Received May 13, 2018, accepted June 14, 2018, date of publication June 27, 2018, date of current version August 7, 2018.
*Digital Object Identifier 10.1109/ACCESS.2018.2850924*

# Coordinated Device-to-Device Communication With Non-Orthogonal Multiple Access in Future Wireless Cellular Networks

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This work was partially supported by the National Research Foundation of Korea (NRF) grant funded by the Korea Government (MSIT) (NRF-2017R1A2A2A05000995) and supported by the MSIT (Ministry of Science and ICT), South Korea, under the Grand Information Technology Research Center Support Program (IITP-2018-2015-0-00742) supervised by the IITP (Institute for Information & Communications Technology Promotion).

**ABSTRACT** We study the problem of user clustering and power assignment for a network comprised of cellular users and underlay device-to-device (D2D) users operating under a non-orthogonal multiple access (NOMA) scheme. Our goal is to maximize the sum-rate of the network by jointly optimizing the user clustering and power assignment. Moreover, we also aim to provide interference protection for the cellular users. The formulated optimization problem is a mixed-integer non-convex problem. Thus, the original problem is decomposed into two subproblems. The first subproblem of user clustering is formulated as a matching game with externalities, where this matching game is solved sequentially while the second subproblem pertaining to power assignment is solved using complementary Geometric programming. Finally, an efficient joint iterative algorithm is proposed that can achieve a suboptimal solution for the mix integer non-convex NP-hard problem. Simulation results show that the proposed algorithm can achieve up to 70% and 92% of performance gains in terms of the average sum-rate in comparison with the general NOMA and traditional orthogonal frequency-division multiple access (OFDMA) schemes, respectively. Moreover, our results show that the proposed scheme significantly enhances the network connectivity in terms of the number of admitted users compared with the traditional OFDMA, NOMA, and D2D schemes.

**INDEX TERMS** Device-to-device (D2D) communication, non-orthogonal multiple access (NOMA), matching theory, user clustering, power assignment, 5G.

## I. INTRODUCTION

Device-to-device (D2D) communication is considered as a promising candidate to handle the unprecedented growth of cellular traffic by enhancing the spectral efficiency when operating in an underlay fashion [1]. In D2D communication, data traffic is directly transmitted from a D2D transmitter to the D2D receiver without routing through a cellular base station (BS). Moreover, D2D communication is based on low power transmission that improves the energy efficiency and enables re-usability of the frequency spectrum, thus, enhancing spectral efficiency [2]. Therefore, D2D communication over wireless cellular networks will play a vital role in boosting the capacity of future 5G systems [1]–[4]. Recently, the potential benefits of enabling D2D communication over cellular networks have gained significant attention, especially for data offload [4], [5], content sharing/dissemination [6], [7], energy efficiency [8], [9], coverage extension [4], and improved spectral efficiency [10], [11]. Moreover, apart from improved spectral efficiency, an additional key requirement in 5G systems would be to handle massive connectivity due to the explosive growth of connected devices in existing cellular networks [4]. Furthermore, the existing cellular networks operate on the orthogonal frequency-division multiple access (OFDMA) scheme whose biggest disadvantage stems from the fact that each spectrum resource (i.e., resource blocks (RBs)) can accommodate only one user, thus, limiting the number of connected users in the system.

