Decentralized Content Dissemination in Fog Radio Access Network Using Unsupervised Learning Empowered Rate-Splitting Framework

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Abstract

Multi-hop device-to-device (D2D) communication-aided decentralized content dissemination is investigated for a fog radio access network (F-RAN). In the proposed framework, two content-sharing D2D links establish a device-cluster. In each device-cluster, the content-holder device-users (DUs) transmit to the content-requester DUs via a relay fog user-equipment (F-UE) over the same radio resource blocks (RRBs). Such RRBs are shared with uplink F-RAN as well. Rate-splitting and common message decoding are used at each device-cluster. A multi-objective resource optimization, for device-clustering, device power allocation, and scheduling of RRBs and relay F-UEs, is devised to simultaneously maximize the overall capacity of D2D links and minimize transmission power of the active devices. The formulated optimization problem is solved in two steps. First, by utilizing two-dimensional principal component analysis based unsupervised-learning technique, a low-complexity device-clustering method is proposed. Second, a Stackelberg resource scheduling game is exploited to obtain the devices’ power allocations and scheduling of RRBs and relay F-UEs among the device-clusters. A decentralized content dissemination framework, referred as rate-splitting for multi-hop D2D (RSMD), is developed. The convergence of the proposed RSMD framework to a Stackelberg-equilibrium and Pareto-efficient outcome is justified. Through extensive simulations, efficiency of the proposed RSMD framework is demonstrated.

I. INTRODUCTION

Leveraging distributed signal processing and caching at the network edge, fog radio access network (F-RAN) presents a disruptive RAN architecture for the beyond 5G and envisioned 6G wireless networks [1]. Cache-enabled device-to-device (D2D) networking is a promising direction for alleviating burden over the constrained fronthaul network in F-RAN. By caching the popular contents at certain edge devices and exploiting D2D networking, the user demands in F-RAN can be locally accommodated without redundant transmission from the centralized cloud-server [2]. However, an efficient interference management in a D2D-aided F-RAN is of paramount importance.
importance. To effectively manage interference in a D2D-aided F-RAN, this work develops a framework that first groups the content-sharing D2D links into multiple clusters by exploiting an unsupervised-learning method, and subsequently, by considering each device-cluster as a rational player, applies game theory to schedule resources among the content-sharing D2D links.

A. Related Works

Interference management in a D2D network is a non-trivial problem when multiple D2D and cellular links share radio resource blocks (RRBs) for content dissemination [3]. State-of-the-art literature investigated power control, resource scheduling, and mode selection to manage the interference in D2D network and a subset of these works can be found in [4]–[6]. Recently, Stackelberg game has been widely exploited for decentralized interference management in D2D network [7]–[11]. Stackelberg game is a leader-follower based bi-level game where both leader and follower independently optimize their individual strategies and the coordination between leader and follower is exploited to achieve an equilibrium state. However, in [7]–[11], the interference among the D2D links was either treated as a noise or entirely ignored via orthogonal RRB allocation. From an information theory perspective, both approaches are sub-optimal.

Meanwhile, multi-hop D2D networking was shown to substantially improve the coverage of D2D links and the power consumption at the mobile devices. In [12], [13], the authors optimized the overall throughput of multi-hop D2D networking by considering fixed relay in the network. Energy-harvesting relay assisted D2D networking was investigated in [14]. Mobile relay assisted D2D networking was exploited to improve coverage of the cell edge users in [15]. In [16], [17], the authors developed 3D-resource matching algorithms for multi-hop D2D network. However, the authors in [17] considered only a one-to-one 3D-matching problem. On the other hand, the authors in [16] developed a computationally intensive dynamic programming based method, which is challenging to apply in a large scale network. To effectively manage interference in multi-hop D2D-aided F-RAN, it is essential to develop a computationally efficient algorithm that can handle a generalized 3D-resource matching among multiple D2D links, relays, and RRBs.

Recently, rate-splitting and common message decoding (RS-CMD) based transmission strategy has been proposed to efficiently mitigate the deleterious impact multi-user interference (MUI) in downlink [18]. Particularly, RS-CMD allows both strong and weak users in a shared RRB to partially cancel the MUI, and thus improves the overall throughput of the system compared to non-orthogonal multiple-access (NOMA). Meanwhile, when the number of antennas in the transmitting nodes are smaller than the number of receiving nodes multiplexed in the same RRB, RS-CMD also outperforms space-division multiple-access. For downlink cellular commu-
nications, RS-CMD was shown to substantially improve the throughput of multi-user broadcast system \cite{19}, cloud-radio access network \cite{20}, and cooperative system with user relaying \cite{21}. Moreover, RS-CMD can also achieve optimal throughput in uplink multi-user access channel \cite{22}. In \cite{23}, the problem of power allocation and decoding order selection was investigated to maximize the sum-rate of uplink RS-CMD system. Recall, the first and second hops in a multi-hop D2D network can be exploited as multi-user access and MUI channels, respectively. Hence, the combination of RS-CMD and multi-hop D2D networking can utilize the proven benefits of RS-CMD to mitigate interference among D2D links in both hops. However, despite promising, such a system was not exploited in the literature of D2D-aided content dissemination network.

An effective clustering of the content-sharing D2D links is required to exploit the benefit of integrating the RS-CMD in D2D-aided F-RAN. In the literature, distance-based user ranking, matching-theory, and coalition-game were exploited for device-clustering \cite{24}–\cite{26}. However, the aforementioned clustering methods were primarily optimized for single-hop network, and suitability of these methods to the multi-hop D2D network is not evident. Recently, a growing interest of learning empowered device-clustering in large scale network has been demonstrated in state-of-the-art literature. The authors in \cite{27}–\cite{29} applied the well-known $K$-means clustering and expectation-maximization (EM) based unsupervised-learning algorithms to form the resource-sharing device-clusters in the NOMA systems. Although the aforementioned unsupervised-learning algorithms were shown to outperform matching-theory based clustering, they have certain limitations for being applied in D2D-aided F-RAN. Specifically, the aforementioned unsupervised-learning algorithms are centralized, and they require the global channel information of the device-users (DUs) at the central server. As a result, the signaling overhead to obtain the required data set is significantly increased which makes the centralized learning empowered clustering algorithms impractical for a large scale F-RAN. Accordingly, a learning empowered device-clustering algorithm, which can efficiently work by using a low signaling overhead, is imperative for RS-CMD enabled and D2D-aided F-RAN.

B. Contributions

To the best of authors’ knowledge, this is the first work that develops a decentralized and low-complexity framework for popular content dissemination among the edge devices in F-RAN by combining multi-hop D2D networking and RS-CMD based transmission strategy. In particular, we make the following two contributions: (i) We develop a communication-efficient and learning empowered algorithm for clustering the resource-sharing D2D links, and (ii) we optimize RS-CMD based transmission strategy for multi-hop D2D networking. The further details of our
contributions are summarized as follows:

1) In the proposed framework, two content-sharing D2D links establish a device-cluster to share the RRBs for data transmission and reception. In each device-cluster, the data of the content-holder (CH) DUs is transmitted to the content-requester (CR) DUs via a relay fog user-equipment (F-UE) over certain RRBs, and such RRBs are also shared with uplink F-RAN. To combat the inter device-cluster interference, the device-clusters are scheduled over orthogonal RRBs, and an RS-CMD strategy is adopted to combat the intra device-cluster interference. A multi-objective optimization problem (MOOP) is formulated to simultaneously maximize the overall capacity of D2D-aided content dissemination and minimize the transmission power of CH DUs and relay F-UEs. Owing to the NP-hardness of the proposed MOOP, a two-step solution is developed.

2) In the first step, to partition the D2D links into non-overlapping clusters, a two-dimensional principle component analysis (2D-PCA) based unsupervised-learning technique is applied. Our proposed method alleviates the burden of global channel state information (CSI) acquisition at the fog access point (F-AP) for clustering the D2D links. A low-complexity device-clustering algorithm is developed, and the Pareto-efficiency of the formed device-clusters is proved.

3) In the second step, a Stackelberg game is formulated to conduct the inter and intra device-cluster resource scheduling. Here, the device-clusters, acting as the followers, perform the power control over the allocated RRBs by using a non-cooperative exact potential game. Meanwhile, the F-AP, acting as a leader, allocates the RRBs and relay F-UEs among the device-clusters based on the bids submitted by the device-clusters, and updates the RRBs’ prices. The best response strategies of both the device-clusters and F-AP are obtained.

4) A decentralized content distribution framework, referred as rate-splitting for multi-hop D2D (RSMD), is proposed. We justify that the proposed RSMD framework provides a Stackelberg-equilibrium (SE) and Pareto-efficient outcome with polynomial computational complexity. Through extensive simulations, we illustrate that the proposed RSMD framework substantially outperforms several benchmark schemes.

The rest of the manuscript has following organizations. Section II provides the overall system model and problem formulation. The learning empowered device-clustering and Stackelberg resource scheduling game are discussed in Sections III and IV, respectively. Section V presents various features of the proposed RSMD framework. Several illustrative simulation results and the concluding remarks are presented in Sections VI ad VII, respectively.
II. SYSTEM MODEL AND PROBLEM FORMULATION

A. System Overview

We consider a D2D-aided F-RAN system, illustrated in Fig. 1, with one serving F-AP, $N$ non-overlapping RRBs, $C$ cellular UEs (CUEs) transmitting to the F-AP in uplink, $M$ DUs that already have acquired certain popular contents from the F-AP, referred as, CH DUs, and $M'$ DUs that require certain popular contents, referred as, CR DUs. Without loss of generality, we consider that each CH DU holds a unique content, $M' > M$, and for each type of popular content, there is at least one CR DU. We assume that both fronthaul capacity and downlink RRBs in F-RAN are almost fully utilized, and accordingly, D2D networking is exploited to transfer contents from the CH DUs to the CR DUs. The CH and CR DUs are considered to be associated with the same network operator, and the information about the contents acquired and requested by the CH and CR DUs, respectively, is known to the network operator. Consequently, for the ensuing analysis we assume that $M$ content-sharing D2D links are formed by the network operator. We consider that in these content-sharing D2D links, the CR DUs are far from their CH DUs, and a multi-hop transmission is required to transfer the contents. Accordingly, the network operator selects a group of smart UEs with signal processing capability, referred as F-UEs, to relay the contents from the CH DUs to CR DUs. On one hand, by using such a cooperation, the F-UEs can obtain the popular contents in advance, and on the other hand, the network operator dose not need to assign additional downlink RRBs to transmit such contents to F-UEs. Essentially, such a cooperation is beneficial for both F-UEs and network operator. Moreover, to encourage the F-
UEs to participate in relaying, the network operator can provide certain rewards (i.e., discounts) to the F-UEs, and the rewards can be proportional to the number of CH DUs assisted by the F-UEs. We denote $L = \{1, 2, \cdots, L\}$ as the set of available relay F-UEs, $M = \{1, 2, \cdots, M\}$ as the set of given content-sharing D2D links, and $N_{sc} = \{1, 2, \cdots, N\}$ as the set of available non-overlapping RRBs. Both DUs and relay F-UEs are equipped with single antenna, and they are half-duplex.

To efficiently use RRBs for content dissemination, clustering of the D2D links is considered. To simplify both the encoding and decoding operations, we consider that each device-cluster contains two content-sharing D2D links. The device-clusters are pairwise disjoint, and the total number of device-clusters in the network is $\lceil \frac{M}{2} \rceil$. Each device-cluster is allocated a set of non-overlapping orthogonal RRBs, and these RRBs are also shared with certain CUEs for uplink data transmission. The CH and CR DUs in a given device-cluster transmit and receive, respectively, over the allocated RRBs by using an RS-CMD strategy. Each device-cluster is assisted by a single relay F-UE, and a relay F-UE can assist multiple device-clusters. The described system is operated on a slotted-time basis where the overall time duration is divided into equal and non-overlapping time-slots (TSs). Moreover, data transmission/reception in each TS is synchronized. Particularly, in the first-half of each TS, the CH DUs of the device-clusters transmit to the selected relay F-UEs, and the relay F-UEs forward the received contents to the corresponding CR DUs in the second-half of the TS. An example scenario considering three device-clusters and two relay F-UEs is depicted in Fig. 1. Along the lines of [30], the aforementioned synchronization can be achieved by sending timing-signals from the F-AP to the DUs and relay F-UEs over the dedicated control channels. For the analytical tractability, we also assume a slowly changing network topology where locations of the DUs and F-UEs remain fixed for a number of TSs.

