Hypergraph-based resource allocation for Device-to-Device underlay H-CRAN network

Pan Zhao¹,²,³, Wenlei Guo¹, Datong Xu¹,³, Zhiliang Jiang⁴, Jie Chai⁵, Lijun Sun¹,³, He Li²,⁶ and Weiliang Han¹,³

Abstract
In the hybrid communication scenario of the Heterogeneous Cloud Radio Access Network and Device-to-Device in 5G, spectrum efficiency promotion and the interference controlling caused by spectrum reuse are still challenges. In this article, a novel resource management method, consisting of power and channel allocation, is proposed to solve this problem. An optimization model to maximum the system throughput and spectrum efficiency of the system, which is constrained by Signal to Interference plus Noise Ratio requirements of all users in diverse layers, is established. To solve the non-convex mixed integer nonlinear optimization problem, the optimization model is decomposed into two sub-problems, which are all solvable quasi-convex power allocation and non-convex channel allocation. The first step is to solve a power allocation problem based on solid geometric programming with the vertex search method. Then, a channel allocation constructed by three-dimensional hypergraph matching is established, and the best result of this problem is obtained by a heuristic greed algorithm based on the bipartite conflict graph and µ-claw search. Finally, the simulation results show that the proposed scheme improves the throughput performance at least 6% over other algorithms.

Keywords
H-CRAN, D2D communication, resources allocation, hypergraph, conflict graph

Introduction
Recently, as more and more mobile devices are included in the wireless network, the demand for the volume of the access point and the system throughput has a rapid growth.¹,² By 2025, the total number of the wireless devices will surpass 75 billion, and the corresponding requirement of data is over 3.3 ZB.³,⁴ In order to meet the requirement of access capacity and system capacity, the Heterogeneous Cloud Radio Access Network (H-CRAN), combined with Device-to-Device (D2D) communication, is introduced into the 5G core network.

In traditional wireless network structure, to guarantee the seamless coverage, the high-power node integrated control and forwarding unit is utilized. However, it is difficult to fulfill the throughput and...
access point volume requirement at the hot area. Thus, in order to increase the capacity of the wireless access network effectively, the H-CRAN network is introduced, which adds centralized baseband processing unit (BBU) entities and distributed remote radio heads (RRHs) components while retaining the original high-power node.\(^5\)\(^-\)\(^7\) For meeting the massive data needs of users in hot areas, RRHs as signal forwarding relay are ultra-densely deployed. All BBU units with control plane are grouped together in a centralized location to form a BBU pool aggregating all resources within cloud computing.\(^8\)\(^-\)\(^10\) Then, BBU pool can not only realize large-scale radio resource allocation but also offer collaborative processing.\(^11\)\(^-\)\(^13\) BBU controls RRH through fronthaul link while BBU pool communication with traditional high-power node via backhaul links. By this way, the networking benefits are fully utilized without increasing the running cost and the energy consumption of network infrastructure.

D2D communication is defined as user equipments (UEs) in physical proximity that directly communicate with each other without passing through cellular infrastructures, which greatly reduce the burden of cellular infrastructure.\(^14\)\(^,\)\(^15\) To efficiently enhance spectral efficiency, in general, D2D communications are considered to utilize the same spectrum as cellular user (CU). Thus, D2D communications have the great potential advantage of high data rate, short delay, low power consumption, and increased network capacity for supporting popular proximity-based applications.\(^16\)

Combining D2D communication with H-CRAN provides larger network capacity and better user experience. Due to the limited spectrum resources of cellular networks, the user in high-density mutual communication RRHs environment with a resource-reused manner as D2D communication, which will bring unpredictable inter-layer interference or co-layer interference.\(^17\)\(^,\)\(^18\) This kind of interference will not only affect the quality of service (QoS) of users but also lead to system performance degradation. Therefore, it is of great importance to make reasonable resource allocation.

**Related works**

To fully boost advantages brought by D2D and H-CRAN, lots of research efforts have been addressed by industry and academia. Based on stochastic geometry framework, Abana et al.\(^19\) analyzed the improvement of performance in terms of coverage and average traffic delivery rate with non-uniform D2D deployment and uniform D2D deployment in H-CRAN. With the same way as Abana et al.,\(^19\) the spectral efficiency performance of system is integrated in Liu et al.\(^20\) for D2D communications with downlink coordinated multipoint (CoMP) in C-RANs, whose mode selection scheme is depended on distance. However, Abana et al.\(^19\) and Liu et al.\(^20\) analyze the influence of D2D communication on the performance of H-CRAN network, but ignore the role of D2D performance itself.

Instead, an improved directed-hypergraph-based local altruistic game is proposed in Sun et al.,\(^21\) which is aiming to maximize D2D access rate and channel reuse rate as well as minimizing the uplink transmission power in multi-cell scenarios. But it only focuses on D2D’s own performance. Expecting to improve the spectrum efficient, the previous studies\(^22\)\(^-\)\(^24\) pay more attention on energy efficient. A resource allocation based on distributed non-cooperative game theory is investigated in Zhou et al.\(^22\) Based on D2D in-band and out-band, a novel energy efficiency spectrum sharing mechanism is proposed in Li et al.\(^23\)\(^,\)\(^24\) and Gui et al.\(^24\) However, their optimized object is the edge user of H-CRAN network. All the above-mentioned works take two-layer hybrid network structure into account, while ignoring the overall system performance.

In order to achieve the maximal overall system throughput, the previous studies\(^25\)\(^,\)\(^26\) considered the downlink reuse scenarios and exploited a many-to-one matching channel allocation to optimize underlaying user access rates, where power allocation is forgotten. Different from above, a joint mode selection and channel allocation scheme are researched in Zhen and Sun\(^27\) to maximize the system uplink throughput, by using game theory on distributed coalition formation. Based on Sun et al.,\(^28\) a distributed and staged resource allocation mechanism is proposed, which considered the mode selection, channel allocation, as well as the power control. Furthermore, a joint mode selection, user connection, and power allocation dynamic scheme are investigated in Mo et al.,\(^29\) which takes the time-varying of traffic and channel into account. However Sun et al.\(^28\) and Mo et al.\(^29\) still considered only D2D users, neglecting the performance improvement of other users.

