AC-POCA: Anticoordination Game Based Partially Overlapping Channels Assignment in Combined UAV and D2D-Based Networks

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Abstract—Device-to-device (D2D)-enabled wireless networks are becoming increasingly popular. However, in remote, rural, and disaster affected areas, it is difficult to construct such wireless networks due to the unavailability or inadequacy of cellular infrastructures. Unmanned aerial vehicles (UAVs) can be a good candidate to promptly construct the D2D-enabled wireless network. However, the assignment of the radio channels of the nodes (i.e., UAVs and user terminals) is challenging due to the availability of only a limited number of orthogonal channels and the interference issue resulted from using arbitrary channels. Furthermore, the dynamic topology and high mobility of nodes in such a combined UAV and D2D-based network make conventional channel assignment (CA) algorithm no longer suitable. In this paper, we formally address this problem, and demonstrate how partially overlapping channels (POCs) and game theory can be exploited to alleviate the problem. In this vein, we propose a distributed anticoordination game based POC assignment algorithm referred to as AC-POCA. In our proposed AC-POCA, the nodes use only local information to play the game, and reach a steady state, uniqueness of which is verified through analysis. Also, the upper bound of AC-POCA (i.e., price of anarchy) is analytically evaluated, which is corroborated by simulation results. In addition, simulation results demonstrate the effectiveness of AC-POCA in terms of good throughput and low signaling overhead in a dynamic environment.

Index Terms—Anticoordination game, channel assignment, device to device (D2D), game theory, partially overlapping channel (PoC), potential game, unmanned aerial vehicle (UAV).

I. INTRODUCTION

Recenrly, unmanned aerial vehicles (UAVs) have appeared as a promising candidate to be exploited as flying base stations [1] to quickly construct efficient and high Quality-of-Service (QoS) wireless networks even in remote and/or rural areas [2]. In addition, the infrastructure of the UAV-based cellular network can be flexibly changed to form a communication network to meet the varying user requirements. On the other hand, in conventional cellular networks [3], the bandwidth and energy are limited at the content servers when multiple users aim to access the same content. This limitation results in increased resource waste and delay [4]. To address this issue, Device-to-Device (D2D) [5]–[8] communication with caching emerged as a complementary solution [9]. D2D communication reuses existing licensed spectrum resources to make under-laid transmission links, which can typically be deployed between smart devices [10]. Furthermore, UAVs, to exploit their earlier mentioned flexibility to construct wireless communication networks in locations lacking adequate cellular infrastructure, have been used to establish D2D links with caching [2]. In this paper, we envision a combined UAV and D2D based network whereby the primary links (i.e., downlink transmission) and secondary links (i.e., D2D underlink communication) are considered as complementary methods for content delivery to offer better performance compared to conventional content delivery approaches. In this paper also, we consider a combined UAV and D2D based network in which the UAVs can be considered as both local content servers and D2D nodes. However, in our proposed combined heterogeneous network, both primary and D2D links share the same spectrum whereby both the UAVs and user terminals typically use multi-radio, multi-channel communications. The spectrum used by both primary and secondary links of the combined network makes the channel resources limited in the entire network, and the nearby channels easily become overlapping. Such overlapping channels in the neighboring UAVs and users can cause severe interference leading to network congestion. To maximize the channel resource utilization, Partially Overlapping Channels (POCs) can be assigned to the UAVs and user nodes. Researches [11], [12] demonstrated that proper assignment of POCs can efficiently avoid interference and improve the aggregate throughput of various communication networks. However, How to efficiently assign POCs to the nodes while minimizing interference is a critical problem. Based on the conventional channel assignment problem, by considering the mobility of UAVs and D2D devices, the
network topology becomes highly dynamic, which means that the link state and interference range of each node may frequently change. However, conventional POCs assignment are typically limited by complex and numerous iterations, which depend on the persistent global information and cause significantly long convergence time. Therefore, the existing POCs assignment in other communication networks may not applicable to the highly dynamic environment considered in our work. This poses a further challenge to the channel assignment problem. In this paper, based on the combined UAV and D2D network, we address those issues, and propose an Anti-Coordination Game [13] based dynamic POC Assignment algorithm, referred to as AC-POCA. The contributions of our work, in this paper, are as follows.

1) We present a combined UAV and D2D based network and justify the adopted network topology. Then, we analyze the new features of channels assignment problems in the combined network.

2) According to the new features of our proposed network, we use the anti-coordination game to model the channel assignment problem in the considered network that uses local information and lead to quick convergence time.

3) Based on the high mobility of UAV and D2D combined network, the dynamic topology based POC assignment algorithm is further designed to deal with situations in which the network environment is dynamically changed.

4) We prove the existence and uniqueness of the steady state in AC-POCA and demonstrate its superior performance over comparable methods in both mixed and dynamic environments.

The remainder of this paper is organized as follows. Section II surveys related works on combined UAV and D2D based network, and also on the channel assignment problem. Section III presents the considered network architecture and interference model. Then, this section further discusses the formulation of our problem. In Section IV, our Anti-Coordination game based dynamic POC assignment algorithm called AC-POCA is proposed. Section V provides a proof of the uniqueness of the steady state in our proposal. The performance evaluation of AC-POCA is presented in Section VI. Finally, Section VII concludes the paper.

II. RELATED RESEARCH WORK

Caching based D2D communication was considered for cellular networks that demonstrated improved performance [9], [14]. The work in [4] further combined D2D caching and social attributes into a conventional content sharing system and proposed a new hyper-graph framework. But all these research works did not take into consideration the shortcoming of cellular infrastructure based content sharing network in remote, rural, or disaster-affected areas.

