \in \zeta} \|g_n - g_i^*\|) \sigma(i) di, \quad (1)$$

where

$$h(\|g_n - g_i^*\|) = \begin{cases} 1, & \|g_n - g_i^*\| \leq R_n, \\ 0, & \text{otherwise.} \end{cases} \quad (2)$$

Eq.(2) indicates that as long as area i is within the detection range of UAV n in the network, it will be considered successfully covered by UAV n with all data traffic collected. Hence, U_{ζ} represents the coverage performance (says reward) of mission area I under UAV set ζ . Specially, the overall coverage reward of UAV network is $U_{\mathcal{N}}$.

From the above description, data traffic collected by distributed UAVs will be transmitted through the UAV-to-UAV link to the central control UAV for processing. In the UAV-assisted sensor network, most of the power energy consumed by wireless sensors is derived extensively from a transmission operation that consists of sending and receiving. Therefore, motivated by the work in [24], we adopt expressions to estimate the energy consumption for transmitting and receiving of each sensor node through RF signals, which are given by:

$$\begin{aligned} \text{Receiving : } E_r &= E_0. \\ \text{Transmitting : } E_t(d_{i,j}) &= \begin{cases} E_0 + \varepsilon_s \cdot d_{i,j}^2, & d_{i,j} < d_0, \\ E_0 + \varepsilon_t \cdot d_{i,j}^4, & d_{i,j} \geq d_0. \end{cases} \end{aligned} \quad (3)$$

where $d_{i,j}$ represents the distance between UAV i and j , E_0 is the energy consumed by radio when performing transmitting and receiving. ε_s and ε_t represents the energy consumed by transmitting one bit of data at a shorter distance and at a longer distance respectively.

Thus, consider the data transmission through link of UAV i and UAV j , the overall energy consumption per bit of data is derived as follows:

$$E(d_{i,j}) = E_r + E_t(d_{i,j}) \quad (4)$$

In a coalition, cluster head UAV plays an important role in connecting coalition members and the upper central UAV, so as to achieve data transmission. Suppose the overall energy consumption function of the whole network is defined as follows:

$$E_0 = \sum_{m=1}^M \left(\sum_{n \in CO_m} (E(d_{n,cl_m}) \cdot U_{\mathcal{N}}) + E(d_{0,cl_m}) \cdot U_{CO_m} \right), \quad (5)$$

where cl_m represents the coalition m 's cluster head UAV, U_n and U_{CO_m} is UAV n and UAV set CO_m 's mission reward, indicating the data traffic they collect. Eq. (5) contains two items, the first item represents the energy consumption of data transmission, which is collected from coalition m 's cluster member UAV to m 's cluster head UAV. The second item represents the energy consumption of data transmission, which is transmitted from coalition m 's cluster head UAV to the upper central UAV. Therefore, Eq.(5) reflects the overall energy consumption of the whole UAV network when all data is transmitted to the central UAV.

From the above formulation, it can be concluded that UAV deployment is affected by the importance of ground data traffic distribution, while the energy consumption of path is also limited by the communication distance between UAVs. When the battery can't support long distance UAV communication, the deployment of UAV coverage can be severely affected, making our proposed

problem fall into a dilemma. It is meaningful to accurately characterize the relationships between coverage reward and energy consumption. Therefore, according to Eq.(1) and Eq.(5), we have the whole UAV network's coverage utility:

$$U1 = U_N - \rho \cdot E_0, \quad (6)$$

where ρ represents the weight coefficient, indicating the importance of reward and transmission energy consumption. Here, ρ is calculated and measured from parameters of UAVs and mission requirements environment. Therefore, the setting of ρ decides the mission requirements and has a strong reference value of weighing the gain and cost. What's more, some constraints for both variables can be set under the condition of driven mission, such as guarantee of minimal reward and limitation of maximal energy consumption. For intuitive comparison, the object of this model is maximizing the whole UAV network's coverage utility through adjusting UAVs' state:

$$\mathcal{G} : s_n^{opt} = \arg \max U1, n \in \mathcal{N}. \quad (7)$$

Here, solving \mathcal{G} can obtain an efficient multi-UAV deployment and coalition transmission mechanism, which makes UAVs achieve better coverage reward without producing much energy consumed by data transmitting and receiving.

3. A Coalition Formation Game Approach for Coverage Utility Maximization

Notably, solving \mathcal{G} is challenging due to the enormous strategies (positions and coalitions), an effective method is required to simplify the process: Step 1 (Reward optimization): Carry out coverage optimization deployment under current coalition formation. Step 2 (Coverage utility maximization): Under the fixed deployment of UAVs, coalition selection method is considered to maximize $U1$. Step 3) Repeat the above steps till $U1$ reaches maximization. This approach can not only avoid the computing complexity caused by multi-strategies, but also be able to work out the optimal solution of \mathcal{G} .