B. Rate-splitting Enabled Transmission

We study the RS-CMD enabled transmission in the $j$-th device-cluster. The $j$-th device-cluster is denoted by $S_j = \{S_j(1), S_j(2)\}$ where $S_j(1)$ and $S_j(2)$ denote the indices of the D2D links belong to the $j$-th device-cluster. We assume that the CH DUs of the $j$-th device-cluster transmit to the CR DUs via the $l$-th relay F-UE over the $n$-th RRB. The link between CH DUs and relay is an uplink rate-splitting multiple-access channel, and the CH DUs transmit three different data streams to the relay to achieve the optimal uplink throughput [23]. Without loss of generality, the CH DU having stronger channel gain splits its data into two streams and transmits a superposition coded signal, and the CH DU having weaker channel gain transmits a single data stream. We assume $h_{j(1),l,n}^{(U)} > h_{j(2),l,n}^{(U)}$ where $h_{j(1),l,n}^{(U)}$ (resp. $h_{j(2),l,n}^{(U)}$) is the channel gain between the CH DU of
\(s_j(1)\) (resp. \(s_j(2)\)) D2D link and the \(l\)-th relay F-UE over the \(n\)-th RRB. The transmitted signals from the CH DUs of \(s_j(1)\) and \(s_j(2)\) D2D links are expressed as, \(x^{S-R}_{j(1),l,n} = \sum_{i=1}^{2} \sqrt{P^{(i)}_{j(1),l,n}} s_j(1),i\) and \(x^{S-R}_{j(2),l,n} = \sqrt{P^{(2)}_{j(2),l,n}} s_j(2),\) respectively. Here, \(P^{(i)}_{j(1),l,n}\) is the transmission power of the \(i\)-th data stream (where \(i = 1, 2\)) of the CH DU in \(s_j(1)\) D2D link; \(P^{(2)}_{j(2),l,n}\) is the transmission power of the CH DU in \(s_j(2)\) D2D link; \(\{s_j(1),i\}\) and \(s_j(2)\) are the transmitted messages with \(E[|s_j(1),i|^2] = 1\) and \(E[|s_j(2)|^2] = 1\). As a result, the received signal at the \(l\)-th relay F-UE over the \(n\)-th RRB is obtained as \(Y_{l,n}^{(U)} = h_{j(1),l,n}^{(U)} x^{S-R}_{j(1),l,n} + h_{j(2),l,n}^{(U)} x^{S-R}_{j(2),l,n} + n_a + \sqrt{P_c,n} h_{e,l,n}\). Here, \(n_a\) is the additive white Gaussian noise with variance \(\sigma^2\); \(P_c,n\) is the uplink transmission power of the \(c\)-th CUE over the \(n\)-th RRB; and \(h_{e,l,n}\) is the interference channel gain. By applying a successive interference cancellation (SIC) scheme, the \(l\)-th relay F-UE decodes the received data streams in the order of \(s_j(1),1, s_j(2),\) and \(s_j(1),2\) \cite{23}. The transmission rate scheduled from the CH DUs in the \(j\)-th device cluster is obtained as \(R_{j(1),l,n}^{(U)} = R_{j(2),l,n}^{(U)} = R_{j(1),l,n}^{(U)} + R_{j(2),l,n}^{(U)} + R_{j(1),l,n}^{(U)}\). Here, \(R_{j(1),l,n}^{(U)} = \frac{1}{2} \log_2 \left( 1 + \frac{A_{j,l,n}^{(1)}}{B_{j,l,n}^{(1)}} \right), \\
R_{j(2),l,n}^{(U)} = \frac{1}{2} \log_2 \left( 1 + \frac{A_{j,l,n}^{(2)}}{B_{j,l,n}^{(2)}} \right), \quad A_{j,l,n}^{(1)} = P_{j(1),l,n} |h_{j(1),l,n}^{(U)}|^2 \quad \text{and} \quad A_{j,l,n}^{(2)} = P_{j(2),l,n} |h_{j(2),l,n}^{(U)}|^2, \quad B_{j,l,n}^{(1)} = P_{j(1),l,n} |h_{j(1),l,n}^{(U)}|^2 + P_{j(2),l,n} |h_{j(2),l,n}^{(U)}|^2 + \sqrt{P_c,n} |h_{e,l,n}|^2 + \sigma^2, \quad B_{j,l,n}^{(2)} = P_{j(2),l,n} |h_{j(2),l,n}^{(U)}|^2 + \sqrt{P_c,n} |h_{e,l,n}|^2 + \sigma^2.\) \(1\)

(1)

After decoding, the \(l\)-th relay F-UE re-encodes the received data into a common message and two private messages for the CR DUs of \(s_j(1)\) and \(s_j(2)\) D2D links. The transmitted signal from the \(l\)-th relay F-UE is given as \(x_{l,R}^{R-D} = \sqrt{Q_{l,C,n}} s_c + \sqrt{Q_{l,j(1),n}} s_{j(1),p} + \sqrt{Q_{l,j(2),n}} s_{j(2),p}\), where \(s_c\) denotes the common message encoded for both the CR DUs, and \(\{s_{j(1),p}, s_{j(2),p}\}\) denote the private messages encoded for the CR DUs of \(s_j(1)\) and \(s_j(2)\) D2D links, respectively. Evidently, the relay F-UE broadcasts the common message with \(Q_{l,C,n}\) transmission power, and the private messages with \(Q_{l,j(1),n}\) and \(Q_{l,j(2),n}\) transmission powers. The received signals at the CR DUs of the \(j\)-th device-cluster are expressed as \(Y_{j(i),l,n}^{(D)} = h_{j(i),l,n}^{(D)} x_{l,R}^{R-D} + \sqrt{P_c,n} h_{e,j(i),n} + n_a, \forall i = 1, 2\). Here, \(h_{j(i),l,n}\) (resp. \(h_{j(i),l,n}\)) is the channel gain between the \(l\)-th relay F-UE and \(s_j(1)\) (resp. \(s_j(2)\)) CR DU over the \(n\)-th RRB; and \(\{h_{e,j(1),n}, h_{e,j(2),n}\}\) denote the interference channel gains from the \(c\)-the CUE over the \(n\)-th RRB. The \(l\)-th relay F-UE schedules certain rate for the common message as such both the CR DUs can decode it. To determine the common message rate, we denote \(k_j = \arg \min \left( \frac{|h_{j(1),l,n}^{(D)}|^2}{\sqrt{P_c,n} |h_{e,j(1),n}|^2 + \sigma^2}, \frac{|h_{j(2),l,n}^{(D)}|^2}{\sqrt{P_c,n} |h_{e,j(2),n}|^2 + \sigma^2} \right).\) The data rate scheduled for
the common message is expressed as \( R_{l,j,n}^C = \frac{1}{2} \log_2 \left( 1 + \frac{\hat{A}^{(1)}_{j,l,n}}{\hat{B}^{(1)}_{j,l,n}} \right) \) where

\[
\hat{A}^{(1)}_{j,l,n} = Q_{l,c,n} |h^{(D)}_{j,(k_j),l,n}|^2 \\
\hat{B}^{(1)}_{j,l,n} = (Q_{l,j,(1),n} + Q_{l,j,(2),n}) |h^{(D)}_{j,(k_j),l,n}|^2 + P_{c,n} |h_{c,(k_j),n}|^2 + \sigma^2.
\]

(2a) (2b)

After decoding the common message, both CR DUs decode their own private message while canceling the interference of the common message by applying an SIC scheme, and considering the other DU’s private message as an interference. Thus, the scheduled rates of transmitted private messages for the CR DUs of the \( S_j(1) \) and \( S_j(2) \) D2D links are obtained as \( R_{l,j(1),n}^{D} = \frac{1}{2} \log_2 \left( 1 + \frac{\hat{A}^{(2)}_{j,l,n}}{\hat{B}^{(2)}_{j,l,n}} \right) \) and \( R_{l,j(2),n}^{D} = \frac{1}{2} \log_2 \left( 1 + \frac{\hat{A}^{(3)}_{j,l,n}}{\hat{B}^{(3)}_{j,l,n}} \right) \), respectively. Here,

\[
\hat{A}^{(2)}_{j,l,n} = Q_{l,j(1),n} |h^{(D)}_{j,(k_j),l,n}|^2 \quad \text{and} \quad \hat{A}^{(3)}_{j,l,n} = Q_{l,j(2),n} |h^{(D)}_{j,(k_j),l,n}|^2 \\
\hat{B}^{(2)}_{j,l,n} = Q_{l,j(2),n} |h^{(D)}_{j,(k_j),l,n}|^2 + P_{c,n} |h_{c,(k_j),n}|^2 + \sigma^2 \\
\hat{B}^{(3)}_{j,l,n} = Q_{l,j(1),n} |h^{(D)}_{j,(k_j),l,n}|^2 + P_{c,n} |h_{c,(k_j),n}|^2 + \sigma^2.
\]

(3a) (3b) (3c)

The total data rate scheduled from the relay F-UE to the CR DUs in the \( j \)-th device-cluster is obtained as \( R_{j,l,n}^{D} = R_{l,j,n}^{C} + R_{l,j(1),n}^{D} + R_{l,j(2),n}^{D} \). Therefore, the achievable throughput of the \( j \)-th device-cluster over the \( l \)-th relay F-UE and the \( n \)-th RRB is obtained as \( R_{j,l,n} = \min \left( R_{j,l,n}^{(U)}, R_{j,l,n}^{(D)} \right) \).

C. Problem Formulation

We denote \( S = \{ S_1, S_2, \ldots, S_T \} \) by the collection of all the device-clusters where \( S_j \) is the set of content-sharing D2D links belong to the \( j \)-th device cluster, and \( T = \{ 1, 2, \ldots, \lceil \frac{M}{2} \rceil \} \) is the indices of the device-clusters. Assuming that both the \( l \)-th relay F-UE and the \( n \)-th RRB are allocated to the \( j \)-th device-cluster, the CH DUs’ and the relay F-UE’s transmission power vectors in the \( j \)-th device-cluster are denoted by \( P_{j,l,n} = [ P_{j(1),l,n}, P_{j(2),l,n}, P_{j(2),l,n} ]^T \) and \( Q_{j,l,n} = [ Q_{l,j(1),n}, Q_{l,j(2),n}, Q_{l,c,n} ]^T \), respectively. The overall transmission power matrix is denoted by \( P = [ P_{1,1,1,}, P_{1,1,2,}, \ldots, P_{\lceil \frac{M}{2} \rceil,R,N} ] \) and \( Q = [ Q_{1,1,1,}, Q_{1,1,2,}, \ldots, Q_{\lceil \frac{M}{2} \rceil,R,N} ] \). We also introduce two binary variables, \( x_{l,j} \in \{ 0, 1 \} \) and \( y_{n,l,j} \in \{ 0, 1 \} \) such that \( x_{l,j} = 1 \) if the \( l \)-th relay F-UE is selected to assist the \( j \)-th device-cluster and \( x_{l,j} = 0 \) otherwise; and \( y_{n,l,j} = 1 \) if the \( n \)-th RRB is assigned to the \( j \)-th device-cluster and \( l \)-th relay F-UE and \( y_{n,l,j} = 0 \), otherwise.

We formulate an optimization problem, given as P0 at the top of next page, to simultaneously maximize the sum-throughput of the device-clusters and minimize the overall transmission power of the CH DUs and relay F-UEs. In P0, C1 is a device-cluster formation constraint implying that device-clusters are pairwise disjoint and consist of two content-sharing D2D links; C2 implies
s.t. \( j \)th device-cluster over the CLUE(s), respectively; C3 provides the orthogonal allocation of the RRBs among the device-clusters; C4 provides the transmission power budget constraints in each device-cluster with \( P^{(D)}_{\text{max}} \) and \( P^{(C)}_{\text{max}} \) as the maximum transmission power limit of the CH DU(s) and relay F-UE(s), respectively; C5 provides a QoS constraint for the device-clusters in terms of a minimum rate requirement \( C_{\text{min}} \); C6 implies that for each shared RRB, the uplink interference at the F-AP caused by the device-cluster(s) will be bounded where \( I_{j,l,n}^{(1)} \) and \( I_{j,l,n}^{(2)} \) denote the uplink interference caused by the CH DUs and relay F-UE of the \( j \)-th device-cluster over the \( n \)-th RRB, respectively, and \( I_{th} \) is an accepted interference level.

P0 is an MOOP. Recall, a weighted-sum approach provides the Pareto-optimal solution to an MOOP. By introducing \( \mu_n \geq 0 \) as a set of positive weight-factors, \( \forall n \in N_{sc} \), we reformulate P0 as P0.1 at the top of current page. In P0.1, the second term of \( \{U_j\} \) can be interpreted as the overall cost charged to the \( j \)-th device-cluster for re-using the \( n \)-th RRB, and it is proportional to the uplink interference at the F-AP caused by the \( j \)-th device-cluster over the \( n \)-th RRB. Thus, \( \mu_n \) can be referred as the \( n \)-th RRB’s price, and it is adjusted by F-AP as a control signal to protect the QoS of the CLUEs in uplink.

**Lemma 1:** P0.1 is an NP-hard optimization problem.

**Proof:** The proof is provided in Appendix A.

Owing to NP-hardness of P0.1, in the ensuing Sections, we obtain sub-optimal yet efficient...
solution to P0.1 by decoupling device-clustering and resource-scheduling in two sub-problems.