UAV based wireless networks recently emerged as an attractive technique for facilitating public safety and military communications [15]. This is because the UAVs can be rapidly deployed as aerial base stations to form a flexible cellular network [1], [16]. In [2], the deployment of a UAV-based communication network over a given geographical area was analyzed. The analysis demonstrated the feasibility of deploying UAVs in D2D enabled cellular networks. While the UAVs equipped with reasonably large storage and computing ability can be considered as content-centric server nodes in the cellular network [17], [18], to the best of our knowledge, no previous work has investigated the importance of a combined UAV and D2D based network technology for supporting content delivery in networks. In addition, even if such networks are designed, they are inherently multi-radio, multi-channel environments that are prone to interference due to use of overlapping channels. The situation is aggravated with the underlay and overlay spectrum sharing modes in cellular/D2D networks. As a remedy, POC assignment has been considered by researchers in other multi-radio, multi-channel networks such as wireless mesh networks and so forth. Therefore, in the remainder of this section, we review the relevant works on POC in the literature.

The work in [19] proposed a new channel assignment strategy based on non-overlapping channels, and demonstrated how this contributes to spectrum utilization and improves the bandwidth available to the network users. On the other hand, the works in [20], [21] demonstrated that the use of overlapping channels leads to better performance in contrast to three non-overlapping channels for wireless networks. Following this finding, new heuristic channel assignment algorithms were proposed in [22]. In our earlier work in [23], instead of heuristics, an optimal channel assignment exploiting POCs for wireless mesh networks was proposed. However, earlier research works did not consider the effect of algorithm convergence time and how to adjust the algorithm to the highly dynamic network scenario. Furthermore, in the existing works, many channel assignment algorithms are based on the traffic loads of nodes without taking into account the situation of dynamic traffic load. In the dynamic traffic load scenario, the traffic load of each load may change frequently which means that the channel assignment should be correspondingly changed also. In addition, the dynamic topology of the network was not considered by existing research works whereby the nodes may move frequently. In such a case, the distance between each node may dynamically change and the condition of the respective links change correspondingly. In other words, when the network topology changes, the channels should also be reassigned to cope with the new topology. However, the long convergence time and need of global information make it difficult to reassign the channels frequently. Because both the dynamic traffic load and dynamic network topology exist in our considered combined UAV and D2D network, the earlier model [23] which used cooperative game may not be applicable to such networks. Therefore, a new model is required for the POC utilization in such networks, which we discuss in the following section.

III. SYSTEM MODEL AND PROBLEM FORMULATION

Our considered system model is illustrated in Fig. 1. The figure depicts a combined UAV and D2D based network comprising primary and secondary communication links. The primary communication is carried over inter-UAV and UAV-device links. On the other hand, secondary communication is facilitated by D2D links. In both primary and D2D links, the reuse of overlapping/partially-overlapping channels is assumed.
Because the channel sharing model is employed to reuse the overlapping channels, all links in primary and D2D communications will interfere with one another that will cause congestion in the network. The interference problem due to using overlapping channels is also illustrated in the figure that leads to network congestion and degraded network throughput. Furthermore, the mobility of both UAV and devices leads to high dynamic topology of network which makes the channel interference problem more complex. Unlike other wireless networks which operate assuming that the network elements can be simply borrowed from the existing literature, we argue that the combined UAV and D2D based network has some unique properties and challenges. Therefore, we aim to focus on its network aspect in the remainder of this section by describing our considered network and interference models followed by a formal problem formulation.

A. Network Model

Consider the combined UAV and D2D based network as a three-dimensional topology. Also, consider the UAV and users sharing the same channels. Therefore, in the remainder of the paper, we refer to both the UAVs and devices as “nodes”. Also, the notations used in this section and in the remainder of the paper are listed in Table I for ease of reference. Let $N$ denote the number of existing nodes in the system that are represented by the set, $A_{\text{old}} = \{a_1, a_2, \ldots, a_N\}$. Each node in the considered network is represented by its own features, i.e., latitude, longitude, and height. In contrast to the traditional wireless network, the proposed network exhibits high flexibility, and nodes can move and be added or removed according to situational demands. If $M$ nodes are added to the network, they are denoted by $B = \{b_1, b_2, \ldots, b_M\}$. Therefore, the total nodes, in the considered system, are represented by $A = A_{\text{old}} \cup B = \{a_1, a_2, \ldots, a_N, a_{N+1}, a_{N+2}, \ldots, a_{N+M}\}$.