From the above articles, it is obviously seen that fully utilizing the advantages of D2D communication could effectively improve the coverage, spectrum efficiency, power efficiency, throughput, and other performance of the H-CRAN network. However, most of the research are interested in enhancing the performance of underlaying network such as RRH users or D2D user. Only a few works concerned with the whole system situation. Some of the literature which optimizes global performance only show solicitude for channel allocation and abandons the role of power control. Therefore, a joint power allocation and channel selection scheme is quite essential.

**Main contributions**

In this article, to maximize overall H-CRAN throughput and guarantee the QoS requirements of each H-CRAN layer, jointly optimizing the performance of
overall H-CRAN with power allocation and channel allocation is considered. This resource allocation is formulated into a nonlinear integer programming problem with constraints on maximum power, Signal to Interference plus Noise Ratio (SINR), and channel number. To deal with this optimization problem, a two-step optimization framework is utilized to decompose the original problem into two sub-problems. The main contributions are as follows.

- A joint optimization resource allocation is proposed in this article, which not only focuses on the power allocation but also takes the channel allocation into account. To better adapt to the H-CRAN, a semi-centralized scheme is utilized, which is effectively suitable for the distinct processing characteristics of BBU pool.
- Different from binary mapping model, the 3D mapping-based solid geometric programming and hypergraph is introduced. The solid geometric programming is used to map power and its constraints. The hypergraph is investigated to capture the complex multiple co-channel relationship.
- Considering the complexity, the non-convex mixed integer programming original problem is decomposed into two sub-problems, the power allocation and channel allocation. Then, based on 3D mapping-based model, the Geometric Vertex Search approach and bipartite conflict graph are used to solve power and channel allocation problem.
- The simulation results validate that the proposed algorithm has a significant gain over the others in terms of throughput and user access rate. Furthermore, the proposed algorithm is easier to implement based on BBU pool.

The contents of this article are as follows. In section “System model,” the system model and optimization problem are explained. In section “Problem decomposition and algorithm design,” the solid geometric programming and hypergraph matching model are proposed, correspondingly Geometric Vertex Search approach and 3D Matching Game are elaborated to search the optimal power allocation and channel allocation. Section “Numerical results” is numerical results of the proposed algorithm and the performance of system. The conclusion is revealed in section “Conclusion.”

**System model**

**System model**

As illustrated in Figure 1, an H-CRAN with D2D communication system contains $M$ macro-cell users (MUEs), which is $M \in \{MUE_m | m = 1, \ldots, M\}$. The BBU pools equipped with a high-power base station

![Figure 1](H-CRAN with D2D communication system model.png)
(e.g. eNB) is the center unit of the network. \(K\) D2D pairs are located among the wireless environment, where \(K \in \{D_k| k = 1, \ldots, K\}\). Each D2D pair is composed of a transmitter \(D_{xt}\) and a receiver \(D_{ot}\). In addition, \(R\) set of RRHs are equipped to provided service, where \(R \in \{RRH_r|r = 1, \ldots, R\}\). The R-UEs in each RRH are denoted as \(N_r \in \{RUE_r^i| i = 1, \ldots, N_r\}\). The total number of all RUEs in H-CRAN is denoted as \(N = \sum_{r \in R} N_r\), and whose set is represented as \(N \in \{RUE_n| n = 1, \ldots, N\}\).

For simplicity, we divide the uplink resources into equal sized sub-channels and exploit \(L \in \{Ch_l| l = 1, \ldots, L\}\) to denote the set of all sub-channels. To protect the communication requirements of MUE, one MUE occupied one sub-channel (i.e. MUE \(m\) occupied one sub-channel \(l \in L\)). Considering the limited spectrum resources, the RRH users and D2D pairs communicate by multiplexing the channel resources of MUE users. Besides, to prevent high interference, one channel is limited to serve at most one RRH user as well as one D2D pair, while one RRH user at one sub-channel shares with at most one D2D pair. For example, D2D-2 and RUE-3 reuse the uplink resource of MUE-3, so the \(D_{ot}\) suffer interference from \(MUE_3\) and \(RUE_3\). In the same time, eNB received interference signal from RUE-3 and \(D_{ot}\) and RRH-3 received interference signal from RRH and \(D_{ot}\). To prevent excessive interference, each sub-channel is occupied by one MUEs, one RUEs, and one DUEs. Therefore, interference cannot occur between users in the same layer (i.e. no interference exists between D2D pairs as same as RUEs).

For macrocell, the link gain of the \(n\)th MUE is denoted as \(h_m\), and \(g^K_m, n\) is denoted as the interference gain from the \(n\)th RUE and \(g^K_m, n\) is denoted as the interference gain from the \(k\)th D2D pair. For RRHs, the link gain of the \(n\)th RUE in RRH-\(r\) is denoted as \(h^n_r\). For convenience, let \(h_n\) to denote the link gain of the \(n\)th RUE in overall system, for example, \(h_n = h^n_r\). Similarly, \(g^K_m, n\) is denoted as the interference gain from the \(m\)th MUE, \(g^K_m, n\) is denoted as the interference gain from the \(k\)th D2D pair. For \(k\)th D2D pair, the link gain is denoted as \(h_k\). Let \(g^n_m, k\) represent the interference gain from the \(n\)th RUE and \(g^K_m, k\) represent the interference gain from the \(m\)th MUE. Owing to channel reciprocity, \(g^n_m, n\) is equal to \(g^n_m, n\) and \(g^K_m, k\) is equal to \(g^K_m, k\). The main notation are listed in Table 1.