Recently, a novel access scheme namely non-orthogonal multiple access (NOMA) is being considered for alleviating the challenges of OFDMA scheme by providing a high spectral efficiency and a high number of connections [12]–[14]. In NOMA, multiple users can be scheduled over the same spectrum resource by exploiting the spectrum resource gain differences, however, these users cause inter-user interference [13]. This inter-user interference problem can be solved by using the successive interference cancellation (SIC) technique at the receiver [15]. Furthermore, significant challenges are required to be met in terms of resource and power assignment to reap the full benefits of NOMA. Resource and power assignment in NOMA is significantly different from the OFDMA scheme, as in NOMA, multiple users are scheduled over the same resource. Power domain multiplexing is then used for transmission at the transmitter side and SIC is used at the receiver side to decode and cater the inter-user interference. Thus, traditional approaches based on OFDMA systems do not apply to NOMA based systems. For resource allocation in NOMA, a significant challenge is to find the optimal set of users to form a cluster that can share the same resource. Therefore, an efficient user clustering and power assignment approach is required that can cluster NOMA users over the limited spectrum resources and allocate optimal transmit power to each user in the cluster. Furthermore, inspired by the potential benefits of D2D communication, we also investigate the potential benefits of enabling the D2D communication under the NOMA scheme. However, enabling D2D communication under the NOMA scheme requires handling an additional challenge of interference management. Enabling D2D communication in an underlay setting can significantly degrade the network performance if both cross-tier and co-tier interference are not well handled [24].

### A. RELATED WORKS

Resource allocation in underlay D2D networks has gained considerable attention and a number of recent works [16]–[24] have been presented to advance the resource allocation process. For instance, in [16] and [17], Yu *et al.* and Janis *et al.* present centralized resource allocation solutions that are controlled by the base-station for sharing resources and managing the interference between cellular users and D2D users. These centralized based solutions are not suitable for dense setting of D2D networks [4]. Moreover, device-centric architectures that enable distributed control are more compatible with dense D2D settings, as, in a dense setting, the number of choices exponentially grow with the number of D2D users. Thus, centralized solutions [16], [17] will fail and incur massive overhead concerning required computation and signaling. In [18], a distributed resource allocation scheme is studied for enabling an ad-hoc D2D network. Indeed, the presented approach results in improved network throughput, however, significant message passing is required in this approach. Similarly, the work in [19] improved the performance of D2D systems by jointly addressing the problem of power control and reuse partner selection. Fractional programming has been applied in D2D systems to improve the resource and energy usage in [20]. Game theoretic based solutions can play a vital role in enabling distributed control in a D2D network as investigated in [21]. Similarly in [22], improved performance for D2D networks has been accomplished by proposing a game-theoretic based solution (coalition games) to address the joint power and resource allocation problem. In [23], a novel approach based on matching games is proposed to handle power and channel allocation for a D2D enabled system. The network throughput can be further improved if multiple D2D users are scheduled on the same resources subject to interference management, such as in [24] and opposed to the works in [19], [20], [22], and [23], in which only one D2D user is present on one resource block. Moreover, in most of the recent works [18]–[20], [22], and [23], D2D communication is enabled only during the uplink transmission. However, the interference characteristics of downlink transmission are significantly different and these approaches cannot be tailored to be applied during the downlink transmission [24]. Thus, novel approaches are required to share the downlink resources [25]. Furthermore, all these aforementioned works have investigated resource allocation problems only for the OFDMA based systems.

NOMA systems can further boost the spectral efficiency and alleviate the challenges of OFDMA systems in terms of limited connections per resource blocks. Recently, various aspects of the NOMA scheme have been investigated in the literature [26]–[32]. In [26], a maximum weighted sum-rate solution based on Lagrangian duality and dynamic programming has been proposed for the joint power and channel allocation problem in multi-carrier NOMA systems. Similarly, an energy efficient solution via matching theory and DC programming is investigated for the joint power and channel allocation problem in [27]. A heuristic algorithm for user clustering followed by optimal power allocation is presented in [28]. Similarly, an iterative joint solution based on many-to-many matching games and geometric programming is presented for the joint sub-channel assignment and power allocation problems in [29]. Indeed, these aforementioned works advance the system's performance compared to the tradition OFDMA systems in terms of spectral efficiency and number of admitted users in the system. To further boost the spectral efficiency and the number of connections of NOMA systems, a novel NOMA-based D2D communication scheme is presented in [30] and [31], where a new concept of D2D groups is introduced in which one D2D transmitter transmits to a group of D2D receivers using the NOMA technique. Moreover, these D2D groups share the resource block with the cellular tier. Improved performance was observed by enabling the D2D group, however, the existing work did not consider NOMA-based cellular links and assumed that the cellular users were using OFDMA. Use of the NOMA technique both for the cellular and D2D links can improve the network performance in terms of spectral efficiency and number of connected devices such as the work in [32]. However, these works have ignored the rise in complexity on resource constrained D2D devices, which may not be capable of performing power domain multiplexing at the D2D transmitter and SIC at the receiver.

