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Article

Group Buying-based Data Transmission in Flying Ad-hoc Networks: A Coalition Game Approach

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Abstract: In scenarios such as natural disasters and military strike, it is common for unmanned aerial vehicles (UAVs) to form groups to execute reconnaissance and surveillance. To ensure the effectiveness of UAV communications, repeated resource acquisition issues and transmission mechanism design need to be addressed urgently. In this paper, we build an information interaction scenario in a Flying Ad-hoc network (FANET). The data transmission problem with the goal of throughput maximization is modeled as a coalition game framework. Then, a novel mechanism of coalition selection and data transmission based on group-buying is investigated. Since large-scale UAVs will generate high transmission overhead due to the overlapping resource requirements, we propose a resource allocation optimization method based on distributed data content. Comparing existing works, a data transmission and coalition formation mechanism is designed. Then the system model is classified into graph game and coalition formation game. Through the design of the utility function, we prove that both games have stable solutions. We also prove the convergence of the proposed approach with coalition order and Pareto order. Binary log-linear learning based coalition selection algorithm (BLL-CSA) is proposed to explore the stable coalition partition of system model. Simulation results show that the proposed data transmission and coalition formation mechanism can achieve higher data throughput than the other contrast algorithms.

Keywords: unmanned aerial vehicle (UAV); data transmission; resource allocation; coalition graph game; coalition formation game; stable coalition partition; Nash equilibrium.

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1. Introduction

Unmanned aerial vehicle (UAV) communication technology has been widely applied in many mission scenarios, such as detection and monitoring. In scenarios such as natural disasters and military strike, UAVs can support terrestrial networks and provide a variety of communication means, which greatly promote wireless communication technology [1]. UAVs can intelligently handle various task requirements due to its self-organizing characteristics[2–5]. Information interaction plays a vital role among UAVs, while communicating mission such as data sharing and relay transmission can be carried out in a cooperative manner [6,7]. In that situation, we focus on efficient transmission of information and quality assurance of UAV communication, which determines the execution capability of cooperative UAV groups. Note that data transmission is performed in a routing manner, we study Flying Ad-hoc Networks (FANET) and optimize the problem by characterizing appropriate routing mechanism.

Much work so far has focused on this project, especially on information collection and transmission. In [8], the authors considered a multi-UAV information collection scenario, and obtained the trade-off between communication and computational energy by proposing a mixed-integer optimization formulation. Target tracking and area mapping can be well settled by this application. Effective cooperative mechanisms are also studied, where UAV groups can improve task handing efficiency. Authors in [9] investigated the problems of UAV node placement and communication resource allocation. In this model, a one rotary-wing UAV was served as a relay to optimize system throughput. Besides, a terrestrial communication network was introduced in [10], where UAVs provided an efficient scheme to achieve wireless coverage for the ground terminals. An expression to estimate the energy consumption for transmitting and receiving through RF signals is introduced in [11]. In our previous work, energy consumption function is adopted to study the tradeoff between the coverage performance and transmission overhead, then we proposed an efficient multi-UAV cooperative deployment model to optimize the coverage utility [12].

Data transmission under the cooperative mechanism will bring benefits to FANETs. However, most of works have placed too much emphasis on communication link quality and data processing, while ignoring the characteristics of the data resources themselves. In fact, data resources acquired by different UAVs usually exist overlapping content (e.g. flight instruction). An efficient solution is urgently needed to solve the data waste phenomenon in high data transmission cost situation.

Group buying mechanism is introduced in spectrum market, where the high cost problem of spectrum acquisition can be effectively solved [13]. By utilizing this mechanism, UAVs form different groups and transmit single data once in groups, instead of repeatedly required the same data from the central UAV. Authors in [14] proposed a context-aware group buying mechanism in resource acquisition, and modeled the problem as the coalition formation game (CFG) [15] for sharing data traffic and reduce overlapping download and transmission cost. Note that coalition formation game can well describe the relationships between UAVs, it can be the basis for investigating cooperative manners of UAVs. In terms of the overlapping data content of information, we utilized a overlapping coalition formation (OCF) game model to optimize the cost of spectrum group-buying in [16].

However, the definition of transmission overhead and the transmission mechanism within the UAV coalition has been simplified. Hence, inspired by the design of packet delivery ratio channel model in [17], we propose a coalition selection and data transmission model based on group buying mechanism. In the proposed model, data throughput is used to describe the overhead caused by the transmission path. What's more, coalition game is introduced to explore the stable partitions of the problem.

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

- The data transmission probability based on multi-hop routing is introduced to measure the throughput of data packet transmission through UAV-to-UAV links. The designed utility function can reflect both link qualities and the efficiency of resource transmission. This provides theoretical support for the UAVs' coalition selections and the formation of internal stable structures.
- We propose a coalition game framework to solve resource allocation and data transmission problems. In the framework, coalitional graph game characterizes the inner coalition structure (transmission mechanism). Data resource allocation of UAVs is analyzed in coalition formation game (CFG). Both games are proved to have stable states, indicating the effectiveness of our proposed model.
- A cooperative coalition selection mechanism is proposed to improve the performance of system model. Binary log-linear learning based coalition selection algorithm (BLL-CSA) is designed to execute cooperative exchange mechanism. Simulation results show that the BLL-CSA achieves better performance than contrast algorithms. The performance with coalition order are better than that with the Pareto order, while Pareto order cost less convergence times.

Note that this work introduces the packet delivery ratio channel model in [17], the main differences are as follows: 1) This paper considers the different data packet contents required by all UAVs. According to the deployment relationships between the given UAVs, the transmission mechanism is studied by rationally selecting UAVs to cooperate and designing the multi-hop forwarding scheme. 2) The data transmission problem with the goal of maximal throughput is modeled as a coalition game framework. Then, a coalition selection mechanism is investigated to converge our problem to the stable solution.

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The rest of the paper is organized as follows. Section 2 shows the system model of multi-UAV cooperative transmission model based on group buying. The latter part is problem formulation. In Section 3, a coalition graph game for system model is analyzed to characterize the internal structure of the UAV groups. Coalition formation game is investigated in Section 4, and a learning algorithm is designed to converge the proposed problem to the stable state. Section 5 gives simulation results and analysis. Finally, the concluding remarks are given in Section 6.

2. System Model and Problem Formulation

2.1. System model

We consider a Flying Ad-hoc network (FANET) consisted of N UAVs. There are two sorts of UAVs: one is central control UAV (set to one in this scenario), and the other is UAVs that exists in groups (formation). The central control UAV has a stronger battery life and sufficient spectrum resources. It plays the role of flying base station for UAV groups, providing data resources and instructions for other UAVs. UAVs can be able to get all information in context awareness and location awareness. In that case, group-buying is introduced to overcome high cost of repeated resource acquisition. When UAV groups have resource requirements (e.g., spectrum), they request the central control UAV and obtain the resources through the designed data transmission mechanism. Due to the high transmission loss caused by long distance of data packets, it requires UAV groups to utilize some UAVs as relays to reduce loss and improve transmission quality.