| Notation | Description |
|----------|-------------|
| \(M, M\) | M-UEs’ set, M-UEs’ number |
| \(K, K\) | D2D pairs’ set, D2D pairs’ number |
| \(N_r, N\) | R-UEs’ set, R-UEs’ number |
| \(R, R\) | RRHs’ set, RRHs’ number |
| \(L\) | Channels’ set, Channels’ number |
| \(h_m\) | MUE-m link gain |
| \(h_k\) | D2D pair-k link gain |
| \(g_{n, l}\) | RUE-\(l\) in RRH-\(r\) link gain |
| \(g^K_m, n\) | The interference gain of MUE-\(m\) from the RUE-\(n\) |
| \(g^{2f}_m, k\) | The interference gain of D2D pair-k from RUE-\(n\) |
| \(g^{2f}_m, n\) | The interference gain of MUE-\(m\) from D2D pair-k |
| \(x_M^{l, m}\) | The allocation status of M-UE on the channel \(l\) |
| \(x_N^{l, n}\) | The allocation status of R-UE on the channel \(l\) |
| \(x_{K, l}^{k, m}\) | The allocation status of D2D pair on the channel \(l\) |
| \(p_M\) | The \(m\)th M-UE maximum transmission power |
| \(p_N\) | The \(n\)th R-UE maximum transmission power |
| \(p^K\) | The \(k\)th D2D pair maximum transmission power |
| \(P\) | R-UE maximum transmission power |
| \(P_M\) | M-UE maximum transmission power |
| \(P_N\) | The SINR thresholds for D2D pairs |
| \(P^K\) | The SINR thresholds for R-UEs |
| \(P_M\) | The SINR thresholds for M-UEs |

D2D: Device-to-Device; RRH: remote radio heads; SINR: Signal to Interference plus Noise Ratio.

\[
x_M^{l, m} = \begin{cases} 
1, & \text{when MUE}_m \text{ use channel } l \\
0, & \text{otherwise}
\end{cases} \quad (1)
\]

\[
x_N^{l, n} = \begin{cases} 
1, & \text{when R-UE n is allocated to } l \\
0, & \text{otherwise}
\end{cases} \quad (2)
\]

\[
x_{K, l}^{k, m} = \begin{cases} 
1, & \text{when D2D k is allocated to } l \\
0, & \text{otherwise}
\end{cases} \quad (3)
\]

We assume that the \(l\)th channel is shared by at most one M-UE, one R-UE, and one D2D pair simultaneously, which cannot be shared by two or more UEs in the same type. And each M-UE is assigned a channel

\[
\sum_{m = 1}^{M} x_M^{l, m} \leq 1, \quad \sum_{q = 1}^{Q} x_N^{l, q} \leq 1, \quad \sum_{m = 1}^{M} x_M^{l, m} = 1, \quad \forall l \in L \quad (4)
\]

\[
\sum_{l = 1}^{L} x_{K, l}^{k, m} \leq 1, \quad \sum_{l = 1}^{L} x_N^{l, n} \leq 1, \quad \sum_{l = 1}^{L} x_M^{l, m} = 1, \quad \forall l \in L \quad (5)
\]

Let \(p^{K}_k\), \(p^{N}_n\), and \(p^{M}_m\) represent the optimal transmission power variable of D2D pair \(k\), R-UE \(n\) and M-UE \(m\) on the channel \(l\), respectively. \(\sigma^2\) represents
obtained. As constraint (18) shows, each type of user on channel \( l \) should satisfy their QoS requirement. Constraints (15)–(17) force the transmit power of D2D pairs (R-UE, M-UE) on channel \( l \) to be 0 in case \( \gamma^K_{k,l} = 0 \) (\( x_{n,l} = 0 \), \( x_{m,l} = 0 \)) and their power must not exceed the maximum power. Constraints (13) and (14) ensure that each M-UE is assigned with one sub-channel and each R-UE is assigned with at most one sub-channel as well as each D2D pair.

Problem decomposition and algorithm design

The optimization problem \( \mathcal{P}1 \) is non-convex NP-hard due to the binary nonlinear constraints, which cannot be solved by traditional optimization method. To solve this problem, a two-step scheme containing power allocation and channel allocation is proposed in the following section. Moreover, the detailed communication procedure of the proposed scheme is given.

Power allocation based on Geometric Vertex Search

In this section, the optimal power allocation scheme is addressed by Geometric Vertex Search method. In order to maximize the throughput of the D2D pair, the original problem is transformed to \( \mathcal{P}2 \), in which the R-UE and M-UE have their own QoS requirements. Here, a simplified case containing one D2D pair, one R-UE, and one M-UE is considered in \( \mathcal{P}2 \)

\[
\mathcal{P}2 : \max_{p^K_{k,l}, p^N_{n,l}, p^M_{m,l}} \left( R^K_{k,l} + R^N_{n,l} + R^M_{m,l} \right)
\]

subject to

\[
0 \leq p^K_{k,l} \leq \bar{p}^\text{max}_K, \forall k \in \mathcal{K}, l \in \mathcal{L} \tag{20}
\]

\[
0 \leq p^N_{n,l} \leq \bar{p}^\text{max}_N, \forall n \in \mathcal{N}, l \in \mathcal{L} \tag{21}
\]

\[
0 \leq p^M_{m,l} \leq \bar{p}^\text{max}_M, \forall m \in \mathcal{M}, l \in \mathcal{L} \tag{22}
\]

\[
\gamma^K_{k,l} \geq \gamma^K_{\text{min}}, \gamma^N_{n,l} \geq \gamma^N_{\text{min}}, \gamma^M_{m,l} \geq \gamma^M_{\text{min}} \tag{23}
\]

By adopting solid geometric approach, the SINR constraints of the power maximum problem are transformed to equation constraints as follows

\[
f^K_{k,l} = \frac{p^K_{k,l}}{\sigma^2 + \bar{p}^\text{max}_M r^K_{m,k} + \bar{p}^\text{max}_N r^N_{n,k}} = 0 \tag{24}
\]

\[
f^N_{n,l} = \frac{p^N_{n,l}}{\sigma^2 + \bar{p}^\text{max}_K r^K_{k,n} + \bar{p}^\text{max}_M r^M_{m,n}} = 0 \tag{25}
\]

\[
f^M_{m,l} = \frac{p^M_{m,l}}{\sigma^2 + \bar{p}^\text{max}_K r^K_{k,m} + \bar{p}^\text{max}_N r^N_{n,m}} = 0 \tag{26}
\]

Considering equations (24)–(26), the power \( p^N_{n,l}, p^K_{k,l}, \) and \( p^M_{m,l} \) span a 3D space. In the 3D space, equations (24)–(26) are the three planes, where \( \gamma \) is the slope of the plane and \( p \) is the intercept at the \( p \) axis. The transparent cube with the edge of black solid line represents...
the bound of the individual power. The yellow, black, and gray planes represent the SINR constraint conditions of D2D pairs M-UEs and R-UEs, respectively. The intersection of the three planes in 3D space, which is bounded by yellow, black, and gray planes and the three faces of the transparent cube, forms a feasible power region. In order to avoid a computationally expensive exhaustive search, a near optimal solution is proposed.