In distributed multi-agent control system, players interact with each other and make self-determined strategies. Motivated by that, the proposed UAV efficient deployment problem can be formulated as a game. According to Eq.(6), the utility function consists of two items, and we focus on achieving global optimization. Formally, the game is denoted by $\mathcal{G} = (\mathcal{N}, \{S_n\}_{n \in \mathcal{N}}, \{u_n\}_{n \in \mathcal{N}})$, where $\mathcal{N} = \{1, 2, \dots, N\}$ is a set of UAVs, $S_n = G_n \otimes C_n$ (\otimes is Cartesian product) represents the a set of available joint state profiles, where G_n and $C_n = \{1, 2, \dots, M\}$ represents a set of the available positions and coalitions for each UAV n respectively. Denote an element of G_n and C_n as g_n and c_n . u_n represents the utility function and can be expresses as $u_n(s_n, s_{-n})$, where $s_n \in S_n$ represents the state selection of UAV n and $s_{-n} \in S_1 \otimes S_2 \otimes \dots \otimes S_{n-1} \otimes S_{n+1} \otimes \dots \otimes S_N$ is the state profiles of all the UAVs excluding n , the same is true with g_{-n} and c_{-n} .

Definitions are given in the following to analyze the properties of the coalition formation game.

Definition 1 (Coalition formation game, CFG[21]). A (hedonic) coalition formation game is given by a pair (\mathcal{N}, P) , where $P = (\succ_1, \succ_2, \dots, \succ_n)$ denotes the preferences profile, specifying for each player $i \in \mathcal{N}$ its preference relation \succeq_i .

It should be noted that a coalition partition is denoted as a set $\Pi = \{CO_m\}_{m=1}^M$ which partitions N , where the subsets CO_m are called coalitions and are disjoint. Let $CO_\Pi(i)$ denote the set CO_m i.e. if

$$\forall i \in \mathcal{N} : CO_m \in \Pi, \quad i \in CO_m. \quad (8)$$

Apparently, \mathcal{G} is a typical CFG. UAVs in \mathcal{G} make decisions through different preference relation, and form different coalition partitions. But first of all, the UAV deployment should be discussed first given the coalition partition Π .

3.1. Analysis of the mission reward maximization

1) Utility Function: As discussed before, each UAV prefers a higher coverage performance and less energy consumption of transmission. Accordingly, we consider the UAV n 's marginal coverage contribution and measure the coverage utility of mission area I of UAV n as follows:

$$u_n^*(g_n, g_{-n}) = \int_I h\left(\min_{k \in \mathcal{N}} (\|g_k - g_i^*\|)\right) \sigma(i) di - \int_I h\left(\min_{k \in \mathcal{N} \setminus n} (\|g_k - g_i^*\|)\right) \sigma(i) di - \rho \cdot E_0(CO_n). \quad (9)$$

In step 1, given the method that coverage optimization deployment should be done before coalition selection each loop, we have the following equation:

$$\mathcal{P}_1 : \max u_n^*(g_n, g_{-n}) \quad (10)$$

2) Analysis of \mathcal{G}_1 :

Considering the cooperative behaviours among UAVs should be well depicted, potential game is adopted, which applies to distributed multi-agent system and can associate with the local utility and global utility of each participant [25] [26]. Hence, combining with the distributed self-organizing characteristics of UAVs, the whole system can make decisions to achieve more efficient performance. Here, the definition of Nash equilibrium (NE) is shown in the following, indicating the steady state of a noncooperative game.

Definition 2 (Nash equilibrium (NE) [27]). A position selection profile $g^* = (g_n^*, \dots, g_{-n}^*)$ is a pure strategy NE of game $\mathcal{G}_1 = (\mathcal{N}, \{S_n\}_{n \in \mathcal{N}}, \{u_n\}_{n \in \mathcal{N}})$ if and only if no player n can improve its utility by changing its states, i.e.,

$$u_n^*(g_n^*, g_{-n}^*) \geq u_n^*(g_n, g_{-n}^*), \quad \forall n \in \mathcal{N}, \forall g_n \in G_n, g_n \neq g_n^*. \quad (11)$$

Definition 3 (Exact potential game [28]). For utility function $u_n^*(g_n, g_{-n})$ in a game $\mathcal{G}_\infty = (\mathcal{N}, \{S_n\}_{n \in \mathcal{N}}, \{u_n\}_{n \in \mathcal{N}})$, if there exists a potential function $\phi : G_n \rightarrow \mathbf{R}$, for arbitrary position strategy selection changes from g_n to g'_n , the following equation is true:

$$u_n^*(g_n, g_{-n}) - u_n^*(g'_n, g_{-n}) = \phi(g_n, g_{-n}) - \phi(g'_n, g_{-n}), \quad \forall n \in \mathcal{N}, \forall g_n, g'_n \in G_n. \quad (12)$$

then this game is called exact potential game (EPG) and has at least one NE point.