### B. CONTRIBUTIONS

In this paper, we aim to present a scalable and distributed solution for a network consisting of both NOMA-based cellular users and D2D users. Different from the aforementioned works such as [30] and [31], in this paper, we only adopt the NOMA technique to schedule a set of cellular users on the spectrum resource, whereas D2D users reuse these spectrum resources in an orthogonal manner subject to interference protection for the cellular tier. The motivation of using traditional D2D users opposed to NOMA-based D2D users (as in [30] and [31]) is to reduce the computation on the resource constrained D2D devices, and hence it is more practically applicable. Moreover, if the interference is well managed, the number of D2D users that can join the network is not strictly limited as in the NOMA-based D2D users, in which generally two or three D2D users can be scheduled to maintain low SIC receiver complexity such as in [30] and [31]. This motivates us to develop a solution for underlay D2D users by coordinating them with the NOMA-based cellular users. Then, user clustering is the main challenge to be addressed in a D2D enabled NOMA network. User clustering aims to find a group of NOMA-based cellular users and a set of D2D users that can be scheduled on the same resource blocks forming a cluster such that the network sum-rate is maximized. In this paper, we formulate an optimization problem for scheduling a set of NOMA-based cellular users and D2D users that form a cluster on resource blocks subject to interference management. Then, transmission power will be allocated to each user for interference management. Our key contributions can be summarized as follows:

- First, the joint user clustering and power assignment problem is formulated for users (NOMA-based cellular and traditional D2D users). The objective of this problem is to maximize the sum-rate of the network while providing interference protection for the cellular users. The formulated problem is a mixed-integer non-convex optimization problem and is combinatorial in nature. It is thus extremely difficult, if not impossible, to obtain the globally optimal solution for the proposed problem. Therefore, to obtain a low complexity solution, we decompose the formulated problem into two subproblems, user clustering, and power assignment.
- Second, the user clustering subproblem is also a combinatorial problem and is NP-hard, thus requiring exponential computation efforts to obtain the optimal solution. Inspired by the ability of matching games to solve combinatorial problems, we present two low-complexity algorithms that operate sequentially based on one-to-many matching games with externalities. Moreover, we also prove the stability and convergence of the proposed matching game based solutions.
- The subproblem pertaining to power assignment is addressed by using the complementary geometric programming (CGP) and the arithmetic-geometric mean approximation (AGM). An efficient and low-complexity solution is presented to address the non-convex power assignment subproblem. Finally, an iterative joint algorithm is developed which converges to a suboptimal solution of the proposed original problem.
- Simulation results show the convergence of the proposed framework. Moreover, the results show that our proposed approach can achieve up to 70% and 92% of performance gains with regard to the average sum-rate in comparison with the general NOMA and traditional OFDMA schemes, respectively.

The rest of this paper is organized as follows. System model and problem formulation are presented in Section II. In Section III, we present the formulation of the user clustering subproblem as a matching game and derive distributed algorithms for this subproblem. The solution pertaining to the non-convex power assignment subproblem is discussed in Section IV. Simulation results of our proposed solution are presented in Section V. In the final section, we draw the main conclusions.