Here a set of UAV group is defined as $\mathcal{N} = \{1, 2, \ldots, n, \ldots, N\}$. The serial number of the central UAV is set to 0. For each UAV $n \in \mathcal{N}$, its three dimensional coordinates is denoted as $g_n = (x_n, y_n, z_n)$. All the data resource requirements is defined as $\mathcal{S}$. For ease of calculation, assume that all data packets' size are the same. The data requirements for UAV n can be described as $A_n = (a_n^1, a_n^2 \cdots a_n^{l_n})$, where l_n represents the the size of UAV n's data packet, a_n^k is the content of UAV n's k_{th} data, $1 \le k \le l_n$.

In UAV-to-UAV communication, the transmission distance can significantly affect the quality of the link. In [17], the authors analyzed the experiments in the same RF band and collected data such as distance, data packet and orientation. The experiments is carried out using the AR Drone 2.0 platform [18]. Then, a mathematical channel model is designed, from which the packet delivery ratio (PDR) of collected data can be well predicted given the distance between two nodes. The generic form of the proposed PDR channel model is given by:

$$\mathrm{Pb}(d) = e^{d_h d^{k_1}}, \tag{1}$$

where $d_h = -\ln(2)/R^{k_1}$ represents the distance between two UAVs when the packet success rate is 50% in the links. k_1 is transmission coefficient. Pb(d) represents the success probability of packet transmission within two UAV nodes. It can reflect both link qualities and the efficiency of resource transmission. As can be seen from the above, the success probability of packet transmission is determined by the transmission distance. Besides, the function is strictly nonincreasing, Pb(d)$\in [0, 1)$, and can be derived as 0 and 1 at $d = 0$ and at $d = \infty$, respectively. All features of the channel model meet the characteristics of data packet transmission in the link layer. For convenience, let $d_{i,j}$ be the distance between UAV i and j.

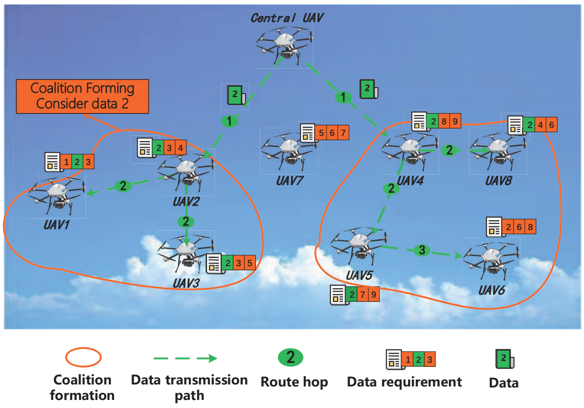

Figure 1. A diagram of data multi-hop transmission considering coalition formation in UAV networks.

Fig.1 shows a diagram of data multi-hop transmission considering coalition formation in UAV networks. First, the set of available coalition is denoted as $\mathcal{M}$, i.e., $\mathcal{M} = \{1, 2, \ldots, M\}$. In the scene, distributed UAV with spectrum resources demand form different coalition considering specific data content (says data 2). Then the coalition cluster-head UAV downloads data from the central UAV through UAV-to-UAV links, and transmits data to the members of its coalition through designed multi-hop routing mechanism. Suppose $\varepsilon = \{\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_s, \ldots, \varepsilon_S\}$ is the sets of all existing UAV-to-UAV links for data transmission. For $i, j \in \mathcal{N}$, let $e_{i,j}$ be the link status from node i to j. Specially, we say the link exists considering data content s, if $e_{i,j} \in \varepsilon_s$. The value of $e_{i,j}$ is set to be $d_{i,j}$, representing the distance between current link.

2.2. Problem formulation

From the above system model, the coalition selection problem considering overlapping data requirements should be addressed to reduce overall spectrum requirement overhead. Context awareness is introduced to describe the relation among different UAVs' data contents. But first, the relation in coalition should be well studied.

In order to maximize the overall data transmission throughput in different coalitions, the connected graph is considered to depict the UAV-to-UAV links. For the UAV group in coalition m considering content requirement s, the coordinates of cluster head UAV is g_{ch_m}. Then, in UAV n's current forming coalition based on data content s, the data packet transmission probability through multi-hop path from cluster head UAV to UAV n can be derived as follows:

$$f(\varepsilon_s, n) = \begin{cases} 1 & n = \mathrm{ch_m}, \\ \prod\limits_{e_{i,j} \in \varepsilon_{s,n}} \mathrm{Pb}(e_{i,j}), & \text{otherwise}. \end{cases} \tag{2}$$

Here, $\varepsilon_{s,n} \in \varepsilon_s$ represents the set of links of from the cluster head UAV ch_{c_n} to the cluster member UAV n.

Denote the coordinate of the central UAV as g_0. When content $s \in \mathcal{S}$ is taken into consider, the network can form a coalition partition $\mathcal{M} = \{1, 2, \ldots, m, \ldots, M\}$. The UAV subsets which belong to coalition m based on content s is described as $CO_m^s = \{n \in \mathcal{N} : s \in A_n, c_n = m\}$. The packet transmission speed is defined as T_s, then we characterize the transmission throughput of UAVs in coalition m when considering data content s as follows:

$$\mathrm{Th}(\varepsilon_s, m) = T_s \cdot \sum_{n \in CO_m^s} \left(\underbrace{\mathrm{Pb}(|g_0 - g_{ch_m}|)}_{1_{\mathrm{st}} hop} \cdot \underbrace{f(\varepsilon_s, n)}_{other \mathrm{hops}} \right). \tag{3}$$

The function consists of two items, the first item is the transmission probability of one data content transmitted from the central UAV to the coalition m. The latter item of the equation is the successful transmission probability of single data packet transmitted from cluster head UAV to cluster member UAV n.

Therefore, the total transmission throughput of the whole network when content s is considered can be calculated as follows:

$$T(\varepsilon_s) = \sum_{m \in \mathcal{M}} \mathrm{Th}(\varepsilon_s, m). \tag{4}$$

Obviously, the longer the path per hop, the lower the probability of transmission success, and similarly, the more hops, the smaller the overall throughput, so there will be no major league or single-coalition full path formation. Therefore, the transmission throughput of the whole network based on all data is:

$$T = \sum_{s \in \mathcal{S}} T(\varepsilon_s) = \sum_{s \in \mathcal{S}} \sum_{m \in \mathcal{M}} \mathrm{Th}(\varepsilon_s, m). \tag{5}$$

Our object is to maximize the data throughput of the whole network by adjusting the network structure of the UAV group and coalition selection considering different contents.

$$(\mathcal{P}) : (\varepsilon_{s,n}, c_n) = \arg\max T. \quad n \in \mathcal{N}, s \in \mathcal{S}. \tag{6}$$

From the view of each data $s \in \mathcal{S}$, our object is to obtain an independent solution in the FANET, including the optimal data transmission mechanism and resources allocation approach. In the next two sections, we model the problem as a coalitional graph game and a coalition formation game, and analyze the proposed model. The key of solving $\mathcal{P}$ is to accurately characterize UAVs' action and prove the stability of the proposed coalition game framework.