III. UNSUPERVISED LEARNING EMPOWERED DEVICE-CLUSTERING

A. Low-complexity Device-clustering Algorithm Using 2D-PCA

We seek to employ 2D-PCA [31] to determine a set of uncorrelated vectors, referred as the principle component vectors (PCVs), that can extract the most useful information of the channel matrices of the DUs. In the proposed method, each DU needs to upload only a set of PCVs of its channel matrix to the F-AP instead of the whole channel matrix. Essentially, the communication efficiency of the device-clustering process is considerably improved. The required steps of the proposed device-clustering method are discussed as follows.

a) Feature selection: Let $H_m \in \mathbb{R}^{L \times N}$ be the matrix of effective-channel gains for the $m$-th content-sharing D2D link where $H_m = [H_{m,1}, H_{m,2}, \ldots, H_{m,L}]^T$, and $H_{m,l} \in \mathbb{R}^{1 \times N}, \forall m \in \mathcal{M}$. Particularly, $H_{m,l} \triangleq \left[ \min \left( \tilde{h}_{m,l,1}^{(U)}, \tilde{h}_{m,l,1}^{(D)} \right), \ldots, \min \left( \tilde{h}_{m,l,N}^{(U)}, \tilde{h}_{m,l,N}^{(D)} \right) \right]$ where $\tilde{h}_{m,l,n}^{(U)} = \frac{h_{m,l,n}}{\epsilon_{c,m,n}}$ and $\tilde{h}_{m,l,n}^{(D)}$ denote the channel-response normalized by interference channel gain at the first and second hops, respectively.

b) Feature transformation: The basic idea is to transform $H_m, \forall m \in \mathcal{M}$, to a lower-dimension matrix by using an orthogonal projection as such the maximum amount of variation is retained. The optimal projection directions are determined as the eigen-vectors of the auto-covariance (ACV) matrix of $H_m$, defined as, $S_m \triangleq \mathbb{E} \left[ (H_m - \mathbb{E}[H_m])^T (H_m - \mathbb{E}[H_m]) \right]$ where $\mathbb{E}[:]$ is the statistical expectation operator [31]. In the absence of channel statistics information, the ACV matrix can be computed from the channel training samples stored at the CH DUs. Suppose, $\{H_{m,i}^{(i)}\}, i = 1, 2, \ldots, I$, are the $I$ channel training samples stored at the CH DU of the $m$-th D2D link, and $H_{m,i}$ is the sample average. Therefore, the ACV matrix is evaluated as $S_m = \frac{1}{I} \sum_{i=1}^{I} \left( H_{m,i}^{(i)} - \mathbb{E}[H_m] \right)^T \left( H_{m,i}^{(i)} - \mathbb{E}[H_m] \right)$. Since $S_m$ is a symmetric and $N \times N$ square matrix, a singular value decomposition (SVD) of $S_m$ is expressed as $S_m = \mathbb{V}_m \Sigma_m \mathbb{V}_m^T$. Here, $\mathbb{V}_m$ is a matrix of $N$ orthogonal eigen-vectors of $S_m$, sorted in a decreasing order of the eigen-values of $S_m$; $\Sigma_m$ is an $N \times N$ diagonal matrix containing squares of the eigen-values of $S_m$; and the $n$-th diagonal element of $\Sigma_m$ is denoted by $\sigma_n$. A set of the first $d$ eigen-vectors, correspond to the first largest $d$ eigen-values of $S_m$, constitute the optimal projection directions. The CH DU of the $m$-th D2D link computes the first $d$ PCVs of its channel matrix as $Y_{m,i} = H_m \mathbb{V}_m^{(i)}, \forall i = 1, 2, \ldots, d$. Here, $\mathbb{V}_m^{(i)}$ is the $i$-th column vector of $\mathbb{V}_m$. It is worth noting that the computed PCVs have a decreasing order of their variance, i.e., the first PCV includes the highest amount of the variability of the channel matrix. In the reduced dimension, the channel information of the $m$-th
D2D link is expressed in terms of a collection of PCVs, and it is denoted as the feature matrix
\( B_m = [Y_{m,1}, Y_{m,2}, \cdots, Y_{m,d}] \in \mathbb{R}^{L \times d} \). Because of the dimensionality reduction, there is certain loss of variance, defined as \( \epsilon_m = 1 - \frac{\sum_{n=1}^{d} \epsilon_n}{\sum_{n=1}^{L} \epsilon_n} \) [32, eq. 7]. The required number of PCVs to reliably represent D2D links' channel information is determined such that \( \epsilon_m \) is small, \( \forall m \in \mathcal{M} \).

**Algorithm 1** Low-complexity device-clustering algorithm

1: **Input:** Feature matrices, \( B_m, \forall m \in \mathcal{M} \).
2: **Initialize:** \( \mathcal{F} = \emptyset, \mathcal{F}^c = \mathcal{M}, S_j = \emptyset, \forall j \in \mathcal{T} \).
3: **while** \( \mathcal{F}^c \neq \emptyset **do**
4:   **Determine** \( \hat{k}(m) = \arg\min_{k \in \mathcal{F}^c, k \neq m} d(B_m, B_k), \forall m \in \mathcal{F}^c \).
5:   **Calculate** \( \Delta_m = \min_{k \in \mathcal{F}^c, k \neq \{m, \hat{k}(m)\}} d(B_m, B_k) - d(B_m, B_{\hat{k}(m)}), \forall m \in \mathcal{F}^c \).
6:   **Select** \( m^* = \arg\max_{m \in \mathcal{F}^c} \Delta_m \).
7:   \( S_j \leftarrow S_j \cup \{m^*, \hat{k}(m^*)\} \), \( j = j + 1 \).
8: **Update** \( \mathcal{F} \leftarrow \mathcal{F} - \mathcal{F}^c \). \( \mathcal{F}^c \leftarrow \mathcal{M} \setminus \mathcal{F} \).
9: **end while**
10: **for** \( j = 1 : |\mathcal{T}|, \ j' = 1 : |\mathcal{T}|, \text{ and } \ j' \neq j \ **do**
11:   **If** \( d(B_{S_j(1)}, B_{S_j(2)}) + d(B_{S_{j'}(1)}, B_{S_{j'}(2)}) < d(B_{S_j(1)}, B_{S_{j'}(2)}) + d(B_{S_{j'}(1)}, B_{S_{j'}(2)}) \), swap the current members between the \( j \)-th and \( j' \)-th device-clusters.
12: **end for**
13: **Output:** Non-overlapping device-clusters \( S_1, S_2, \cdots, S_{|\mathcal{T}|} \).

c) **Algorithm development:** For clustering the D2D links, we utilize the notion of feature distance. The feature distance between the \( m \)-th and the \( k \)-th D2D links is defined as \( d(B_m, B_k) = \sum_{i=1}^{d} \left\| Y_{m,i} - Y_{k,i} \right\|_2 \). The small and large values of \( d(B_m, B_k) \) indicate the low and high channel disparity between the \( m \)-th and \( k \)-th D2D links, respectively. We can justify that in an RS-CMD enabled device-cluster, a low channel-disparity between the component D2D links improves the sum-rate of content dissemination over the allocated RRBs. Thus, device-clustering is cast as an optimization problem of pairing D2D links so that the feature distances between the component D2D links of the clusters are minimized. Such an optimization problem is formulated as

\[
P_1: \min_{S_1, S_2, \cdots, S_{|\mathcal{T}|}} \max_{j \in \mathcal{T}} d(B_{S_j(1)}, B_{S_j(2)}) \tag{6a}
\]

subject to

\[
\begin{align*}
S_j &= \{S_j(1), S_j(2)\}, S_j \cap S_{j'} = \emptyset, \forall j, j' \in \mathcal{T} \\
S_j(1) &\in \{1, 2, \cdots, M\}, S_j(2) \in \{1, 2, \cdots, M\}, S_j(1) \neq S_j(2), \forall j \in \mathcal{T}. \tag{6b}
\end{align*}
\]

To solve \( P_1 \), we exploit the characteristics of the device-clustering process. Specifically, if the \( m \)-th D2D link prefers the \( k \)-th D2D link over the \( e \)-th D2D link to form a device-cluster, \( d(B_m, B_k) < d(B_m, B_e) \) is satisfied, and the quantity \( d(B_m, B_e) - d(B_m, B_k) \) can be interpreted as the loss function for clustering the \( m \)-th D2D link with its less preferred D2D link. Hence, \( P_1 \)
can be solved by minimizing such a loss function for clustering any two D2D links. The overall steps of the proposed device-clustering procedure is summarized as Algorithm 1. In Algorithm 1, \( \mathcal{F} \) denotes the set of the clustered D2D links, \( \mathcal{F}^c \) denotes the set of un-clustered D2D links, and \( \Delta_m \) is a metric providing the cost experienced by the \( m \)-th D2D link for not being clustered with its most preferred D2D link. In the proposed device-clustering, each D2D link first learns the eigen-vectors of its channel matrix by using a set of channel training samples. Subsequently, each D2D link locally computes the required parameters (i.e., set of PCVs) and uploads such parameters to F-AP for executing Algorithm 1. Accordingly, the proposed device-clustering is an unsupervised-learning process.

### B. Properties of Algorithm 1

**a) Complexity:** The computational complexity of Algorithm 1 depends on the complexity of computing the PCVs, and determining the set of device-clusters. The complexity of computing the PCVs is mainly due to the SVD decomposition of the ACV matrix at the DUs. Since SVD of an \( N \times N \) matrix requires \( O(N^3) \) complexity, the overall complexity of computing the PCVs is \( O(MN^3) \). On the other hand, at each iteration in Steps 3-9, Algorithm 1 requires \( \mathcal{F}^c \) computations to form a device-cluster. Since at each iteration of Algorithm 1, two D2D links are clustered together, \( \mathcal{F}^c \) evolves as \( M, M-2, M-4, \cdots \) as the number of iterations increases. Therefore, to form all the device-clusters, Algorithm 1 requires \( M^2 \) and \( M(M + 1) \) iterations for odd and even \( M \), respectively, which is approximated as \( O(M^2) \). As a result, the overall computational complexity of Algorithm 1 is \( O(MN^3 + M^2) \).

**b) Pareto-efficiency:** Two different device-clusters \( S_j = \{m,k\} \) and \( S'_j = \{m',k'\} \) are defined as Pareto-improvement pair if by swapping their current members, their overall feature distances are strictly reduced, i.e., \( d(B_m, B_k) + d(B_{m'}, B_k) < d(B_m, B_k) + d(B_{m'}, B_{k'}) \).

**Proposition 1:** The output of Algorithm 1 does not contain any Pareto-improvement pair.

**Proof:** The proof is provided in Appendix B.

**Proposition 2:** The device-cluster set, \( S \), obtained by Algorithm 1 is Pareto-efficient

**Proof:** The proof is provided in Appendix C.

### IV. Stackelberg Resource Scheduling Game

Based on the device-clusters formed in Algorithm 1 the resource scheduling among these device-clusters is obtained from the following optimization problem.

\[
P_2 : \max_{P \geq 0, Q \geq 0, x \in \{0,1\}, y \in \{0,1\}, \mu \geq 0} \sum_{j \in \mathcal{T}} U_j \quad \text{s.t.} \quad C_2, C_3, C_4, C_5, C_6.
\]  

(7)
To efficiently solve P2 in a decentralized manner, we propose a Stackelberg resource scheduling game. In the proposed game, the F-AP and device-clusters play the role of leader and followers, respectively. The device-clusters solve the following optimization problem to maximize their payoff by performing power control over the allocated resources.

\[
P2.1 : \max_{P \geq 0, Q \geq 0} \left\{ \sum_{j \in \mathcal{T}} U_j \right\| C_4, C_5 \right\}.
\]

On the other hand, the F-AP first, by acting as a coordinator, solves the following optimization problem to allocate RRBs and relay F-UEs among the device-clusters.

\[
P2.2 : \max_{x \in \{0, 1\}, y \in \{0, 1\}} \left\{ \sum_{j \in \mathcal{T}} U_j \right\| C_2, C_3 \right\}.
\]

Finally, the F-AP, acting as leader, determines the RRBs’ prices by solving the following problem.

\[
P2.3 : \max_{\mu \geq 0} \left\{ \sum_{j \in \mathcal{T}} U_j \right\| C_6 \right\}.
\]

A. Followers’ Power-control Strategy

1) Exact Potential Game Formulation: We consider that the assignment of the relay F-UE(s) and RRB(s) among the device-clusters, and the RRBs’ prices are given. Particularly, the \( j \)-th device-cluster, \( \forall j \in \mathcal{T} \), is assigned with the \( l_j \)-th relay F-UE and \( N_j \) set of RRBs where \( \bigcup_{j=1}^{|\mathcal{T}|} N_j = N_{sc}, N_j \cap N_j' = \emptyset, \forall j \neq j' \), and \( \bigcup_{j=1}^{|\mathcal{T}|} l_j \in \mathcal{L} \). We use a non-cooperative power-control game (NCPCG) to solve P2.1. An NCPCG is defined by the tuple \( \mathcal{G} = \{ \mathcal{S}, (\Pi_j)_{j \in \mathcal{T}}, (\Gamma_j)_{j \in \mathcal{T}} \} \).

Here, \( \mathcal{S} \) is the set of players (i.e., non-overlapping device-clusters), \( \Pi_j \) is the strategy space of the \( S_j \) player defined as \( \Pi_j = \{ P_{j,l_j,n}, Q_{j,l_j,n} \| \sum_{n \in N_j} R_{j,l_j,n} \geq C_{\text{min}}, P_{j,l_j,n} \geq 0, Q_{j,l_j,n} \geq 0, n \in N_j \} \), and \( \Gamma_j \) is the payoff of the \( S_j \) player which is defined as

\[
\Gamma_j \left( \{ P_{j,l_j,n}, Q_{j,l_j,n} \| \{ x, y, \mu \} \right) = \sum_{n \in N_j} (1 - \lambda_{j,l_j,n}) R_{j,l_j,n}^{(U)} + \lambda_{j,l_j,n} R_{j,l_j,n}^{(D)}
\]

\[
- \sum_{n \in N_j} \mu_n \left( \sum_{i=1}^{3} P_{j,l_j,n}[i] + \sum_{i=1}^{3} Q_{j,l_j,n}[i] \right) T - \sigma_j^T \left[ \sum_{n \in N_j} \sum_{i=1}^{2} P_{j,l_j,n}[i], \sum_{n \in N_j} P_{j,l_j,n}[3], \sum_{n \in N_j} \sum_{i=1}^{3} Q_{j,l_j,n}[i] \right]^T.
\]

In (11), \( \sigma_j = [\sigma_{j,1}, \sigma_{j,2}, \sigma_{j,3}]^T \) is a vector of the prices per unit transmission power consumption at the CH DUs and relay F-UE in the \( j \)-the device cluster and \( \lambda_{j,l_j,n} \in (0, 1) \) is a parameter. Owing to the flow conservation at the relay, the optimal value of \( \lambda_{j,l_j,n} \) is obtained such that
\( R^{(U)}_{j,l,n} = R^{(D)}_{j,l,n} \) is satisfied, \( \forall j,n \). We consider that the device-clusters are selfish, rational players, and choose their power allocation strategy to maximize their payoffs. A Nash-equilibrium (NE) of the considered NCPCG is obtained when every player in the game operates by using its best response strategy (BRS), and consequently, no player can further improve its payoff by using an alternative strategy. The NE is formally defined as follows.