## II. SYSTEM MODEL AND PROBLEM FORMULATION

Consider the downlink transmission of a macro base station (MBS), as shown in Fig. 1. The MBS serves a set of cellular users (CUs) denoted by $\mathcal{M}$, where the number of CUs is $M$. Moreover, a set of D2D users (pairs) denoted by $\mathcal{N}$ share the same system bandwidth with the CUs, where the number of D2D users is $N$. The MBS considers the system bandwidth,

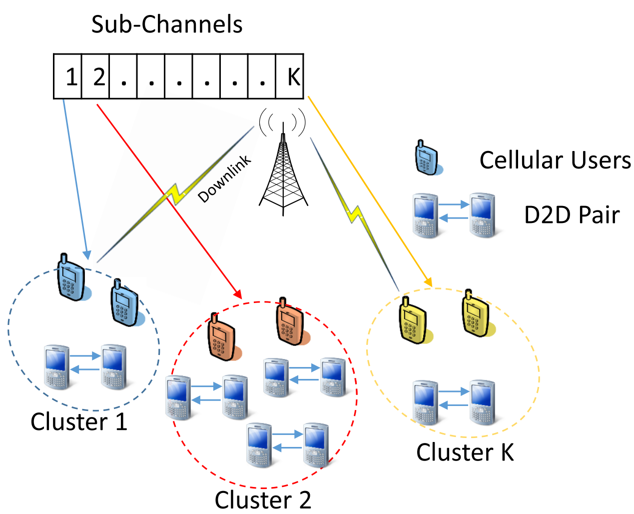



**FIGURE 1.** System model of D2D enabled NOMA network.

which is divided into a set of subchannels[1] denoted by $\mathcal{S}$, each of bandwidth $B$.

### A. CHANNEL MODEL

In our model, users (NOMA-based CUs and D2D users) that are scheduled over a subchannel form a cluster. We assume that each cluster operates in an orthogonal manner on a different subchannel. Moreover, the total number of users per cluster can range between 2 and $|\mathcal{M}| + |\mathcal{N}|$. However, in a NOMA enabled system, the implementation complexity of SIC at the receiver increases with the number of users scheduled at the same subchannel (i.e., $\mathcal{O}(U^3)$, where $U$ represents the number of users [12]). Therefore, in this paper, we assume a simple case in which only two users (i.e., NOMA-based CUs) can be scheduled on the same subchannel or the same cluster to keep the receiver complexity comparatively low. This assumption is in line with several recent works such as [27], [30], and [31]. However, we do not limit the number of D2D users on a subchannel, which is handled through the maximum interference threshold set by the CUs on a subchannel. Let $\mathcal{S}$ be the set of clusters (i.e., each subchannel is allocated to each cluster) and $\mathcal{M}_k$ and $\mathcal{N}_k$ represent the scheduled CUs and D2D users on the $k$-th cluster, respectively. Let $P_T$ represent the maximum transmission power of the MBS, and $P_m$ be the assigned power to CU $m$. Moreover, $h_m = \chi_m/\mathcal{D}(d_m)$ represents the complex coefficient of the subchannel between CU $m$ and the MBS, where $\chi_m$, $\mathcal{D}(\cdot)$, and $d_m$ represents the gain of Rayleigh fading channel, path loss function, and distance between CU $m$ and the MBS, respectively. Then, the received signal by CU $m$ from MBS in the $k$-th cluster can be given by

$$y_m^k = h_m\sqrt{P_m}x_m^k + \sum\nolimits_{m'\neq m|m'\in\mathcal{M}_k} h_m\sqrt{P_{m'}}x_{m'}^k + \sum\nolimits_{n\in\mathcal{N}_k} h_{n,m}\sqrt{P_n^d}x_n^k + z_m, \quad (1)$$

where $x_m$ be the transmitted symbol for CU $m$, $h_{n,m}$ is the channel gain between D2D user $n$ and CU $m$, $P_n^d$ is the transmit power of D2D user $n \in \mathcal{N}$, and $z_m$ be the additive white Gaussian noise.