**TABLE I**

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
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<tbody>
<tr>
<td>$N$</td>
<td>Number of existing nodes in the network</td>
</tr>
<tr>
<td>$A$</td>
<td>Set of nodes in the network</td>
</tr>
<tr>
<td>$A_n$</td>
<td>Set of unhappy nodes in the network</td>
</tr>
<tr>
<td>$M$</td>
<td>Number of new added nodes in the network</td>
</tr>
<tr>
<td>$B$</td>
<td>Set of nodes after $M$ nodes are added to the network</td>
</tr>
<tr>
<td>$f_{q,p}$</td>
<td>Effective spectral overlapping level between channels $q$ and $p$</td>
</tr>
<tr>
<td>$\delta$</td>
<td>Interference distance between two channels</td>
</tr>
<tr>
<td>$IR(\delta)$</td>
<td>Interference range for a channel separation between two channels</td>
</tr>
<tr>
<td>$d$</td>
<td>Distance between nodes operating with two channels</td>
</tr>
<tr>
<td>$df_n$</td>
<td>Distance between two nodes in time slot $n$</td>
</tr>
<tr>
<td>$S$</td>
<td>Common strategy space of players</td>
</tr>
<tr>
<td>$S_i$</td>
<td>Strategy of $i$th player</td>
</tr>
<tr>
<td>$C$</td>
<td>Set of all channels</td>
</tr>
<tr>
<td>$</td>
<td>C</td>
</tr>
<tr>
<td>$\Psi$</td>
<td>Game profile of network</td>
</tr>
<tr>
<td>$M_i$</td>
<td>Utility of player $i$</td>
</tr>
<tr>
<td>$IF_q$</td>
<td>Interference factor of channel $q$</td>
</tr>
<tr>
<td>$h$</td>
<td>Hop count to the gateway</td>
</tr>
<tr>
<td>$k$</td>
<td>Topology control factor measure whether a node can connect to the gateway or not</td>
</tr>
<tr>
<td>$U_i$</td>
<td>Social welfare of player $i$</td>
</tr>
<tr>
<td>$U_{NET}$</td>
<td>Social welfare of the game</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>Convergence speed control parameter</td>
</tr>
<tr>
<td>$P_{i,q}$</td>
<td>Performance of decreased overhead</td>
</tr>
<tr>
<td>$ID_{a_i}$</td>
<td>Identification parameter of node $a_i$</td>
</tr>
<tr>
<td>$G_d$</td>
<td>N-player game</td>
</tr>
<tr>
<td>$M$</td>
<td>Utility matrix in game</td>
</tr>
<tr>
<td>$x$</td>
<td>Selection probability of any strategy in the strategy space $S$</td>
</tr>
<tr>
<td>$supp(x)$</td>
<td>Support function of $x$</td>
</tr>
<tr>
<td>$br(x)$</td>
<td>Set of the best responses to $x$ in pure strategy</td>
</tr>
<tr>
<td>$w^{C}(x)$</td>
<td>Set of the worst responses to $x$ in pure strategy</td>
</tr>
<tr>
<td>$U_{\Psi}^{C}(x)$</td>
<td>The social welfare of the worst Nash Equilibrium (NE) case when common channel assignment is employed</td>
</tr>
<tr>
<td>$U_{\Psi}^{N,NET}^{N,NET}(x)$</td>
<td>The social welfare of the best NE case when the topology with Non-Interfering (NI) links and hop count is the Shortest Path (SP)</td>
</tr>
</tbody>
</table>

In order to transmit the users’ content data, the nodes in our considered network are assumed to comprise 802.11 2.4 GHz links and multiple radios with up to 11 channels. As mentioned earlier, both primary and D2D links share those channels. However, the non-overlapping channels are limited (e.g., channels 1, 6, and 11). On the other hand, using overlapping channels in an arbitrary fashion results in severe interference and eventually network congestion. In order to alleviate this problem and improve the aggregate throughput of the considered network, we aim to exploit POCs. Even though POCs can also interfere with each other, their interference range is significantly smaller than the typical overlapping channels [24]. Such reduced interference range of POCs enables an increased number of parallel transmissions, and, thus, leads to increased network capacity.

The issue of assigning POCs can be considered to be an optimization problem in which the available communication channels need to be mapped to network interfaces for minimizing signal interference and maximizing the communication capacity. The interference range is defined as the distance within which interference occurs. Furthermore, in a network having multi-channels connections, there are four different types of
interferences which should be addressed due to their influence of network capacity: co-channel interference, orthogonal channels interference, adjacent channels interference, and self interference [23]. Next, we present a model to describe these different types of interferences.

B. Interference Model

The Interference Matrix or “I-Matrix” method in [24] may be used to model the above-mentioned types of interferences in order to carry out appropriate channel assignment. I-Matrix employs a special matrix to record the interference of each node and determines whether the chosen channel is viable or not to a given link exploiting POC. In order to record the interference of each node, a metric called Interference Factor (IF) is defined to measure the interference between channels. IF represents a ratio of geographical distance and interference range between two operating radios. \( f_{p,q} \) expresses the effective spectral overlapping level between channels \( p \) and \( q \).

The works in [25] and [26] conducted experiments to measure \( f_{p,q} \) under real conditions for different channel separations. Here, we use the result of those works to construct Table II, where \( IR(\delta) \) refers to the interference range for a channel separation between channels \( p \) and \( q \), \( \delta = |p - q| \) denotes the interference distance between channels \( p \) and \( q \).

<table>
<thead>
<tr>
<th>( \delta )</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>( IR(\delta) )</td>
<td>132.6</td>
<td>90.8</td>
<td>75.9</td>
<td>46.9</td>
<td>32.1</td>
<td>0</td>
</tr>
</tbody>
</table>

Now, let \( d \) refer to the distance between nodes operating with channels \( p \) and \( q \). If the nodes use the same channel, \( d \) is set to zero. Then, \( f_{p,q} \) is calculated in the following three cases respectively:

1) \( f_{p,q} = 0 \): when \( \delta \geq 5 \) or \( d > IR(\delta) \).

When the nodes are assigned orthogonal channels or have enough distance to avoid interference, no interference occurs between the radios.

2) \( 1 \leq f_{p,q} < \infty \): when \( 0 \leq \delta < 5 \) and \( d \leq IR(\delta) \).

When overlapping interference occurs, the distance between the nodes is smaller than the interference range. In this case, IF should be a ratio proportional to the distance between the nodes. IF can be calculated as follows:

\[
\frac{f_{p,q}}{d} = \frac{IR(\delta)}{d}.
\] (1)

3) \( f_{p,q} = \infty \): when \( 0 \leq \delta < 5 \) and \( d = 0 \).

This happens because of the self interference problem. Hence, two overlapping channels (\( \delta < 5 \)) are not viable to be assigned to the node due to their full interference.

After we have modeled the interference factor of POC, we further use the Interference Vector and I-Matrix to measure the interference situation of each node.