**Definition 1:** The tuple \( \{ P^*_{j,l,n}, Q^*_{j,l,n} \} \) is an NE power allocation strategy of the NCPCG \( G \), if for all \( \{ P_{j,l,n}, Q_{j,l,n} \} \in \Pi_j, S_j \in S \), the following condition is satisfied.

\[
\Gamma_j \left( \{ P^*_{j,l,n}, Q^*_{j,l,n} \} \left| \{ x, y, \mu \} \right. \right) \geq \Gamma_j \left( \{ P_{j,l,n}, Q_{j,l,n} \} \left| \{ x, y, \mu \} \right. \right).
\] (12)

**Lemma 2:** The NCPCG \( G \) is an exact potential game and it posses an NE power allocation strategy.

**Proof:** The proof is provided in Appendix D.

**Lemma 3:** The NE power allocation of the NCPCG \( G \) is the BRS of the players. The \( j \)-th player’s BRS, \( \forall j \in T \), is obtained as

\[
\text{BRS}_j : \{ P^*_{j,l,n}, Q^*_{j,l,n} \} = \arg \max_{P \geq 0, Q \geq 0} \Gamma_j \left( \{ P_{j,l,n}, Q_{j,l,n} \} \left| \{ x, y, \mu \} \right. \right)
\] (13a)

\[
\text{subject to } \sum_{n \in N_j} R_{j,l,n} \geq C_{\text{min}}.
\] (13b)

The proof of Lemma 3 is a direct consequence of [33, Corollary 2.2]. In what follows, we obtain NE power allocations for each device-cluster by solving \( \text{BRS}_j, \forall j \in T \).

1) **NE Strategy:** \( \text{BRS}_j \) is an NP complete problem with sum-of-functions-of-ratio in both objective function and constraint. Using an auxiliary variable approach proposed in [34], we establish the following proposition to effectively solve \( \text{BRS}_j \).

**Proposition 3:** \( \text{BRS}_j \) is equivalent to the following optimization problem:

\[
\max_{P \geq 0, Q \geq 0, Z \geq 0, X \geq 0} \mathcal{F}^{(1)}_j (Z, X) + \mathcal{F}^{(2)}_j (P, Q, Z, X) - \Psi_j (P, Q)
\] (14)

where \( Z = \left[ \sum_{i \in \{1,2,3 \}, n \in N_j} Z^{(i)}_{j,l,n} \right] \) and \( X = \left[ \sum_{i \in \{1,2,3 \}, n \in N_j} X^{(i)}_{j,l,n} \right] \) are two auxiliary variables. The expressions of \( \mathcal{F}^{(1)}_j (Z, X) \), \( \mathcal{F}^{(2)}_j (P, Q, Z, X) \), and \( \Psi_j (P, Q) \) are given as (15), (16), and (17) at the top of next page. Here, \( \omega^{(1)}_{j,l,n} = \frac{1 - \lambda_{j,l,n} + \nu^{(1)}_j}{2 \log 2} \) and \( \omega^{(2)}_{j,l,n} = \frac{\lambda_{j,l,n} + \nu^{(2)}_j}{2 \log 2} \), \( \nu^{(1)}_j \) and \( \nu^{(2)}_j \) are two positive parameters, and \( I_{c,l,n} = P_{c,n} |h_{c,l,n}|^2 + \sigma^2 \).

**Proof:** The proof is provided in Appendix E.

By using primal-decomposition, eq. (14) is decomposed to outer and inner optimization
\[ \mathcal{F}_j^{(1)}(Z, X) = \sum_{n \in \mathcal{N}_j} \sum_{i=1}^{2} \omega_{j,l,n}^{(1)} \left( \log \left(1 + Z_{j,l,n}^{(i)}\right) - Z_{j,l,n}^{(i)} \right) \]
\[ + \sum_{n \in \mathcal{N}_j} \sum_{i=1}^{3} \omega_{j,l,n}^{(2)} \left( \log \left(1 + X_{j,l,n}^{(i)}\right) - X_{j,l,n}^{(i)} \right), \]
\[ \mathcal{F}_j^{(2)}(P, Q, Z, X) = \sum_{n \in \mathcal{N}_j} \sum_{i=1}^{2} \omega_{j,l,n}^{(1)} \left( 1 + Z_{j,l,n}^{(i)} \right) A_{j,l,n}^{(i)} \]
\[ + \sum_{n \in \mathcal{N}_j} \omega_{j,l,n}^{(1)} \log \left(1 + \frac{P_{j,l,n}^{(2)} \left|h_{j,l,n}^{(1)}\right|^2}{I_{c,l,n}}\right) + \sum_{n \in \mathcal{N}_j} \sum_{i=1}^{3} \omega_{j,l,n}^{(1)} \left( 1 + X_{j,l,n}^{(i)} \right) \hat{A}_{j,l,n}^{(i)} \]
\[ = \sum_{n \in \mathcal{N}_j} \mu_n \left( \sum_{i=1}^{3} P_{j,l,n}^{[i]} + \sum_{i=1}^{3} Q_{j,l,n}^{[i]} \right) \]
\[ + \sigma_j^T \left[ \sum_{n \in \mathcal{N}_j} \sum_{i=1}^{2} P_{j,l,n}^{[i]} \hat{B}^{[i]}_{j,l,n} \right] \]
\[ \Psi_j(P, Q) = \sum_{n \in \mathcal{N}_j} \mu_n \left( \sum_{i=1}^{3} P_{j,l,n}^{[i]} + \sum_{i=1}^{3} Q_{j,l,n}^{[i]} \right) \]
\[ + \sigma_j^T \left[ \sum_{n \in \mathcal{N}_j} \sum_{i=1}^{2} P_{j,l,n}^{[i]} \hat{B}^{[i]}_{j,l,n} \right] \]

problems. The outer and inner optimization problems are given as, respectively,
\[ \max_{Z \geq 0, X \geq 0} \mathcal{F}_j^{(1)}(Z, X) + \mathcal{F}_j^{(2)}(P, Q, Z, X) \] (18)

and
\[ \max_{P \geq 0, Q \geq 0} \mathcal{F}_j^{(2)}(P, Q, Z, X) - \Psi_j(P, Q) . \] (19)

Moreover, by using the quadratic-transformation of fractional programming problem [34, Theorem 1], the inner optimization problem is further converted to a bi-convex optimization problem given as (20) at the top of current page. In (20), \( \alpha = \left[ \alpha_{j,l,n}^{(i)} \right]_{i \in \{1,2\}, n \in \mathcal{N}} \) and \( \beta = \left[ \beta_{j,l,n}^{(i)} \right]_{i \in \{1,2,3\}, n \in \mathcal{N}} \) are two sets of auxiliary variables introduced to transform the fractions to quadratic functions.
The satisfying the KKT optimality conditions, optimal power allocations of the

\[ P_{j(1),l_j,n}^{(1)*} = \frac{\omega_{j,l_j,n}^{(1)}}{\mu_n + \sigma_{j,1} + \left(\alpha_{j,l_j,n}^{(1)} \left| h_{j,j(1),l_j,n}^{(U)} \right| \right)^2}, \forall n \in \mathcal{N}_j, l_j \in \mathcal{L} \tag{21a} \]

\[ P_{j(1),l_j,n}^{(2)*} = \left[ \frac{\omega_{j,l_j,n}^{(1)}}{\mu_n + \sigma_{j,1} + \left(\alpha_{j,l_j,n}^{(1)} \left| h_{j,j(1),l_j,n}^{(U)} \right| \right)^2} - I_{c,l_j,n} \right]^+, \forall n \in \mathcal{N}_j, l_j \in \mathcal{L} \tag{21b} \]

\[ P_{j(2),l_j,n}^{*} = \frac{\omega_{j,l_j,n}^{(2)}}{\mu_n + \sigma_{j,2} + \left(\alpha_{j,l_j,n}^{(2)} \left| h_{j,j(1),l_j,n}^{(U)} \right| \right)^2}, \forall n \in \mathcal{N}_j, l_j \in \mathcal{L}. \tag{21c} \]

\[ Q_{l_j,c,n}^{*} = \frac{\omega_{j,l_j,n}^{(1)}}{\mu_n + \sigma_{j,3} + \left(\beta_{j,l_j,n}^{(1)} \left| h_{j,k(j),l_j,n}^{(D)} \right| \right)^2} \tag{22a} \]

\[ Q_{l_j,j(1),n}^{*} = \frac{\omega_{j,l_j,n}^{(2)}}{\mu_n + \sigma_{j,3} + B_{j,l_j,n}^{(2)}} \tag{22b} \]

\[ Q_{l_j,j(2),n}^{*} = \frac{\omega_{j,l_j,n}^{(2)}}{\mu_n + \sigma_{j,3} + B_{j,l_j,n}^{(2)}} \tag{22c} \]

\[ \alpha_{j,l_j,n}^{(i)*} = \frac{\sqrt{\omega_{j,l_j,n}^{(1)}}}{A_{j,l_j,n}^{(i)} + B_{j,l_j,n}^{(i)}} \tag{23a} \]

\[ \beta_{j,l_j,n}^{(i)*} = \frac{\sqrt{\omega_{j,l_j,n}^{(2)}}}{A_{j,l_j,n}^{(i)} + B_{j,l_j,n}^{(i)}} \tag{23b} \]

**Lemma 4:** The NE strategy power allocation strategy of \( G \) is obtained by solving \( (18) \) and \( (20) \) via alternating optimization, \( \forall j \in \mathcal{T} \).

**Proof:** The proof is provided in Appendix \[ \square \]

\( a) \) **Optimal \( \{ P^*, Q^* \} \):** For the given \( \{ \alpha, \beta \} \) and \( \{ Z, X \} \), eq. \( (20) \) is a convex optimization problem of \( \{ P, Q \} \). Therefore, by satisfying the Karush-Kuhn-Tucker (KKT) optimality conditions to \( (20) \), the CH DUs’ optimal power allocations in the \( j \)-th device cluster, \( \forall j \in \mathcal{T} \), are obtained as \( (21a)-(21c) \) at the top of current page where \( [a]^+ = \max(a, 0) \). Similarly, by satisfying the KKT optimality conditions, optimal power allocations of the \( l_j \)-th relay F-UE in the \( j \)-th device cluster, \( \forall j \in \mathcal{T} \), are obtained as \( (22a)-(22c) \) at the top of current page. In \( (22b) \)
and (22c), \( B_{j,l,n} = \left( \beta_{j,l,n}^{(1)} h_{j,l,n}^{(D)} \right)^2 + \left( \beta_{j,l,n}^{(2)} h_{j,l,n}^{(1)} \right)^2 + \left( \beta_{j,l,n}^{(3)} h_{j,l,n}^{(2)} \right)^2. \)

b) Optimal \( \{\alpha^*, \beta^*\} \): For the given \( \{P, Q\} \) and \( \{Z, X\} \), eq. (20) is a convex optimization problem of \( \{\alpha, \beta\} \). By satisfying the KKT optimality conditions, the optimal \( \{\alpha^*, \beta^*\}, \forall n \in \mathcal{N}_j, l_j \in \mathcal{L}, j \in \mathcal{T}, \) are obtained as (23a)-(23b) at the top of previous page.

c) Optimal \( \{Z^*, X^*\} \): For the given \( \{P, Q\} \), eq. (18) is a strict convex optimization problem of \( \{Z, X\} \). By satisfying the KKT optimality conditions, \( \forall n \in \mathcal{N}_j, l_j \in \mathcal{L}, j \in \mathcal{T}, \) we obtain

\[
Z_{j,l,n}^{(i)^*} = \frac{A_{j,l,n}^{(i)}}{B_{j,l,n}^{(i)}}, i = 1, 2 \quad \text{and} \quad X_{j,l,n}^{(i)^*} = \frac{\tilde{A}_{j,l,n}^{(i)}}{\tilde{B}_{j,l,n}^{(i)}}, i = 1, 2, 3. \tag{24}
\]

d) Optimal \( \{\lambda^*, \sigma^*, \nu^*\} \): A one-dimensional bi-section search in the \((0, 1)\) interval is conducted to find the optimal \( \{\lambda_{j,l,n}^*, \nu_{j,l,n}^*\} \) such that \( R_{j,l,n}^{(U)} = R_{j,l,n}^{(D)} \) is satisfied, \( \forall n \in \mathcal{N}_j, l_j \in \mathcal{L}, j \in \mathcal{T}. \) Meanwhile, the parameters \( \{\nu_{j,l,n}^{(1)}, \nu_{j,l,n}^{(2)}\} \) and \( \{\sigma_{j,1}, \sigma_{j,2}, \sigma_{j,3}\} \) are iteratively updated by applying projected gradient decent method. For the brevity, the detailed analyses are omitted.

