This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVT.2019.2936894, IEEE Transactions on Vehicular Technology

A Game Theoretic Approach for Mobility Prediction Clustering in Unmanned Aerial Vehicle Networks

Na Xing, Qun Zong, *Member, IEEE*, Liqian Dou, *Member, IEEE*, Bailing Tian, and Qing Wang, *Member, IEEE*

***Abstract*—Unmanned aerial vehicle (UAV) swarms have attracted great interests in numerous civil and military scenarios due to their flexible deployment and mobility. The increased network size poses a challenge for the network scalability. Clustering as an effective scheme, is able to provide efficient communication and network performance. In order to adapt to the change of network topology, the link subsistence probability is used to evaluate the mobility of UAVs. However, the UAVs usually perform tasks collaboratively, which leads to their movements are typically group-based. To this end, a coalition game theoretic framework is proposed to cluster UAVs into coalitions in a distributed autonomous manner, based on the group and the mobility information. The proposed game allows the UAVs with the same group, as much as possible, into one coalition under some constraints, such as cluster size and cluster diameter. To solve the game, each UAV makes its decision whether to switch based on the coalition value. Finally, some comparisons are provided to illustrate the efficiency of the proposed algorithm.**

***Index Terms*—Unmanned aerial vehicles, Clustering, Coalition game, Link subsistence probability, Switch operation.**

I. INTRODUCTION

RECENT advances in artificial intelligence, communication, sensors, and control technologies have witnessed a significant increase of unmanned aerial vehicles (UAVs), ranging from the high-altitude and long-endurance ones which may be used singly to execute missions, to the low-cost and short-range ones which may be used in swarms [1]–[3]. With their ease of deployment, low acquisition and maintenance costs, and high flexibility [4], the latter ones have been of particular interest in civil and military fields, including surveillance [5], relay communication [6], rescue operation [7]. Moreover, connecting those UAVs via a communication network to build multi-UAV networks, can greatly expand their ability for complex tasks [8].

Multi-UAV networks are viewed as a special form of mobile ad hoc networks (MANET) with non-centralized architecture [9]. Specially, numerous compelling applications, such as cooperative targets search or the surveillance for earthquake and forest fire disasters, etc., rely on the interaction among UAVs. UAV-to-UAV (U2U) information sharing is recognized as an effective solution to provide the high quality of service. However, in cases of facing a wide range of area or many complex tasks, it needs to deploy UAV swarms [10]. As a result, the number of nodes in the network will have a sharp increase and the network with flat structure may cause the degradation performance. Moreover, the dynamic characteristics of UAVs network also bring challenges to the stability of network topology [11]. To this end, the clustered multi-UAV network is proposed to handle the scalability and stability issues. Note that clustering and resource allocation (RA) are the important processes in operating a clustered network. Here, we focus on the clustering process and know that the inter-cluster RA is much less efficient than the intra-cluster RA [12].

In the clustering process, nodes are divided into several clusters. Most existing clustering methods firstly select some nodes as cluster heads (CHs) based on specified indicators, such as residual energy, signal strength and geographical position [13]–[15]. The CHs are responsible for the intra-cluster radio resource allocation and the communication with command center. Other nodes as cluster members could connect to the command center through the intra-cluster links with their cluster head rather than to establish a remote connection [12], [16]. This hierarchical network structure can not only reduce the number of long-distance communication, which can prolong the lifetime and enhance the reliability of the entire network, but also reuse radio resources to improve the network performance. Furthermore, by reducing the complexity of network management, clustering could provide efficient and steady routes with low routing overhead during route discovery and forwarding [17], [18].

However, these works focus on ad hoc networks without special organization. The nodes are quite equal to each other. While UAVs usually execute the task coordinately, such as multi-UAV target tracking and mapping applications [19]. In such networks, UAVs with the same task form a group. They have a similar mobility model with almost the same velocity and direction. Furthermore, the communication traffic mainly occurs in the same group. Therefore, it's necessary to design a group-based clustering algorithm. Moreover, due to the high mobility of UAVs, the network connectivity usually cannot be guaranteed [2]. For these characteristics, in order to reduce cluster switching operation and improve the network stability, it needs to predict the movements of UAVs. In this case, many clustering algorithms are proposed, which jointly consider mobility and some other criteria [20]–[22], such as degree,

N. Xing, Q. Zong, L. Dou, B. Tian and Q. Wang are with the School of Electrical and Information Engineering, Tianjin University, Tianjin 300072, China, (e-mail: xingna, zongqun, douliqian, bailing_tian, wangq@tju.edu.cn).

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVT.2019.2936894, IEEE Transactions on Vehicular Technology

connectivity and energy. But this lacks a theoretical framework and leads to frequent changes in clusters.

Due to the UAVs' high dynamism, the centralized optimization would bring high computing complex and large control cost. To address this challenge, there is a need for distributed and autonomous systems [23]. Hence, game theory is adopted, which is a very powerful mathematical tool for modeling and analyzing interactions between several decision makers [24], [25]. As a branch of game theory, coalition game theory is used to study the behavior of players when they cooperate, and provide a relevant framework for clustering. It has been widely applied in wireless communication and signal processing, and brought new insights for task allocation, interference management, power control, etc [26]–[28].

Therefore, in this paper, a distributed clustering algorithm is proposed which takes into account the cluster size and cluster diameter constraints. The coalition game theory is designed to model the cluster formation by identifying UAVs to players and clusters to coalitions. Each UAV makes its decision based on the coalition value. Considering the group and mobility information of UAVs, the proposed clustering achieves the optimal partition, which can allow the UAVs with the same group, as much as possible, into one cluster and efficiently improve the network stability.

A. Related Work

Clustering is one of the important research topics to manage the network in a more efficient way. Many works have shown that the hierarchical network is more stable and scalable as compared to flat structure [29].

Single-metric clustering: Lowest ID and highest degree (LID/HD) algorithms [30] are early examples of clustering. Every node broadcasts beacon messages and compares the ID or degree based on local information. Then the node is selected as a cluster head if it has the lowest ID or the highest degree in its neighborhood and the other nodes as cluster members are associated with the nearest cluster head. However, these clustering algorithms don't take into account the mobility characteristic which causes the network instability.

Combined-metrics clustering: As extensions to the LID/HD, some algorithms consider multiple metrics to form the most suitable clustering. A popular kind is the weighted clustering algorithm, which can flexibly assign the weighting factors for each metric. For example, a clustering algorithm is proposed for the UAV networking in near-space, where the ground stations calculate the initial cluster according to geography information. Then the cluster heads are selected based on the connection endurance time, node degree and remnant energy [21]. A similar idea is applied in the cluster-based location-aided routing protocol, which is proposed for UAV fleet networks and takes the relative speed and tactical value into consideration [31]. In order to improve connection stability, another cluster head selection algorithm is proposed for flying ad hoc networks based on the distance from ground control station and residual energy [13]. For efficient communication, a bio-inspired clustering scheme for flying ad hoc networks is proposed, where a path detection function based on the weighted residual energy, number of neighbors, and distance between the UAVs is used for route selection [32]. While different from the weighted clustering algorithm, some works apply fuzzy logic to synthesize multiple parameters. For instance, the residual energy, moving speed and pause time have been used to select cluster heads [33]. Moreover, in GPS-denied area, the fuzzy-inference system could be used to estimate the positions of UAVs [17]. However, the works aforementioned cannot update clusters according to the trend of movements. One possible solution is to design the mobility prediction strategy.