Lemma 1. Given the current coalition partition Π , \mathcal{G}_1 is an EPG and has at least one NE point.

Proof. Here we construct the potential function as follows:

$$\phi(g_n, g_{-n}) = \int_I h\left(\min_{k \in \mathcal{N}} (\|g_k - g_i^*\|)\right) \sigma(i) di - \rho \cdot E_0(CO), \quad (13)$$

which also represents the global coverage utility of UAV network. Assume an arbitrary UAV n change its position profile from g_n to g'_n , then we have the following formulation:

$$\begin{aligned} u_n^*(g_n, g_{-n}) - u_n^*(g'_n, g_{-n}) &= \int_I h\left(\min_{k \in \mathcal{N}} (\|g_k - g_i^*\|)\right) \sigma(i) di - \int_I h\left(\min_{k \in \mathcal{N}, g_n = g'_n} (\|g_k - g_i^*\|)\right) \sigma(i) di \\ &\quad - \int_I h\left(\min_{k \in \mathcal{N} \setminus n} (\|g_k - g_i^*\|)\right) \sigma(i) di + \int_I h\left(\min_{k \in \mathcal{N} \setminus n, g_n = g'_n} (\|g_k - g_i^*\|)\right) \sigma(i) di + \rho \cdot (E_0(CO'_n) - E_0(CO_n)) \end{aligned} \quad (14)$$

Intuitively, for each UAV $k \in \mathcal{N} \setminus n$, its individual coverage performance is completely unaffected by above action changes, so is the energy consumption of UAV set $CO_k, k \in \mathcal{N} \setminus c_n$. Thus the result of the last four items from Eq.(14) is identically zero. Then we derive the following equation according to Eq.(13) and Eq.(14):

$$u_n^*(g_n, g_{-n}) - u_n^*(g'_n, g_{-n}) = \phi(g_n, g_{-n}) - \phi(g'_n, g_{-n}), \quad (15)$$

the proof work has been done in [7]. Therefore, according to definition 3, \mathcal{G}_1 is an EPG with coverage utility U_I serving as the potential function. It can be concluded that \mathcal{P}_1 has at least one NE point. Note that designed potential function refers to overall coverage utility. Hence the NE solution of \mathcal{P}_1 turns to be the pure strategy NE point of \mathcal{G}_1 . which can be effectively helpful for the proof of the stability in the proposed model \mathcal{G} . \square

Motivated by the learning algorithm design in [7], we introduce a coverage optimization deployment algorithm based on binary log-linear learning (CODA-BLL) to execute coverage maximization deployment. The proposed algorithm is mainly based on the binary log-linear learning, which was proved to guarantee convergence of Nash equilibrium[7][29]. Given the current coalition selection profiles, the algorithm is executed one time to explore a optimal deployment for coverage utility per loop. Here we design Eq. (16) as UAVs' position selection probability function, where β is the learning parameter ($\beta > 0$).

$$q_n^g = \frac{\exp\{\beta u_n^*(g_n, g_{-n})\}}{\exp\{\beta u_n^*(g_n, g_{-n})\} + \exp\{\beta u_n^*(g'_n, g_{-n})\}}. \quad (16)$$

Algorithm 1: One time coverage optimization deployment algorithm based on Binary log-linear learning (CODA-BLL)

Initialization: Input UAVs' current state profiles $\{s_n\}_{n \in \mathcal{N}}$.

Step 1: Randomly select UAV n , calculate its coverage performance $u_n^*(g_n, g_{-n})$ of current UAV deployment state according to Eq.(9).

Step 2: For slected UAV n , choose an expected action g'_n from the G_n . The selected UAV n computes its current coverage performance $u_n^*(g_n, g_{-n})$ and the expected utility $u_n^*(g'_n, g_{-n})$ according to Eq.(6).

Step 3: UAV n choose a position deployment according to Eq. (16) and update its state g_n .

Step 4: Output UAVs' state $\{s_n\}_{n \in \mathcal{N}}$.