**Algorithm 2 NE Power Allocation Strategy For The \( j \)-th Device-cluster**

1: **Input:** Assigned relay F-UE \( l_j \in \mathcal{L} \) and set of RRBs \( \mathcal{N}_j, T_{\text{max}}. \)
2: **Initialize** \( \{P_j^{(1)}(1), P_j^{(2)}(1), P_j^{(3)}(1)\} \) and \( \{Q_{lj,(1),n}, Q_{lj,(2),n}, Q_{l,l,c,n}\} \), and calculate initial values of \( \{\alpha_{j,l,n}^{(1)}, \beta_{j,l,n}^{(1)}\} \) and \( \{Z_{j,l,n}^{(1)}, X_{j,l,n}^{(1)}\} \) by using (23a), (23b), and (24), \( \forall n \in \mathcal{N}_j. \)
3: **Initialize** \( \lambda_{j,l,n}^{\text{low}} = 0, \lambda_{j,l,n}^{\text{up}} = 1, \) and \( \lambda_{j,l,n} = \frac{\lambda_{j,l,n}^{\text{low}} + \lambda_{j,l,n}^{\text{up}}}{2} ; \{\nu_{j,l,n}^{(1)}, \nu_{j,l,n}^{(2)}\} ; \{\sigma_{j,1}, \sigma_{j,2}, \sigma_{j,3}\}; t = 1;
4: **repeat**
5: **Update** \( \{P_j^{(1)}(1), P_j^{(2)}(1), P_j^{(3)}(1)\} \) and \( \{Q_{lj,(1),n}, Q_{lj,(2),n}, Q_{l,l,c,n}\} \) by using (21a)-(22c), \( \forall n \in \mathcal{N}_j. \)
6: **Update** \( \{Z_{j,l,n}^{(1)}, X_{j,l,n}^{(1)}\} \) by applying the updated power allocations to (24), \( \forall n \in \mathcal{N}_j. \)
7: **Update** \( \{\alpha_{j,l,n}^{(1)}, \beta_{j,l,n}^{(1)}\} \) by applying the updated power allocations and the updated \( \{Z_{j,l,n}^{(1)}, X_{j,l,n}^{(1)}\} \) to (23a) and (23b), respectively, \( \forall n \in \mathcal{N}_j. \)
8: **If** \( R_{j,l,n}^{(U)} > R_{j,l,n}^{(D)} \), \( \lambda_{j,l,n}^{\text{up}} \leftarrow \lambda_{j,l,n}, \) and if \( R_{j,l,n}^{(U)} < R_{j,l,n}^{(D)} \), \( \lambda_{j,l,n}^{\text{low}} \leftarrow \lambda_{j,l,n}. \) Update \( \lambda_{j,l,n} = \frac{\lambda_{j,l,n}^{\text{low}} + \lambda_{j,l,n}^{\text{up}}}{2} ; \forall n \in \mathcal{N}_j. \)
9: **Update** \( \{\nu_{j,l,n}^{(1)}, \nu_{j,l,n}^{(2)}\} \) and \( \{\sigma_{j,1}, \sigma_{j,2}, \sigma_{j,3}\} \) using projected gradient decent method; \( t = t + 1. \)
10: **until** \( t > T_{\text{max}} \) or Convergence

By using an alternating optimization, we develop Algorithm 2 to obtain NE power allocation strategy of the CH DUs and relay F-UE in the \( j \)-th device-cluster. The properties of Algorithm 2 in terms optimality, complexity, and implementation are discussed as follows.

**Proposition 4:** Algorithm 2 converges to a local optimal solution to P2.1.

**Proof:** The proof is provided in Appendix C.
**Complexity:** To complete the Steps 5-9, Algorithm 2 requires in total \(21|N_j|\) computations where \(|\cdot|\) denotes the cardinality of a set. Since a projected gradient decent method requires \(O\left(\frac{1}{\epsilon}\right)\) iterations with \(\epsilon\)-accuracy, the overall computational complexity of Algorithm 2 is \(O\left(\frac{N}{\epsilon}\right)\).

**Implementation:** At the beginning of a TS, both CH and CR DUs of a device-cluster send pilots to the associated relay F-UE. Next, by using the Steps 5-7 in Algorithm 2, the relay F-UE determines the transmission powers in both hops. Subsequently, relay F-UE broadcasts the updated transmission powers of the first hop to the CH DUs, CH DUs update the parameters \(\{\sigma_{j,1}, \sigma_{j,2}\}\), and send these parameters to the relay F-UE. Meanwhile, relay F-UE updates the remaining parameters, such as, \(\{\lambda_{j,l,j,n}\}, \{\nu_{j}^{(1)}, \nu_{j}^{(2)}\}\), and \(\sigma_{j,3}\). The last two steps are repeated until convergence. Finally, the relay F-UE broadcasts the scheduled rate over the allocated RRBs, given as \(\min\left(R_{j,l,j,n}^{(U)}, R_{j,l,j,n}^{(D)}\right), \forall n \in N_j\), to both the associated CH and CR DUs.

### B. Leader’s Resource Assignment and Price Update Strategy

1) **Solution to P2.2:** We denote \(L_j \in L\) and \(N_j \in N_{sc}\) as the set of available relay F-UEs and RRBs for the \(j\)-th device-cluster, \(\forall j \in T\). Using Algorithm 2, the \(j\)-th device-cluster determines a bid matrix, \(\hat{U}_{l,n}^{(j)} = \left[R_{j,l,n} \left(P_{j,l,n}^{*}, Q_{j,l,n}^{*}\right) - \mu_n \left(\sum_{i=1}^{3} P_{j,l,n}^{*}[i] + \sum_{i=1}^{3} Q_{j,l,n}^{*}[3]\right)\right]^{+}\). (25)

In (25), \(\{P_{j,l,n}^{*}, Q_{j,l,n}^{*}\}\) are the optimal power allocations of the \(j\)-th device-cluster over the \(l\)-th relay F-UE and \(n\)-the RRB. Using the aforementioned bid matrices, P2.2 can be expressed as

\[
\max_{x, y \in \{0, 1\}} \sum_{j \in T} \sum_{n=1}^{N} x_{l,j} y_{n,j} \hat{U}_{l,n}^{(j)} \quad \text{s.t.} \quad C2, C3. \tag{26}
\]

Eq. (26) is a bilinear integer programming problem, and it can be efficiently solved by using the alternating optimization [35]. Considering that \(\{y_{n,l,j}\}\) is given, eq. (26) can be simplified as

\[
\max_{x \in \{0, 1\}} \sum_{j \in T} \sum_{l=1}^{L} x_{l,j} \tilde{U}_{l}^{(j)} \quad \text{s.t.} \quad C2 \tag{27}
\]

where \(\tilde{U}_{l}^{(j)} = \sum_{n:y_{n,l,j}=1} \hat{U}_{l,n}^{(j)}\). Eq. (27) is a semi-assignment problem and its optimal solution can be obtained in polynomial time by using the shortest augmenting path (SAP) algorithm [36]. Applying the solution to (27) to (26), eq. (26) can be expressed as

\[
\max_{\tilde{y} \in \{0, 1\}} \sum_{j \in T} \sum_{n=1}^{N} \tilde{y}_{n,j} \tilde{U}_{n}^{(j)} \quad \text{s.t.} \quad C3 \tag{28}
\]
where \( \tilde{U}_n^{(j)} = \sum_{l} x_{l,j} \tilde{U}_{l,n}^{(j)} \) and \( \tilde{y}_{n,j} \) is a new binary variable, i.e., \( \tilde{y}_{n,j} = 1 \) if the \( n \)-th RRB is assigned to the \( j \)-th device-cluster, and \( \tilde{y}_{n,j} = 0 \) otherwise. For a given solution to (27), the optimal solution to (28) is obtained as

\[
\tilde{y}_{n,j}^* = \begin{cases} 
1, & \text{if } j = \arg \max_{j' \in T} \tilde{U}_{j}^{(n)} \\
0, & \text{otherwise.}
\end{cases}
\]  

(29)

Subsequently, we recover \( \{y_{n,l,j}\} \) as \( y_{n,l,j} = \tilde{x}_{l,j} \tilde{y}_{n,j}^*, \forall n, l, j \). By solving (27) and (28) iteratively, a convergent solution to (26) is obtained. The overall steps are summarized in Algorithm 3. The local optimality and computational complexity of Algorithm 3 are discussed as follows.

Algorithm 3 Assignment of RRBs and Relay F-UEs Among the Device-clusters

1: Input: Bid matrix, \( \hat{U}_j \), \( \forall j \in T \), \( T_{max} \).
2: Initialize: \( \{y_{n,l,j}\}, \forall n,l,j \); \( t = 1 \).
3: repeat
4: Calculate \( \tilde{U}_{l,n}^{(j)} \), \( \forall l,j \) by using the current value of \( \{y_{n,l,j}\} \).
5: Solve (27) by using the SAP algorithm of [36] and update \( \{x_{l,j}\} \).
6: Calculate \( \tilde{y}_{n,j}^{(j)} \) by using (29) and update \( \{y_{n,l,j}\} \); \( t = t + 1 \)
7: until \( \sum_{j \in T} \sum_{l=1}^{L} \sum_{n=1}^{N} x_{l,j} y_{n,l,j} \tilde{U}_{l,n}^{(j)} \) converges or \( t > T_{max} \)
8: Output: \( x_{l,j}^* \) and \( y_{n,l,j}^* \), \( \forall n,l,j \).

Proposition 5: Algorithm 3 provides a local-optimal solution to (26).

Proof: The proof is provided in Appendix H.

Computational complexity: To solve (27) in Step 5 of Algorithm 3, \( O(|T|^2L) \) computational complexity is required [36, Proposition 6]. Meanwhile, to execute Step 7 in Algorithm 3, total \( N|T| \) number of operations are required. Using the fact that \( |T| = \lceil \frac{M}{2} \rceil \), the overall computational complexity of Algorithm 3 is \( O(|T|^2L + |T|N)) = O (\lceil \frac{M}{2} \rceil^2 L + \lceil \frac{M}{2} \rceil N) \).

2) Pricing of the RRBs: To optimally solve P2.3, F-AP requires the global CSI and optimization parameters of the network. However, in practice, F-AP only knows the bid matrix submitted by the device-clusters and the allocation of the relay F-UEs and RRBs among the device-clusters. Hence, P2.3 is equivalent to the following feasibility problem.

\[
\text{find } \mu_n, \forall n \in N_{sc} \text{ s.t. } \sum_{j \in T} \sum_{l=1}^{L} x_{l,j}^* y_{n,l,j}^* \max \left(I_{j,l,n}^{(1)}, I_{j,l,n}^{(2)} \right) \leq I_{th}, \forall n \in N_{sc} \quad (30)
\]

where \( \{x_{l,j}^*, y_{n,l,j}^*\} \) are obtained from the output of Algorithm 3. The uplink interference in the \( n \)-th RBB becomes minimum (i.e., zero) and maximum for \( \mu_n \to \infty \) and \( \mu_n \to 0 \), respectively. Therefore, certain \( \mu_n \) must exist for which \( I_{n}^{(\text{up})} = I_{th} \) is satisfied where \( I_{n}^{(\text{up})} = \)
\[ \sum_{j \in T} \sum_{l=1}^{L} x_{l,j}^s y_{n,j,l}^s \max \left( I_{n,l,j}^{(1)}, I_{n,l,j}^{(2)} \right). \]  
A bi-section search is conducted to determine prices of the RRBs. Particularly, \( \mu_{n}^{(\text{low})} \) and \( \mu_{n}^{(\text{up})} \) are set as the lowest and highest price of the \( n \)-th RRB, and initial prices of the RRBs are set as \( \mu_{n} = \frac{\mu_{n}^{(\text{low})} + \mu_{n}^{(\text{up})}}{2}, \forall n \in \mathcal{N}_{sc}. \) Applying the initial price(s) to Algorithm 2, the bid matrices of the device-clusters are updated, and by using the updated bid matrices in Algorithm 3, the resource assignments are updated. Subsequently, the updated \( I_{n}^{(\text{up})} \), \( \forall n \in \mathcal{N}_{sc} \), is calculated. If \( I_{n}^{(\text{up})} > I_{th} \), \( \mu_{n}^{(\text{low})} \leftarrow \mu_{n} \) is applied, and \( I_{n}^{(\text{up})} < I_{th} \), \( \mu_{n}^{(\text{up})} \leftarrow \mu_{n} \) is applied. Then the price of the \( n \)-th RRB is updated as \( \mu_{n} = \frac{\mu_{n}^{(\text{low})} + \mu_{n}^{(\text{up})}}{2}, \forall n \). The aforementioned procedure is repeated until \( |I_{n}^{(\text{up})} - I_{th}| \) approaches a predefined small value, \( \forall n \in \mathcal{N}_{sc}. \)

V. DEVELOPMENT AND PROPERTIES OF RSMD FRAMEWORK

a) Implementation and convergence: A flowchart of the proposed RSMD framework is illustrated in Fig. 2. For implementing the RSMD framework, the time horizon is divided into multiple macro-TSs of \( T_{th} \) seconds where each macro-TS contains multiple TSs. The proposed RSMD framework has two phases, namely, device-clustering and resource scheduling phases. At the beginning of each macro-TS, by using Algorithm 1 the suitable device-clusters are established. These device-clusters remain fixed for the remaining duration of the macro-TS, and the resource scheduling phase is iteratively updated at each TS. At the start of a TS, by using
Algorithms 2 and 3, the power allocations in the device-clusters and the scheduling of RRBs/relay F-UEs among the device-clusters are determined, respectively. Then, the CH DUs transmit to the CR DUs by using the allocated resources. Meanwhile, F-AP measures the received uplink interference at the RRBs, and updates the prices of the RRBs. The updated RRB prices are used by the device-clusters to determine the power allocations and bid matrices in the next TS. The proposed RSMD framework has a decentralized implementation. Particularly, the transmission powers of the CH DUs and relay F-UE in each device-cluster are determined based on only the local CSI. Meanwhile, the device-clustering and resource assignment among the device-clusters are determined by exchanging information among the DUs and F-AP over the control channels.

**Definition 2**: SE is a state where both the followers’ and leader’s (sub) game achieve NE. Under the converged RRBs’ prices, \( \mu^* \), \( \{P^*, Q^*, x^*, y^*, \mu^*\} \) will be an SE outcome if

\[
\mathcal{V}_L(x^*, y^*|P^*, Q^*, \mu^*) \geq \mathcal{V}_L(x, y|P^*, Q^*, \mu^*), \forall \{x, y\} \in \{0, 1\}
\] (31a)

\[
\Gamma_j(P^*, Q^*|x^*, y^*, \mu^*) \geq \Gamma_j(P, Q|x^*, y^*, \mu^*), \forall \{P, Q\} \geq 0, j \in T
\] (31b)

where \( \mathcal{V}_L(\cdot) \) denotes the leader’s utility, i.e., \( \mathcal{V}_L(x^*, y^*|P^*, Q^*, \mu^*) = \sum_{j \in T} U_j(P^*, Q^*, x^*, y^*, \mu^*) \), and where \( U_j(\cdot) \) is defined in (5).