3. Coalitional Graph Game for Data Transmission

We firstly focus data transmission when the group-buying mechanism is determined. Notably, traditional centralized solution can't afford the high computational burden of solving $\varepsilon_{s,n}$ due to the enormous edge (link) selection strategies. Besides, random establishment of UAV-to-UAV links may cause the FANETs suffer from low data throughput. In this section, we formulate the problem of data transmission in FANETs as a game. Here, a coalitional graph game model is introduced to coordinate all the UAV-to-UAV links among UAVs of the entire network. According to the previous description, the interactions among the UAVs is an action graph $G(\mathcal{N}, \varepsilon)$ [19]. In this model, each UAV decides to connect to or be connected to other UAVs in order to maximize its own utility that takes into account data throughput as well as link maintaining cost.

Definition 1 (Coalitional graph game [15]). *We call $\mathcal{G}_a = (G(\mathcal{N}, \varepsilon), \{U1_n\}_{n \in \mathcal{N}})$ a coalitional graph game where:*

- *$\mathcal{N}$ is a set of all nodes (including central UAV)*
- *ε is the set of all edges (UAV-to-UAV links). For any $i, j \in \mathcal{N}$, we say the link from i to j exists, if $e_{i,j} \in \varepsilon$.*
- *C_n is the available coalition selections for each $n \in \mathcal{N}$, let $c_n \in C_n$ denote the coalition selection for n.*
- *$U1_n$ represents the utility function of UAV n while playing its strategy.*

Consider the characteristics of routing mechanism in one coalition, the strategy of each UAV $n \in \mathcal{N}$ should be the UAV of n's own previous hop. Formally, denote a_n as the strategy selection of UAV n, where $a_n \in CO_{c_n}$. Thus, learning from [19][20], a local strategy is called a feasible local strategy $a_n \in A_n$ if and only if: (1) $U1_n(G) \geq U1_n(G')$, (2) $U1_{a'_n}(G) \geq U1_{a'_n}(G')$ for $a_n \neq n, a'_n \neq n$. Here, G is the current graph, and G' is the consequent graph by UAV n's local strategy a'_n. In summary, the local utility function is derived and given in the following.

1) Utility function

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Given an action graph $G(\mathcal{N}, \varepsilon_s)$, the UAV n's local utility function can be expressed as :

$$U1_n(G) = \sum_{i \in CO^s_{c_n}} \left(\underbrace{\mathrm{Pb}\left(\left|g_0 - g_{ch_{c_n}}\right|\right)}_{1_{st}hop} \cdot \underbrace{f(\varepsilon_s, i)}_{other\mathrm{hops}} \right). \tag{7}$$

It can be seen that $U1_n(G) = \mathrm{Th}(\varepsilon_s, c_n)/B$, representing the transmission probability for data packet s in coalition c_n and is determined by UAV n's connecting drone's selection a_n, which affects ε_s eventually. It should be pointed out that the value of $U1_n(G)$ and $U1_{a_n}(G)$ are the same, since two functions both represent the current coalition c_n's transmission probability for data s.

Centralized approach will cause much calculation load. In that case, a distributive network formation algorithm is proposed for each UAV n to carry out in our coalitional graph game, which is classified as follows:

Algorithm 1: Maximum throughput network formation algorithm

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1)Set $\mathcal{K} = \{\mathrm{ch}_{c_n}\}$.
2)**while:** All UAVs in coalition c_n are connected considering data content s, i.e. $\mathcal{K} = CO^s_{c_n}$.
1: Find $(i, j) = \arg\min d_{i,j}$, $j \in \mathcal{K}$, UAV $i \in K1$, where $K1 = \{i \in CO^s_{c_n} : i \notin \mathcal{K}\}$.
2: Find UAV m if $m = \arg\max U1_{a_i}(G)$ where $a_i = m$.
3: Offer UAV i and UAV m a new link $e_{i,m}$. Add i and $e_{i,m}$ into K and ε^n_s respectively.
End
3)Output routing link ε^n_s.

Note that the proposed algorithm actually focuses on maximizing the current utility of coalition c_n, thus we can obtain ε_s and ε by setting up different data content and UAV. Next, the convergency of the proposed network formation games is analyzed.

2) Convergency and stability

To study the properties of stability, definition of local Nash network is given in the following.

Definition 2 (Local Nash network [19]). *A network graph G is a local Nash network in which no node n can improve its utility by a unilateral change its feasible local strategy $U_n(G)$.*

Note that there exists an upper bound of overall data resource requirements, best response algorithm can finally converge the problem to the stable state. So we design a best response algorithm in network formation. In the algorithm, UAV n select its strategy by improving the value of its local utility. Knowing that the value of $U2_n(G)$ equals to that of $U2_{a_n}(G)$, we can conclude that our proposed model is a feasible local strategy. Suppose the proposed algorithm will converge to a final graph G^*. In addition, In graph G^*, no UAV can be able to improve $U1_{a_n}(G)$ through adjusting strategy a_n due to the proposed algorithm, which satisfy the characteristic of definition 2.

Therefore, under the feasible local strategy $U_n(G)$ and the network formation algorithm, the coalitional graph game $\mathcal{G}_a$ is proved to be a local Nash network. Generally, pairwise stability exists in G^*, which indicates that $\mathcal{G}_a$ can achieve a stable state.

4. Coalition Formation Game for Resources Allocation based on Group Buying

Since UAVs in FANETs should form coalitions to optimize the overall performance of the proposed model. Consequently, properties of the coalition formation game is studied in this section.

Definition 3 (Coalition formation game, CFG[15]). *A (hedonic) coalition formation game is given by a pair $(\mathcal{N}, P)$, where $P = (\succ_1, \succ_2, \ldots, \succ_n)$ denotes the preferences profile, specifying for each player $i \in N$ his preference relation $\succ_i$.*

4.1. Game model

Suppose the available coalitions of UAV n is denoted as C_n. Formally, the game can be characterized as $\mathcal{G}_b = (\mathcal{G}_a, \{C_n\}_{n \in \mathcal{N}}, \{U2_n\}_{n \in \mathcal{N}})$, where $U2_n$ represents UAV n's utility function and is expresses as $U2_n(c_n, c_{-n})$, in which $c_{-n} \in C_1 \otimes C_2 \otimes \cdots \otimes C_{n-1} \otimes C_{n+1} \otimes \cdots \otimes C_N$ is the state profiles of all the UAVs excluding n. In $\mathcal{G}_b$, the value of a coalition CO depends solely on the members of that coalition, with no dependence on the other UAVs in $\Pi \setminus CO$. So $\mathcal{G}_b$ is the characteristic form.