3.2. Analysis of the stable coalition partition

1) Utility Function: In step 2, under fixed deployment, UAV n 's individual energy consumption can be expresses as follows:

$$T1(c_n) = \sum_{k \in CO_{\Pi}(n)} (E(d_{k,cl_{c_n}}) \cdot U_k) + E(d_{0,cl_{c_n}}) \cdot U_{CO_{\Pi}(n)}, \quad (17)$$

where $g_{c_n}^{cl}$ represents the three-dimensional position of coalition c_n 's cluster head UAV. $T1(c_n)$ represents the coalition c_n 's data traffic energy consumption from the terrestrial to the central controller.

Then, for each UAV $n \in \mathcal{N}$, it makes coalition selection through its individual coverage utility, which can be derived as follows:

$$u_n(c_n, c_{-n}) = u_n^*(g_n, g_{-n}) - \rho \cdot E_0(c_n). \quad (18)$$

In definition 1, the preference relation is introduced, which decides whether a player prefer to join or leave the coalition. Notably, the preference relation can affect the convergence and the stable state of

the final structure of CFG [30]. Next, an ordinary preference order called Pareto order is adopted to analyze the property of the proposed game model.

Definition 4 (Pareto order). In CFG, its preference relation \succ_n satisfies Pareto order if for each player $n \in \mathcal{N}$ and all coalition partition $CO', CO \in \Pi$, there exists the following formula:

$$CO \succ_n CO' \iff u_n(CO) > u_n(CO') \wedge u_i(CO) > u_i(CO' \setminus \{n\}), \forall i \in CO \setminus \{n\}, \\ u_i(CO') < u_i(CO' \setminus \{n\}), \forall i \in CO' \setminus \{n\}. \quad (19)$$

In Pareto order, each player n obeys the principle that they won't make strategy to damage the utility of other players i in the original or new coalition. Hence, the profit of all coalition partition will not decrease. Due to the limited profit players can get, Pareto order can be a very strong proof of stable coalition partition.

The UAVs' coalition selection satisfies the definition of preference profiles, which also indicates that \mathcal{G}_2 is a typical CFG according to definition 1. Typically, in a CFG, the most important part is the formation criteria, which determines the structure of coalitions. Here we consider the Pareto order [31], which rests with the preference on the individual payoffs of the players rather than the coalition value [21]. Afterwards, coalition formation rule is required when the preference order is determined.

Authors in [32] introduced merge and split rule, which is used for forming or breaking coalition. Both rules focus on the profits of all the players in the coalition. For example, any pair of coalition CO and CO' can be merged into one coalition when all the players have an increased profit. On the contrary, a coalition can be split into coalition CO and CO' since each players in their new coalition can achieve a better profit. It is noted that according to Eq.(18), for each UAV n , the first item of its individual coverage utility function is fixed due to the stability of \mathcal{G}_1 .

2) Analysis of CFG: In this part, we analyze the stability of the proposed CFG through the given preferences and rules, and then solve the problem.

Definition 5 (Stable coalition partition[19]). A partition Π is said to be stable if no player can improve its utility by arbitrarily change its strategy, i.e. if

$$u_n(c_n, c_{-n}) \geq u_n(c_n, c'_{-n}), \forall n \in \mathcal{N}, \forall c_n, c'_n \in C_n, c_n \neq c'_n. \quad (20)$$

then Π is thought to have a stable coalition partition.

Theorem 1. With the preference relation of Pareto order, the CFG \mathcal{G}_2 can be converged to the stable coalition partition.

Proof. 1) Note that given the coalition selection profiles $\{c_n\}_{n \in \mathcal{N}}$ of UAVs in step 1, reward maximization model \mathcal{G}_1 is proved to be an EPG and has at least one NE point through lemma 1. According to definition 2, there exists at least one position selection profile for UAVs if and only if no UAV n can improve its utility by changing its state under current coalition selection.

2) In the step of coverage utility maximization, the utility function can be derived as $u_n(c_n, c_{-n})$ since UAVs' deployment is determined. Based on the above description, Pareto order is used for coalition selection while each UAV n take $u_n(c_n, c_{-n})$ as its payoff. In the above description, the sets of players (UAVs) and strategies ($\{C_n\}_{n \in \mathcal{N}}$) are limited, and Pareto order can improve current coalition's utility without damage any other UAVs, so that the profit of all coalitions can finally converge to a peak. Denote CO^* as the final coalition partition. If CO^* is not stable, then there exists a UAV, says n , its arbitrarily change will improve $u_n(CO^*)$, which contradicts the previous argument of limited profit. Finally, we can conclude from definition 5 that there exists a stable coalition partition Π in CFG \mathcal{G}_2 with Pareto order. \square

3.3. Algorithm design of CFG model

Based on the existence of the stable state in the above section, next we are going to solve the stable state of \mathcal{G} by designing algorithm. However, due to the diversity of UAV set and strategy sets (position and coalition), the kind of optimal selection approach often falls into trap loop, that is, local optimum.