**Definition 3**: In a Pareto-efficient efficient outcome the leader has no incentive to change the converged prices of the resources, and the adopted strategies of the followers, under the converged prices, result in socially optimal welfare across all the followers [11].

**Proposition 6**: The resource scheduling phase of the RSMD framework provides an SE and Pareto-efficient outcome.

**Proof**: The proof is provided in Appendix I.

b) **Overall complexity**: Considering \( \epsilon \) is the error tolerance level, the bi-section method of updating RRBs’ prices require \( O \left( \frac{N}{\epsilon^2} \right) \) iterations. Based on the reported complexity of Algorithms 2 and 3, the worst-case computational complexity of the resource-scheduling phase is obtained as \( O \left( \frac{N}{\epsilon} \left( \left[ \frac{M}{2} \right] \frac{NL}{\epsilon} + \left[ \frac{M}{2} \right] N + \left[ \frac{M}{2} \right]^2 L \right) \right) \approx O \left( \frac{1}{\epsilon} \left( \left[ \frac{M}{2} \right] \frac{N^2 L}{\epsilon} + \left[ \frac{M}{2} \right]^2 NL \right) \right) \). Considering both the device-clustering and resource-scheduling phases, the overall computational complexity of RSMD framework is obtained as \( O \left( \frac{1}{\epsilon} \left( \left[ \frac{M}{2} \right] \frac{N^2 L}{\epsilon} + \left[ \frac{M}{2} \right]^2 NL \right) + MN^3 \right) \). Consequently, the required computational complexity of RSMD framework is polynomial.

c) **Low-complexity implementation**: The resource scheduling phase of the proposed RSMD framework requires \( O \left( \left[ \frac{M}{2} \right] LN \right) \) information exchanges between the DUs and F-AP at each TS. To reduce the information exchanges, a decomposed power allocation and resource assignment (D-PARA) is proposed. In D-PARA, the device-clusters are formed at the start of a macro-TS.
by using Algorithm 1. Then, by using Algorithm 2 and the initial prices announced by the F-AP, each device-cluster determines the bid matrix of its desired resources, and uploads the bid matrix to the F-AP. By using Algorithm 3, F-AP assigns resources for the device-clusters. Following this stage, the data transmission at the device-clusters over the assigned resources is started. At the end of each remaining TS of the considered macro-TS, F-AP measures the uplink interference at the RRBs, updates the prices of the RRBs, and broadcasts the updated prices. Based on the received prices, the CH DUs and relay F-UEs adjust their transmission powers at the start of next TS. The main difference between RSMD and D-PARA is that in D-PARA, the resources (i.e., relay F-UE and RRBs) are assigned for the device-clusters at the start of a macro-TS, and such a resource assignment remains fixed for the entire remaining duration of the macro-TS. Therefore, unlike RSMD, the iteration between power control and resource assignment is not required, and consequently, the information exchanges are significantly reduced in D-PARA.

VI. NUMERICAL SIMULATION RESULTS

For simulations, we consider an F-RAN system with one F-AP, 30 CH and CR DUs, 10 relay F-UEs, and 36 RRBs. The DUs and relay F-UEs are uniformly distributed in a 500\,m × 500\,m square region with the F-AP in the center. Without further specification, we consider $P_{\text{max}}^{(D)} = P_{\text{max}}^{(C)} = 0.5$ Watt, $C_{\text{min}} = 1$ bits/s/Hz, $I_{th} = -80$ dBm, and $\sigma^2 = -174$ dBm. The channel coefficients of the D2D links are generated by using Rayleigh distributed fading and the 3GPP path loss model, given by, $131.1 + 42.8 \log_{10}(d)$ dB (where $d$ is the distance in kilometers). For power allocation, the channel coefficients of both hops in each device-cluster are assumed to be perfectly estimated. For the sake of performance comparison, we also consider the following benchmark schemes.

- **Treat interference as noise (TIN) and multicasting:** Here, Algorithms 1 and 3 are used for device-clustering and resource scheduling among the device-clusters, respectively. However, in the first hop of each device-cluster, no SIC scheme is employed at the relay F-UE, i.e., the inter-DU interference is completely treated as noise, and in the second hop, a multicasting is employed, that is, the relay F-UE first combines the entire messages of both CR DUs into a common message and then transmits such a common message using a single rate.

- **Fixed resource allocation with water-filling power allocation (FRA/WF-PA):** Each D2D link is optimized without any device-clustering. The orthogonal RRBs are equally allocated among the D2D links and a many-to-one matching is used to select relay F-UE for the D2D links. Conventional WF-PA algorithm is adopted at both CH DUs and relay F-UEs.

- **Orthogonal resource allocation with water-filling power allocation (ORA/WF-PA):** Each D2D link is scheduled over certain orthogonal RRBs without any device-clustering.
Fig. 3: Throughput and convergence performance of the proposed RSMD and benchmark schemes considering $L = 6$ relay F-UEs, $N = 36$ RRBs, $N_R = 5$ and $d = 15$ PCVs.

Conventional WF-PA algorithm is used for power allocation at the D2D links, and Algorithm 3 is used to dynamically schedule relay F-UEs and RRBs among the D2D links.

Fig. 3a compares the sum-throughput of the proposed and benchmark schemes for different number of D2D links. It is clearly evident that device-clustering improves the system throughput even when the number of D2D links is smaller than the number of RRBs. This is because, in the device-clustering enabled systems, the interference between two D2D links over the shared RRBs is mitigated via power control, and consequently, the sum-throughput of the D2D links is increased. Fig. 3a depicts that for 30 D2D links, the proposed RSMD achieves 28.34%, 38.89%, and 45.69% larger throughput compared to the TIN/Multicasting, FRA/WF-PA, and ORA/WF-PA schemes, respectively. Such a performance gain is non-surprising since TIN/Multicasting is a special case of RSMD, and both FRA/WF-PA and ORA/WF-PA use a conservative RRB allocation scheme compared to RSMD. Fig. 3a also depicts that the performance gap between the proposed RSMD and D-PARA schemes is small. Since D-PARA considerably reduces the information exchange between the device-clusters and F-AP without significantly affecting sum-throughput, it is attractive for low-complexity decentralized content dissemination network.

Fig. 3b illustrates convergence of the proposed RSMD framework with respect to the number of Stackelberg game rounds. For all the considered number of D2D links, the average sum-throughput achieved by the proposed RSMD converges when number of Stackelberg game rounds is at least 10. Consequently, the rapid convergence of the proposed scheme is guaranteed.

Fig. 4a compares sum-throughput of the proposed and benchmark schemes for different number of relay F-UEs in the network. As the number of available relay F-UEs is increased, the probability of selecting the most suitable relay F-UEs for the competing device-clusters (or
D2D links) is increased. Obviously, the sum-throughput is increased with the number of relay F-UEs. Fig. 4a depicts that proposed RSMD considerably outperforms the benchmark schemes. For instance, RSMD achieves 39.02%, 52.85% and 132.44% larger throughput compared to TIN/Multicasting, FRA/WF-PA, and ORA/WF-PA schemes, respectively, in the presence of 5 relay F-UEs. Moreover, the performance gap between RSMD and the benchmark schemes remain almost same even for large number of relay F-UEs. Essentially, the proposed RSMD is efficient for both small and large number of relay F-UEs in the network. Finally, as expected, Fig. 4a depicts that both RSMD and D-PARA achieve almost same throughput for all the relay F-UEs.

The first and second sub-figures of Fig. 4b illustrate sum-throughput and overall transmission power consumption of the proposed and benchmark schemes vs. $N_R$ (i.e., the maximum allowable device-clusters (or D2D links) per relay F-UE), respectively. When $N_R$ is increased, more device-clusters (or D2D links) can be associated with their most preferred relay F-UEs. However, due to the power allocation constraint, given by C4 in (4), the allocated power per device-cluster (or D2D links) in the second hop is reduced as $N_R$ is increased. Consequently, the first sub-figure of Fig. 4b depicts that the sum-throughput of both RSMD and benchmark schemes is reduced as $N_R$ is increased. Meanwhile, when $N_R$ is increased, the number of active relay F-UEs in the system is decreased. Consequently, the overall transmission power consumption is also decreased. Accordingly, the second sub-figure of Fig. 4b illustrates that the overall transmission power consumption of both RSMD and benchmark schemes is reduced with the increase of $N_R$. Therefore, the value of $N_R$ needs to be suitably selected to strike a balance between the transmission power saving and throughput reduction of the proposed RSMD scheme.
(a) Throughput vs. number of RRBs ($N$). 

(b) PN-throughput comparison between the proposed and global CSI based device-clustering methods.

Fig. 5: Performance of the proposed RSMD and benchmark schemes for different number of RRBs, $N$, considering $M = 10$ D2D links, $L = 5$ relay F-UEs, $N_R = 2$ and $d = 4$ PCVs.

RRBs. As expected, the performance gap between the proposed RSMD and D-PARA is small. Meanwhile, the proposed RSMD considerably outperforms the benchmark schemes. For instance, with $N = 12$ RRBs, the proposed RSMD achieves 36.05%, 40.80% and 44.98% larger throughput compared to TIN/Multicasting, FRA/WF-PA, and ORA/WF-PA schemes, respectively. Such an performance gap is more pronounced when the number of RRBs is increased. For instance, with $N = 36$ RRBs, the proposed RSMD achieves 39.02%, 52.85% and 132.44% larger throughput compared to TIN/Multicasting, FRA/WF-PA, and ORA/WF-PA schemes, respectively.

Fig. 5b illustrates the power-normalized (PN)-throughput of the RSMD scheme considering 10 and 20 D2D links in the system. The PN-throughput is defined as the ratio of the sum-throughput to overall transmission power. As the number of active D2D links in the system is increased, the number RRBs allocated per device-cluster is reduced, and accordingly, the PN-throughput of the system is reduced. For example, Fig. 5b depicts that as the number of D2D links is increased from 10 to 20, the PN-throughput of the RSMD scheme is reduced by 1.8958 and 1.9091 times for $N = 12$ RRBs and $N = 36$ RRBs, respectively. Fig. 5b also illustrates the PN-throughput of the RSMD scheme using a global CSI based device-clustering method where the F-AP is assumed to have the global channel information of all the D2D links for performing the device-clustering. As expected, the global CSI based device-clustering achieves an improved PN-throughput compared to the proposed 2D-PCA based device-clustering. However, the performance between these two device-clustering methods is small. For instance, with $N = 36$ RRBs, the proposed 2D-PCA based device-clustering achieves 94.51% and 93.69% of optimal PN-throughput for 10 and 20 D2D links, respectively. Note that, in the considered example, only 4 PCVs are used for performing the 2D-PCA based device-clustering. Obviously,
(a) Throughput and transmission power vs. $I_{th}$ (in dBm) with $M = 20$, $L = 5$, $N_R = 4$, $N = 36$, and $d = 4$ PCVs.

(b) Comparison between the proposed and global CSI based device-clustering methods for different number of PCVs.

Fig. 6: Performance comparison among different schemes for two different settings: (i) $M = 10$, $L = 5$, $N_R = 2$, and $N = 36$, and (ii) $M = 20$, $L = 5$, $N_R = 4$, and $N = 36$.

for $N = 36$ RRBs, the proposed 2D-PCA based device-clustering requires 90% less signaling overhead compared to a global CSI based device-clustering. Thus, the proposed 2D-PCA based device-clustering substantially reduces the signaling overhead without significantly affecting the system performance.

The first and second sub-figures of Fig. 6a plot the sum-throughput and overall transmission power of the D2D network, respectively, for different interference thresholds at the F-AP. As the interference threshold is increased, the F-AP can tolerate more interference in uplink, and consequently, both the transmission power and sum-throughput of the D2D network are increased. Moreover, for large interference thresholds, the CH DUs and active relay F-UEs can operate with their maximum transmission power budgets. Hence, the achievable sum-throughput is saturated as the interference threshold becomes large as depicted from the first sub-figure of Fig. 6a. The first sub-figure of Fig. 6a also depicts that RSMD achieves the largest sum-throughput for all the interference thresholds. Note that, the improved throughput of RSMD requires increase of the overall transmission power. Nevertheless, the second sub-figure of Fig. 6a depicts that for small interference thresholds, RSMD requires a similar transmission power to all other schemes, and for large interference threshold (i.e., $I_{th} = -70$ dBm), RSMD requires 7.64% and 18.71% less transmission power compared to TIN/Multicasting and FRA/WF-PA schemes, respectively.

The sub-figures of Fig. 6b compare the proposed and global CSI based device-clustering methods for different number of PCVs. The first sub-figure of Fig. 6b illustrates that the proposed 2D-PCA based device-clustering achieves improved throughput compared to a global CSI based device-clustering. In particular, the throughput improvement of the proposed 2D-PCA based device-clustering ranges from 0.83% to 4.92% and 0.69% to 2.53% for 10 and 20 D2D links,
respectively. Such a throughput improvement comes at the cost of increased overall transmission power as depicted from the second sub-figure of Fig. 6b. In particular, compared to a global CSI based device-clustering, the increase of the overall transmission power of the proposed 2D-PCA based device-clustering ranges from 9.15% to 15.41% and 8.32% to 14.65% for 10 and 20 D2D links, respectively. However, such an increase of the transmission power is affordable since both the transmission power budget and uplink interference constraints are satisfied. Meanwhile, despite the substantial reduction of the signaling overhead, the achievable throughput of the proposed 2D-PCA based device-clustering does not deteriorate compared to a global CSI-based device-clustering. Certainly, our proposed 2D-PCA based device-clustering has a clear merit.