It is proved that when the maximized sum rate is achieved, at least one of the powers reaches its maximum power. However, the sum rate expression in equation (19) is non-convex with respect to arbitrary combinations of varying powers. Consequently, for arbitrary number of transmitters, the optimal powers may not necessarily lie on the vertices of the power region, leading to a possibly infinite set of points to test. Since the objective function on the boundary and SINR constraint is a quasi convex function, their optimal solution has the same power. Then, the optimal power of throughput can be obtained by finding the optimal solutions of SINR, which lies on the corners or vertices of the power region as shown in Table 2.

### Table 2. Set of optimal power.

| Points number | Set of optimal powers |
|---------------|-----------------------|
| 9             | \( \{P_K, P_M\}_m \times f_k, P_N^\max \) \( \{P_K, P_M\}_m \times f_k, P_N^\max \) \( \{P_K, P_M\}_m \times f_k, P_N^\max \) |
| 9             | \( P_K^\max, P_M^\max \times f_k, P_N^\max \) \( P_K^\max, P_M^\max \times f_k, P_N^\max \) \( P_K^\max, P_M^\max \times f_k, P_N^\max \) |
| 9             | \( P_K^\max, P_M^\max \times f_k, P_N^\max \) \( P_K^\max, P_M^\max \times f_k, P_N^\max \) \( P_K^\max, P_M^\max \times f_k, P_N^\max \) |
| 1             | \( P_K^\max, P_M^\max \times f_k, P_N^\max \) \( P_K^\max, P_M^\max \times f_k, P_N^\max \) \( P_K^\max, P_M^\max \times f_k, P_N^\max \) |

is obtained. According to the one-to-one correspondence between M-UEs and channels, we can use \( R_{m,n,k} \) to represent \( R_l \). And a three-dimensional throughput matrix \( R_{M \times N \times K} \) is obtained by all possible combinations of D2D pairs, M-UEs, and R-UEs. To find a subset \( T_{M \times N \times K} \in R_{M \times N \times K} \) that maximizes throughput is the objective. Similarly, we define a binary variable \( \xi_{m,n,k} \) to indicate the channel allocation state of M-UE \( m \), R-UE \( n \), and D2D \( k \)

\[
\xi_{m,n,k} = \begin{cases} 
1 & x_{m,n}^X = x_{n,k}^Y = 1 \\
0 & \text{otherwise}
\end{cases}
\]  

The original problem \( P1 \) transformed into a problem \( P3 \). Due to the formulated NP-hard problem is too complex to solve this problem via classical optimization approaches

\[
P3 : \max \xi_{m,n,k} \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{k=1}^{K} \xi_{m,n,k} \times R_{m,n,k} \\
s.t. \sum_{l \in L} \xi_{m,n,k} \leq 1, l \in \{m, n, k\} \\
\sum_{l \in L} \xi_{m,n,k} \geq 1, l \in L
\]

To address it, first \( P3 \) is modeled as a maximum weighted three-uniform hypergraph matching problem based on graph theory. Then, the initial solution of the weighted 3D matching problem is solved based on conflict graph by maximum independent set. Finally, the close-to-optimal solution is obtained in quasi-polynomial time by iterative updating independent set with \( \mu \)-claw searching. To facilitate understanding of the channel allocation scheme, some notations and definitions used are introduced as follows.

**Definition 1 (hypergraph).** Denote a non-empty set of all elements as \( \mathcal{V}^H \), and a family of finite subsets of \( \mathcal{V}^H \) of \( \mathcal{V}^H \) is denoted as a set \( E^H \); for example, \( \cup_{\mathcal{V} \in E^H} \mathcal{V} \). Then, a hyperedge \( \mathcal{E}^H \) can be defined as pair \( \mathcal{E}^H = (\mathcal{V}^H, \mathcal{E}^H) \), where \( \mathcal{V}^H \) is called vertex set and \( \mathcal{E}^H \) is called hyperedge set. If each hyperedge \( \mathcal{E}^H \in \mathcal{E}^H \) have a weight \( \omega(e^H) \), then, the hypergraph \( \mathcal{G}^H \) is called weight hypergraph, expressed as \( \mathcal{G}^H = (\mathcal{V}^H, \mathcal{E}^H, \omega(e^H)) \).

**Definition 2 (k-uniform hypergraph).** Based on Definition 1, we know that each hyperedge \( e^H \) is an arbitrary set of vertices. Define \( |e^H| \) as the cardinality of a hyperedge as the number of vertices in \( e^H \). Then, a hypergraph is called \( k \)-uniform hypergraph, if every hyperedge in \( \mathcal{G}^H \) has the same cardinality \( k \).

**Definition 3 (bipartite conflict graph).** A bipartite conflict graph \( G^C = (\mathcal{V}^C, \mathcal{E}^C) \) is a special construct in graph theory. Its vertex set is divided into two parts \( \mathcal{V}^C_1 \) and \( \mathcal{V}^C_2 \), where \( \mathcal{V}^C_1 \cap \mathcal{V}^C_2 = \emptyset \) and \( \mathcal{V}^C \cap \mathcal{V}^C_2 = \emptyset \). If any \( a \in \mathcal{V}^C_1 \) and \( b \in \mathcal{V}^C_2 \) are not disjoint (e.g. adjacent), there is an edge connection between them. Thus, if two sets intersect, they are called to be adjacent (neighbor).
Definition 4 ($\mu$-claw). In bipartite conflict graph $G^C$, a $\mu$-claw denoted as $C_\mu$ is an induced sub-graph of $G^C$, which consisted of a center and talons $T_{C_\mu}$. $T_{C_\mu}$ is a set consisting of $\mu$ independent nodes. There exists at least one common element between the center node and the node containing talons $T_{C_\mu}$. The center node connected with all independent nodes is the common adjacent node of talons.