Mobility-aware clustering: Mobility is a prominent characteristic of mobile networks, and is the main factor causing rapidly changing network topology and intermittent communication links. Therefore, it's necessary to apply the mobility prediction strategy for forming and maintaining clusters. One of the early works for mobility prediction in multi-UAV networks uses the link expiration time [22], where a dictionary trie structure prediction algorithm is proposed to calculate the probability of neighbor set. The UAVs having the longest lasting neighbor set and the largest degree in their neighborhoods are selected as the cluster heads and the other UAVs will join the cluster head which has longer link expiration time with it. In the near future, UAVs are expected to be deployed to support a plethora of applications. UAVs can cooperate with vehicular ad hoc networks on the ground to provide a global vision of the connected segments [34]. A UAV-assisted reactive routing protocol is introduced to make the data delivery more reliable in vehicular ad hoc networks. This protocol exploits in conjunction with the flooding process to estimate accurately the expiration time of the discovered routing paths [35]. Another mobility prediction scheme is proposed, which uses the Doppler shifts to estimate relative speeds [36]. In bio-inspired mobility prediction clustering algorithm [37], the movement stability and link subsistence probability are adopted as the clustering criterions. For improving network stability, the UAV associates to the cluster head that can provide it with the largest virtual communication fluxes. In order to reduce the computation and routing overhead, the connectivity probability between any two UAVs is predicted based on the movement parameter, which is used to select cluster heads [20]. While some works focus on the link availability, which is defined as the probability that a link will be continuously available from t_0 to $t_0 + t$, given that it is active at t_0 [38]. This probability is used to predict the movement of nodes which is regarded as a stochastic process. In the distributed gateway selection algorithm [39], the influence of link availability and boundaries are considered to calculate the stability of UAVs. However, a central gateway is required to collect the stability information and compute the network partition parameter, which increases the overhead of central gateway. And the link availability is suitable for the two dimensional environment. These algorithms don't tackle the problem of clustering with group structure. Therefore, in this work, we are interested in a distributed clustering solution that considers the group and mobility characteristics.

Game Theory: Game theory has recently become prevalent in the field of resource allocation, network formation, jamming

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVT.2019.2936894, IEEE Transactions on Vehicular Technology

and many others [40]–[42]. Nowadays, in order to solve the clustering problem, there are many games proposed. For example, a hybrid game theory is proposed to model clustering problem in wireless sensor networks, which considers both node degree and distance to base station [43]. Furthermore, to achieve energy efficiency, an anti-coordination game is used to present a cost and payment-based clustering algorithm [44]. In order to provide efficient and stable routes for data dissemination in vehicular ad hoc networks, an evolutionary game theoretic framework is proposed to solve the clustering problem [18]. The node with highest throughput in a cluster is selected as the cluster head. And each member is associated with one of the cluster heads which provides the highest signal-to-noise ratio. In addition, the problem of correlation-aware clustering is studied by an evolutionary coalitional game, which clusters machine-type devices into coalitions based on data correlation and potential energy savings [45]. What's more, using coalition game theory, a novel generic distributed node clustering algorithm is designed to fill the theoretical gap in ad hoc networks. Both structured and unstructured networks are analyzed [12] by defining the corresponding revenue functions and heuristics to select candidate nodes for switch operations. Note that, it has to be mentioned that the impact of mobility is not taken into account in most works, which makes them unsuitable to mobile scenarios. Hence, in this study, based on group and mobility information, we use the coalition game theory framework to solve the clustering problem in multi-UAV networks.

B. Contribution

In this paper, we conceive a distributed clustering algorithm that can dynamically group UAVs into different clusters. Meanwhile, the algorithm is run at every UAV. The main contributions of this work are:

- A system model is proposed to find the partition that minimizes the average communication delay under the cluster constraints. The constraints include cluster size and cluster diameter, which have a greatly effect on the communication performance of multi-UAV networks.
- A coalition formation game framework is developed to model the clustering problem, identifying players to UAVs and coalitions to clusters. Using this approach, the decision-making process is performed in an automated and fully distributed fashion. In addition to group information, the link subsistence probability is used as mobility information to calculate the coalition value.
- In order to solve the game, a distributed coalition formation algorithm is presented, which determines the candidate switch operations and selects the best switch operation. It could converge to the stable state rapidly and improve the network performance.

C. Outline of Paper

The rest of this paper is organized as follows: In Section II, system model is given. The clustering algorithm based on coalition formation theory is presented in Section III. Section IV is dedicated to the simulation results. Finally, conclusions are drawn in Section V.

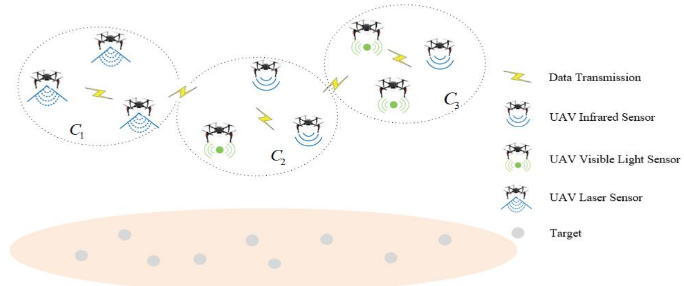


Fig. 1. Multi-UAV network scenario for targets search.

II. System Model

N UAVs which form multiple groups, are deployed to search targets in an unknown area. The set of groups G is defined as $\{G_1, ..., G_M\}$ where M is the number of groups. Let n_m^g be the size of UAVs of group G_m. Different kinds of sensor equipments can be utilized in various UAV platforms as illustrated in Fig. 1. Here, we consider each UAV group equips with one type of sensing devices (e.g., infrared sensors, visible light sensors, laser sensors, and etc.). In order to improve the search performance, UAVs in the same group need share real-time sensing information. However, the group characteristics and the dynamic UAV network topology bring in new challenges to clustering optimization.

To address these issues, a mobility prediction clustering algorithm is proposed to guarantee the communication performance among UAVs in this paper. To simplify the analyses, the set of UAVs are denoted by $\mathcal{N} = \{1, 2, ..., N\}$. The network graph can be defined as $\mathcal{G}(\mathcal{V}, \mathcal{E})$ where $\mathcal{V}$ represents the set of vertices (N UAVs) and $\mathcal{E}$ denotes the set of edges. Two UAVs i and j are neighbors if $(i, j) \in \mathcal{E}$, which depends on a minimum threshold value of signal-to-noise ratio (SNR) between UAV i and UAV j. A clustering solution leads to a partition $\mathcal{C}$, which is composed of K disjoint clusters noted C_k with $k \in \{1, ..., K\}$. Let n_k^c be the size of cluster C_k.

A. Channel Model

In this subsection, channel model is introduced. For U2U communication, when UAV i transmits signals to UAV j, the received power at UAV j from UAV i is expressed as

$$P_{i,j}^r = P_{i,j} h_{i,j} d_{i,j}^{-\alpha}, \tag{1}$$

where $P_{i,j}$ is the transmission power from UAV i to UAV j, and $h_{i,j}$ is the power gain of small scale fading channel, which is distributed exponentially with a unit mean [11]. $d_{i,j}$ is the distance between UAV i and UAV j and α is the mean path loss exponent. Therefore, the SNR from UAV i to UAV j is shown as

$$\Gamma_{i,j} = \frac{P_{i,j} h_{i,j} d_{i,j}^{-\alpha}}{N_0}, \tag{2}$$

where N_0 is assumed as additive white Gaussian noise. The successful packet transmission probability can be expressed

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVT.2019.2936894, IEEE Transactions on Vehicular Technology

by

$$P(\Gamma_{i,j} \geq \eta) = P\left(h_{i,j} \geq \frac{\eta d_{i,j}^{\alpha} N_0}{P_{i,j}}\right) = \exp\left(-\frac{\eta d_{i,j}^{\alpha} N_0}{P_{i,j}}\right), \quad (3)$$

where η is the SNR threshold. Here, the average transmission delay is defined as [11], [46]

$$w_{i,j} = \bar{R}_{i,j}(T_1 + T_2), \quad (4)$$

where T_1 and T_2 are the packet preparation delay and the packet transmission delay respectively. $\bar{R}_{i,j}$ is the average number of retransmissions, which can be calculated as follows

$$\bar{R}_{i,j} = \frac{1}{P(\Gamma_{i,j} \geq \eta)}. \quad (5)$$

B. Problem Formulation

In this paper, our objective is to find the partition $\mathcal{C} = \{C_1, C_2, ..., C_k\}$ that minimizes the average communication delay under the cluster constraints. The average communication delay is used to measure the performance of a clustering solution. The optimization problem can be formulated as follows:

$$\min_{\mathcal{C}} \frac{1}{N} \sum_{i \in \mathcal{V}, j \in \mathcal{V}} \pi_{i,j} \tau_{i,j}(\mathcal{C}). \quad (6)$$