VII. Conclusion

We investigated the decentralized content dissemination in F-RAN system by integrating RS-CMD strategy with multi-hop D2D networking. A novel optimization of device-clustering, interference-aware device power allocation, and scheduling of RRBs and relay F-UEs among the device-clusters was performed. A sub-optimal yet efficient and convergent solution was proposed where the device-clusters were determined by exploiting a 2D-PCA based unsupervised-learning technique, and the remaining resource optimizations were conducted by using a Stackelberg game. Simulation results confirmed the following two observations: (i) the proposed 2D-PCA based device-clustering substantially reduces the signaling overhead, especially when the number of RRBs is large, while achieving the similar throughput of a global CSI based device-clustering method, and (ii) owing to an optimized RS-CMD strategy, our proposed scheme substantially improves the sum-throughput of the system compared to the benchmark schemes.

Appendix A

P0.1 will be an NP-hard problem if its corresponding decision problem is NP-complete. The decision problem of P0.1 can be expressed as follows. For a given DU and relay power allocation, is it possible to find a set of device-clusters and corresponding resource scheduling as such C2-C6 constraints are satisfied? To solve such a decision problem, we assume that certain D2D links in the network are pair-wise conflicting in a sense that they severely interfere with each other at any relay F-UE, and as a result, if they are clustered together, the effective rate of the resultant device-cluster is zero. Essentially, the overall decision problem has two phases. The first phase is equivalent to a set-partitioning problem, i.e., whether the overall set of D2D links can be partitioned into $\left\lceil \frac{M}{2} \right\rceil$ disjoint sets as such no set (i.e., device-cluster) contains two
conflicting D2D links. The second phase is to decide whether the relay F-UEs and RRBs can be scheduled among these device-clusters subject to C2-C6 constraints. Clearly, the second phase is equivalent to a multiple Knapsack problem. Since, both set-partitioning and multiple Knapsack problems are NP-complete, the decision problem of P0.1 is also reduced to an NP-complete problem. Hence, P0.1 is an NP-hard problem. ■

APPENDIX B

Algorithm 1 sequentially forms device-clusters \( S_1, S_2, \cdots, S_{|T|} \). We first proof that \( S_j \) and \( S_{j+1} \) device-clusters are not Pareto-improvement pair, \( \forall j \). Without loss of generality, we assume that \( S_j = \{m, k\} \) and \( S_{j+1} = \{m', k'\} \), and both the \( m \)-th and \( m' \)-th D2D links prefer to be clustered with the \( k \)-th D2D link. Since the \( m \)-th D2D link is selected to choose its favorite cluster partner prior to the \( m' \)-th D2D link, as per Step 6 of Algorithm 1 \( \Delta_m > \Delta_{m'} \) is satisfied. As per Step 5 of Algorithm 1 \( \Delta_m = \min_{e \neq k} d(\mathbb{B}_m, \mathbb{B}_e) - d(\mathbb{B}_m, \mathbb{B}_k) \) and consequently, \( \Delta_m \leq d(\mathbb{B}_m, \mathbb{B}_{k'}) - d(\mathbb{B}_m, \mathbb{B}_k) \). Meanwhile, for the \( m' \)-th D2D link, we obtain \( \Delta_{m'} = d(\mathbb{B}_{m'}, \mathbb{B}_{k'}) - d(\mathbb{B}_{m'}, \mathbb{B}_k) \). Since \( \Delta_m > \Delta_{m'} \), \( d(\mathbb{B}_m, \mathbb{B}_{k'}) - d(\mathbb{B}_m, \mathbb{B}_k) > d(\mathbb{B}_{m'}, \mathbb{B}_{k'}) - d(\mathbb{B}_{m'}, \mathbb{B}_k) \Rightarrow d(\mathbb{B}_m, \mathbb{B}_{k'}) + d(\mathbb{B}_{m'}, \mathbb{B}_k) > d(\mathbb{B}_m, \mathbb{B}_k) + d(\mathbb{B}_{m'}, \mathbb{B}_{k'}) \). Accordingly, \( S_j \) and \( S_{j+1} \) device-clusters can not be Pareto-improvement pair, \( \forall j \). Moreover, if \( S_j \) and \( S_{j+k} \) device-clusters are Pareto-improvement pair, \( \forall j \) and \( k > 1 \), they must swap their members at Step 11 of Algorithm 1 As a matter of fact, the final device-cluster set of Algorithm 1 does not contain any Pareto-improvement pair. ■

APPENDIX C

\( S \) will be Pareto-efficient if any \( S' \) set does not exist where compared to the device-clusters in \( S \) set, at least one device-cluster in \( S' \) set has a strictly smaller feature distance between its component D2D links, and rest of the device-clusters in \( S' \) set have similar feature distances between the component D2D links. For a proof by contradiction, we assume that \( S \) is not Pareto-efficient. However, Proposition 1 depicts that the device-clusters obtained by Algorithm 1 do not contain any Pareto-improvement pair. Certainly, by exchanging the current D2D links between any two device-clusters of \( S \) set, it is not possible to obtain another set \( S' \) so that \( \sum_{j=1}^{M} d(\mathbb{B}_{S'_j(1)}, \mathbb{B}_{S'_j(2)}) < \sum_{j=1}^{M} d(\mathbb{B}_{S_j(1)}, \mathbb{B}_{S_j(2)}) \) is satisfied. Even if \( \sum_{j=1}^{M} d(\mathbb{B}_{S'_j(1)}, \mathbb{B}_{S'_j(2)}) = \sum_{j=1}^{M} d(\mathbb{B}_{S_j(1)}, \mathbb{B}_{S_j(2)}) \) is satisfied, since \( \{d(\mathbb{B}_{S'_j(1)}, \mathbb{B}_{S'_j(2)})\} \) are strictly positive, it is not possible to unilaterally reduce feature distance between the component D2D links of a certain device-cluster without increasing feature distance between the component D2D links of another device-cluster. Consequently, the device-cluster set, \( S \), obtained by Algorithm 1 is Pareto-efficient. ■
where \( n \) is defined as

\[
\Xi_{j,l,n} = (1 - \lambda_{j,l,n}) R_{j,l,n}^{(U)} + \lambda_{j,l,n} R_{j,l,n}^{(D)} - \sigma_j^T \left[ \sum_{i=1}^{2} P_{j,l,n}[i], P_{j,l,n}[3], \sum_{i=1}^{3} Q_{j,l,n}[i] \right] \]

To justify that (33) is an exact potential function for NCPCG \( \mathcal{G} \), recall that the assignments of the relay F-UEs and RRBs among the players (i.e., device-clusters) are given. Particularly,
For a given $G$ for the game $\mathcal{G}$, therefore, as per the definition of the exact potential game, eq. (33) is an exact potential function. The multipliers correspond to the constraints $C7$, $C8$, and $C9$, respectively, the Lagrangian of (38) is

\[
\Gamma_j \left( \{ P_{j,l,j,n}, Q_{j,l,j,n} \} \right) \mid \{ x, y, \mu \} - \Gamma_j \left( \{ P'_{j,l,j,n}, Q'_{j,l,j,n} \} \right) \mid \{ x, y, \mu \}.
\]

Therefore, as per the definition of the exact potential game, eq. (33) is an exact potential function for the game $\mathcal{G}$, and consequently, $\mathcal{G}$ is an exact potential game. Moreover, since every potential game possesses at least one NE solution, $\mathcal{G}$ must possess at least one NE power allocation strategy. This completes the proof of Lemma 2. ■

APPENDIX E

The proof follows similar steps of [34, Theorem 3]. Since at the optimality of (13a), $R_{j, l,j,n}^{(U)} = R_{j, l,j,n}^{(D)}$ is satisfied, the constraint (13b) can be equivalently written as two individual rate constraints, such as, $\sum_{n \in \mathcal{N}_j} R_{j, l,j,n}^{(U)} \geq C_{\min}$ and $\sum_{n \in \mathcal{N}_j} R_{j, l,j,n}^{(D)} \geq C_{\min}$. Introducing two auxiliary variables $\{ Z_{j, l,j,n}^{(i)} \}$ and $\{ X_{j, l,j,n}^{(i)} \}$, $\text{BRS}_j$ is equivalently expressed as the following optimization problem.

\[
\max_{\{ P, Q, Z, X \} \geq 0} F_j^{(0)} \triangleq \sum_{n' \in \mathcal{N}_j} \left[ \sum_{i=1}^{2} (1 - \lambda_{j, l,j,n}) \log_2 \left( 1 + Z_{j, l,j,n}^{(i)} \right) + R_{j, l,j,n}^{(U)} + \sum_{i=1}^{3} \lambda_{j, l,j,n} \log_2 \left( 1 + X_{j, l,j,n}^{(i)} \right) \right] - \Psi_j (P, Q)
\]

\[
\text{s.t.} \left\{ \begin{array}{l}
C7: \quad \sum_{n \in \mathcal{N}_j} \left( \sum_{i=1}^{2} \log_2 \left( 1 + Z_{j, l,j,n}^{(i)} \right) + R_{j, l,j,n}^{(U)} \right) \geq C_{\min} \\
C8: \quad \sum_{n \in \mathcal{N}_j} \left( \sum_{i=1}^{3} \log_2 \left( 1 + X_{j, l,j,n}^{(i)} \right) \right) \geq C_{\min} \\
C9: \quad A_{j, l,j,n}^{(i)} \geq Z_{j, l,j,n}^{(i)}, i = 1, 2; \quad \frac{A_{j, l,j,n}^{(i)}}{B_{j, l,j,n}} \geq Z_{j, l,j,n}^{(i)}, i = 1, 2, 3.
\end{array} \right.
\]

(38)

For a given $P, Q$, eq. (38) is a strict concave optimization problem of $Z, X$, and it has zero duality-gap. Assuming that $P, Q$ are given and $\nu_{j}^{(1)}, \nu_{j}^{(2)}, \{ \Omega_i \}$ and $\{ \Omega_i \}$ are the Lagrangian multipliers correspond to the constraints C7, C8, and C9, respectively, the Lagrangian of (38) is
Hence, eq. (13a) can be equivalently solved by maximizing (40) with respect to $P$ values of $G$ to an NE strategy of $G$. As a result, the solution obtained by solving (18) and (20) via alternating optimization converges to an algorithm that monotonically improves the players’ payoffs, must converge to an NE strategy. Every exact potential game exhibits the finite improvement property [33, Lemma 2.3]. Essentially, payoff and converge to a local optimum of (13a). Recall that $G$ is an exact potential game, and because of the transmission power constraint, each player’s payoff is bounded above. Hence, the Lagrangian dual-function is defined as

$$L^*_j = \max_{Z, X} L_j | \Omega_i = \Omega^*_i, \Omega_i = \Omega^*_i \}$$

where $\Omega_i = \frac{\omega_i^{(1)}}{1 + Z_{j,l,i,n}^{(1)}}$, $\Omega_i = \frac{\omega_i^{(2)}}{1 + X_{j,l,i,n}^{(1)}}$, $\forall i = 1, 2, \text{ and } \Omega_i = \frac{Z_{j,l,i,n}^{(1)}}{X_{j,l,i,n}^{(1)}}$, $\forall i = 1, 2, 3$ where $\{Z_{j,l,i,n}^{(1)}\}$ and $\{X_{j,l,i,n}^{(1)}\}$ are the optimal values of $\{Z_{j,l,i,n}\}$ and $\{X_{j,l,i,n}\}$, respectively. As depicted from (39), $Z_{j,l,i,n}^{(1)} = \frac{A_{j,l,i,n}^{(1)}}{B_{j,l,i,n}^{(1)}}$ and $X_{j,l,i,n}^{(1)} = \frac{A_{j,l,i,n}^{(1)}}{B_{j,l,i,n}^{(1)}}$; otherwise, $L^*$ will approach infinity. Hence, $L^*_j$ is obtained as

$$L^*_j = F_j^{(1)}(Z, X) + F_j^{(2)}(P, Q, Z, X) - \Psi_j (P, Q)$$

Using a primal-decomposition, we can justify $\max_{\{P, Q, Z, X\} \in C} F_j^{(0)} = \max_{\{P, Q, Z, X\} \in C} F_j^{(0)}$. Owing to the strict concavity of (38) for a given $P$, $Q$, $\max_{\{P, Q, Z, X\} \in C} F_j^{(0)} = \max_{\{P, Q, Z, X\} \in C} F_j^{(0)}$. As such, we obtain $\max_{\{P, Q, Z, X\} \in C} F_j^{(0)} = \max_{\{P, Q, Z, X\} \in C} L^*_j$. Hence, eq. (13a) can be equivalently solved by maximizing (40) with respect to $P$, $Q$, $Z$, $X$.}

**APPENDIX F**

Using the similar steps to [34, Proposition 1], it can be readily verified that by solving (18) and (20) via alternating optimization, a monotonically non-decreasing sequence $\{\Gamma_j\}$ is obtained. Because of the transmission power constraint, each player’s payoff is bounded above. Hence, the solution obtained by alternatively solving (18) and (20) monotonically improves the player’s payoff and converge to a local optimum of (13a). Recall that $G$ is an exact potential game, and every exact potential game exhibits the finite improvement property [33, Lemma 2.3]. Essentially, an algorithm that monotonically improves the players’ payoffs, must converge to an NE strategy. As a result, the solution obtained by solving (18) and (20) via alternating optimization converges to an NE strategy of $G$. ■
Every NE strategy of an exact potential game is a local maximizer of the potential functions associated with the game [33]. As per Lemma 4, Algorithm 2 converges to an NE strategy for the exact potential game, \( G \), and hence, it obtains a local optimal solution to the exact potential function \( W(\cdot, \cdot) \) in (33). We can further justify that when the parameters \( \{\nu_j^{(1)}, \nu_j^{(2)}\} \) and \( \{\sigma_{j,1}, \sigma_{j,2}, \sigma_{j,3}\} \) are converged, \( W(\cdot, \cdot) \) becomes the partial Lagrangian dual-function of P2.1. Therefore, a local maximizer of \( W(\cdot, \cdot) \) must satisfy the first-order optimality condition for P2.1. As a result, Algorithm 2 converges to a local optimal solution to P2.1. □