Based on the above definition, the channel allocation process is as follows:

- As Figure 2(a) shows, we transform the original channel allocation problem into a 3D matching problem according to the assumption that each M-UE corresponds to channel one by one. Let $V^H = M \cup N \cup K$ represent the vertices set of hypergraph $G^H$. Let M-UE, R-UE, and D2D pair denote the three vertices in hyperedge $E^H$ (e.g. $e_{m,n,k}$ denotes the combination of the $m$th M-UE, $n$th R-UE, and $k$th D2D), and the throughput $R_{m,n,k}$ represents the weight of corresponding hyperedge, for example, $\omega(e_{m,n,k}) = R_{m,n,k}$. Therefore, the channel allocation problem can be modeled as a maximum weight three-uniform hypergraph matching problem. According to graph theory, a matching is a set...
of non-adjacent edges such that no edge covers common vertex. And maximum matching is defined as a matching with the largest number of edges in all possible matching results. Then, a maximum weight hypergraph matching is to capture a subset of disjoint hyperedges, such that the number of hyperedges and the sum of weight is largest.

- To simplify the original hypergraph, the hyperedges which do not satisfy equation (27) is removed. Thus, a feasible hypergraph $G^F$ is obtained as shown in Figure 2(b), which is a sub-graph of original hypergraph $G^H$. For example, $(e_{1,1,2})$-entry is one of the feasible hyperedges; however, $(e_{1,1,1})$ entry is not a feasible hyperedge.

- If each hyperedge in hypergraph is denoted as a vertex, such as the hyperedges $(e_{1,1,2})$-entry in Figure 2(c) is presented as a vertex $v_{1}^f$, then the feasible hypergraph $G^F$ can be transformed as bipartite conflict graph $G^C$. According Definition 3, let $V_A$ and $V_B$ denote the two vertices set of conflict graph. Define $V_A$ as a maximum independent set of $G^C$, then $V_B = V_A \cup V_B - V_A$ is a family of adjacent set of $V_A$. So, if any hyperedge $v^c_6 \in V_A$ and hyperedge $v^c_5 \in V_B$, they have the same vertex and an edge between them. If the adjacent vertexes of $B$ in $S$ are denoted as $N(B,S)$, then the adjacent vertexes of $v^f_1 \in V_A$ are $\{v^f_1,v^c_6,v^c_5\} \in V_B$, for example, $N(v^f_1) = N(v^c_2,v^c_3)$ = $\{(v^c_2,v^c_3), (v^c_1,v^c_3), (v^c_1,v^c_2)\}$. As Figure 2(c) shows, by constructing bipartite conflict graph, the maximum weight hypergraph matching is converted into a maximum independent set $V_A$ with largest weight searching problem in conflict graph.

- Based on Definition 4, we know that for any center node $v^c_6$, there exist $\mu$ mutually independent adjacent nodes of $v^c_6$. Note that, for $k$-uniform hypergraph, there are at most $k + 1$ mutually disjoint neighbors.32,33 In other words, the conflict graph corresponding to this hypergraph is $k + 1$-claw free, for example, any vertex in it cannot find a $k + 1$-claw. As shown in Figure 2(c), there are three adjacent vertexes for $v^c_1$; in fact, it only has two talons, as $v^c_5$ and $v^c_6$ occupy the same elements. Similarly, the vertex $v^c_5$ has five adjacent vertexes, but it only possesses three talons, since $v^c_5$ and $v^c_6$ occupy the same elements and $v^c_5$ and $v^c_6$ occupy the same elements. Based on $\mu$-claw theory, if there exists a $\mu$-claw (including talons $v^c_1,v^c_2,\ldots,v^c_6$) to enhance the overall performance for a given center vertex $v^c_a$ in independent set $V_A$ of conflict graph $G^C$, then add $T_{C_a}$ into $V_A$ and remove all the edges intersecting with them out of $V_A$. After that, the matching result is best.

With the above knowledge, the proposed channel allocation scheme contains the following steps:

1. Construct Hypergraph based on $M,N,K$, and $R_{m,k}$;
2. Find the Feasible Hypergraph from the original Hypergraph;
3. Construct a Bipartite Conflict Graph to map the feasible hypergraph;
4. Initialize the solution of the independent set by a heuristic greedy algorithm;
5. Search the $\mu$-claw for any vertex of the identified solution;
6. Update the result if a superior performance is achieved by any neighborhood.

The pseudo-code details are shown in the following Algorithm 1 and Algorithm 2. Note that the vertex number of $V_A$ is denoted as $|V_A|$.

### The procedure of proposed scheme

As Figure 3 illustrates, the detailed communication procedure of the proposed scheme is given. The channel state information (CSI) of all H-CRAN uplinks and