In our system model, from the perspective of the UAV, coalitions considering different data content will have common UAV members. Hence, UAVs in $\mathcal{G}_b$ play their strategies to form an overlapping coalition structure, from all of which they could get the benifit[21]. This satisfies the characteristic of overlapping coalition formation game (OCF game). However, in the system model analysis of this paper, we focus on the coalition formation based on different data content, which also avoids the formation of overlapping coalitions. All in all, the model $\mathcal{G}_b$ is built into a CFG.

Given the stable state of coalition graph game $\mathcal{G}_a$, then the network topology $G(\mathcal{N}, \varepsilon)$ is determined, so the local utility function of UAV n can be denoted as follows:

$$U2_n(c_n, c_{-n}) = \mathrm{Th}(\varepsilon_s, m) = \mathrm{Th}_n(c_n, c_{-n}). \tag{8}$$

According to Eq.(8), the UAV n's local utility represents the data throughput of its current coalition, and is determined by both itself and other UAVs in CO_{c_n}. This shows that the value of this coalition depend on the joint actions selected by all UAVs in this coalition, which illustrates that $\mathcal{G}_b$ is a nontransferable utility (NTU) game [22].

In CFG, coalition partitions are denoted as a set $\Pi = \{CO_m\}_{m=1}^{M}$ which partitions all the UAVs $\mathcal{N}$. According to the definition 3, the coalition selection of UAV i is determined by its preference relation $\succ_i$, next two orders are introduced as the basis for evaluation of game analysis. UAVs evaluate and select coalition strategies under different orders, which directly affects the stable solution of the model.

Definition 4 (Pareto order [23]). *The preference relation of coalition partition Π satisfies pareto order if for arbitrary UAV n and coalition CO and CO',*

$$\begin{aligned} CO \succ_n CO' \Longrightarrow & U2_i(CO') < U2_i(CO' \setminus n), \forall i \in CO' \setminus \{n\}, \\ & U2_i(CO) > U2_i(CO') \wedge U2_i(CO) > U2_i(CO \setminus n), \forall i \in CO \setminus \{n\}. \end{aligned} \tag{9}$$

In Pareto order, for the UAV n completing the coalition selection, neither the profit of the UAVs in its original coalition CO nor that in its new coalition CO' will be damaged. This feature ensures that the overall profit of the coalition partitions Π will never fall, which provides sufficient theoretical support for the proof of the stable partition. The Pareto order is available for both (transferable utility) TU and NTU games [15].

Though stable partition can be obtained with Pareto order, optimal solution of $\mathcal{P}$ can not be guaranteed. Motivated by the work in [24], we adopt coalition order and solve the proposed problem by mapping the overall utility of system model to UAV's local utilities.

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Definition 5 (Coalition order). *The preference relation of coalition partition Π satisfies coalition order if for arbitrary UAV n and coalition CO and CO',*

$$\begin{aligned} CO \succ_n CO' \Longrightarrow & U2_n(CO) + \sum_{i \in CO \setminus n} U2_i(CO) \\ & > U2_n(CO') + \sum_{i \in CO' \setminus n} U2_i(CO'). \end{aligned} \tag{10}$$

In coalition order, UAV n selects coalition by considering the total utility of both original coalition CO and new coalition CO'. Hence, it can bring the maximal profit for the system model, which will be reflected in the subsequent proof and simulation.

Authors in [25] introduced two simple rules called merge and split rule, which is employed to form or break the coalitions. Both rules concern with the value of the coalition. For example, in merge rule, coalition CO and CO' are agreed to merge into a coalition $CO^* = CO \cup CO'$ when this new coalition is preferred by the UAVs, of which all UAVs can improve its profit. On the contrary, a coalition CO^* can be split into coalition CO and CO' when each UAVs in their new coalition can achieve a better profit. However, these two rules overemphasize the role of the entire coalition. During the formation process, the UAVs in the same coalition will change the strategy in batches. In such orders, once the initial selections are poor, UAVs will be trapped prematurely in their fixed combination with some other UAVs. In addition, in the late stage of convergence, little effect will do the coalition structure under the corresponding rules. Hence, it is even difficult to make actions, resulting in useless calculations.

In order to avoid those problems (local optimum, invalid calculation, etc.) caused by traditional rules, we design the following mechanism for coalition selection.

Definition 6 (Coalition selection mechanism). *For UAV $n \in CO_1$, it will select CO_2, when the newly formed coalition can achieve a better utility.*

$$n \longrightarrow CO_2 \Longleftrightarrow U2_n(CO_1, CO_2) \geq U2_n(CO_1 \setminus n, CO_2 \cap n) \; \forall CO_1, CO_2 \in \Pi, . \tag{11}$$

Under different rules, the utility function of this mechanism has different definitions. For example, in the Pareto rule, the coalition selection of UAV n achieves the better respective benefits of the two coalition; In the coalition order, UAV n selects coalition considering the common profit of both coalitions. This mechanism can realize the functions of both two rules, and avoid the batch strategy selection of the UAVs. Therefore, even if the strategy selection of the UAVs goes to a detour, it can still be on the right track soon. The next subsection will introduce the analysis of the stable partition of CFG under the given coalition selection mechanism.

4.2. Analysis of the stable coalition partition

Definition 7 (Stable coalition partition[14]). *A coalition partition Π is said to be stable if no player (says n) can benefit from moving from his coalition CO_{c_n} to another existing coalition $CO_{c'_n}$ with the corresponding order, i.e. if*

$$\forall i \in \mathcal{N}: \quad U2_i(c_n, c_{-n}) \geq U2_i(c'_n, c_{-n}), \quad c_n \neq c'_n, \tag{12}$$

then Π is thought to be a stable coalition partition.

In the following, stability of the final coalition partition is demonstrated based on coalition selection mechanism with different orders.

Theorem 1. *The proposed CFG $\mathcal{G}_b$ with Pareto order has at least one stable coalition partition.*

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Proof. To begin with, according to the description in Section 3, for arbitrary partitions $\Pi = \{CO_m\}_{m=1}^{M}$, the coalitional graph game G_a can achieve a stable state, representing the stability of the internal coalition structure.

Then we consider CFG $\mathcal{G}_b$, from the above description, the utility of each coalition involving its associated UAVs will not be damaged under this rule. Due to the fixed original data information, the local utility is bound to be limited. Therefore, the coalition partition on the system will shift continuously between finite states [26].

□

Before the proof of stable coalition partition with coalition order, Exact potential game (EPG) is first introduced. Considering the distributed characteristics under the multi-agent system, the formation of coalitions under this rule can be characterized by the EPG through UAVs' strategy selections.