1) Interference Vector: The Interference Vector is shown in Table III that is calculated based on all the IFs between one channel to all 11 channels. The table keeps track of the distance \( d_{p} \) to the nearest assigned radio in channel \( p \).

2) I-Matrix: Each node updates its own Interference Vectors of all 11 channels, which form an I-Matrix according to Table IV. Also, the node updates I-matrix when any channel assignment is changed.

Based on the aforementioned network and interference models, we are now ready to formulate the research problem.

C. Problem Formulation

Each node in the proposed network shown in Fig. 1 wants to be assigned a proper channel to maximize its throughput based on its own traffic demands. However, each node also wants its channel to be different from its neighboring node such that the interference is minimum. When the nodes improve their own connectivity through assignment of proper channels, the total connectivity will be improved also. However, this means that each node acts selfishly to obtain the best possible channel assignment. Without the help of a central controller (e.g., a ground station), the nodes need to use a distributed channel assignment procedure. In such a distributed scenario, the channel assignment problem can be represented by the properties of an anti-coordination game played by the nodes.

1) Anti-Co-Ordination Channel Assignment Game: Games such as the game of chicken and hawk-dove game in which players score the highest when they choose opposite strategies are called anti-coordination games. We use the Anti-Co-ordination game property that if and only if the strategy in the game has a total bandwagon, it satisfies the interference property of the channel assignment model. In our network, each node is considered as a decision maker of the game, and the assignment of channel is considered as a strategy. Thus, we can model the interactions among nodes as an anti-coordination channel.
assignment game. The game has finite sets of nodes, referred to as players \( A = \{a_1, a_2, \ldots, a_N\} \) with a common strategy space \( S \). In our work, we assign the channel(s) to a node’s (i.e., player’s) radios by its chosen strategy. We express the strategy of the \( i \)th player as \( s_i \in S, s_i = \{k_{i,1}, \ldots, k_{i,c}, \ldots, k_{i,|C|}\} \), where \( k_{i,c} \) is a binary value. When channel \( c \) is assigned to a player, we set \( k_{i,c} \) to 1, and 0 otherwise. \(|C|\) refers to the number of channels for the channel set \( C \). The Cartesian product of the players’ strategy vector is defined as the game profile of the network, \( \Psi = \times_{i \in A} s_i = s_1 \times s_2 \times \cdots \times s_N \). A game profile is composed of each strategy of every player. \( s_{-i} \) means the strategy set chosen by all other players except player \( i \).

2) Player Utility: The objective of the game is to maximize the network throughput. However, in the anti-coordination game, a player only focuses on his utility. We define the utility of a player \( i \) as \( M_i \). This utility can be a proportional measure of the connectivity of each node as shown in (2). Each link with channel \( q \)'s capacity is evaluated according to its interference factor, denoted by \( IF_q \). The link data rate \( R \) is used to measure the traffic load of the player. The importance of a player also depends on two topology control factors, \( h \) and \( k \), which mean its hop count to the gateway (GW) for content server, and whether it can connect to the GW or not. Here, \( h \) and \( k \) are used to measure how efficiently these links connect to the gateway (GW). The work in [23] assumes that the utility is linearly proportional to the hop count \( h \). However, that assumption has a shortcoming when the network is large whereby the utility of any node far away from the gateway decreases quite fast and finally approaches 0, and therefore, is eventually ignored in the next anti-coordination game. Hence, in this work, we adopt a natural logarithmic function \( \ln (h + 2) \), where \( h + 2 \) is used to avoid the denominator of the utility function to become 0 and, this exhibits better performance in larger networks. \( k \) is set to 1 if the node can indirectly reach the GW, and 0 otherwise.

\[
M_i = k \sum_{q \in C} \frac{R}{IF_q + 1} \ln (h + 2) \tag{2}
\]

3) Social Welfare: The social welfare means the total utility of the network. Each player has its utility function \( U_i(\Psi) \) dependent on its own strategy and other players’ strategies. Because we defined an anti-coordination game, the social welfare of the game, \( U_{NET}(\Psi) \), can be represented as follows.

\[
U_{NET}(\Psi) = U_i(\Psi) = \sum_{i \in A} M_i, \forall i. \tag{3}
\]

By modeling the channel assignment as an anti-coordination game, we may use the game theoretical properties to guarantee optimized network performance. In such a game, the players will change their interdependent strategies in \( S \) to improve their utilities, which correspondingly improve the value of \( U_{NET} \). Then, several important issues arise: (i) how the players play the game to improve the social welfare, (ii) whether they ever reach a consensus, or steady state, (iii) if the topology changes, how the game goes on to reach such a steady state, and (iv) how efficient this steady state performance would be. In the following section, we propose an algorithm to allow the nodes to play such a game and address the afore-mentioned issues by proving the existence of a steady state and evaluating its performance.

IV. AC-POCA: PROPOSED ANTI-COORDINATION CHANNEL ASSIGNMENT GAME

In this section, our main objective is to design an optimal channel assignment algorithm using game theoretic approach. In this vein, we first show that our formulated game is a potential game [27].

In our prior research in [23], if a game is in a state of Nash Equilibrium (NE) whereby the players arrive at an agreement, the game can be considered to be in a steady state. Strategy \( s^* \in S \) is an NE if the game utility satisfies the following.

\[
U_i(s^*) \geq U_i(s_i^*, s_{-i}) \forall s_i \in S_i, \forall i \in A. \tag{4}
\]

In our formulated game in Section III-C, there exists a potential function \( P \) as follows,

\[
P(s_i, s_{-i}) - P(s_i', s_{-i}) = U_i(s_i', s_{-i}) - U_i(s_i, s_{-i}) \forall i, s_i, s_i'. \tag{5}
\]

where \( s_i' \) and \( s_i'' \) stand for two arbitrary strategies. It is straightforward that the network utility function (3) itself is a potential function for the game. Hence, we have,

\[
P = U_i(\Psi) = U_{NET}(\Psi), \forall i. \tag{6}
\]

Thus, our considered problem is a potential game. In potential games, the existence of NE can be proved. Also, such games have several useful properties. The first property is that the finite potential game possesses at least one pure strategy NE [27]. The second property is that All NEs are either local or global maximizers of the utility function [27]. The third property states that there are well-known learning schemes to reach these function maximizers such as best response and better response [28].