---

**Algorithm 1. Iterative Algorithm for Channel Allocation Based on Hypergraph.**

**Input:** The set $M,N,K$ and Throughput matrix $R_{m,n,k}$

**Output:** Maximum Throughput and its corresponding Match result, for example, independent set $V_A$

1. Find a feasible hypergraph from the original hypergraph.
2. Construct a bipartite conflict graph based on the feasible hypergraph.
3. Initialize the set $V_A$ according to Algorithm 2.
4. Sort the vertex $v^c_6 \in V_A$ based on hyperedge weight $\omega(e_{m,n,k})$ of this vertex, and set $i = 1$.
5. Calculate the adjacent set $V_B$ and sort the vertex $v^c_6 \in V_B$ according to hyperedge weight in descending order.
6. Set $\mu = 1$.
7. While $\mu \leq 3$ do:
   8. Search the $\mu$-claw $C_a$ for each vertex $v^c_a \in V_A$ as the center node of $C_a$.
   9. If there exist talons $T_{C_a}$ in a $\mu$-claw $C_a$ such that $\omega^2(V_A - N(T_{C_a}) \cup T_{C_a}) > \omega^2(V_A)$, then:
      10. $V_A = (V_A - N(T_{C_a}) \cup T_{C_a}) \cup T_{C_a}$, go to 4.
   11. else:
      12. $\mu = \mu + 1$
   13. end if
   14. end while
   15. if $i < |V_A|$ then
      16. $i = i + 1$, go to 5.
   17. end if
D2D links by eNB and RRHs with fronthaul links, which is assumed following quasistatic block fading distribution, is perfectly acquired BBU pool node. Then, the BBU pool further performs baseband signal processing and resource allocation, which consists of three main stages. In Stage 1, the optimal transmit power is found by relaxing the constraints in equation (18), and correspondingly, the throughput matrix is obtained for each MUE, RUE, and D2D pair. In Stage 2, a weighted hypergraph model is constructed for sub-channel allocation problem. In Stage 3, the total achievable throughput system is obtained with the proposed algorithm. Finally, the calculation result is fed back to all the users through eNB and RRHs (Figure 4).

Numerical results

In this section, we present the simulation results and their corresponding analysis. We consider three-tier H-CRAN with one eNB, some RRUs, and some D2D pairs. As shown in Figure 5, the macrocell is assumed with a radius of 1000 m. The RRUs with 200–300 m coverage distance located in the edge of the macrocell. The D2D pairs are randomly distributed in the coverage of the macrocell, and D2D communication range is within 20–60 m. Both M-UEs and R-UEs are correspondingly distributed within the coverage of eNB and RRUs, respectively. Specific simulation parameters and values are listed in Table 3.

To evaluate the performance, we compared the performance of our proposed algorithm with the iterative Kuhn and Munkres (IKM) algorithm in Liu et al., which transforms the 3D matching problem into three iterative two-dimensional matching problems, and the greedy 3D matching algorithm (GDM) in Wang et al., which arrange all the hyperedges in descending order on the basis of their weights and then obtain the sub-optimal solution in a greedy manner with low complexity. In the following simulation results, greedy iterative hypergraph matching (GIHM) is used to represent our proposed algorithm. They all are used to optimize the three-dimensional matching problem. We also evaluate the performance of the three schemes in terms of system throughput and the admitted rate with different parameter settings. All the results averaged over 200 random trials.

Figure 6 shows the total throughput at different D2D radius and RRH coverage radius. It is observed that the throughput gain decreases when the distance of the D2D pair or RRH-RUEs become farther apart. The reason is that the D2D link would be weaker with increasing separation distance of the D2D pair or the RRH-RUEs under constant transmit power. Moreover, it is seen that performance GDM is worst. The reason is that the GDM is based on the heuristic descending algorithm and searches an independent set of hyperedges with the highest weight. It ignores the effect of intersecting hyperedges on performance. The IKM outperforms GDM approaches, because it converts the 3D match into a 2D match and then solves it based on iterative algorithm, which can only guarantee the optimality of the 2D match while cannot guarantee the most positive of the three-dimensional match. The proposed scheme performs the best among other algorithms.
schemes, and this is because the scheme is modeled with hypergraph matching and solved by conflict graph based on greedy algorithm and multiple iterations. The near-optimal throughput is achieved as shown in Figure 2. When D2D distance is 20 m, the proposed algorithm can improve throughput performance by 6.25% and 30% as compared to other schemes.

Figure 7 is presented to show that the proposed algorithm increases the throughput of the H-CRAN combined with D2D with different number of D2D pairs and R-UEs. Obviously, the total throughput is enhanced as the number of D2D pairs and R-UEs increase. As it was observed, the turning point of the number of D2D pairs is 18. The throughput growth rate is significant when the number of D2D in the system is smaller. However, the throughput curve rises slowly when the number of D2D in the system is larger than it. Since the \( \min(M,N,K) \) in the three-partite hypergraph \( G^m \) has limited the maximum number of non-intersecting hyperedges in independent sets, the total throughput grows rapidly when the vertex number in one dimension is less than that of the other two
dimensions; otherwise, the throughput growth rate is small. Moreover, it is easy to see that the proposed algorithms provide a better performance for D2D communication comparing with IKM and GDM algorithms. When D2D pairs’ number is 18, the total throughput of our proposed algorithm has a gain about 6% and 34% over that of IKM and GDM algorithms, respectively.

In Figure 8, the impact of the minimum SINR requirement on the users’ throughput performance is further evaluated. It is shown that the throughput increases slightly, when the minimum SINR of RUEs is less than 7. The reason is that the increase in the minimum SINR requirement of RUEs will bring larger transmit power of RUEs, which will inevitably increase throughput. When the minimum SINR of RUEs is less than 13 and more than 7, the throughput decreases significantly. This is because in order to meet the minimum SINR requirements of RUEs, the increasing power will bring too much interference to other users, which will reduce the user admitted rate. It is not difficult to see in Figure 11. In addition, the larger minimum QoS requirements of D2D pairs, the smaller total throughput, regardless of the matching algorithm are used. The reason is the similarity of increasing minimum QoS requirement of R-UEs. Once again, the performance of our proposed algorithms is better than the IKM and GDM algorithms.