$$s.t. \quad n_k^c \leq n_{\max}, \forall k, \quad (7)$$

$$\omega(C_k) \leq \omega, \forall k, \quad (8)$$

where $\pi_{i,j}$ is the communication probability between UAV i and UAV j. Here, we assume the communication traffic is generated within the same group. Therefore, $\pi_{i,j} = 1$ if $i \in G_m$ and $j \in G_m$. Otherwise $\pi_{i,j} = 0$. $\tau_{i,j}$ is the communication delay, which is defined as

$$\tau_{i,j}(\mathcal{C}) = \sum_{(i',j') \in q_{i,j}} \gamma_{i',j'} w_{i',j'}, \quad (9)$$

where $q_{i,j}$ is the shortest path between UAV i and UAV j, which can be expressed as $q_{i,j} = ((i, i_1), (i_1, i_2), ..., (i_H, j))$. The shortest path is calculated by the link average transmission delay and cluster structure. It is difficult to have an exact expression for delay. For simplicity, due to the inter-cluster RA is much less efficient than the intra-cluster RA, let $\gamma_{i',j'} = 1$ if (i', j') is the intra-cluster link and $\gamma_{i',j'} = 2$ if (i', j') is the inter-cluster link. A cluster will satisfy if it fulfills the cluster size and cluster diameter constraints. $n_{\max}$ is the cluster size constraint, which is generally enforced. ω is the cluster diameter constraint, which is closely related to the communication delay and overhead in intra-cluster. Here, the cluster diameter is defined as the length of the longest shortest path between any two UAVs in a cluster.

Note that a feasible clustering solution is to make the UAVs in the same group into one cluster. However, it cannot work well in the following two cases. One is that the members in the same group may not be neighbors, such as [19] and clusters with a large number of hops is not desirable. Another case is that the number of UAVs in the same group varies, such as [47] and the cluster size should be neither too small nor too large. Importantly, it is not an easy task to find the best partition

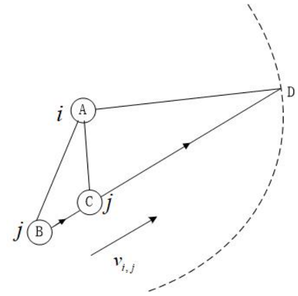


Fig. 2. An example for the relative movement scenario.

with the increase of network size. Therefore, in this paper, we focus on finding a feasible suboptimal solution. Two specific goals are given below. The first one is in order to control the number of clusters and inter-cluster links, let each cluster contain as many UAVs as possible with similar movements under cluster constraints. The second one is to make the UAVs from the same group, as much as possible, into one cluster. In addition, the UAVs are mobile, which makes a centralized approach encounter high computing complex and large control cost when the network scale grows. Hence, it's necessary to find a distributed cluster formation framework where each UAV could make its own switch operation decision.

III. Clustering Algorithm based on Coalition Formation Game

(6) is just a network cost function used to assess the quality of partition. In order to provide efficient communication, every cluster in the partition should fulfill cluster size and diameter constraints. However, mobility may change the cluster state. To reduce dissatisfaction, we use a mobility prediction strategy in clustering. When the clustering algorithm takes into account group and mobility characteristics, it is likely to provide more stable networks and better quality-of-service. In addition, coalition game theory could provide a suitable framework in the presence of constraints. Hence, it is used to model the cluster formation.

A. Mobility Prediction Strategy

In this paper, the link subsistence probability is used. Each UAV in the network broadcasts Hello packets periodically. Based on the received signal, the link subsistence probability between any two UAVs can be calculated. Fig. 2 shows the approaching scenario. Assume UAV i is static and located in position A, and UAV j moves with a relative speed $v_{i,j}$ towards UAV i. Considering the relative speed and direction remain constant in a small time interval t and the UAV j receives Hello packet successfully at positions B and C. Dashed line indicates part of the transmission range boundary of UAV i. The link subsistence probability can be calculated as follows [37]

$$L_{i,j} = \begin{cases} \frac{d_{C,D}}{v_{i,j} T}, & \frac{d_{C,D}}{v_{i,j}} < T \\ 1, & \frac{d_{C,D}}{v_{i,j}} \geq T \end{cases} \quad (10)$$

where T is the threshold value. Therefore, if the two UAVs have approximately same speed and direction, $L_{i,j} = 1$. $d_{C,D}$

and $v_{i,j}$ can be calculated based on the received Hello packets [36], [37]. In addition, the receding scenario uses the same method.

B. Coalition Formation Game Model

In coalition games, a set of players want to cooperate by forming coalitions to improve the performance of individual and the whole network. Note that the coalition is the term used in game theory, and here it is synonymous with cluster. First, the notion of coalition structure is given below [26].

Definition 1: A coalition partition or a coalition structure is defined as the set $\Pi = \{C_1, ..., C_K\}$ which partitions the UAVs set $\mathcal{N}$, i.e., $\forall k$, $C_k \subseteq \mathcal{N}$ are disjoint coalitions verifying $\bigcup_{k=1}^{K} C_k = \mathcal{N}$.

Then, the coalition game is defined by the pair $(\mathcal{N}, u)$, which are explained as follows:

- Players. $\mathcal{N}$ denotes the set of UAVs.
- Coalition Value. In this paper, the coalition value $u(C_k)$ depends on whether the constraints are satisfied, which is defined as:

$$u(C_k) = \begin{cases} r(C_k), & \text{if} \quad n_k^c \leq n_{\max}, \omega(C_k) \leq \omega, \\ 0, & otherwise, \end{cases} \tag{11}$$

where with $r(\emptyset) = 0$, $r(C_k)$ is defined as:

$$r(C_k) = F_1(C_k) \cdot \epsilon + \frac{1-\epsilon}{M} \sum_{m \in \mathcal{I}(C_k)} F_2(C_k), \tag{12}$$

where $\epsilon \in [0, 1]$ is used to make a trade off between the two goals. Let $\epsilon = 1$ represent no group characteristic. $\mathcal{I}(C_k)$ is the index of groups with at least one member in coalition C_k. $n_{m,k}^{g,c}$ is the number of UAVs of group G_m in coalition C_k. $F_1(C_k)$ and $F_2(C_k)$ are the functions to achieve the two goals respectively, which can be expressed as follows:

$$F_1(C_k) = \left(\min_{(i,j) \in \varepsilon_k^c} L_{i,j} \right) \frac{{n_k^c}^2}{n_{\max}^2}, \tag{13}$$

where $n_{\max}^2$ normalizes $F_1(C_k)$ in $[0, 1]$. The first term is the minimum link subsistence probability, which is used to increase the cluster life time and reduce the number of dissatisfying clusters. ε_k^c are the edges between the members of coalition C_k.

$$F_2(C_k) = \frac{{n_{m,k}^{g,c}}^2}{{n_m^g}^2}. \tag{14}$$

where $n_{m_g}^2$ normalizes $F_2(C_k)$ in $[0, 1]$.

In this work, our coalition game is with transferable utility (TU) where $u(C_k)$ is the total utility of coalition C_k. Since the coalition value only depends on the action chosen by the members in the coalition C_k, the proposed coalition game is in characteristic form. Further, the coalition value has different properties for static networks and mobile networks.