Note that all CUs and D2D users scheduled on a cluster utilize the same subchannel, and then, the signal of any user causes interference to other users operating in the same cluster. Thus, each NOMA-based CU needs to perform SIC after receiving the superposed signals in order to demodulate its target message [29]. Generally, in NOMA, the lowest power level is assigned to highest channel gain user and its signal can be recovered correctly after removing interference from the signal of other multiplexed users via the SIC decoding [29]. On the other hand, lower channel gain users are assigned high power levels and they treat other users' signal as the noise [28], [29]. In NOMA, the decoding order of SIC is decided based on channel gains normalized by the noise as the CUs that have higher comparative channel gains can cancel the interference by any lower channel gain CU [28]. Moreover, CUs treat the signals of D2D users as interference and are not decoded. Therefore each D2D user has to control its transmit power in order to maintain the interference to CUs in the same cluster under a predefined threshold. Now, we define the user scheduling variables $\beta_m^k$ and $\alpha_n^k$ for the CU $m$ and D2D user $n$, respectively, as follows:

$$\beta_m^k = \begin{cases} 1 & \text{if CU } m \text{ is scheduled into cluster } k, \\ 0 & \text{otherwise,} \end{cases}$$

and

$$\alpha_n^k = \begin{cases} 1 & \text{if D2D user } n \text{ is sceduled into cluster } k, \\ 0 & \text{otherwise.} \end{cases}$$

Then, the achievable date rate for a CU $m$ scheduled on the $k$-th cluster is given as:

$$R_{m,CU}^k = \log_2\left(1 + \frac{P_m|h_m|^2}{I_m^k + \sum\limits_{n\in\mathcal{N}} \alpha_n^k|h_{n,m}|^2P_n^d + z_m}\right), \quad (2)$$

where $I_m^k$ is the interference that CU $m \in \mathcal{M}_k$ experiences due to the other CUs in the $k$-th cluster and the term $\sum_{n\in\mathcal{N}} \alpha_n^k|h_{n,m}|^2P_n^d$ represents the interference produced by $n$ D2D users on CU $m$ due to reuse of subchannel pertaining to cluster $k$.

$$I_m^k = \sum\nolimits_{m'\in\mathcal{M}|\frac{|h_{m'}|^2}{z_{m'}} > \frac{|h_m|^2}{z_m}} \beta_{m'}^k P_{m'}|h_m|^2. \quad (3)$$

Similarly, the achievable rate for D2D user $n$ on the $k$-th cluster is given as:

$$R_{n,D2D}^k = \log_2\left(1 + \frac{P_n^d|h_n|^2}{I_n^k + \sum\limits_{n'\in\mathcal{N}\setminus\{n\}} \alpha_{n'}^k|h_{n',n}|^2P_{n'}^d + z_n}\right), \quad (4)$$

where $I_n^k$ is the interference that D2D user $n \in \mathcal{N}_k$ experiences from the transmissions of all the CUs in $k$-th cluster and $\sum_{n'\in\mathcal{N}\setminus\{n\}} \alpha_{n'}^k|h_{n',n}|^2P_{n'}^d$ represents the co-tier interference produced by the other scheduled D2D users on D2D user $n$. Here,

$$I_n^k = \sum_{m\in\mathcal{M}} \beta_m^k|h_{BS,n}|^2P_m, \quad (5)$$

and $h_{BS,n}$ is the channel gain between MBS and D2D user $n$.

### B. PROBLEM FORMULATION

In this subsection, we formulate the joint user clustering (i.e., scheduling users into clusters) and power assignment problems for the downlink D2D enabled NOMA system. We aim to maximize the network sum-rate both for the CUs and D2D users by scheduling the best set of users (CUs and D2D users) and managing interference caused due to the reuse of the RBs by the D2D users. The joint user clustering

[1] We use the term "subchannels" and "resource blocks (RBs)" interchangeably.

and power assignment (JUCPA) optimization problem can be stated as:

$$\begin{aligned}
&\textbf{JUCPA}:\\
&\max_{\boldsymbol{\beta},\boldsymbol{\alpha},P} \sum_{k\in\mathcal{S}}\left(\sum_{m\in\mathcal{M}}\beta_m^k R_{m,CU}^k+\sum_{n\in\mathcal{N}}\alpha_n^k R_{n,D2D}^k\right)\\
&\text{s.t.: } C_1: \sum\nolimits_{k\in\mathcal{S}}\sum\nolimits_{m\in\mathcal{M}}\beta_m^k P_m \le P_T,\\
&\qquad C_2: \sum\nolimits_{n\in\mathcal{N}}\sum\nolimits_{m\in\mathcal{M}}\alpha_n^k |h_{n,m}|^2 P_n^d \le \theta^k, \quad \forall k\in\mathcal{S},\\
&\qquad C_3: \sum\nolimits_{k\in\mathcal{S}}\beta_m^k=1, \quad \forall m\in\mathcal{M},\\
&\qquad C_4: \sum\nolimits_{k\in\mathcal{S}}\alpha_n^k=1, \quad \forall n\in\mathcal{N},\\
&\qquad C_5: \beta_m^k\in\{0,1\}, \alpha_n^k\in\{0,1\}, \quad \forall m\in\mathcal{M}, n\in\mathcal{N},\\
&\qquad C_6: P_m\ge 0, P_n^d\ge 0, \quad \forall m\in\mathcal{M}, n\in\mathcal{N}, \qquad (6)
\end{aligned}$$

where $\boldsymbol{\beta} \triangleq \{\beta_m^k\}$, $\forall m \in \mathcal{M}, k \in \mathcal{S}$ is the CU allocation matrix, $\boldsymbol{\alpha} \triangleq \{\alpha_n^k\}$, $\forall n \in \mathcal{N}, k \in \mathcal{S}$ is the D2D user allocation matrix, and $P \triangleq \{P_m, P_n\}$, $\forall m \in \mathcal{M}, n \in \mathcal{N}$ is the power assignment vector. Constraint $C_1$ states that the total MBS power and constraint $C_2$ guarantees the total interference produced from all D2D users in each cluster does not exceed a threshold. The *user scheduling constraints* $C_3$ and $C_4$ ensure that each CU and D2D user, respectively can be assigned to at most one NOMA cluster. The integer variables $\alpha$ and $\beta$ are represented by constraint $C_5$. Finally, the last constraint $C_6$ represents the non-negative transmit power.

The **JUCPA** problem presented in (6) is a mixed-integer non-convex optimization problem [34] due to the interference term in the objective function and integer variables (i.e., $C_3$ and $C_4$). It is thus extremely difficult, if not impossible, to obtain the globally optimal solution to (6) through efficient algorithms in polynomial time. Therefore, we will focus on developing low-complexity algorithms that produce locally optimal solutions to (6) rather than a global optimal solution, as it is difficult to quantify the gap that the algorithms can achieve. To tackle the above problem, we decompose the original problem into two subproblems. The first subproblem of user clustering is then modeled using matching theory and we present two low-complexity algorithms for solving the user clustering subproblem. Moreover, we assume that the power levels are kept fixed during the user clustering phase. Then for a fixed user cluster, we address the power assignment subproblem, we propose a solution based on complementary geometric programming (CGP) and the arithmetic-geometric mean inequality (AGM). Finally, an iterative solution is proposed to find a suboptimal solution to the problem presented in (6). In the next section, we present the user clustering problem and the solution, which is based on matching theory.

## III. MATCHING GAME FOR USER CLUSTERING

In this section, we assume that transmit power assigned for both the CUs and D2D users are both given and fixed, i.e., $P$. Thus, we obtain the user clustering subproblem as follows:

$$\begin{aligned}
&\textbf{UC}:\\
&\max_{\boldsymbol{\beta},\boldsymbol{\alpha}} \sum_{k\in\mathcal{S}}\left(\sum_{m\in\mathcal{M}}\beta_m^k R_{m,CU}^k+\sum_{n\in\mathcal{N}}\alpha_n^k R_{n,D2D}^k\right)\\
&\text{s.t.: } C_1: \sum\nolimits_{k\in\mathcal{S}}\sum\nolimits_{m\in\mathcal{M}}\beta_m^k P_m \le P_T,\\
&\qquad C_2: \sum\nolimits_{n\in\mathcal{N}}\sum\nolimits_{m\in\mathcal{M}}\alpha_n^k |h_{n,m}|^2 P_n^d \le \theta^k, \quad \forall k\in\mathcal{S},\\
&\qquad C_3: \sum\nolimits_{k\in\mathcal{S}}\beta_m^k=1, \quad \forall m\in\mathcal{M},\\
&\qquad C_4: \sum\nolimits_{k\in\mathcal{S}}\alpha_n^k=1, \quad \forall n\in\mathcal{N},\\
&\qquad C_5: \beta_m^k\in\{0,1\}, \alpha_n^k\in\{0,1\}, \quad \forall m\in\mathcal{M}, n\in\mathcal{N}. \qquad (7)
\end{aligned}$$