In that case, learning algorithms need to be applied to explore the stable state of game. Motivated by the exploring mechanism of a distributed learning algorithm called spatial adaptive play (SAP) in [27], we designed a coalition selection and position deployment algorithm based on Pareto order (CSPDA-PO) to converge the proposed model to the stable coalition state. In each iteration of the algorithm, the chosen UAV updates its coalition selection and makes comparative update under Pareto order, while all the other UAVs maintain their current selection strategy. Learning from theorem 1, the stable solution of \mathcal{P}_1 can be solved out. In the following table, algorithm 2 demonstrates procedures of CSPDA-PO. In Eq. (16), $q_n^g(t)$ represents the coalition selection probability function of UAV n . β is the learning parameter ($\beta > 0$).

Algorithm 2: Coalition selection and position deployment algorithm based on Pareto order (CSPDA-PO)

Initialization: Set $j = 1$ and the position of central UAV g^{cen} , initialize UAVs' state $s_n = \{g_n, c_n, n \in \mathcal{N}\}$ and mission area I 's state $\sigma(i), i \in I$. Specially, each UAV $n \in \mathcal{N}$ chooses different coalition from C_n .

Loop:

Step 1: All UAVs in the network exchange information (coverage deployment and coalition selection) with each other.

Step 2: Randomly select one UAV at each iteration, says n . Input UAVs' current position profiles $\{s_n\}_{n \in \mathcal{N}}$ to Algorithm 1 and obtain optimal coverage deployment $\{s_n^{opt}\}_{n \in \mathcal{N}}$ under given coalition selections of UAVs. $\{s_n\}_{n \in \mathcal{N}} \leftarrow \{s_n^{opt}\}_{n \in \mathcal{N}}$.

Step 3: All the other UAVs repeat the previous coalition selection, i.e., $c_k(j+1) = c_k(j), k \in \mathcal{N} \setminus n$. For the choosing UAV n , it changes its coalition selection to $c'_n \in C_n \setminus c_n$. Update $s'_n = \{g_n^{opt}, c'_n\}$ and input $\{s'_n\}_{n \in \mathcal{N}}$ to Algorithm 1, obtain optimal coverage deployment s_n^{opt} under given coalition selection for UAV n . $\{s'_n\}_{n \in \mathcal{N}} \leftarrow \{s_n^{opt}\}_{n \in \mathcal{N}}$.

Step 4: Set $CO = CO_{c_n}, CO' = CO_{c'_n}$, then UAV n calculate its coverage utility $u_n(j)$ on the original and expected coalition and updates its strategy according to definition 4 (Pareto order), where the relationships of utility are explored using probability formula according to Eq. (21).

$$q_n^c(j) = \frac{\exp\{\beta u_n(c_n, c_{-n})(j)\}}{\exp\{\beta u_n(c_n, c_{-n})(j)\} + \exp\{\beta u_n(c'_n, c_{-n})(j)\}}, \quad (21)$$

where β is the learning parameter ($\beta > 0$) and can be used to adjust convergence performance and speed.

Step 5: $j = j + 1$. If the stop criterion* is satisfied, output UAVs' state $\{s_n\}_{n \in \mathcal{N}}$, else go to Step 1.

*Stop criterion can be described as the following rules: $q_n^c(j)$ is more than a certain value like 0.98 or j reaches predefined maximum number of iteration steps.

Combining the existence of NE in \mathcal{G}_1 with the existence of stable coalition partition in \mathcal{G}_2 , our proposed method can converge the problem \mathcal{P}_1 to a stable state solution.

4. Simulation Results and Discussion

In this section, we carry out simulations to verify the convergence and effectiveness of our proposed approach. Given the simulation parameters in [24], we set $E_0 = 50(nJ/bit)$, $\varepsilon_s = 10(nJ/bit/m^2)$, $\varepsilon_l = 10(nJ/bit/m^4)$. Mission area is uniformly divided into 50×50 cells (each cell's width is 10m). We consider a UAV network consisting of one central control UAV ($g^{cen} =$

$(15, 15, 40)(\times 200m)$) and certain number of UAVs for data collecting and transmission, whose flying altitudes are all set to $30 (\times 10m)$. The amount of data traffic per unit coverage reward is denoted as 1000 MB.

4.1. Diagram form

Assume the prior information of the mission area is known. Specially, a probability density function (PDF) which obeys the normal distribution is intended to describe the importance (data traffic) in the mission area. Fig. 2 (a) shows the color-coded display of the density map for the mission area, so σ_i is denoted as the normalized density of overall data traffic.