For a static network, the subsistence probability is one if two UAVs are neighbors. That is to say, $F_1(C_k)$ only depends on the number of UAVs in the cluster. Obviously, both functions $F_1(C_k)$ and $F_2(C_k)$ are strictly convex. If the cluster fulfills the constraints, this utility function is monotonic. Besides, a game is said to be superadditive if

$$u(C_1 \cup C_2) \geq u(C_1) + u(C_2), \forall C_1, C_2 \subseteq \mathcal{C}, C_1 \cap C_2 = \phi. \tag{15}$$

And a coalition game with TU is said to be convex if its value function satisfies

$$u(C_1) + u(C_2) \leq u(C_1 \cup C_2) + u(C_1 \cap C_2), \forall C_1, C_2 \subseteq \mathcal{C}. \tag{16}$$

The value function of convex games is superadditive. To our coalition game, let two different clusters satisfy the constraints be C_k and C_l. We assume that $C_k \cup C_l$ satisfies the constraints, then

$$\begin{aligned} F_1(C_k \cup C_l) &= \frac{(n_k^c + n_l^c)^2}{n_{\max}^2} \epsilon \\ &\geq \frac{{n_k^c}^2}{n_{\max}^2} \epsilon + \frac{{n_l^c}^2}{n_{\max}^2} \epsilon \\ &= F_1(C_k) + F_1(C_l) \end{aligned} \tag{17}$$

$$\begin{aligned} F_2(C_k \cup C_l) = & \sum_{m \in \mathcal{I}(C_k \cup C_l)} \frac{(n_{m,k}^{g,c} + n_{m,l}^{g,c})^2}{{n_m^g}^2} \\ = & \sum_{m \in \mathcal{I}(C_k \cap C_l)} \frac{{n_{m,k}^{g,c}}^2 + {n_{m,l}^{g,c}}^2 + 2 n_{m,k}^{g,c} n_{m,l}^{g,c}}{{n_m^g}^2} \\ & + \sum_{m \in \mathcal{I}(C_k), m \notin \mathcal{I}(C_l)} \frac{{n_{m,k}^{g,c}}^2}{{n_m^g}^2} + \sum_{m \notin \mathcal{I}(C_k), m \in \mathcal{I}(C_l)} \frac{{n_{m,l}^{g,c}}^2}{{n_m^g}^2} \\ \geq & F_2(C_k) + F_2(C_l) \end{aligned} \tag{18}$$

Therefore, $u(C_k \cup C_l) \geq u(C_k) + u(C_l)$. The utility function in the static networks is superadditive and the TU game is convex. However, the group characteristic of UAVs and the constraints limit the formation of the grand coalition.

For a mobile network, in order to adapt to mobility and reduce the number of clusters that fail to satisfy constraints, $F_1(C_k)$ depends on the minimum link subsistence probability and the number of UAVs in the cluster. Therefore, the utility function isn't monotonic and superadditive. The TU game isn't convex. However, if some UAVs are close or in the same group, they will merge. Next, let's recall the notion of switch operation [48]. A transfer of a UAV from one coalition to another is called a switch operation:

Definition 2: A switch operation $\sigma_{k,l}(\mathcal{P})$ is defined as players $\mathcal{P}$ decide to leave their current coalition $C_k \in \Pi$, and join another coalition $C_l \in \Pi \cup \{\emptyset\}$, $C_l \neq C_k$. Hence, $\sigma_{k,l}(\mathcal{P}) : C_k \mapsto C_k \setminus \mathcal{P}$, and $C_l \mapsto C_l \cup \mathcal{P}$.

Though the decision of switch operation would be made by UAVs individually, the utility of the entire network should also be considered. Then, we have the following definition.

Definition 3: For a switch operation $\sigma_{k,l}(\mathcal{P})$, C_k, C_l are the related coalitions before the switch operation, and $C_{k'}$, $C_{l'}$ with $k' = k \setminus \mathcal{P}$, $l' = l \cup \mathcal{P}$ are the related coalitions after the switch operation respectively. The switch operation gain is defined as:

$$\rho(\sigma_{k,l}(\mathcal{P})) = u(C_{l'}) + u(C_{k'}) - u(C_l) - u(C_k). \tag{19}$$

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVT.2019.2936894, IEEE Transactions on Vehicular Technology

C. Algorithm Description

Given the related concepts of coalition formation game above, the clustering algorithm is designed as follows, which is run at each UAV.

Firstly, let's assume that UAV i belongs to cluster C_k and group G_m. In order to merge the UAVs in group G_m into one coalition, we find the UAV j, which is the neighbor of UAV i in the same group and has the largest degree. Thus, the set S, which is used to form a candidate set for a switch operation, can be obtained by considering all the neighbors of UAV j in group G_m. However, due to the UAVs are mobile, the network topology changes over time. As a consequence, the cluster satisfies the constraints at one time, and may no longer satisfy them later. Therefore, let every UAV i first check if its cluster constraints are satisfied when it starts a decision making procedure. Refer to [12], we give a way to find the sets of candidate UAVs for a switch operation according to the checking result.

- When UAV i starts a decision making process and its cluster satisfies the constraints, let the sets of candidate UAVs for the switch operation be $\{i\}$ and S.
- When UAV i starts a decision making process and its cluster doesn't satisfy the constraints due to the mobility of UAVs, let the set of candidate UAVs for the switch operation be S.

After that, the candidate switch operations are generated between neighbor clusters. Here, two clusters are neighbors if one node in a cluster is the neighbor of one node in another cluster. However, when one constraint of cluster C_k is not satisfied, the cluster value will be $u(C_k) = 0$. Note that, the cluster $C_{l'}$ should satisfy $n_{l'}^c \leq n_{\max}$ and $\omega(C_{l'}) \leq \omega$. In addition, if $n_k^c \leq n_{\max}$ and $\omega(C_k) \leq \omega$, then the switch operation $\sigma_{k,l}(\mathcal{P})$ needs to guarantee $n_{k'}^c \leq n_{\max}$ and $\omega(C_{k'}) \leq \omega$ in order not to break the properties of the cluster. Moreover, the switch operation is valid if $\rho(\sigma_{k,l}(\mathcal{P})) > 0$.

Then, the best switch operation is selected based on $\rho(\sigma_{k,l}(\mathcal{P}))$. To this end, the preferences must be built over the possible switch operation. For evaluating these preferences over the candidate switch operations, the concept of the preference relation or order [12], [26] is introduced.

Definition 4: The preference relation or order $\succ$ is a complete, and transitive binary relation, which is defined over two different switch operations $\sigma_{k,l}(\mathcal{P}_i)$ and $\sigma_{k',l'}(\mathcal{P}_j)$ such that:

$$\sigma_{k,l}(\mathcal{P}_i) \succ \sigma_{k',l'}(\mathcal{P}_j) \Leftrightarrow \rho(\sigma_{k,l}(\mathcal{P}_i)) > \rho(\sigma_{k',l'}(\mathcal{P}_j)). \quad (20)$$

Finally, the best switch operation is performed. A summary of the proposed clustering algorithm is given in Algorithm 1.

Algorithm 1 The clustering algorithm based on coalition formation game

// UAV i belonging to group G_m in cluster C_k, starts a decision-making process.

Find UAV $j \in C_k$, which is the neighbor of UAV i of the same group and has the largest degree.
Initialize the set S, which is obtained by considering all the neighbors of UAV j in group G_m.
  // Find the sets of candidate UAVs for a switch operation
Set $\mathcal{U} = \emptyset$
if the cluster C_k satisfies the constraints **then**
  if the cluster $C_k \setminus i$ satisfies the constraints **then**
    Set $P = \{i\}$.
  end if
  if the cluster $C_k \setminus S$ satisfies the constraints **then**
    Set $P = P \cup \{S\}$.
  end if
else
  Set $P = S$.
end if
  // Generate the candidate switch operations
for each $\mathcal{P} \in P$ **do**
  Set $\mathcal{U} = \{\sigma_{k,\emptyset}(\mathcal{P})\}$
  for each neighbor cluster C_l of C_k **do**
    if the cluster $C_l \cup \mathcal{P}$ satisfies the constraints **then**
      if $\rho(\sigma_{k,l}(\mathcal{P})) > 0$ **then**
        Set $\mathcal{U} = \mathcal{U} \cup \sigma_{k,l}(\mathcal{P})$
      end if
    end if
  end for
end for
  // Select the best switch operation
Find $\mathcal{P}^*$ and l^* such that $\sigma_{k,l^*}(\mathcal{P}^*) \succ \sigma_{k,l}(\mathcal{P})$, $\forall \sigma_{k,l}(\mathcal{P}) \in \mathcal{U}$
  // Perform the switch operation
The UAVs $\mathcal{P}^*$ in cluster C_k leave C_k and join in C_{l^*}. That is, the coalition structure is updated as follows $C_k \mapsto C_k \setminus \mathcal{P}^*$, and $C_{l^*} \mapsto C_{l^*} \cup \mathcal{P}^*$