Definition 8 (Exact potential game [27]). *For utility function $U2_n(c_n, c_{-n})$ in a game $\mathcal{G}_b$, if there exists a function $\phi : C_n \to \mathbf{R}$, for arbitrary UAV's (says n's) coalition strategy changes from c_n to c'_n, the following equation is true:*

$$U2_n(c_n, c_{-n}) - U2_n(c'_n, c_{-n}) = \phi(c_n, c_{-n}) - \phi(c'_n, c_{-n}),\ \forall n \in \mathcal{N}, \forall C_n, c'_n \in C_n. \tag{13}$$

*then this game is called exact potential game (**EPG**) and has at least one Nash equilibrium (NE) point, the function is called potential function.*

The NE point guarantees the stability of the UAV strategy selection and system model utility. When the potential function has physical meaning, the NE point can also determine its final convergence state.

Theorem 2. *The proposed CFG $\mathcal{G}_b$ with coalition order has at least one stable coalition partition.*

By constructing the potential function, we introduce the potential game as a tool to analyze the performance and stability of the designed utility function [28]. In potential game, there exists at least one pure Nash equilibrium. Next is the proof of the theorem 2.

Proof. First, from the view of any data content, says s, the stability of the internal coalition structure has been proved in the above.

Then we construct the potential function as follows: $\phi_n(c_n, c_{-n}) = \sum_{m \in \mathcal{M}} \mathrm{Th}(\varepsilon_s, m)$, which represents the overall transmission throughput of data s. It can be concluded that

$$\begin{aligned}\phi_n(c_n, c_{-n}) - \phi_n(c'_n, c_{-n}) &= \sum_{m \in \mathcal{M} \setminus c_n} \mathrm{Th}_n(c_n, c_{-n}) + \mathrm{Th}_n(c_n, c_{-n}) - \sum_{m \in \mathcal{M} \setminus c'_n} \mathrm{Th}_n(c'_n, c_{-n}) - \mathrm{Th}_n(c'_n, c_{-n}) \\ &= \mathrm{Th}_n(c_n, c_{-n}) - \mathrm{Th}_n(c'_n, c_{-n}).\end{aligned} \tag{14}$$

Note that UAV n's one step strategy only changes the utility of its original coalition c_n and new coalition c'_n, but has no effect on other existing coalition. So the first and the third item are equal in value. According to Eq. (8) and Eq. (14), we have the following formula:

$$\phi_n(c'_n, c_{-n}) - \phi_n(c_n, c_{-n}) = U2_n(c'_n, c_{-n}) - U2_n(c_n, c_{-n}). \tag{15}$$

So the current game can be proved to be an exact potential game (EPG) [29], which has at least one pure Nash equilibrium (NE) point. Since the potential function $\phi_n(c_n, c_{-n})$ numerically refers to the

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overall transmission throughput of the data s, which shows that the constructed utility function can work out the optimal solution of $\mathcal{G}_b$ through local interaction.

According to the characteristic of NE, the coalition partition Π can be proved to be stable considering different data content, for there is no any other player can promote its utility function by changing its coalition selection strategy. Hence, there exists at least one stable coalition partition Π in CFG $\mathcal{G}_b$. □

Theorem 3. *Given the designed coalition mechanism, the proposed CFG $\mathcal{G}_b$ has a stable coalition partition of $\mathcal{P}$.*

Proof. Based on the above proof of the stable partition existence with both orders, there always exists a local Nash network $\mathcal{G}_a$, then $\varepsilon_s, s \in \mathcal{S}$ is derived.

Then, in the designed coalition selection mechanism, definition of utility is different under different orders. For example, in the Pareto order, the shift action of a single UAV increases the profit of the respective UAVs in the old and new coalition. According to the previous description in theorem 1, the coalition partition on the system will shift continuously between finite states, which are fixed stable partition solutions.

In the coalition order, when the exchange mechanism happens, it improves the selected UAVs' local utilities, which are equivalent to the direction towards the overall utility. UAVs that are not in the relevant coalition are not affected as their local utility is determined by other coalitions. It should be noted that the strategy change of a single UAV directly affects the whole system, so the utility of the system can converge to the optimal state. In addition, even if a single UAV's selection mechanism puts the convergence process at a disadvantage, the coalition order will put the path back in the right direction, eventually forming a stable coalition partition $c_n, n \in \mathcal{N}$. It can effectively avoid local optimum, but at the same time, more convergence times will be caused. The proofs of the stable coalition partitions under different data $s \in \mathcal{S}$ are also similarly available. Then, we can explore the network structure of the UAV coalition $\varepsilon_{s,n}$ and coalition selection c_n;

In summary, given the designed coalition mechanism, the proposed CFG $\mathcal{G}_b$ has a stable coalition partition of $\mathcal{P}$. □

Simulation results in the next section verify the existence of $\mathcal{G}_a$'s stable state.

4.3. Algorithm design

In our scenario, UAVs can be able to get all information in context awareness and location awareness, thus coalition selection mechanism can be utilized in a centralized way to solve the proposed problem. It is known that learning algorithms have great efficiency in solving pure strategy NE points [30]. Compared to traditional search algorithms, learning algorithms can significantly improved search efficiency and of the strategy, especially facing diversity strategy sets. The mechanism we propose emphasizes single UAV's strategy selection. Combining the mechanism with the feature of the learning algorithm in exploring and selecting, strategy selection can hardly fall into trap loop (local optimum).

Therefore, we design binary log-linear learning [31] based coalition selection algorithm (BLL-CSA) to approach the equilibrium. BLL-CSA is shown in Algorithm 1, where β is the learning parameter ($\beta > 0$).

The core of the algorithm is the follows the coalition selection mechanism, according to theorem 3, it can converge $\mathcal{P}$ in the solution of the problem

5. Simulation Results and Discussion

In the simulation we consider a planar square scenario where distributed UAVs carry out data transmission. The coordinates of the central UAV are set to (100, 100, 30)(m), where the third dimension coordinate represents the relative height to the scenario. All the experiments considered parameters of proposed PDR model in [17] with 200-byte long packets and parallel UAVs, which makes $k1 = 10.6$,

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Algorithm 2: Binary log-linear learning based coalition selection algorithm (BLL-CSA)

Step 1: Initialize UAVs' state strategies $\{c_n\}_{n\in\mathcal{N}}$ considering data content s.
Loop: $k = 1, 2, \ldots,$ IterationMax
Step 2: Select one UAV randomly, say i. UAVs i generate a new strategy $\widetilde{c_i} \in C_i/\{c_i(j)\}$. On this basis, update strategy with different orders, and the update probability is given as follows:

$$P(c_i(j+1) = c_i(j)) = \frac{exp\{\beta U2_i(c_i(j), c_{-i}(j))\}}{exp\{\beta U2_i(c_i(j), c_{-i}(j))\} + exp\{\beta U2_i(\widetilde{c_i}, c_{-i}(j))\}}. \tag{16}$$

Step 3: Update $c_{-i}(j+1) = c_{-i}(j)$.
End loop:
Step 4: Loop step 1 through 3 and calculate $T(\varepsilon)$ according to Eq.(6)

$R = 64$m. Set transmission rate to be 800 pkts/s, so the packet transmission speed T_s is $160KB/s$. The position of the distributed UAVs will be generated randomly. We considered the data transmission throughput performance under multiple variables i.e. amount of UAVs (N), amount of total data L ($L = max(l_n)_{n\in\mathcal{N}}$), overlap degree of data Od ($Od = \sum_{n\in\mathcal{N}} L_n^{od}/L$ where L_n^{od} represents the number of overlap data in each UAVs), and the border length of the scenario. Given the corresponding parameters, the coordinates of every UAV are randomly generated by simulation. In addition, 100 operations are performed to prevent contingency.