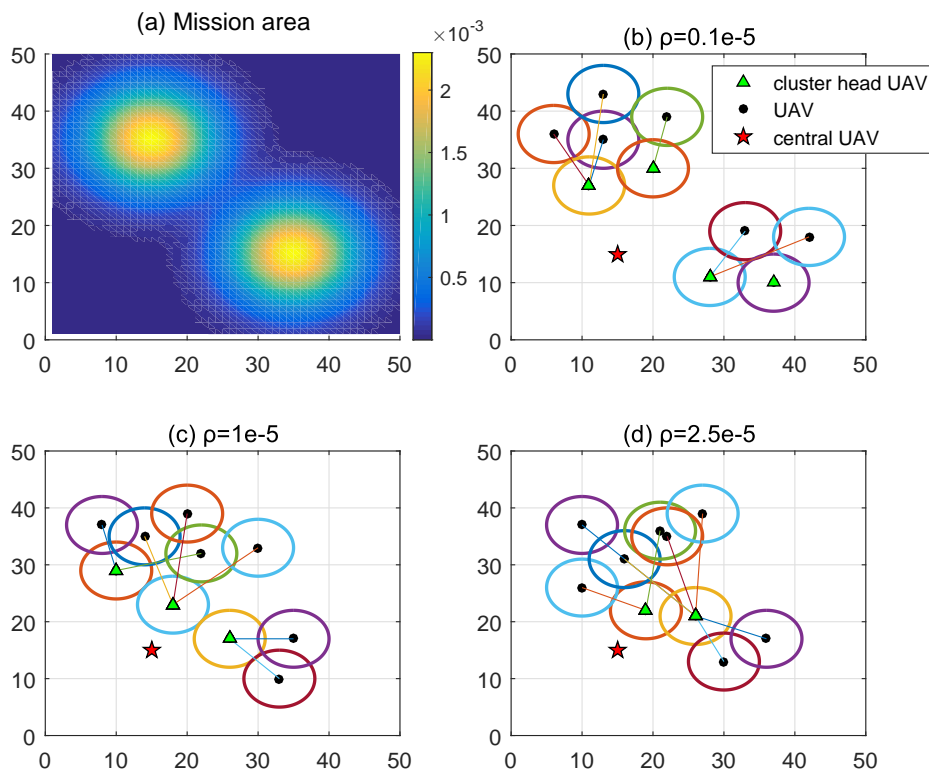


Figure 2. The diagram of 10 UAV deployment and coalition formation under the proposed algorithm

Fig. 2 (b)-(d) illustrates deployment and coalition formation diagram of 10 UAVs under different values of weight coefficient ρ . These figures depict the formation of UAV coalitions and the way data is transmitted. Coalition member UAVs (black dots) send their data to the coalition head UAVs (green triangles), which upload the data to the central UAV (red star). It can be seen that as ρ increases, the UAVs' state is more inclined of forming coalition to minimize the energy consumption, while mission reward becomes less. We analyze that in Eq.(18), UAVs' whole coverage utility is determined by mission reward and energy consumption. After taking the partial derivative of Eq.(18), ρ is the indicator that determines the marginal utility of mission reward and energy consumption.

4.2. Basic performance

In order to better reflect the performance of the proposed approach in UAVs' coverage deployment and coalition formation, we introduce the coverage reward based deployment approach for comparison. In comparison approach, the coverage utility is only depended on the mission reward and there is no coalition formation mechanism. In order to achieve better contrast, we assume that the coverage

reward under the comparison approach converges to that of the proposed approach. Under this premise, we evaluate the overall energy consumption and coverage utility for the specific mission area showed in Fig. 2 (a). As mentioned above, the weight coefficient ρ is the parameter that needs to be calculated and measured from parameters of UAVs and mission environment. For convenience, performance comparisons considering different weight coefficients are paid as reference. To prevent contingency, both algorithms are performed 100 independent trials, then the mean results are acquired. Here we observe some important results from the figures and draw conclusions from the analysis.