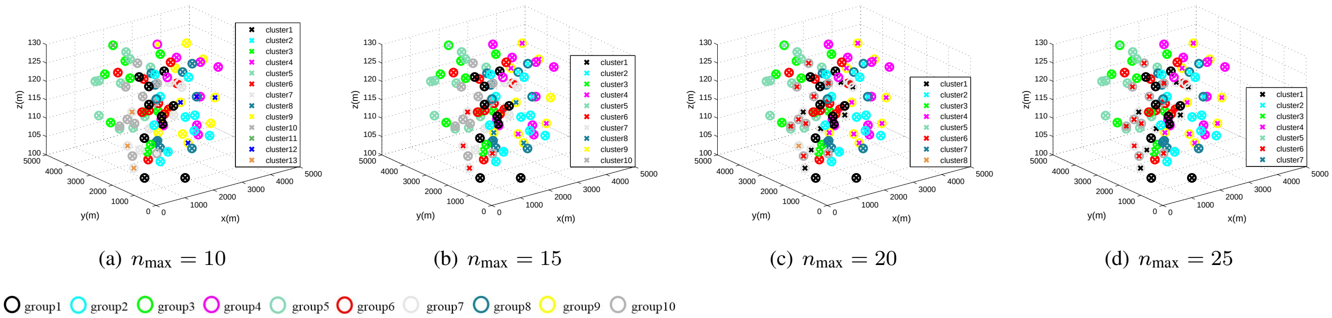
D. Properties Analysis

Proposition 1: *For a static network, starting from any initial coalition partition $\Pi_{initial}$ in which each cluster satisfies all constraints, the proposed clustering algorithm based on coalition formation game always converges to a final coalition partition Π, which is composed of a number of disjoint coalitions.*

Proof: Since the network is static, the subsistence probability will be always one if two UAVs are neighbors. Let Π_n denote the coalition partition after n switch operations (the index n represent the number of switch operations performed by all players). Given the initial coalition partition $\Pi_{initial}$, the proposed clustering algorithm is composed of a sequence of switch operations. Each switch operation transforms the current coalition partition Π into another partition Π'. Therefore, the cluster formation phase consists of a sequence of switch operations such as the following:

$$\Pi_{initial} \to \Pi_1 \to \Pi_2 \to \cdots \to \Pi_n \to \cdots . \quad (21)$$

Since the initial clusters satisfy the constraints, it can be seen that the clusters in the new partition still satisfy the constraints after a switch operation. Thus, by recurrence, the constraints are always satisfied. In addition, every switch operation leads



(a) $n_{\max} = 10$ (b) $n_{\max} = 15$ (c) $n_{\max} = 20$ (d) $n_{\max} = 25$

Fig. 3. Simulation snapshots with different cluster size constraint $n_{\max}$.

to an increase in the total of the coalition values of all coalitions. Given the fact that the number of partitions is finite, the sequence in (21) will always converge to a final coalition partition. Hence, the proposed clustering algorithm based on coalition formation game always converges to a final coalition partition consisting of a number of disjoint coalitions, which completes the proof.

The stability of the resulting coalition partition can be studied using the following stability notion from game theory [49]. In other words, a partition is Nash-stable if there is no UAV has an incentive to deviate from its current coalition.

Definition 5: A partition $\Pi = \{C_1, ..., C_K\}$ is Nash-stable if $\forall k \in K$, $\forall i \in C_k$, $\rho(\sigma_{k,l}(\{i\})) \leq 0$ for all $C_l \in \Pi \cup \emptyset$.

Proposition 2: *Based on Proposition 1, the final coalition partition Π is Nash-stable.*

Proof: For the coalition partition Π, no UAV $i \in \mathcal{N}$ has a switch incentive. Assume that the final coalition partition Π from the proposed clustering algorithm is not Nash-stable. Then, there is a switch operation such that $\rho(\sigma_{k,l}(\{i\})) > 0$. Hence, the UAV i in coalition C_k can trigger a switch operation to join in coalition C_l, which contradicts the fact that Π is the final partition. Therefore, the final coalition partition Π resulting from Proposition 1 is Nash-stable.

IV. Simulation Results

In our simulation, a 5 km $\times$ 5 km square area is considered. Unless stated otherwise, we assume that the number of groups $M = 10$. Considering the different complexity of tasks, the number of UAVs in each group is different but at least one UAV. The SNR threshold is defined by 0dB, which means two UAVs could not communicate if SNR is lower than 0dB. The maximum speed is set to $v_{\max} = 10$m/s and the altitude of UAVs is between 100m and 130m. The transmission power of UAV is 20dBm and the mean path-loss exponent is $\alpha = 4$. The noise power is -100dBm. The delay is $T_1 = 0$ and $T_2 = 50\mu$s [11] and the system carrier frequency is 2.4 GHz. The Hello interval is set to 1s and the simulation time is 100s. The tradeoff parameter is equal to $\epsilon = 10^{-5}$ and all statistical simulation results are averaged over 100 independent runs. Finally, the threshold value to calculate the link subsistence probability is set to $T = 5$ units of time. Performance evaluations for both static and mobility are made via simulations.

A. Mobility Model

In this paper, the low cost and short range UAVs form groups to perform tasks. And the problem of task allocation is assumed to be already completed. In order to imitate the mobility characteristic of UAVs, a new mobility model is proposed based on the Reference Point Group Mobility (RPGM) model [50], in which all UAVs in the same group move according to their assigned task. Here, each UAV group needs to perform a sequence of tasks. The location of these tasks are randomly generated and remain constant in their own interval. Furthermore, we assume the average length of the interval is 20 units of time. Therefore, the movement of a UAV is composed of some random length intervals. UAVs need to change their speed and direction in each interval based on the location of next task. Thus let every UAV choose a random location around each of its task, then toward it flying.

B. Simulation Snapshots

In this subsection, we consider there are 4 different cluster sizes with respective $n_{\max} = 10$, $n_{\max} = 15$, $n_{\max} = 20$ and $n_{\max} = 25$. Note that in order to make a comparison, the movements of UAVs are same in each case. Here, each UAV runs the algorithm periodically with 5 units of time on average to adapt to the changing network topology.

Fig. 3 illustrates the clustering results at the same time where we can see that the number of clusters varies from 13 at $n_{\max} = 10$ to 7 at $n_{\max} = 25$. There are a singleton cluster and two clusters that the cluster size is less than five at $n_{\max} = 10$. These small clusters are inefficient for network performance. From Fig. 3, the average number of groups per cluster is 1.3, 1.7, 1.75 and 2 respectively. This means the proposed algorithm makes the UAVs from the same group, as much as possible, into one cluster. Furthermore, when $n_{\max}$ is large, each cluster contains as many UAVs as possible to control the number of clusters and reduce the number of inter-cluster links.

C. Convergence Analysis

The performance of algorithm is directly related to the convergence speed. Fig. 4 shows the number of iterations needed till convergence of the algorithm, as the size of the network N increases. A boxplot is drawn to detail the statistical result. From bottom to top the different bars show the lowest value,

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVT.2019.2936894, IEEE Transactions on Vehicular Technology

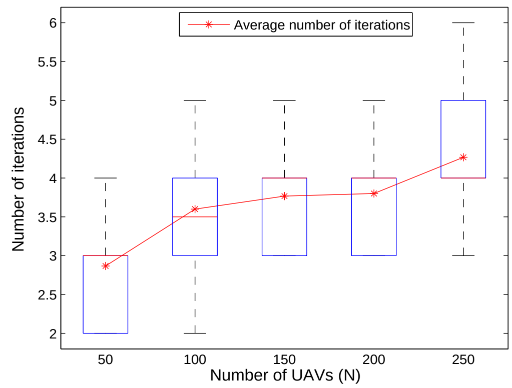


Fig. 4. The number of iterations till convergence.

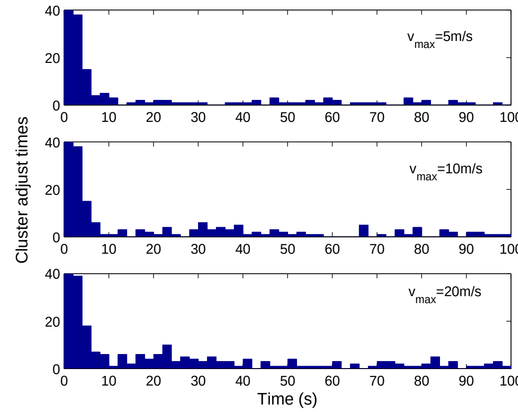


Fig. 6. The cluster adjust times vs. time in a network with $N = 100$ UAVs.