By these properties of a potential game, we can prove that our formulated game can reach a steady state, and all players will reach a consensus. Now, let us call a player \( a_i \) unhappy if \( a_i \) can achieve better utility by changing its channel. Let \( A_u \) indicate the set of unhappy players. We now run the learning schemes to make the unhappy player happy until no unhappy node exists, i.e., \( (A_u = \emptyset) \). With potential and coordination games, learning schemes like best response, better response, smoothed better response, and perfect foresight response may be used to accomplish such goals. These learning schemes are described below.

1) Best response: As expressed in (7), the player searches its entire strategy space and selects the one which yields the best outcome considering the other players’ strategies. This scheme provides fast convergence in polynomial time. In fact, in our game, the number of steps is equal to the number of connected links in network. On the other hand, it requires intensive processing that grows linearly according to the strategy space and has normal probability to get trapped in a local optimum.

\[
s_{i}^{t+1} = \arg \max_{s_i \in S_i} M_i. \tag{7}
\]
2) Better response: As expressed in (8), each player selects a random strategy and keeps it as long as it generates a better outcome than the previous one. Thus, better response provides a less intensive computation at the cost of a slower convergence to the equilibrium, and has normal probability to be trapped in a local optimum.

\[ s_{i+1}^t = \begin{cases} s_{i}^{\text{rand}} & \text{if } M_i(s_{i}^{\text{rand}}, s_{-i}) > M_i(s_{i}^t, s_{-i}) \\ s_{i}^t & \text{otherwise.} \end{cases} \quad (8) \]

3) Smoothed better response: This method uses randomness in the decision process which may lead to convergence to the global NE with a high probability. This uncertainty occurs according to the following probability function:

\[ p(s_{i}^{\text{rand}}, s_{i}^t) = \frac{e^{M_i(s_{i}^{\text{rand}}, s_{-i})/\gamma}}{e^{M_i(s_{i}^t, s_{-i})/\gamma} + e^{M_i(s_{i}^t, s_{-i})/\gamma}}, \quad (9) \]

where \( \gamma \) is a parameter responsible to control the trade-off between the technique’s outcome performance and convergence speed. A large value of \( \gamma \) enables an extensive strategy search and slow convergence. On the other hand, a small \( \gamma \) restricts the search while improving the convergence speed. The player will evaluate the newly selected random strategy against the previous one, and select the new strategy according to (9). Thus, notice that smoothed better response incurs the least intensive computation at the cost of the slowest convergence to NE.

4) Perfect foresight response: While this is similar to the best response technique, it involves the players to form an expectation by discounted average time of action distributions of the next period instant of current action distribution [29]. This method gives one path from any initial state to the NE, but it may be trapped in this point forever. Also, compared to the best response technique, this may result in a higher computation cost.

The above four learning schemes have their own advantages and disadvantages. If the nodes were involved in a cooperative game as shown in our earlier work in [23], smoothed better response technique could be used. However, in such a scenario, when each node changes its channel, all other nodes should update their I-Matrix. This means that the nodes changing their channels need to exchange their channel selection information with the other nodes, thereby significantly increasing the signaling overhead. In addition, with the cooperative game method, each node calculates its utility depending on the strategy selection of all other nodes and the global information. Thus, when the traffic load and topology of the network change, the utility of every node is changed and the channels need be reassigned to all the nodes. During the reassignment of channels, the content transmission and delivery of the whole network may be halted. Both the increase of signaling and waiting time to perform reassignment will cause severe degradation of throughput of network. Therefore, in order to avoid the global channel reassignment and decrease the signaling overhead, our algorithm should be designed independent of other nodes and to converge as fast as possible. In other words, different from the cooperative game in [23], in our anti-coordination game played by the nodes in a decentralized manner, each player’s response only depends on its own utility from local information and does not need to know the utility of the other players. As a result, the channel reassignment only affect local node and neighbors and signaling overhead can be reduced. The performance of decreased overhead, \( P_{sig} \), can be calculated as follows:

\[ P_{sig} = 1 - \frac{|E|}{|E| \times N_{iter} \times |C|}, \quad (10) \]

where \( |E| \) denotes the number of connected links in the network. \( N_{iter} \) stands for the number of iterations by smoothed-better-response.

Thus, we design our Anti-Coordination game based Partially Overlapping Channels Assignment (AC-POCA) algorithm using the best response technique to allow it to converge rapidly and also avoid global channel reassignment. The steps of AC-POCA are shown in Algorithm 1, in which we assume each node has a unique identification parameter \( ID_{a_i \in A} \) for routing purpose. It is worth reminding that due to the features of our combined UAV and D2D based network, the network has a highly dynamic topology and high mobility of nodes. We respectively describe our algorithm in two steps, first we consider the mixed topology of the network and then we consider the dynamic case.