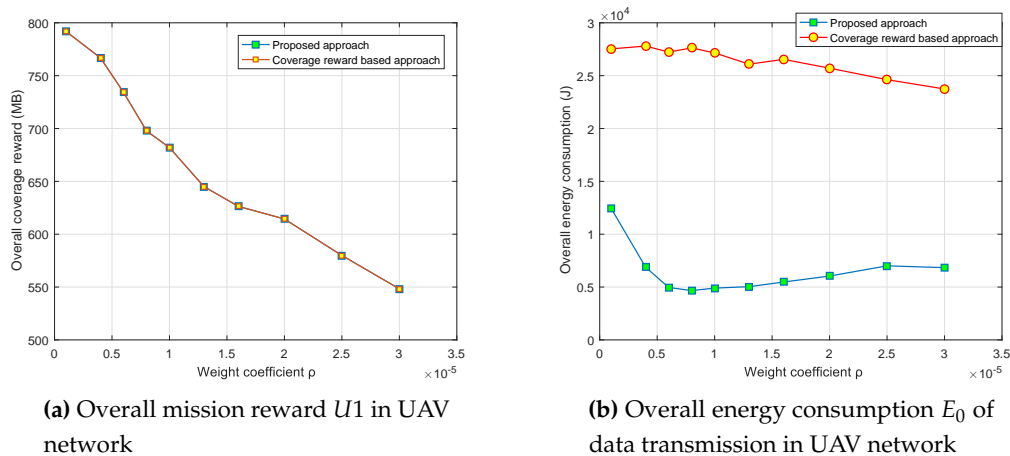


Figure 3. Performance comparison of algorithms based on weight coefficients (10 UAVs)

Fig. 3a and Fig. 3b demonstrates the comparison results. In Fig. 3a, as the weight coefficient ρ scales up, the overall coverage reward U_1 of our proposed approach decreases due to the increased importance of energy consumption. Meanwhile, the overall reward of comparison approach tends to be the same as U_N , as can be expected.

In Fig. 3b, the comparison result shows that the proposed approach can achieve a lower energy consumption E_0 . We analyse that the existence of coalition formation mechanism makes the energy consumption of the proposed approach much less than that of comparison approach. As the weight coefficient scales up, E_0 decreases rapidly at first. It suggests that the whole UAV network is more tended to form coalitions when the weight coefficient increases. Specially, in the late stage, UAVs are not tended to cover high-yielding areas. Thus, energy consumption under the coalition formation mechanism tends to be steady due to the limited data traffic UAVs collection.

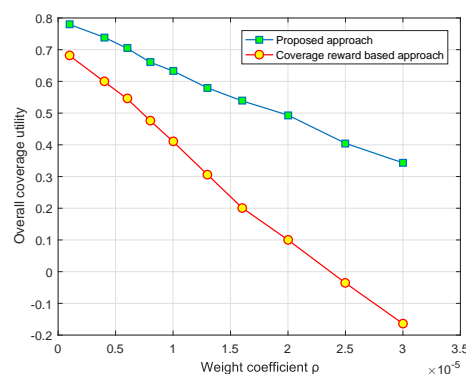


Figure 4. Overall coverage utility U_N in UAV network

The comparison of coverage utility is shown in Fig. 4, which is an important indicator of the entire UAV network. We see that the coverage utility under all approaches decreases as the weighting coefficient increases. And our proposed method can achieve higher coverage utility under the same weight coefficient. This suggests that without a guarantee of coalition formation mechanism, system will obtain a fair reward, but at the same time need more energy consumption, so that the coverage utility is less.