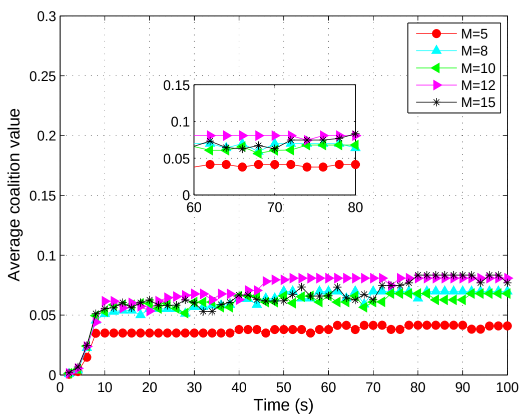


Fig. 5. The average coalition value vs. time in a network with $N = 100$ UAVs.

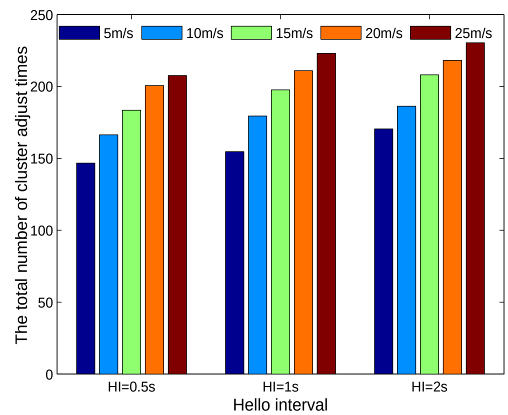


Fig. 7. The total number of cluster adjust times vs. HI values and maximum speed in a network with $N = 100$ UAVs.

first, median and third quartiles, and highest value. During an iteration, all UAVs run the algorithm independently and make a decision whether to switch the current cluster. This figure shows that, as the number of UAVs increases, the total number of iterations required to get the stable network increases. This result is due to the fact that, the number of candidate switch operations increases, thus more iterations are required for the convergence. For instance, the minimum, average and maximum number of iterations vary, respectively, from 2, 2.9, 4 at $N = 50$ UAVs up to 3, 4.2, 6 at $N = 250$ UAVs. Therefore, the figure demonstrates that, our proposed algorithm could converge to a final Nash-stable partition after several iterations. Moreover, the number of iterations is slightly more even for large-scale networks.

D. Performance Evaluation

Let us consider the impact of some factors on the network performance, such as the number of groups, maximum moving speed and the Hello interval.

Fig. 5 illustrates the average coalition value in the cases of different number of groups when $N = 100$ and $v_{\max} = 10$m/s. We can see that with the number of groups M increasing, the average coalition value increases. On one hand, UAVs from the same group are more likely to join a cluster and the number of clusters may increase. On the other hand, the average group size decreases when M increases. However, the average coalition value stays almost unchanged when $M = 5$. Because the cluster modifications have less impact on the coalition value with lower number of groups.

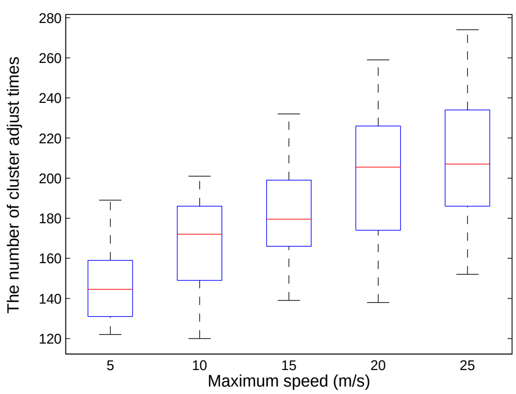
In Fig. 6, the cluster adjust times is presented for a network with $N = 100$ UAVs as the maximum speed varies. To simplify the simulation without losing generality, we consider three scenarios, such as $v_{\max} = 5$m/s, $v_{\max} = 10$m/s and $v_{\max} = 20$m/s. This figure shows that, after a period of time (less than 10s), the frequency of modifications becomes lower. It demonstrates that the proposed algorithm could convergence to form stable clusters. Moreover, the cluster will change following the movement of UAVs. However, UAVs move with high speed would cause the links to be established intermittently and force the network to organize and re-organize frequently, thus increasing the number of modifications.

In Fig. 7, we evaluate the performance of our proposed algorithm on the cluster adjust times when $N = 100$ under different Hello interval (HI) values and maximum speed. At the beginning of the simulation, each UAV creates a cluster

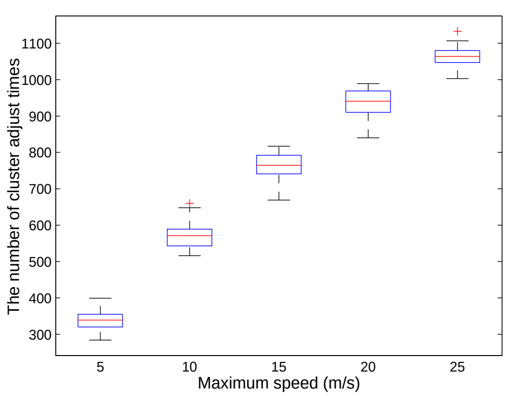
This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVT.2019.2936894, IEEE Transactions on Vehicular Technology

independently. The simulation time is set to 100s. From Fig. 7, we can see that if HI is large, the network would be adjusted more times. thus leading to more communication overhead. This phenomenon means that the mobility predict strategy would be more accurate if the HI is small. Meanwhile, for a same HI, when the UAV speed increases, the probability of a cluster becoming dissatisfied is high, thus increasing the number of modifications.

The above simulations are based on a modified RPGM model. For the sake of generality, we consider a random walk (RW) mobility model. In this model, UAVs change their speed and direction irrelevantly. Therefore, the UAVs don't have group characteristic, thus parameter $\epsilon = 1$. The total number of cluster adjust times is shown in Fig. 8(b). It can be seen that the RW model requires more cluster adjust times than the modified RPGM model. The performance of the modified RPGM model is illustrated in Fig. 8(a).



(a) The modified RPGM model.



(b) The random walk mobility model.

Fig. 8. The cluster adjust times vs. maximum speed.

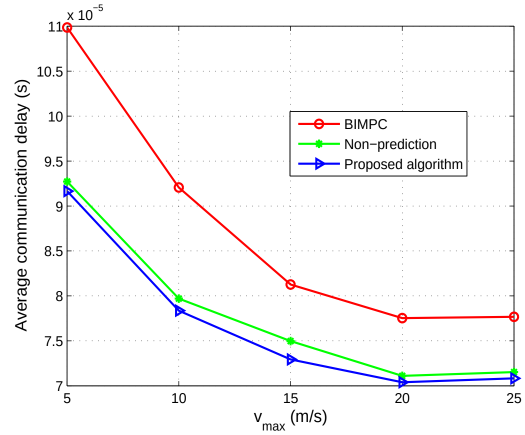


Fig. 9. The average communication delay vs. maximum speed.

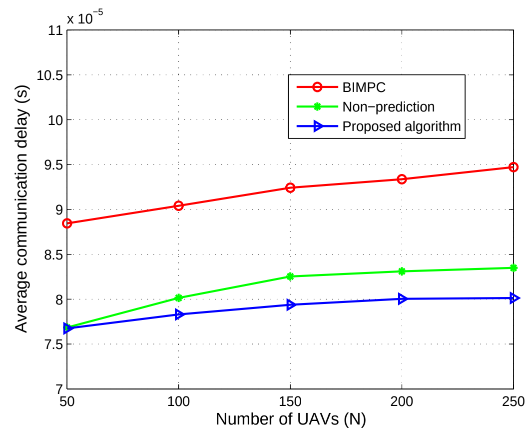


Fig. 10. The average communication delay vs. the number of UAVs.

E. Comparison

There are few clustering algorithms that consider the group characteristic of UAVs. Therefore, we compare our proposed algorithm with the non-prediction scheme [12] and the Bio-inspired mobility prediction clustering (BIMPC) algorithm [37]. In the non-prediction scheme, it doesn't consider the mobility prediction mechanism. In the BIMPC algorithm, cluster heads are elected first.