### A. Mixed Topology

In the initial phase, all the nodes are initialized such that they belong to the unhappy set, \( A_u \). Each node uses a priority queue to store \( A_u \). The priority order of each node in set \( A_u \) is decided by various metrics such as traffic load, number of neighbors, distance to gateway, and so forth. Here, we use a queue to store the unhappy set because with the best response technique, each node only performs channel assignment once (i.e., only one iteration) and will not affect the channel selection of nodes carrying out channel assignment prior to it (i.e., in front of it in the queue). Then consider the I-matrix of each node also initialized in the first case, consider the de-centralized network, where each node only calculates the distance from other nodes in each interfere vector within its transmission range. Then, each node processes the steps is shown within lines 13 to 27 in Algorithm 1 so that the best response strategy is used to assign the POCs. In line 19, after a channel is selected by the calculated utility, a valid threshold \( h_{\text{in}} \), denoting the tolerance to channel interference is used to assess whether the channel selection strategy is valid or not. Then, the node removes itself from the unhappy set \( A_u \) and broadcasts \( ID_{a_i \in A} \) and notification \( qt \) to other nodes to continue those steps until none of the nodes belongs to \( A_u \).

From here on, we present an easy-to-understand example of our proposed algorithm in Fig. 2 that describes a simple scenario where only 4 nodes construct a network. For the sake of simplicity, consider that the distance between each node is 100 meters and the link data rate is 1 Mbps for all links. The assigned channels and overall network utilities for different initial orders of the nodes are listed in Table V. The table demonstrates the different steady states of each link in different initial orders.
TABLE V
CHANNEL ASSIGNMENT USING AC-POCA IN THE DIFFERENT LINKS SHOWN IN Fig. 2 FOR DIFFERENT INITIAL ORDERS OF THE PLAYERS

<table>
<thead>
<tr>
<th>Order</th>
<th>Ch (e1)</th>
<th>Ch (e2)</th>
<th>Ch (e3)</th>
<th>Ch (e4)</th>
<th>(U_{NET})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Order: 1, 2, 3, 4</td>
<td>1</td>
<td>6</td>
<td>0</td>
<td>7</td>
<td>6.529</td>
</tr>
<tr>
<td>Order: 2, 4, 1, 3</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>6</td>
<td>6.529</td>
</tr>
<tr>
<td>Order: 3, 4, 1, 2</td>
<td>6</td>
<td>1</td>
<td>6</td>
<td>11</td>
<td>5.693</td>
</tr>
<tr>
<td>Order: 4, 1, 2, 3</td>
<td>11</td>
<td>6</td>
<td>1</td>
<td>6</td>
<td>5.693</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>Order: 4, 3, 2, 1</td>
<td>1</td>
<td>7</td>
<td>1</td>
<td>6</td>
<td>5.693</td>
</tr>
</tbody>
</table>

Among the 24 possible initial orders, only a few are listed as a simple example.

For example, in row 1, the order \(\{1, 2, 3, 4\}\) means the nodes \(a_1, a_2, a_3,\) and \(a_4\) have the first, second, third, and fourth initial orders, respectively. According to their orders, the four nodes are placed into the unhappy set \(A_u\). Then, the first order node, i.e., \(a_1\) is selected to play the channel assignment game. Node \(a_1\) performs channel assignment on all of its links represented by edges \(\{e_1, e_2\}\). \(e_1\) chooses the first strategy \(s_{1}^{e_1}\) from strategy space \(\{k_1, \ldots, k_i, \ldots, k_{|V|}\}\), and judges whether it satisfies (7). Because \(e_1\) is the first link which the first channel assignment is performed, no other channel will interfere with it. Thus, using line 13 of Algorithm 1, \(e_1\) chooses channel 1 and its interference factor, \(IF\), is zero. In addition, using (2), the utility of \(a_1\) for \(e_1\) is 0.721. If \(a_1\) changes to any other channel on \(e_1\), its utility will not increase. If the utility is larger than a threshold (e.g., 0 in this example), \(a_1\) considers the channel assignment on \(e_1\) to be valid. Similarly, \(a_1\) assigns channel on its remaining link/edge \(e_2\). Because the channel assigned on \(e_1\) interferes with that on \(e_2\), \(a_1\) needs to choose the best channel (e.g., channel 6) so as to make its utility for \(e_2\) the maximum (i.e., 0.721). Thus, \(a_1\)’s utility becomes 1.442.

Regardless of the chosen channel, \(a_1\)’s \(IF\) for \(e_1\) is \(\infty\) mentioned in Section III-B leading to a utility of 0, which is invalid. Therefore, \(e_3\) is not assigned any channel. For agreeing with the channel already assigned on \(e_2\), \(a_3\) receives its maximum utility of 1.822. Then, \(a_3\) is removed from \(A_u\). At this point, \(a_4\) is the final unhappy player remaining in \(A_u\), which commences its channel assignment game. Because channels have been already assigned to both its links \((e_1\) and \(e_4\)), \(a_4\) does not need to carry out further channel assignment and receives its maximum utility of 1.443. Thus, the total network utility \(U_{NET}\) with this initial order in row 1 of Table V is 6.529.

B. Dynamic Topology

Furthermore, in our combined UAV and D2D based network, the network topology may dynamically change due to the distance changed between the nodes, new nodes arrival, and old nodes departure. When the network topology changes, how the game can reach a new steady state should also be considered. In such a case, we focus on the distance \(d_f\) between the nodes. The node arrival and departure are also special cases of distance change. Here, we define \(d_{f_n}\) as the distance between node \(a_i\) and \(a_{i+1}\) during the time-slot \(n\). So, the different strategy is chosen by the difference from \(d_{f_{n-1}}\) to \(d_{f_n}\). Those different strategies are considered within lines 4 to 9 of Algorithm 1. The lines 4 and 5 show the case of a new node joining the network, lines 6 and 7 show a case whereby the distance between two nodes are far enough to disrupt/break the link. Lines 8 and 9 show the case where the interference range is changed by the distance change between the two nodes. Then, the steps of mixed channel assignment shown within lines 12 to 23 are repeated so that until none of the nodes belongs to \(A_u\). In this algorithm, each node performs this algorithm by itself. Only when the assignment steps are finished, the broadcast to notify other nodes is performed. Unlike the conventional channel assignment algorithm, nodes calculate their utilities and perform assignment only by local information, except the I-matrix update phase. As shown in the case of the mixed topology, each mixed initial order leads to a unique steady state and the node only performs channel assignment once. This implies that the joining node in the unhappy queue will not interfere with others in front of it. When the environment of the node is changed, the node just pushes itself into the unhappy queue again. This means that even the node reassigns its channel, it will not interfere with the channel assignment of other nodes. Compared with the conventional channel assignment algorithm whereby all nodes should reassign their channels when the topology of the network is changed which causes network transmission to be totally halted, our AC-POCA algorithm can significantly improve the throughput of the network.