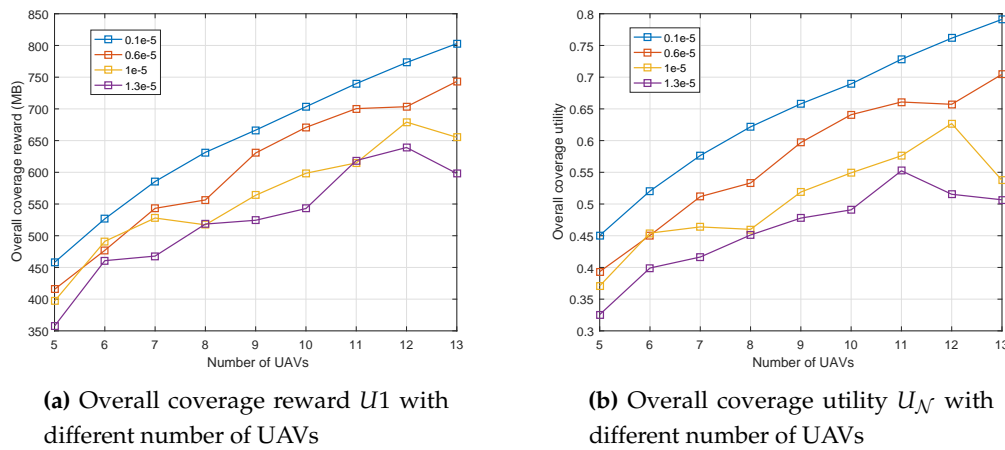


Figure 5. Coverage performance consider number of UAVs and weighting coefficient

Fig. 5a and Fig. 5b show changes in overall coverage reward and overall coverage utility for different numbers of UAVs, respectively. From the figure, we observe that the coverage performance improves as the number of UAVs increases, which are consistent with the fact that more UAVs can be able to collect more data information from the ground. However, when the number of UAVs reaches to a certain number, the increase in coverage utility will slow down until eventually declining. The main reason says there is an upper bound for coverage reward due to the limited data information. Meanwhile, in the coalition structure, more UAVs mean more transmission paths, and the high-energy consumption of the increasing transmission paths will make it worthless. Note that the model with the increase of weighting coefficients will also make the model focus more on energy consumption, so coverage utility will decrease with the increase of the weighting coefficient, even reaching the "saturated" state in advance (e.g. eleven UAVs with $\rho = 1.3e-5$ and twelve UAVs with $\rho = 1e-5$). Therefore, the performance shows such a fluctuant shape.

4.3. Convergence performance

In order to deeply investigate convergence performance, we choose $\rho = 1e-5$ as a contrastive index of both approaches. Fig. 6(a) shows the diagram of the convergence state of UAV deployment and coalition formation. Convergence performance of different algorithms is shown in Fig. 6(b)-(d). We observe that all the indicators converge after a certain number of iterations, which indicates that our proposed method can achieve a stable state solution of the system model. The coverage reward of the comparison algorithm converges to the same value. However, since there is no coalition formation mechanism for comparison approach, its energy consumption and coverage utility converge to a worse level, which is consistent with the previous description.

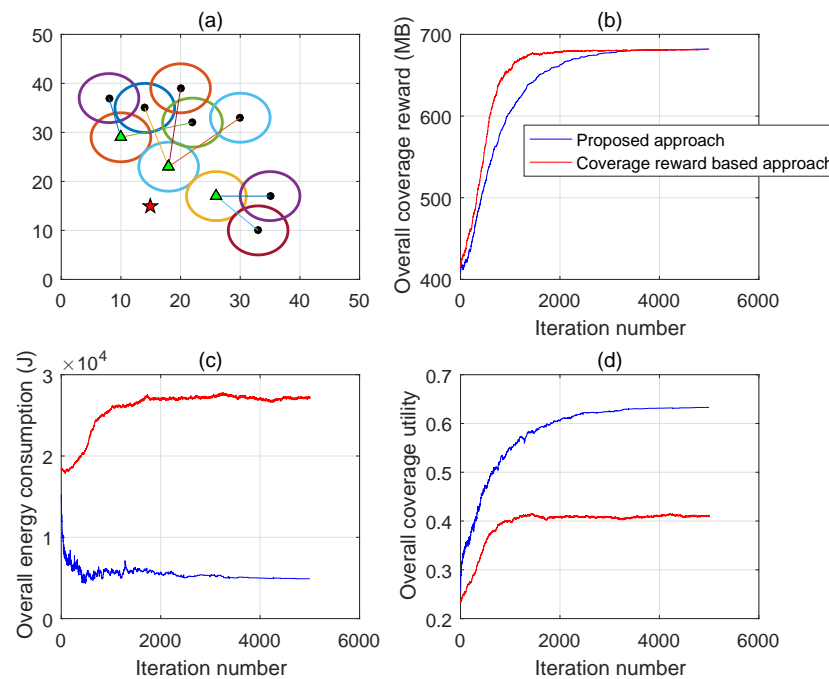


Figure 6. The performance convergence graph of the proposed model ($\rho = 1e - 5$)

To summarize, the simulation results illustrate the proposed cooperative multi-UAV deployment model based on coalition formation can well describe UAVs' cooperative behaviors. What's more, the setting of the weight coefficients can provide theoretical reference for different task requirements. At last, the proposed approach can achieve higher coverage utility comparing with comparison approach, reflecting the good performance of coalition formation mechanism and efficiency of the proposed model.

5. Conclusion

In this paper, we proposed an efficient cooperative UAV deployment model in the UAV-assisted sensor network. A multi-UAV coverage deployment and transmission mechanism was established, and the coverage utility and corresponding energy consumptions under the network structure were studied based on cooperation. The system model was transformed into a coalition formation game (CFG). The CFG with Pareto order was proved to have at least a stable coalition partition. Then coalition selection and position deployment algorithm based on Pareto order (CSPDA-PO) was designed to perform coalition selection. Finally, simulations were performed to validate the effectiveness of our proposed approach, indicating the proposed model can well describe UAVs' cooperative behavior and have better performance comparing other approaches in UAV network.

Author Contributions: Lang Ruan and Yuli Zhang conceived and designed the model; Lang Ruan performed the game analysis and simulation; Yuli Zhang and Dianxiong Liu analyzed the game proof and simulation result; Lang Ruan wrote the paper; and Jin Chen, Han Jiang and Qiuju Guo provided some suggestions and revised the paper.

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