In Figure 9, the impact of the number of admitted underlaying users with different D2D radius and RRH coverage radius. The result shows that the number of admitted

| Table 3. Parameters of system. |
|--------------------------------|
| Parameter                   | Value                          |
| --                          | --                             |
| Macro-cell radius           | 1 km                           |
| RRH radius                  | 200 m, 300 m                   |
| D2D distance, r             | 20, 30, ..., 60 m              |
| Number of D2D pairs, K      | 12, 14, ..., 20                |
| Number of R-UEs, N          | 18, 20                         |
| Number of M-UEs, M          | 20                             |
| Maximum power of D2D pair   | 23 dBm                         |
| Maximum power of R-UE       | 20 dBm                         |
| Maximum power of M-UE       | 23 dBm                         |
| Noise spectral density      | –117 dBm                       |
| Path loss model for M-UE links | 127 + 30log(d(km))           |
| Path loss model for R-UE links | 128.1 + 37.6log(d(km))       |
| Path loss model for D2D links | 148 + 40log(d(km))           |
| Min SINR of D2D pairs, γ^K_{min} | 3 dB, 7 dB                   |
| Min SINR of R-UEs, γ^N_{min} | 5, 6, ..., 13 dB              |
| Min SINR of M-UEs, γ^M_{min} | 3 dB                           |

RRH: remote radio heads; D2D: Device-to-Device; SINR: Signal to Interference Plus Noise Ratio.
underlaying users of all the schemes decreases as the D2D pairs and RRH-RUEs distance increase. However, with the increase in D2D distance, the decline rate is gradually slow, and the performance gap between algorithms also decreases. The reason is that a larger distance of D2D pairs or RRH-RUEs represents a weaker link, thus it is more likely that D2D or RRH-RUEs transmission can be accomplished without losing other constraint. When D2D distance is 20 m, the performance of the proposed algorithm increases about 3% and 21% as compared to other schemes.

Figure 9. Admitted rate versus the distance of D2D pairs.

Figure 10. Admitted rate versus the number of D2D pairs.

From Figure 10, the performance of the schemes in terms of the number of admitted underlaying users is investigated for different number of D2D pairs and R-UEs. It is easy to find that the more D2D pairs or RUEs are there, the higher number of admitted underlaying users is, which is consistent with that shown in Figure 7, further verifying that underlaying communication can improve the system throughput. Besides, the number of admitted rate increases distinctly with the enhancement of the number of D2D pairs in small region. Since in small region, the number of D2D pairs’ constraint becomes the major factor that narrows the feasible region of the number of admitted underlaying users. While the number of D2D pairs increases gradually, the raise in the admitted rate tends to be gentle owing to the fact that the number of D2D pairs constrains the admitted rate increment.

From Figure 11, the performance of the schemes in terms of the access number of underlaying users is investigated for different minimum SINR requirements of D2D pairs and R-UEs. It is easy to observe that when $\gamma_{\text{min}}^N$ is not sufficiently large, the admitted rate decreases slowly with the increase in $\gamma_{\text{min}}^N$ because the admitted rate of the underlaying users is less affected by low QoS requirement. However, the feasible region of the problem shrinks significantly for large $\gamma_{\text{min}}^N$, which causes the fast decline of the admitted rate in system. Besides, it also shows that the admitted rate declines sharply as the minimum SINR of D2D pairs $\gamma_{\text{min}}^K$ is large, which demonstrates that both $\gamma_{\text{min}}^N$ and $\gamma_{\text{min}}^K$ parameters affect admitted rate at the same time. The reason is that it is more difficult for the D2D pairs and RUEs to find suitable channel which satisfy the QoS constrains of MUEs, RUEs, and D2D pairs simultaneously. When $\gamma_{\text{min}}^K$ is 5, the total throughput of our proposed algorithm surpasses that of IKM and GDM algorithm with amount about 6.3% and 41.5%, respectively.

Figure 11. Admitted rate versus the SINR threshold of R-UEs.

Conclusion

In this article, a joint optimization problem to maximize the system capacity of hybrid scenario of the H-
CRAN and D2D communication is presented. By step-by-step scheme, the original NP hard problem is decomposed into two sub-problems, for example, the power allocation and the channel allocation. In the first problem, the 3D optimal power programming problem is solved by the sub-channel allocation based on Geometric Vertex Search. Then, with bipartite conflict graph and the $\mu$-claw searching, the optimal result of the channel allocation problem based on the 3D hyper-graph is achieved. Simulation shows that system throughput and access rate are affected in terms of D2D number, D2D distance, and RUE SINR requirements. The throughput of the proposed scheme has about 6.2% gain over other scheme as well as and the access rate of the proposed scheme has at least 3% gain over other scheme. Therefore, the proposed scheme is beneficial.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This work was supported in part by the National Natural Science Foundation of China (Grant Nos 61973104 and 61803146), Open Foundation of State key Laboratory of Networking and Switching Technology (Beijing University of Posts and Telecommunications; Grant Nos SKLNST-2019-2-05 and SKLNST-2019-2-09), the Basic Scientific Research Special Fund of Henan University of Technology (Grant No. 2015RCJH18), the Key Research Projects of Henan Higher Education Institutions (Grant No. 20BS100003), Henan University Science and Technology innovation Talents Support Program (Grant No. 19HASTIT027), Doctoral Foundation (Grant No. 2018BS074), Open Fund of Key Laboratory of Grain Information Processing and Control (Grant Nos KFJJ-2020-114 and KFJJ-2018-103), the Dean Project of Key Laboratory of Cognitive Radio and Information Processing, Ministry of Education (Grant No.CRKL180104), and the Scientific and Technological Project in Henan Province of China (Grant No. 202102210362).