Next, we need to demonstrate that for a given initial order of the nodes, the proposed AC-POCA algorithm has a unique steady state. The following section analyzes the uniqueness of the steady state for a given initial order of nodes.
Algorithm 1: Anti-coordination Game-based Partially Overlapping Channel Assignment (AC-POCA) Algorithm.

Input: Each node \( a_i (i \in [N]) \) in \( A \)

Output: The selected strategy \( s_{\text{sel}} \) of each link

1: Initialization: unhappy set \( A_u \leftarrow A \)
2: Set a priority order to every node in set \( A_u \)
3: for each time slot \( n \) do:
   4: \( \forall a_i \in A \)
   5: \( q_t \leftarrow 0 \)
   6: if \( df_{n-1} = \infty \) and \( df_n < \infty \) then
      7: Put \( a_{i+1} \) into set \( A \) and \( A_u \)
   else if \( df_n = \infty \) then
      9: Put \( a_i \) and \( a_{i+1} \) into set \( A_u \)
   else if \( |df_n - df_{n-1}| > d_h \) then
      11: Put \( a_i \) into set \( A_u \)
   end if
3: while \( |A_u| \neq 0 \) and \( q_t = 0 \) do
4: Select the first order node \( a_{fo} \) in unhappy set \( A_u \)
5: if \( a_{fo} = a_i \) then
6: for each link \( e_i \) of node \( a_i \) do
7: \( s_{\text{sel}}^t \leftarrow \text{first strategy in } \{k_{i,1}, \ldots, k_{i,c}, \ldots, k_{i,|C|} \} \)
8: while \( s_{\text{sel}}^t \) does not satisfy (7) do
9: \( s_{\text{sel}}^{t+1} \leftarrow \text{next strategy} \)
10: end while
11: if \( s_{\text{sel}}^t \) is valid strategy\( (M_i < h_u) \) then
12: \( s_{\text{sel}}^{t+1} \leftarrow \emptyset \)
13: else
14: \( s_{\text{sel}}^{t+1} \leftarrow s_{\text{sel}}^{t} \)
15: end if
16: end for
17: \( q_t \leftarrow 1 \)
18: Broadcast \( q_t, ID_{a_i} \), and \( s_{i+1}^{t+1} \), and all nodes update I-Matrix
19: end if
20: if all link \( e_i = \emptyset \) then
21: Remove \( a_i \) from \( A \)
22: end if
23: Remove \( a_{fo} \) from unhappy set \( A_u \)
24: end while
25: end if

V. ANALYSIS ON UNIQUE STEADY STATE

From our previous work in Section IV, we already know the existence of a steady state (i.e., NE) in our game. To further prove its uniqueness, we use several definitions as follows. As mentioned in Section III, we consider our game as a \( N \)-player game, \( G = (S, M) \), where \( S \) is the common pure strategy space \( S = S_i \), \( \forall i \). \( M \) represents the utility matrix and \( x \) means a selection probability of any strategy in the strategy space, \( S \). \( \text{supp}(x) \) indicates the support function of \( x \). When a player chooses strategy \( x \), \( \text{br}(x) \) and \( \text{wr}(x) \), respectively, represent the sets of the best and worst responses to \( x \) in pure strategy.

VI. PERFORMANCE EVALUATION

In this section, we evaluate our proposed AC-POCA algorithm by first analyzing the Price of Anarchy (PoA) to derive the upper bound. Then, computer-based simulation results are provided to further verify the effectiveness of the proposal.

A. Price of Anarchy (PoA)

The PoA measures how the efficiency of a system is degraded because of the selfish behavior of its agents or players [31]. The PoA measure can be extended to diverse systems including game-theoretic models. In our proposed AC-POCA algorithm, the players (i.e., nodes) can be trapped at a local optimum point where none of the players is willing to change strategy even if the system performance is still distant from the desirable global optimum. Because of this, the efficiency of our game-theoretic algorithm needs to be evaluated through PoA analysis. According to its definition, PoA may be expressed as follows:

\[
\text{PoA} = \max_{\Psi} \frac{U_{\text{NET}}(\Psi)}{\min_{\Psi'} U_{\text{NET}}(\Psi')}, \Psi, \Psi' \in \Psi. \tag{12}
\]

In our earlier work in [23], we demonstrated that the worst and best NEs are the two situations of common channel assignment and non-interfering links channel assignment. Thus, with the definition of PoA, its upper bound is further expressed as follows.

1) The worst NE for MRMC networks is the Common Channel (CC) assignment: \( U_{\text{NET}}^{CC}(\Psi) \).
2) The best NE for MRMC networks is a topology with Non-Interfering (NI) links and hop count is the Shortest Path (SP): \( U_{\text{NET}}^{NI-SP}(\Psi) \).

Thus, PoA of (12) can be rewritten as follows.

\[
\text{PoA} = \frac{U_{\text{NET}}^{NI-SP}(\Psi)}{U_{\text{NET}}^{CC}(\Psi)}. \tag{13}
\]

In the remainder of the section, computer-based simulation results are provided to further verify our analysis.