Fig. 9 depicts the average communication delay with different maximum speed. With the increment of maximum speed, we can observe that the average communication delay decreases because larger speed provides a more similarity. The UAVs from the same group are more likely to merge into one cluster. The communication delay in the proposed algorithm is lower than that of the non-prediction scheme, due to the efficient prediction mechanism. When compared with the BIMPC algorithm, our proposed can achieve 12% lower communication delay on average, because the BIMPC algorithm does not consider the group characteristics of UAVs.

Fig. 10 shows the average communication delay with different number of UAVs. It is shown that the average communication delay increases with more UAVs in the network. Due to the cluster constraints, a larger UAVs not only divides the UAVs from the same group into multiple clusters, but also leads to a larger number of inter-cluster links. Therefore, more average communication delay is generated by the inter-cluster links.

In addition, Table I shows the number of clusters that fail

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVT.2019.2936894, IEEE Transactions on Vehicular Technology

to satisfy the constraints during 100s simulation. We can see from the simulation results, as the maximum speed increases, the number of clusters that fail to satisfy the constraints increases. This is due to the fact that, as the UAVs move faster, clusters are more likely to fail to satisfy the constraints. Moreover, our proposed algorithm is able to predict a change in the topology and reacts before the cluster fails to satisfy the constraints, while the BIMPC scheme does not consider the cluster size constraint.

Table I The total number of clusters that fail to satisfy constraints during 100s simulation for different maximum speed

	$v = 5$	$v = 10$	$v = 15$	$v = 20$	$v = 25$
BIMPC scheme	266	282	292	287	312
Non-prediction	1	2	4	5	5
Proposed algorithm	1	1	2	3	3

V. Conclusions

This paper studies a new clustering problem in the multi-UAV network. By considering some constraints, such as the cluster size and cluster diameter, the stable clusters are achieved via considering group information and exploiting the link subsistence probability induced by UAV mobility. The clustering problem is modeled as a coalition formation game among UAVs that interact in order to form disjoint coalitions. To solve the game, we introduce an algorithm that allows the UAVs to join or leave the coalitions based on their preferences which capture the goal and constraints achieved by the coalition. In this way, the proposed coalition formation algorithm converges to a Nash-stable solution. Simulation results show the UAVs can self-organize into independent coalitions. The results also demonstrated that the proposed algorithm achieves notable gains compared with other approach.

References

[1] B. Tian, L. Liu, H. Lu, Z. Zuo, Q. Zong, and Y. Zhang, “Multivariable finite time attitude control for quadrotor UAV: Theory and experimentation,” *IEEE Transactions on Industrial Electronics*, vol. 65, no. 3, pp. 2567–2577, 2018.

[2] L. Gupta, R. Jain, and G. Vaszkun, “Survey of important issues in UAV communication networks,” *IEEE Communications Surveys & Tutorials*, vol. 18, no. 2, pp. 1123–1152, 2016.

[3] B. Tian, Z. Zuo, X. Yan, and H. Wang, “A fixed-time output feedback control scheme for double integrator systems,” *Automatica*, vol. 80, pp. 17–24, 2017.

[4] S. Hayat, E. Yanmaz, and R. Muzaffar, “Survey on unmanned aerial vehicle networks for civil applications: A communications viewpoint,” *IEEE Communications Surveys & Tutorials*, vol. 18, no. 4, pp. 2624–2661, 2016.

[5] Y. Zhou, N. Cheng, N. Lu, and X. S. Shen, “Multi-UAV-aided networks: Aerial-ground cooperative vehicular networking architecture,” *IEEE Vehicular Technology Magazine*, vol. 10, no. 4, pp. 36–44, 2015.

[6] Y. Zeng, R. Zhang, and J. L. Teng, “Wireless communications with unmanned aerial vehicles: opportunities and challenges,” *IEEE Communications Magazine*, vol. 54, no. 5, pp. 36–42, 2016.

[7] M. Erdelj, E. Natalizio, K. R. Chowdhury, and I. F. Akyildiz, “Help from the sky: Leveraging UAVs for disaster management,” *IEEE Pervasive Computing*, vol. 16, no. 1, pp. 24–32, 2017.

[8] A. E. Gil, K. M. Passino, S. Ganapathy, and A. Sparks, “Cooperative task scheduling for networked uninhabited air vehicles,” *IEEE Transactions on Aerospace & Electronic Systems*, vol. 44, no. 2, pp. 561–581, 2008.

[9] I. Bekmezci, O. K. Sahingoz, and S. Temel, “Flying ad-hoc networks (FANETs): A survey,” *Ad Hoc Networks*, vol. 11, no. 3, pp. 1254–1270, 2013.

[10] B. Tian, H. Lu, Z. Zuo, and W. Yang, “Fixed-time leader-follower output feedback consensus for second-order multiagent systems,” *IEEE Transactions on Cybernetics*, vol. 49, no. 4, pp. 1545–1550, 2019.

[11] Q. Zhang, M. Jiang, Z. Feng, W. Li, and M. Pan, “IoT enabled UAV: Network architecture and routing algorithm,” *IEEE Internet of Things Journal*, vol. 6, no. 2, pp. 3727–3742, 2019.

[12] R. Massin, C. J. L. Martret, and P. Ciblat, “A coalition formation game for distributed node clustering in mobile ad hoc networks,” *IEEE Transactions on Wireless Communications*, vol. 16, no. 6, pp. 3940–3952, 2017.

[13] J. H. Park, S. C. Choi, H. R. Hussen, and J. Kim, “Analysis of dynamic cluster head selection for mission-oriented flying ad hoc network,” in *International Conference on Ubiquitous & Future Networks*, 2017, pp. 21–23.

[14] B. Wu, Y. Feng, H. Zheng, and X. Chen, “Dynamic cluster members scheduling for target tracking in sensor networks,” *IEEE Sensors Journal*, vol. 16, no. 19, pp. 7242–7249, 2016.

[15] Z. Wang, L. Liu, M. C. Zhou, and N. Ansari, “A position-based clustering technique for ad hoc intervehicle communication,” *IEEE Transactions on Systems Man & Cybernetics Part C*, vol. 38, no. 2, pp. 201–208, 2008.

[16] C. Cooper, D. Franklin, M. Ros, F. Safaei, and M. Abolhasan, “A comparative survey of VANET clustering techniques,” *IEEE Communications Surveys & Tutorials*, vol. 19, no. 1, pp. 657–681, 2017.

[17] A. Bradai, K. Fekher, K. Singh, and M. Atri, “Localization and energy-efficient data routing for unmanned aerial vehicles: Fuzzy-logic-based approach,” *IEEE Communications Magazine*, vol. 56, no. 4, pp. 129–133, 2018.

[18] A. Khan, M. Abolhasan, and N. Wei, “An evolutionary game theoretic approach for stable and optimized clustering in VANETs,” *IEEE Transactions on Vehicular Technology*, vol. 67, no. 5, pp. 4501–4513, 2018.

[19] M. Thammawichai, S. P. Baliyarasimhuni, E. C. Kerrigan, and J. Sousa, “Optimizing communication and computation for multi-UAV information gathering applications,” *IEEE Transactions on Aerospace & Electronic Systems*, vol. 54, no. 2, pp. 601–615, 2018.

[20] J. Shu, Y. Ge, L. Liu, and L. Sun, “Mobility prediciton clustering routing in UAVs,” in *International Conference on Computer Science and Network Technology*, 2012, pp. 1983–1987.

[21] K. Liu, J. Zhang, and T. Zhang, “The clustering algorithm of UAV networking in near-space,” in *Proceedings of the 8th International Symposium on Propagation and EM Theory, Antennas, ISAPE*, 2008, pp. 1550–1553.

[22] C. Zang and S. Zang, “Mobility prediction clustering algorithm for UAV networking,” in *Proceedings of the IEEE Globecom Workshops*, 2012, pp. 1158–1161.

[23] X. Cao, P. Yang, M. Alzenad, X. Xi, D. Wu, and H. Yanikomeroglu, “Airborne communication networks: A survey,” *IEEE Journal on Selected Areas in Communications*, vol. 36, no. 9, pp. 1907–1926, 2018.