5.1. Basic performance

Fig.2 shows an diagram form of data 1's transmission under coalition game model (using coalition order). It can be seen that the UAVs containing the requirement of data 1 finally form four coalition, and the central control UAV transmits data through the multi-hop mechanism. From the diagram there is no long-distance UAV-to-UAV link, which proves that the proposed model can effectively avoid high data transmission loss caused by long transmission path. This is consistent with the practical meaning of the system model.

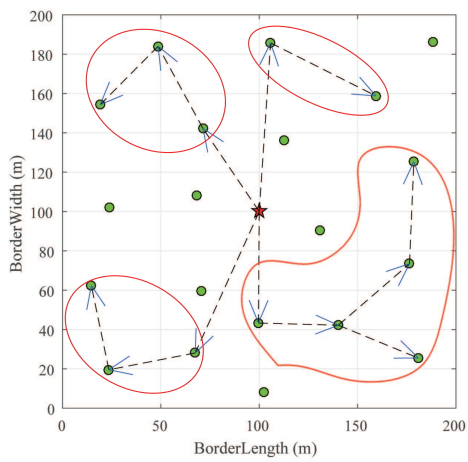

Figure 2. An diagram form of data 1's allocation and transmission under coalition game model.

Fig.3 shows the convergence curve of the proposed algorithm (coalition order and Pareto order), suggesting that by using proposed multi-UAV cooperative transmission approach based on group-buying, the game model can finally converge to a stable state.

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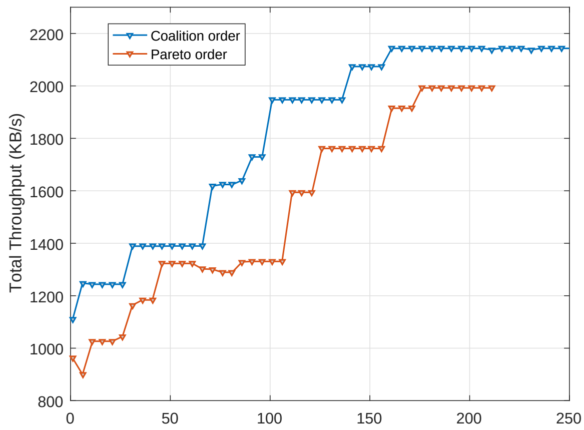
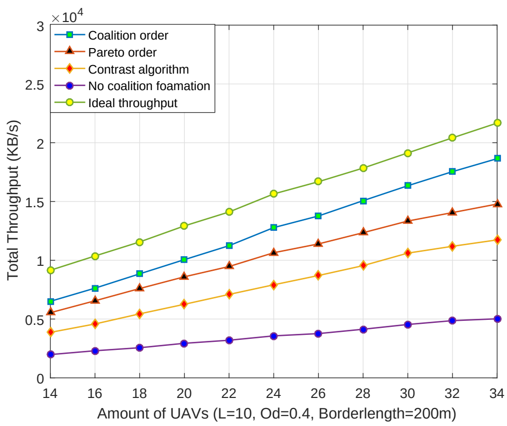


Figure 3. Convergence curve of the proposed approach with different orders.

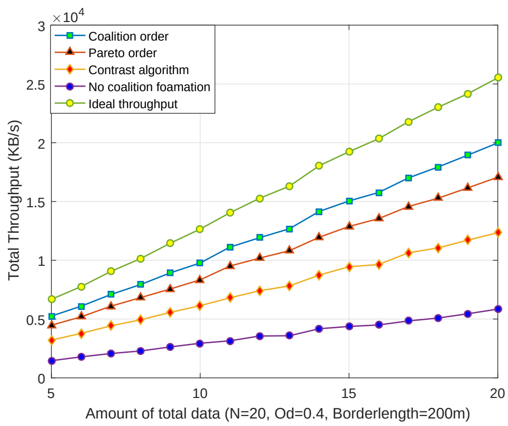
5.2. Different orders and contrast algorithms

In this subsection, we adopt a contrast algorithm, which only consider each UAV's overall data packet and form coalition partitions without overlap. The algorithm without coalition formation is also designed as a comparison method. In no coalition formation algorithm, there is no relay among UAVs, and all data transmission is carried out through the direct links with the central UAV. In addition, the ideal throughput is defined, which assume that there exists no energy loss in UAV-to-UAV links. By designing these comparison algorithms, we evaluate the performance of the model based on the proposed approach in different orders and contrast algorithms. When a comparison is preformed with one parameter, we set other parameters as specific values to facilitate the comparison.

It can be seen from Fig.4a that as the amount of UAVs and the data length increase, the data throughput will increases. The main reason is that given the setting of remaining parameters, increase of UAV numbers, data length or the overlap degree will directly lead to an improvement in the total data requirement, which is actually the ideal data throughput.



(a) The total data throughout considering amount of UAVs.



(b) The total data throughout considering total data length

Figure 4. Performance comparisons of algorithms based on UAV amount and total data length.

From Fig.4b, we can find that the total data throughput of our proposed algorithm can achieve a higher data throughput. In particular, the data throughput with coalition order is better than

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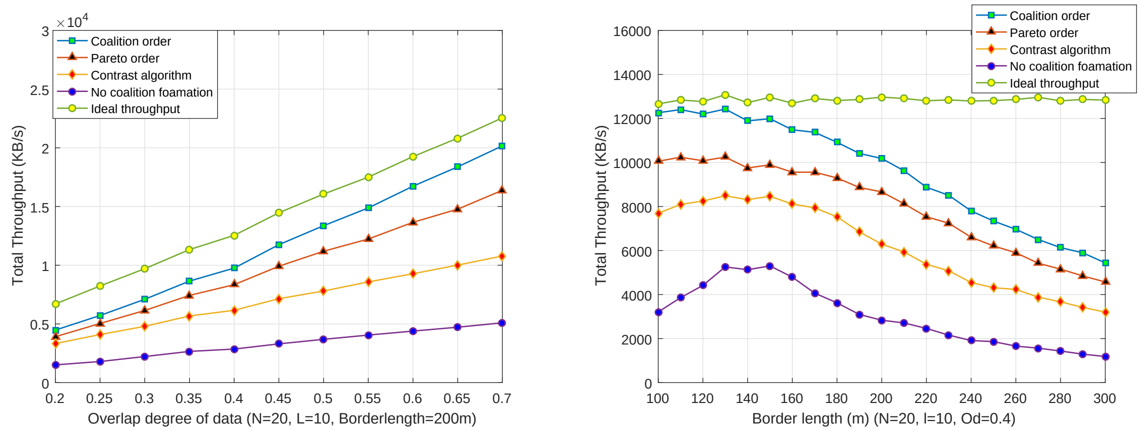
that with Pareto order. The main reason is that UAVs in coalitions have a greater probability and a stronger desire to leave the current coalition in search of better performance owing to the definition of coalition selection mechanism. In the case of Pareto order, however, UAVs are likely to be stuck with coalition members, because leaving the coalition could reduce profit for other members of the coalition. Moreover, in coalition order, the potential function refers to the overall throughput of the system model, then the algorithm with designed utility function can behave much better than the Pareto order. It is consistent with the description of Theorem 3.