The user clustering (**UC**) subproblem in (7) is a combinatorial problem due to the integer variables. Thus, it is difficult to find an optimal solution and solving it in a practical amount of time becomes NP-hard for a reasonable network size (CUs and D2D users) and set of subchannels [24], [34]. Inspired by the ability of the matching theory to solve combinatorial problems in a distributed manner, we map our combinatorial problem (7) to a matching game [35]–[37]. To solve user clustering problem, we present two distributed matching games that operate in a sequential manner to find a stable solution. In the first matching game, the CUs and subchannels act as players. The aim is to find the set of CUs that can be scheduled for transmission on the same subchannel and form a cluster. Then, based on the output of this matching (i.e., $\boldsymbol{\beta}$), we design the second matching game in which the D2D users and subchannels act as players of the game. The details of these games are discussed in the following subsections.

### A. CELLULAR USERS MATCHING GAME

In NOMA, users (NOMA-based CUs) that are scheduled over a subchannel form a NOMA cluster. Note that to schedule CUs, channel gain difference is exploited and CUs with a significant difference in channel gains are scheduled together to form a NOMA cluster. The main reason behind this assumption is that users with strong channel gains can decode their signal by removing the signal pertaining to the weak users via the SIC. Therefore, our aim is to find the set of CUs that can be scheduled for transmission on the same subchannel to form a NOMA cluster. Moreover, to keep low receiver complexity in NOMA [12], we assumed that only two CUs can be scheduled on the same subchannel similar to the works in [27], [30], and [31]. Therefore, our aim is to find two CUs with significantly different channel gains that can be scheduled on the same subchannel. To find the set of CUs with different gains in the network, we classify the CUs' into two classes, A and B. Class A represents the strong CUs in the network in terms of channel gains with the MBS whereas Class B corresponds to weak CUs. The reason behind classifying CUs into two classes[2] is that we want to only schedule two CUs per cluster.

[2]The proposed scheme can be extended for any number of classes based on the number of CUs to be scheduled on a cluster. However, the complexity of SIC at the receiver increases with the number of scheduled CUs [12].

To classify CUs, we present a CU classification algorithm based on the well-known *K-means* algorithm [33]. We define two classes of CUs and assume that the MBS first obtains the channel state information (CSI) of all the CUs, and we then run Algorithm 1 to classify the CUs into two classes. Initially, the channel gain of each CU is given as inputs along with the required classes, i.e., $K = 2$. By employing the *K-means* algorithm, each CU is assigned to one of the $K$ classes. Members of a class are indistinguishable in terms of channel gains between them and the MBS and significantly different from the members of other class in terms of channel gains.

**Algorithm 1** *K-Means* Based Users Classification

1: input: $\mathcal{M}, K = 2, t = 1$.
2: initialize $K$ centroids randomly, i.e., $\lambda_1,\ \lambda_2, \ldots \lambda_k$
3: **repeat**
4: $\quad t = t + 1$
5: $\quad$ **for** $i \in \mathcal{M}$ **do**
6: $\quad\quad x_i = \min_k |||h_i|^2 - \lambda_k^t||^2$
7: $\quad$ **for** $k \in K$ **do**
8: $\quad\quad \lambda_k^t =$ mean of $|h_i|^2$ such that $x_i \in$ class $k$
9: **until** ${\lambda_k}^{t-1} = {\lambda_k}^t$;
10: output: $K$ classes, i.e., $\mathcal{K} = \{A, B\}$.