[24] G. Bacci, S. Lasaulce, W. Saad, and L. Sanguinetti, “Game theory for networks: A tutorial on game-theoretic tools for emerging signal processing applications,” *IEEE Signal Processing Magazine*, vol. 33, no. 1, pp. 94–119, 2016.

[25] W. Saad, Z. Han, M. Debbah, A. Hjorungnes, and T. Basar, “Coalitional game theory for communication networks,” *IEEE Signal Processing Magazine*, vol. 26, no. 5, pp. 77–97, 2009.

[26] W. Saad, H. Zhu, T. Basar, M. Debbah, and A. Hjorungnes, “Hedonic coalition formation for distributed task allocation among wireless agents,” *IEEE Transactions on Mobile Computing*, vol. 10, no. 9, pp. 1327–1344, 2011.

[27] J. Cao, T. Peng, Z. Qi, R. Duan, Y. Yuan, and W. Wang, “Interference management in ultra-dense networks: A user-centric coalition formation game approach,” *IEEE Transactions on Vehicular Technology*, vol. 67, no. 6, pp. 5188–5202, 2018.

[28] H. Khayatian, R. Saadat, and J. Abouei, “Coalition-based approaches for joint power control and relay selection in cooperative networks,” *IEEE Transactions on Vehicular Technology*, vol. 62, no. 2, pp. 835–842, 2013.

[29] E. Sakhaee and A. Jamalipour, “The global in-flight internet,” *IEEE Journal on Selected Areas in Communications*, vol. 24, no. 9, pp. 1748–1757, 2006.

[30] M. Gerla and T. C. Tsai, “Multicluster, mobile, multimedia radio network,” *Wireless Networks*, vol. 1, no. 3, pp. 255–265, 1995.

[31] N. Shi and X. Luo, “A novel cluster-based location-aided routing protocol for UAV fleet networks,” *International Journal of Digital*

Content Technology & Its Applications, vol. 6, no. 18, pp. 376–383, 2012.

[32] A. Khan, F. Aftab, and Z. Zhang, "BICSF: Bio-inspired clustering scheme for FANETs," *IEEE Access*, vol. 7, pp. 31 446–31 456, 2019.

[33] J. S. Lee and C. L. Teng, "An enhanced hierarchical clustering approach for mobile sensor networks using fuzzy inference systems," *IEEE Internet of Things Journal*, vol. 4, no. 4, pp. 1095–1103, 2017.

[34] O. S. Oubbati, A. Lakas, F. Zhou, M. Gunes, N. Lagraa, and M. B. Yagoubi, "Intelligent UAV-assisted routing protocol for urban VANETs," *Computer Communications*, vol. 107, pp. 93–111, 2017.

[35] O. S. Oubbati, N. Chaib, A. Lakas, P. Lorenz, and A. Rachedi, "UAV-assisted supporting services connectivity in urban VANETs," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 4, pp. 3944–3951, 2019.

[36] M. Ni, Z. Zhong, and D. Zhao, "MPBC: A mobility prediction-based clustering scheme for ad hoc networks," *IEEE Transactions on Vehicular Technology*, vol. 60, no. 9, pp. 4549–4559, 2011.

[37] Y. Yu, L. Ru, and K. Fang, "Bio-inspired mobility prediction clustering algorithm for ad hoc UAV networks," *Engineering Letters*, vol. 24, no. 3, pp. 328–337, 2016.

[38] Q. Han, Y. Bai, L. Gong, and W. Wu, "Link availability prediction-based reliable routing for mobile ad hoc networks," *IET Communications*, vol. 5, no. 16, pp. 2291–2300, 2011.

[39] F. Luo, C. Jiang, J. Du, J. Yuan, Y. Ren, S. Yu, and M. Guizani, "A distributed gateway selection algorithm for UAV networks," *IEEE Transactions on Emerging Topics in Computing*, vol. 3, no. 1, pp. 22–33, 2015.

[40] A. Goswami, R. Gupta, and G. Parashari, "Reputation-based resource allocation in P2P systems: A game theoretic perspective," *IEEE Communications Letters*, vol. 21, no. 6, pp. 1273–1276, 2017.

[41] L. Xiao, X. Lu, D. Xu, Y. Tang, L. Wang, and W. Zhuang, "UAV relay in VANETs against smart jamming with reinforcement learning," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 5, pp. 4087–4097, 2018.

[42] N. Xing, Q. Zong, B. Tian, Q. Wang, and L. Dou, "Nash network formation among unmanned aerial vehicles," *Wireless Networks*, 2018. [Online]. Available: https://doi.org/10.1007/s11276-018-1866-1

[43] L. Yang, Y. Z. Lu, Y. C. Zhong, X. G. Wu, and S. J. Xing, "A hybrid, game theory based, and distributed clustering protocol for wireless sensor networks," *Wireless Networks*, vol. 22, no. 3, pp. 1007–1021, 2016.

[44] A. Attiah, M. Chatterjee, and C. C. Zou, "A game theoretic approach for energy-efficient clustering in wireless sensor networks," in *Wireless Communications and Networking Conference*, 2017, pp. 1–6.

[45] N. Sawyer, M. N. Soorki, W. Saad, and D. B. Smith, "Evolutionary coalitional game for correlation-aware clustering in machine-to-machine communications," in *IEEE Global Communications Conference*, 2017, pp. 1–6.

[46] D. Hu, J. Wu, and P. Fan, "Minimizing end-to-end delays in linear multihop networks," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 8, pp. 6487–6496, 2016.

[47] S. Yan, M. Peng, and X. Cao, "A game theory approach for joint access selection and resource allocation in UAV assisted IoT communication networks," *IEEE Internet of Things Journal*, vol. 6, no. 2, pp. 1663–1674, 2019.

[48] L. Yang, D. Wu, S. Xu, G. Zhang, and Y. Cai, "Social-energy-aware user clustering for content sharing based on D2D multicast communications," *IEEE Access*, vol. 6, pp. 36 092–36 104, 2018.

[49] A. Bogomolnaia and M. O. Jackson, "The stability of hedonic coalition structures," *Games & Economic Behavior*, vol. 38, no. 2, pp. 201–230, 2002.

[50] X. Hong, M. Gerla, G. Pei, and C. C. Chiang, "A group mobility model for ad hoc wireless networks," in *ACM International Workshop on Modeling, Analysis and Simulation of Wireless and Mobile Systems*, 1999, pp. 53–60.

Na Xing received the B.Eng. degree from Yanshan University, Qinhuangdao, China, in 2013, and the M.Eng. degree in the School of Electrical and Information Engineering from Tianjin University, Tianjin, China, in 2016, where she is currently working toward the Ph.D. degree. Her research interests include game theory and its application in vehicles.

Qun Zong received the B.Eng., M.Eng., and Ph.D. degrees in automatic control from Tianjin University, Tianjin, China, in 1983, 1988, and 2002, respectively. He is currently a Professor in the School of Electrical and Information Engineering, Tianjin University. He serves as an editorial board member of several scientific journals. His main research interests include complex network and flight control.

Liqian Dou received the B.Eng. degree in industrial automation and the M.Eng. and the Ph.D. degrees in control science and engineering, in, respectively, 1999, 2005 and 2008 from Tianjin University. He is currently an Associate Professor in the School of Electrical and Information Engineering, Tianjin University, Tianjin, China. His current research interests include game theory, modeling and control of complex system.

Bailing Tian received the B.Eng., M.Eng., and Ph.D. degrees in automatic control from Tianjin University, Tianjin, China, in 2006, 2008, and 2011, respectively. He was an Academic Visitor in the School of Electrical and Electronic Engineering, University of Manchester, Manchester, U.K., from June 2014 to June 2015. He is currently a distinguished research fellow in the School of Electrical and Information Engineering, Tianjin University, Tianjin, China. His main research interests include finite time control and integrated guidance and control for vehicles.

Qing Wang received the B.Eng. and M.Eng. degrees in electronic engineering and the Ph.D. degree in communication engineering, in, respectively, 2004, 2007 and 2009 from Tianjin University, Tianjin, China, where she is currently an associate professor. From October 2007 to April 2009, she was a Visiting Student with the School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore. Her current research interests include wireless communication and passive radar.