(a) The total data throughout considering overlap degree of data.

(b) The total data throughout considering border length of scenario

Figure 5. Performance comparison of algorithms based on data overlap degree and border length of scenario.

As a matter of fact, When other variables are fixed, UAV amount and data length can directly affect overlap degree. Therefore, we now execute a comparative analysis of algorithm performance considering overlap degree of data. It can be seen intuitively from Fig.5a shows that as the overlap degree of data increases, the proposed approaches can achieve higher data throughput. The performance with the coalition order is also better than that with the Pareto order (analysis is the same as above). In summary, It shows the system model under coalition game framework can be well solved and the effectiveness of our proposed approaches is testified.

In the following, we take into account the relationships between total data throughput and border length, while the UAVs' data overlap degree is fixed. As shown in the Fig.5b, when the border length of the scenario is small, our proposed approaches can achieve high data throughput. Especially with coalition order, the performance is even close to the ideal throughput. However, as the border width of the scenario reaches to a certain value, the performance of the proposed approaches drops sharply, but is still more efficient than the comparison algorithms. We analyze that the characteristics of the channel model explain the phenomenon. Under the setting parameters, when the distance between UAVs is 64m, the transmission probability is only 50 %. When it comes to more than about 100 meters, the quality of UAV-to-UAV links become so poor that it cannot perform the transfer task. Under the premise of fixed UAV numbers, the increase of the border length in scenario makes it impossible to maintain the proper distance of among UAVs, leading to the overload of our system model.

5.3. Convergence performance

In the previous subsection, we analyzed the effects of the proposed approaches on the system model with two different orders. Next we compare the convergence performance of both orders. In the algorithm, we set one loop, in which all UAVs is traversed one time. When the UAV strategy in

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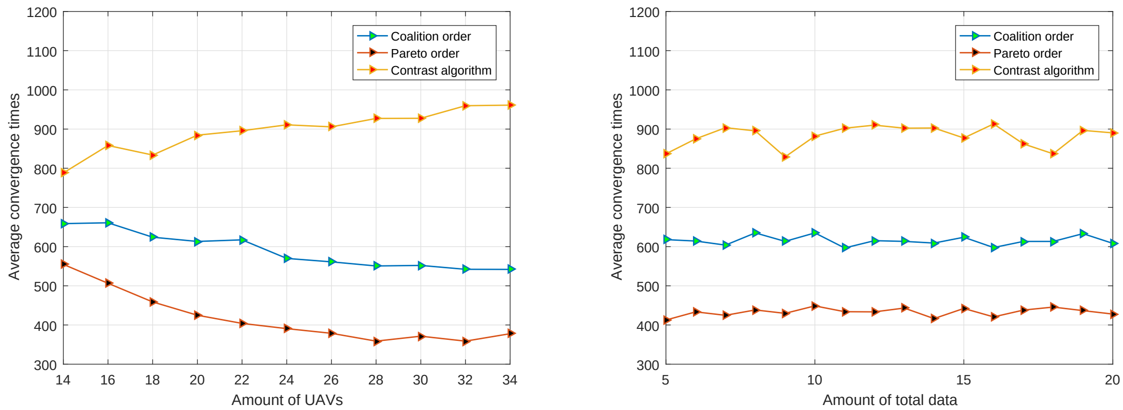
the three-round loop remains unchanged, the algorithm is considered to converge. Then the average convergence times is defined to characterize the convergence performance.

In order to make a better comparison, we also add a comparison algorithm described in the above. The upper bound of the iterations is set to 1000. Owing to the similar results, we present the average convergence times of the algorithm considering the UAV amount and total data length. In order to avoid contingency, simulations randomly generate the position of each UAV and data content given the specified overlap degree. An average calculation of 100 operations is carried out. It is shown in both Fig. 6a and Fig. 6b that compared with the contrast algorithm, the proposed method can converge the model to stable state in a shorter time, wherein the performance of Pareto order is better, which is consistent with the description in the previous section.



(a) The average convergence times considering UAV amount

(b) The total data throughput considering border length of scenario

Figure 6. The average convergence times of different amount of user and data with different methods..

In summary, we have drawn several conclusions: 1) The proposed coalition selection algorithm based on log-linear learning (BLL-CSA) can accurately describe the formations of UAV and the data transmission manner, and achieve higher data throughput of the system model. 2) Compared to the coalition order, with which the optimal solution of $\mathcal{P}$ can be obtained, Pareto order can converge the problem to the stable partition solution more speediness, but at the same time discard some of the performance.

6. Conclusion

In this paper, the resources allocation and data transmission problem in Flying Ad-hoc networks (FANETs) was modeled as a joint coalition game. First, we investigated a novel mechanism of data transmission to study inner coalition structure. Then, a resource allocation optimization based on group buying was presented for coalition forming. The game was classified into graph game and coalition formation game (CFG), both of which were proved to have stable solutions through the design of utility function and network formation algorithm. Meanwhile, performance comparisons were analyzed with coalition order and Pareto order. The simulation results showed that the designed data transmission and coalition formation mechanism can achieve higher data throughput in transmission than the other contrast algorithms. The proposed approach with Pareto order converged the problem to the stable partitions more speediness, while with the coalition order, our model can obtain an optimal solution. This work effectively improves the transmission efficiency in the UAV-to-UAV communication, which is of great significance in detection and surveillance.