ORCID iD

Pan Zhao https://orcid.org/0000-0002-0480-8619

References

1. Chettri L and Bera R. A comprehensive survey on Internet of things (IoT) toward 5G wireless systems. IEEE Internet Things J 2020; 7(1): 16-32.
2. Halabian H. Distributed resource allocation optimization in 5G virtualized networks. IEEE J Sel Areas Commun 2019; 37(3): 627–642.
3. Evans D. The Internet of things: how the next evolution of the Internet is changing everything. Cisco, TX; San Jose, CA: White Paper, 2011.
4. Chambers J. Former Cisco CEO John Chambers predicts 500 billion connected devices by 2025. New York: Business Insider, 2015.
5. Yu N, Song Z, Du H, et al. Dynamic resource provisioning for energy efficient cloud radio access networks. IEEE Trans Cloud Comput 2019; 7(4): 964–974.
6. Yuan Z, Ying W and Zhang W. Energy efficient resource allocation for heterogeneous cloud radio access networks with user cooperation and QoS guarantees. In: Wireless communications networking conference, Doha, Qatar, 3–6 April 2016. New York: IEEE.
7. Zhong Y, Quek TQS and Zhang W. Complementary networking for C-RAN: spectrum efficiency, delay and system cost. IEEE Trans Wirel Commun 2017; 16(7): 4639–4653.
8. Liao Y, Song L, Yonghui LI, et al. How much computing capability is enough to run a cloud radio access network? IEEE Commun Lett 2016; 21(1): 104–107.
9. Sun S, Kadoch M, Gong L, et al. Integrating network function virtualization with SDR and SDN for 4G/5G networks. IEEE Netw 2015; 29(3): 54–59.
10. Huq KMS, Muntaz S, Rodriguez J, et al. Enhanced C-RAN using D2D network. IEEE Commun Mag 2017; 55(3): 100–107.
11. Alqerm I and Shihada B. Sophisticated online learning scheme for green resource allocation in 5G heterogeneous cloud radio access networks. IEEE Trans Mob Com 2018; 17(10): 2423–2437.
12. Liu T, Tong J, Guo Q, et al. Energy efficiency of massive mimo systems with low-resolution adcs and successive interference cancellation. IEEE Trans Wirel Commun 2019; 18(8): 3987–4002.
13. Chen N, Rong B, Zhang X, et al. Scalable and flexible massive mimo precoding for 5G H-CRAN. IEEE Wirel Commun 2017; 24(1): 46–52.
14. Zhou Z, Peng M and Zhao Z. Joint data-energy beamforming and traffic offloading in cloud radio access networks with energy harvesting-aided D2D communications. IEEE Trans Wirel Commun 2018; 17(12): 8094–8107.
15. Zhao G, Chen S, Qi L, et al. Mobile-traffic-aware offloading for energy- and spectral-efficient large-scale D2D-enabled cellular networks. IEEE Trans Wirel Commun 2018; 18(6): 3251–3264.
16. Lai WK, Wang Y, Lin H, et al. Efficient resource allocation and power control for LTE-A D2D communication with pure D2D model. IEEE Trans Veh Technol 2020; 69(3): 3202–3216.
17. Dominic S and Jacob L. Distributed interference-aware admission control and resource allocation for underlaying D2D communications in cellular networks. Sadhana 2019; 44(6): 138.
18. Alamouti S and Sharafat AR. Device-to-device communications in multi-cell LTE-advanced networks with cloud radio access network architecture. IEEE Commun Stand Mag 2018; 2(1): 90–94.
19. Abana MA, Peng M, Zhao Z, et al. Coverage and rate analysis in heterogeneous cloud radio access networks with device-to-device communication. IEEE Access 2016; 4: 2357–2370.
20. Liu J, Min S, Quek TQS, et al. D2D enhanced coordinated multipoint in cloud radio access networks. *IEEE Trans Wirel Commun* 2016; 15(6): 4248–4262.

21. Sun Y, Du Z, Xu Y, et al. Directed-hypergraph-based channel allocation for ultradense cloud D2D communications with asymmetric interference. *IEEE Trans Veh Technol* 2018; 67(8): 7712–7718.

22. Zhou Z, Dong M, Ota K, et al. Energy-efficient resource allocation for D2D communications underlaying cloud-RAN based LTE-A networks. *IEEE Internet Things J* 2016; 3(3): 428–438.

23. Li Z, Gui J, Xiong N, et al. Energy-efficient resource sharing scheme with out-band D2D relay-aided communications in C-RAN-based underlay cellular networks. *IEEE Access* 2019; 7(1): 19125–19142.

24. Gui J, Li Z and Zeng Z. Improving energy-efficiency for resource allocation by relay-aided in-band D2D communications in C-RAN-based systems. *IEEE Access* 2017; 7(3): 8358–8375.

25. Mao X, Zhang B, Chen Y, et al. Matching game based resource allocation for 5G H-CRAN networks with device-to-device communication. In: 2017 IEEE 28th annual international symposium on personal, indoor, and mobile radio communications (PIMRC), Montreal, QC, Canada, 8–13 October 2017. New York: IEEE.

26. Wang L, Wu H, Ding Y, et al. Hypergraph-based wireless distributed storage optimization for cellular D2D underlays. *IEEE J Sel Areas Commun* 2016; 34(10): 2650–2666.

27. Zhen W and Sun Y. Mode selection and resource allocation in uplink device-to-device enabled cloud radio access networks. In: 2017 *IEEE international conference on communications workshops (ICC Workshops)*, Paris, 21–25 May 2017. New York: IEEE.

28. Sun Y, Peng M and Poor HV. A distributed approach to improving spectral efficiency in uplink device-to-device enabled cloud radio access networks. *IEEE Trans Commun* 2018; 66(12): 6511–6526.

29. Mo Y, Peng M, Xiang H, et al. Resource allocation in cloud radio access networks with device-to-device communications. *IEEE Access* 2017; 5(2): 1250–1262.

30. Berman P. A d/2 approximation for maximum weight independent set in d-claw free graphs, 2000, https://link.springer.com/chapter/10.1007/3-540-44985-X_19#citeas

31. Furer M and Yu H. Approximate the k-set packing problem by local improvements, 2014, https://arxiv.org/abs/1307.2262

32. Wang L, Wu H, Ding Y, et al. Hypergraph-based wireless distributed storage optimization for cellular D2D underlays. *IEEE J Sel Areas Commun* 2016; 34(10): 2650–2666.

33. Miao L, Bai B and Chen W. 4-DMWM approach for caching based optimal D2D pairing and channel allocation: centralized and distributed algorithm design. *IEEE Access* 2016; 4: 9213–9224.

34. Liu Y, Wang W, Chen H-H, et al. Secrecy rate maximization via radio resource allocation in cellular underlaying V2V communications. *IEEE Trans Veh Technol* 2020; 8(2): 625–628.

35. Wang B, Zhang R, Chen C, et al. Interference hypergraph-based 3D matching resource allocation protocol for NOMA-V2X networks. *IEEE Access* 2019; 7(4): 90789–90800.