APPENDIX H

The convergence of Algorithm 3 to a local optimal solution to (26) can be established from [35, Theorem 1]. For the completeness of the proof, we denote the value of the objective function of (26) as \( V_L(x, y) \). Moreover, we denote \( \{x^{(t+1)}, y^{(t+1)}\} \) and \( \{x^{(t)}, y^{(t)}\} \) as the output of Algorithm 3 at the \( t \)-th and \( (t+1) \)-th iterations, respectively. Since, in the step 5 of Algorithm 3, eq. (27) is solved by using an optimal SAP algorithm of [36], \( V_L(x^{(t)}, y^{(t)}) \leq V_L(x^{(t+1)}, y^{(t+1)}) \) is satisfied. Moreover, the step 7 of Algorithm 3 optimally solves (28), and consequently, \( V_L(x^{(t+1)}, y^{(t)}) \leq V_L(x^{(t+1)}, y^{(t+1)}) \) is satisfied. Therefore, we obtain \( V_L(x^{(t)}, y^{(t)}) \leq V_L(x^{(t+1)}, y^{(t+1)}) \). In other words, Algorithm 3 generates a sequence, \((x^{(t)}, y^{(t)})\), that non-decreasingly improves the solution to (26). Since the optimal solution to (26) is bounded above, Algorithm 3 must converge to a local optimal solution to (26). □

APPENDIX I

We first justify that the resource scheduling phase of the RSMD framework is convergent. The strategy tuple at the \( t \)-th iteration, \( t = 1, 2, \ldots \), is denoted by \((P^{(t)}, Q^{(t)}, x^{(t)}, y^{(t)}, \mu^{(t)})\) where \((P^{(t)}, Q^{(t)})\) is obtained from Algorithm 2, \((x^{(t)}, y^{(t)})\) is obtained from Algorithm 3, and \( \mu^{(t)} \) is determined according to the RRB price updating method described in Section IV.B(3). Note that, \( \forall t, P^{(t)} \propto \frac{1}{\mu^{(t-1)}} \) and \( Q^{(t)} \propto \frac{1}{\mu^{(t-1)}} \). Therefore, when \( \{\mu^{(low)}_n\} \) and \( \{\mu^{(high)}_n\} \) are sufficiently small and large, respectively, the bi-section method of updating RRB’s prices will always converge to certain \( \mu^*_n \) such that \(|I_n^{(up)}-I_n^{(th)}|\) approaches a small value, \( \forall n \in N_{sc} \). Meanwhile, for any given set of RRB prices, the resource scheduling phase of the RSMD framework provides a block-coordinate ascent for P2. Since the objective function of P2 is bounded above, a block-coordinate ascent must converge. Consequently, as \( t \) increases, the strategy tuple \((P^{(t)}, Q^{(t)}, x^{(t)}, y^{(t)}, \mu^{(t)})\) converges to a stationary outcome, denoted as, \((P^*, Q^*, x^*, y^*, \mu^*)\). Next, we justify that such an outcome is both SE and Pareto-efficient.
Under \((P^*, Q^*, x^*, y^*, \mu^*)\), \((x^*, y^*)\) is the outcome of the leader’s resource assignment strategy when the followers’ power allocations are given by \((P^*, Q^*)\) and RRBs’ prices are given by \(\mu^*\). According to Proposition 5, \((x^*, y^*)\) provides a local optimal solution to (26). Therefore, eq. (31a) is satisfied. On the other hand, \((P^*, Q^*)\) provides the BRS strategy of the followers’ potential game with the resource assignment profile \((x^*, y^*)\). Hence, according to Lemma 3, eq. (31b) is also satisfied. Consequently, as per Definition 2, \((P^*, Q^*, x^*, y^*, \mu^*)\) is an SE outcome.

Meanwhile, if F-AP changes the RRBs’ prices from \(\{\mu^*_n\}\) to other values, in response, the device-cluster(s) will also change their transmission powers. In such a case, the state of the game will deviate from an SE, and F-AP has to re-update the prices of the RRBs to achieve an SE state. Therefore, F-AP has no incentive to alter the RRBs’ prices once the prices satisfy the interference constraints. On the other hand, as per Proposition 4, \((P^*, Q^*)\) ensures a socially optimal utility for the followers under the converged prices of the RRBs. Consequently, as per Definition 3, \((P^*, Q^*, x^*, y^*, \mu^*)\) is also a Pareto-efficient outcome.

REFERENCES

[1] Z. Zhao et al., “Federated-learning-enabled intelligent fog radio access networks: Fundamental theory, key techniques, and future trends,” *IEEE Wireless Commun.*, vol. 27, no. 2, pp. 22-28, Apr. 2020.
[2] L. Pu et al., “D2D fogging: An energy-efficient and incentive-aware task Offloading framework via network-assisted D2D collaboration,” *IEEE J. Sel. Areas Commun.*, vol. 34, no. 12, pp. 3887-3901, Dec. 2016.
[3] T. D. Hoang, L. B. Le, and T. L.-Ngoc, “Resource allocation for D2D communication underlaid cellular networks using graph-based approach,” *IEEE Trans. Wireless Commun.*, vol. 15, no. 10, pp. 70997113, Oct. 2016.
[4] Y. Chen et al., “Resource allocation for device-to-device communications underlaying heterogeneous cellular networks using coalitional games,” *IEEE Trans. Wireless Commun.*, vol. 17, no. 6, pp. 4163-4176, Jun. 2018.
[5] H. Dai, Y. Huang, R. Zhao, J. Wang, and L. Yang, “Resource optimization for device-to-device and small cell uplink communications underlaid cellular networks,” *IEEE Trans. Veh. Technol.*, vol. 67, no. 2, pp. 1187-1201, Feb. 2018.
[6] J. Zhao, Y. Liu, K. K. Chai, Y. Chen, and M. Elkashlan, “Joint subchannel and power-allocation for NOMA enhanced D2D communications,” *IEEE Trans. Commun.*, vol. 65, no. 11, pp. 5081-5094, Nov. 2017.
[7] Y. Shun, M. Peng, and H. V. Poor, “A distributed approach to improving spectral efficiency in uplink device-to-device-enabled cloud radio access networks,” *IEEE Trans. Commun.*, vol. 66, no. 12, pp. 6511-6526, Dec. 2018.
[8] R. Yin et al., “Joint spectrum and power allocation for D2D communications underlaying cellular networks,” *IEEE Trans. Veh. Technol.*, vol. 65, no. 4, pp. 21822195, Apr. 2016.
[9] Y. Yuan, T. Yang, H. Feng, and B. Hu, “An iterative matching-Stackelberg game model for channel-power allocation in D2D underlaid cellular networks,” *IEEE Trans. Wireless Commun.*, vol. 17, no. 11, pp. 74567471, Nov. 2018.
[10] Z. Chang, Y. Hu, Y. Chen, and B. Zeng, “Cluster-oriented device-to-device multimedia communications: Joint power, bandwidth, and link selection optimization,” *IEEE Trans. Veh. Technol.*, vol. 67, no. 2, pp. 15701581, Feb. 2018.
[11] N. Sawyer and D. B. Smith, “Flexible resource allocation in device-to-device communications using Stackelberg game theory,” *IEEE Trans. Commun.*, vol. 67, no. 1, pp. 653-666, Jan. 2019.
[12] M. Hasan et al., “Resource allocation under channel uncertainties for relay-aided device-to-device communication underlaying LTE-A cellular networks,” *IEEE Trans. Wireless Commun.*, vol. 13, no. 4, pp. 23222338, Apr. 2014.
[13] B. Ma, H. Shah-Mansouri, and V. W. S. Wong, “Full-duplex relaying for D2D communication in millimeter wave-based 5G Networks,” IEEE Trans. Wireless Commun., vol. 17, no. 7, pp. 99106, Jul. 2018.

[14] X. Liu and N. Ansari, “Green relay assisted D2D communications with dual batteries in heterogeneous cellular networks for IoT,” IEEE Internet Things J., vol. 4, no. 5, pp. 17071715, Oct. 2017.

[15] Q. Wu, G. Y. Li, W. Chen, and D. W. K. Ng, “Energy-efficient D2D overlaying communications with spectrum-power trading,” IEEE Trans. Wireless Commun., vol. 16, no. 7, pp. 44044419, Jul. 2017.

[16] W. Cao, G. Feng, S. Qin, and M. Yan, “Cellular offloading in heterogeneous mobile networks with D2D communication assistance,” IEEE Trans. Veh. Technol., vol. 66, no. 5, pp. 4245-4255, May 2017.

[17] J. Liu et al., “Joint power allocation and user scheduling for device-to-device-enabled heterogeneous networks with non-orthogonal multiple access,” IEEE Access, vol. 7, pp. 62657-62671, May 2019.

[18] Y. Mao, B. Clerckx, and V. Li, “Rate-splitting multiple access for downlink communication systems: Bridging, generalizing, and outperforming SDMA and NOMA,” EURASIP J. Wireless Commun. and Network., no. 133, pp. 154, May 2018.

[19] B. Clerckx, Y. Mao, R. Schober, and H. V. Poor, “Rate-splitting unifying SDMA, OMA, NOMA, and multicasting in MISO broadcast channel: A simple two-user rate analysis,” [Online]. Available: https://arxiv.org/abs/1906.04474.

[20] A. A. Ahmad et al., “Interference mitigation via rate-splitting and common message decoding in cloud radio access networks,” IEEE Access, vol. 7, pp. 80350-80365, July 2019.

[21] Y. Mao, B. Clerckx, J. Zhang, Y. O.K. Li, and M. Arafa, “Max-min fairness of K-user cooperative rate-splitting in MISO broadcast channel with user relaying,” [Online]. Available: https://arxiv.org/abs/1910.07843.

[22] B. Rimoldi and R. Urbanke, “A rate-splitting approach to the Gaussian multiple-access channel,” IEEE Trans. Inf. Theory, vol. 42, no. 2, pp. 364375, Mar. 1996.

[23] Z. Yang, M. Chen, W. Saad, W. Xu, and M. S.-Bahe, “Sum-rate maximization of uplink rate splitting multiple access (RSMA) communication,” [Online]. Available: https://arxiv.org/pdf/1906.04092.pdf.

[24] M. Salehi, H. Tabassum, and E. Hossain, “Accuracy of distance-based ranking of users in the analysis of NOMA systems,” IEEE Trans. Commun., vol. 67, no. 7, pp. 5069-5083, July 2019.

[25] Y. Wu, D. Wu, L. Yang, X. Shi, L. Ao, and Q. Fu, “Matching-coalition based cluster formation for D2D multicast content sharing,” IEEE Access, vol. 7, pp. 739137928, 2019.

[26] C. Xu et al., “Cross-layer optimization for cooperative content distribution in multihop device-to-device networks,” IEEE Internet of Things J., vol. 6, no. 1, pp. 278-287, Feb. 2019.

[27] J. Cui, Z. Ding, P. Fan, and N. A.-Dhahir, “Unsupervised machine learning-based user clustering in millimeter-wave-NOMA systems,” IEEE Trans. Commun., vol. 17, no. 18, pp. 7425-7440, Nov. 2018.

[28] J. Ren, Z. Wang, M. Xu, F. Fang, and Z. Ding “An EM-based user clustering method in non-orthogonal multiple access,” IEEE Trans. Commun., vol. 67, no. 12, pp. 8422-8434, Dec. 2019.

[29] H. Zhang, H. Zhang, W. Liu, K. Long, J. Dong, and V. C. M. Leung, “Energy efficient user clustering, hybrid precoding and power optimization in terahertz MIMO-NOMA systems,” [Online]. Available: https://arxiv.org/pdf/2005.01053.pdf.

[30] Y. Xiao, K.-C. Chen, C. Yuen, Z. Han, and L. A. DaSilva, “A Bayesian overlapping coalition formation game for device-to-device spectrum sharing in cellular networks,” IEEE Trans. Wireless Commun., vol. 14, no. 7, pp. 40344051, Jul. 2015.

[31] J. Yang et al., “Two-Dimensional PCA: A New Approach to Appearance-Based Face Representation and Recognition,” IEEE Trans. Pattern Analysis and Machine Intelligence, pp. 131-137, vol. 26, no. 1, Jan. 2004.

[32] M. B. Ghorbel et al., “Principal component-based approach for profile optimization algorithms in DOCSIS 3.1,” IEEE Trans. Netw. Service and Management, vol. 15, no. 3, pp. 934-945, Apr. 2018.

[33] D. Monderer and L. S. Shapley, “Potential games,” Games and Economic Behavior, vol. 14, no. 1, pp. 124143, May 1996.

[34] K. Shen and W. Yu, “Fractional programming for communication systemsPart II: Uplink scheduling via matching,” IEEE Trans. Signal Process., vol. 66, no. 10, pp. 2631-2644, May 2018.
[35] A. M. Frieze, “A bilinear programming formulation of the 3-dimensional assignment problem,” *Mathematical Programming*, vol. 7, no. 1, pp. 376–379, 1974.

[36] J. Kennington and Z. Wang, “A shortest augmenting path algorithm for the semi-assignment problem,” *Operations Research*, vol. 40, no. 1, pp. 178–187, 1992.