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References

1. Zeng, Y.; Zhang, R.; Teng, J. L. Wireless communications with unmanned aerial vehicles: Opportunities and challenges. *IEEE Communications Magazine* **2016**, *54*, 36-42, DOI: 10.1109/MCOM.2016.7470933.
2. Liu, D.; Xu, Y.; Wang, J.; Xu, Y.; Anpalagan, A.; Wu, Q.; et al. Self-organizing relay selection in UAV communication networks: A matching game perspective. *IEEE Wireless Communications* **2018**, to appear, arXiv:1805.09257v1 [cs.NI].
3. İlker Bekmezci; Sahingoz, O. K.; Şamil Temel. Flying ad-hoc networks (FANETs): a survey. *Ad Hoc Networks* **2013**, *11*, 1254-1270, DOI: 10.1109/MSP.2009.000000.
4. Ruan, L.; Wang, J; et. al. Energy-efficient multi-UAV coverage deployment in UAV networks: a game-theoretic framework. *China Communications*, to appear.
5. Xu, Y.; Ren, G.; Chen, J.; Luo, Y.; Jia, L.; Liu, X.; et al. A one-leader multi-follower bayesian-Stackelberg game for anti-jamming transmission in UAV communication networks. *IEEE Access* **2018**, *6*, 21697-21709, DOI: 10.1109/ACCESS.2018.2828033.
6. Zou, Y.; Jiang, X.; Yan, P.; Zhu, J. Next-generation unmanned aerial vehicle (UAV) cooperative communications. *Journal of Nanjing University of Posts and Telecommunications (Natural Science Edition)* **2017**, *37*, 43-51, DOI: 10.14132/j.cnki.1673-5439.2017.03.005.
7. Fang, T.; Tian, H.; Zhang, X.; Yang, Y.; Zhang, Y.; Xu, Y. Location-aware emergency content delivery in UAV-assisted networks: A game-theoretic approach. submitted to IEEE Access.
8. APAThammawichai, M.; Baliyarasimhuni, S. P.; Kerrigan, E. C.; Sousa, J;. Optimizing communication and computation for multi-UAV information gathering applications. *IEEE Transactions on Aerospace and Electronic Systems* **2018**, *54*, 601-615, DOI: 10.1109/TAES.2017.2761139.
9. Fan, R.; Cui, J.; Jin, S.; Yang, K.; An, J. Optimal node placement and resource allocation for UAV relaying network. *IEEE Communications Letters* **2018**, *22*, 808-811, DOI: 10.1109/LCOMM.2018.2800737.
10. Lyu, J.; Zeng, Y.; Zhang, R.; Teng, J. L;Ṗlacement optimization of UAV-mounted mobile base stations. *IEEE Communications Letters* **2017**, *21*, 604-607, DOI: 10.1109/LCOMM.2016.2633248.
11. Say, S.; Inata, H.; Liu, J.; Shimamoto, S. Priority-based data gathering framework in UAV-assisted wireless sensor networks. *IEEE Sensors Journal* **2016**, *16*, 5785-5794, DOI: 10.1109/JSEN.2016.2568260.
12. Ruan, L.; Chen, J.; Guo, Q.; Jiang, H.; Zhang, Y.; Liu, D. A coalition formation game approach for efficient cooperative multi-UAV deployment. Preprints 2018, 2018090132 DOI: 10.20944/preprints201809.0132.v1.
13. Yang, D.; Xue, G.; Zhang, X. Group buying spectrum auctions in cognitive radio networks. *IEEE Transactions on Vehicular Technology* **2017**, *66*, 810-817, DOI: 10.1109/TVT.2016.2546948.
14. Zhang, Y.; Xu, Y.; Anpalagan, A. Context-aware group buying in ultra-dense small cell networks: unity is strength. *IEEE Wireless Communications* **2018**, accepted, arXiv:1807.08426v1 [cs.GT].
15. Saad, W.; Han, Z.; Debbah, M.; Hjørungnes, A.; Başar, T. Coalitional game theory for communication network. *IEEE Signal Processing Mag., Special Issue on Game Theory* **2009**, *26*, 77-97, DOI: 10.1109/MSP.2009.000000.
16. Ruan, L.; Chen, J.; et al. Context-aware group buying in D2D networks: An overlapping coalition formation game approach. In Proceedings of the 2017 IEEE 17th International Conference on Communication Technology (ICCT), Chengdu, China, Oct 2017, 142-149, DOI: 10.1109/ICCT.2017.8359758.
17. Pinto, L. R.; Moreira, A.; Almeida, L.; Rowe, A. Characterizing multihop aerial networks of COTS multirotors. *IEEE Transactions on Industrial Informatics* **2017**, *13*, 898-906, DOI: 10.1109/TII.2017.2668439.
18. "Parrot AR. drone 2, " [Online]. Available: http://ardrone2.parrot.com, Accessed on: Jan. 21, 2016
19. Wang, T.; Song, L.; Han, Z. Coalitional graph games for popular content distribution in cognitive radio VANETs. *IEEE Transactions on Vehicular Technology* **2013**, *62*, 4010-4019, DOI: 10.1109/TVT.2013.2245353.

20. Derks, J.; Kuipers, J.; Tennekes, M.; Thuijsman, F. Local dynamics in network formation. In Proceedings of Third World Congress of The Game Theory Society, Evanston, IL, Jul 2008.
21. Wang, T.; Song, L.; Han, Z.; Saad, W. Overlapping coalition formation games for emerging communication networks. *IEEE Network* **2013**, *2016*, 46-53, DOI: 10.1109/MNET.2016.7579026
22. Hamilton, J. Game Theory: Analysis of Conflict. by R. B. Myerson. In *Managerial and Decision Economics*, *13*, 369-369, www.jstor.org/stable/2487769.
23. Bogomolnaia, A.; Jackson, M. O. The stability of hedonic coalition structures. *Games & Economic Behavior* **2002**, *38*, 201-230, DOI: 10.1006/game.2001.0877.
24. Zhang, Y.; Xu, Y.; Wu, Q. Context awareness group buying in D2D networks: a coalition formation game-theoretic approach. *IEEE Transactions on Vehicular Technology* minor revision.
25. Bala, V.; Goyal, S;. Noncooperative model of network formation. *Econometrica* **2000**, *68*, 1181-1230.
26. Apt, K. R.; Witzel, A. A generic approach to coalition formation. *International Game Theory Review* **2009**, *11*, 347-367, arXiv:0709.0435v3 [cs.GT].
27. Monderer, D.; Shapley, L. S. Potential games. *Games and Economic Behavior* **1996**, *14*, 124-143, DOI: 10.1006/game.1996.0044.
28. Xu, Y.; Wang, J.; Wu, Q.; Anpalagan, A.; Yao, Y. D. Opportunistic spectrum access in cognitive radio networks: global optimization using local interaction games. *IEEE Journal OF Selected Topics in Signal Processing* **2012**, *6*, 180-194, DOI: 10.1109/JSTSP.2011.2176916.
29. Vcking, B. Congestion games: optimization in competition. *ACiD*, **2006** 9-20.
30. Xu, Y.; Wang, J.; Wu, Q.; Anpalagan, A.; Yao, Y. D. Opportunistic spectrum access in unknown dynamic environment: A game-theoretic stochastic learning solution. *IEEE Transactions on wireless communications* **2012**, *11*, 1380-1391, DOI: 10.1109/TWC.2012.020812.110025.
31. Li, P.; Duan, H. A potential game approach to multiple UAV cooperative search and surveillance. *Aerospace Science & Technology* **2017**, *68*, 403-415, DOI: 10.1016/j.ast.2017.05.031.