B. Simulation Results

Our conducted simulations consider two scenarios, the mixed and dynamic topologies. These simulation scenarios are configured using C++ as follows. First, consider the mixed topology, a grid topology similar to that described in [23] is constructed.
as the wireless system. The distance between the neighboring nodes in the network is set to 120 m. The gateway node is positioned at the edge of the simulated grid that is the farthest from the user devices. The nodes are assumed to be equipped with multi-channels, multi-radios operating with IEEE 802.11g wireless technology. For simplicity, the link data rate is set to 8 Mbps. In our conducted simulations, the numbers of nodes are varied in the range of \{9, 16, 25, 36, 49\}.

In Fig. 3, we simulate our algorithm in different network settings. Here, we set a time based random seed to initialize the order of the players, and repeat the simulation 1000 times to calculate the average utility. It can be noticed from the plot in this figure that the average utility is quite close to the maximum utility of the network. This corroborates our PoA analysis in (13).

Furthermore, we compare the utility of AC-POCA with the cooperative game used in [23] with three learning schemes. For comparison, we use the same player utility function of (2). Here, the three learning schemes of cooperative game are referred to as BS-CO (Best Response), BR-CO (Better Response) and SBR-CO (Smooth Better Response). Then, the result is shown in Fig. 4. From the result, we can see that the utility of AC-POCA is almost the same as BS-CO, and slightly differ from BR-CO and SBR-CO. To compare with the increased iteration times $N_{iter}$ and significant signaling overhead in (10), the slightly lower utility of AC-POCA can be considered as a tradeoff with its significantly lower number of iterations and signaling overhead, which is discussed next.

Now, we compare the performance of our proposed AC-POCA algorithm in the mixed network topology with two existing methods from [23], i.e., Cooperative Channel Assignment Game (CoCAG) with Best Response (BR) and Smoothed Better Response (SBR). For ease of representation, the two compared methods are referred to as CoCAG-BR and CoCAG-SBR, respectively. The comparison is performed in terms of the convergence time performance and signaling overhead.

Next, we compare the convergence speed of AC-POCA and existing CoCAG-BR and CoCAG-SBR algorithms in Fig. 5. In the conducted simulations, we set the factor of finalization criteria in SBR to 85 percent of the maximum utility, which was estimated by a centralized brute force algorithm. The results in the plot in Fig. 5 demonstrate that the proposed AC-POCA method has the fastest convergence speed because it uses the unhappy queue and only exploits the local information available to the nodes.

In order to evaluate the signaling overhead of the proposed AC-POCA in contrast with the other two existing methods, we set the length of signaling packets to 1 Kb and consider that the nodes use flooding to broadcast the notification $qt$ and their channel selection changes. Fig. 6 demonstrates that the signaling overhead is significantly lower with the proposed AC-POCA algorithm compared with that of CoCAG. This is because of the improvement in AC-POCA in terms of convergence speed and optimization of the SBR/BR functions as analyzed earlier in Section IV.

After channel assignment is performed to a link, the link is set to an active to verify if the assigned channel is, indeed, viable. In the wireless network, the number of active links directly impacts the aggregate throughput. Therefore, in Fig. 7, we compare the number of active links in the proposed AC-POCA algorithm with those achieved by two existing heuristic methods, i.e., the original POC assignment approach [24] and the conventional
OC assignment approach. In different network settings, the proposed AC-POCA exhibits the best performance in terms of the number of active links.

Finally, we consider the throughput in the dynamic network topology. Based on the above mixed scenario, we consider the nodes in the network can randomly move. For simplicity of the conducted simulation, both the data generation and node movement are treated as Poisson processes. We set the moving speed as randomly form 10 to 100 meters/s. The node movement time is set randomly, and the movement rate is set to 1/60 s. This means that the node may randomly move from 10 to 100 meters every minute. In such a dynamic scenario, we compare the throughput of AC-POCA and CoCAG which reassign the channels when the topology is similarly changed. The result is demonstrated in Fig. 8, in which the process time is 1000 s. The data generation rate is 125 KB/s in each node. To simplify the simulation, we set the value of $h_v$ in AC-POCA, in each scenario, as the largest one (only when $IF_j = 0$, no interference exists). From the result, it can be noticed that with the growth of the network size, the throughput performance of our proposal is much better than conventional one. This is because of both channel assignment time and iteration time of the conventional channel assignment algorithm become much larger when the number of user increases significantly, as shown in Fig. 5.

VII. CONCLUSION

Recently, caching based D2D-enabled networks emerged as an important element of content delivery system, that require quick network access. However, quick and dynamic network formulation is required to support such a system. In this paper, we demonstrated how multiple UAVs can be used to rapidly construct a D2D-enabled network, which is agile enough to support the content sharing and delivery in the network. However, the radio channel assignment of the nodes is an optimization problem since the number of orthogonal channels is limited and using overlapping channels in adjacent nodes with both primary and D2D links leads to severe interference. Furthermore, in the considered network, the mobility of nodes leads to highly dynamic situation which renders conventional channel assignment algorithms unsuitable. For overcoming those challenges, we presented an interference model and formulated a formal problem. Then, we proposed AC-POCA, a distributed Anti-Coordination game based algorithm for solving the channel assignment problem in the considered combined UAV and D2D based network. Using AC-POCA, the nodes are able to use only local information to reach a steady state in the network. Through analysis, the uniqueness of the steady state in the proposed AC-POCA was also verified. In addition, simulation results were provided to demonstrate that the proposal leads to fast convergence, low signaling overhead, and improved throughput in contrast with the existing methods.

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