In the *K-means* based algorithm, i.e., Algorithm 1, first, the notion of the center of a class (called centroids) is introduced, $\lambda$. The number of centroids is decided based on the number of required classes (line 2). Then, the Euclidean distance is used as a measure to classify the CUs into each class, i.e., we assign each of the CU to the class for which the CU is nearest to the centroid (lines 5-6). Once all CUs are assigned to the class, we recalculate the centroids of the classes (lines 7-8) and then repeat the previous process of assigning CUs to the class with the nearest centroid until the centroids from the previous iteration remain unchanged (line 9). Once this process is completed, $K$ classes with sets of CUs are produced.

### 1) MATCHING GAME FORMULATION

After CU classification is executed, the next goal is to schedule the CUs into clusters. To schedule CUs into clusters, we map the user clustering subproblem into a matching game. In this game, we have two disjoint sets of players, namely the clusters or subchannels, $\mathcal{S}$, and the CUs, $\mathcal{M}$. Moreover, each CU can be scheduled to a single cluster from constraint $C_3$ in (7), however, a cluster can have multiple CUs scheduled on it, i.e., multiple CUs per subchannel. Thus, our game can be represented by the *one-to-many matching* game expressed by the tuple $(\mathcal{M}, \mathcal{S}, \succ_{\mathcal{M}}, \succ_{\mathcal{S}})$. In this game, $\succ_{\mathcal{M}} \triangleq \{\succ_m\}_{m\in\mathcal{M}}$ and $\succ_{\mathcal{S}} \triangleq \{\succ_k\}_{k\in\mathcal{S}}$ denote the CUs and clusters preference relations, respectively. A matching between the two sides can be defined as follows:

*Definition 1: A* matching $\beta$ *is defined as a function from the set* $\mathcal{M} \cup \mathcal{S}$ *into the set of* $\mathcal{M} \cup \mathcal{S}$ *which satisfies for all* $k \in \mathcal{S}$ *and* $m \in \mathcal{M}$*:*

1) $|\beta(m)| \leq 1$ *and* $\beta(m) \in \mathcal{S} \cup \phi$,
2) $|\beta(k)| \leq q_k$ *and* $\beta(k) \in 2^{\mathcal{M}} \cup \phi$,
3) *If* $m \in \beta(k)$ *then* $\beta(m) = k$,
4) *If* $\beta(m) \in k$ *for cluster* $k$ *then* $\beta(k) = m$,

where $q_k$ denotes the quota of cluster $k$. The first condition here represents the constraint $C_3$ in (7). The second condition represents the quota of a subchannel $k$. In this game, we restrict the value of $q_k$ to 2 CUs to reduce the receiver complexity.

In matching games, both sides of players are required to rank each other via the preference profiles. In the formulated game, the CUs have preferences both over clusters and the other CUs scheduled on this cluster (i.e., from (3)). Such preference relations that include interdependencies are known as *externalities* in matching games. These externalities need to be well-handled to obtain a stable solution, otherwise, players may never be able to reach a stable solution as their preference profile would be constantly changing in response to the actions of other players [24].

In this game, to build the CUs preference profile ($\mathcal{P}_m$), each CU calculates the achievable data rate for each cluster (i.e., the first term of the objective function in (7)). Each CU then ranks all clusters in a descending order by using the following utility function:

$$U_m(k, \beta) = R^k_{m,CU}, \quad \forall k. \tag{8}$$

The preference relation $\succ_m$ for any CU $m$ defined over the set of clusters $\mathcal{S}$ can be given as follows:

$$(k, \beta) \succ_m (k', \beta') \Leftrightarrow U_m(k, \beta) > U_m(k', \beta'), \quad \forall k, k' \in \mathcal{S}. \tag{9}$$

Similarly, each cluster aim to choose a set of CUs that can maximize the sum rate over each cluster $k$. Therefore, the cluster uses the following utility to create its preference profile ($\mathcal{P}_k$):

$$U_k(\mathcal{A}, \beta) = \sum\nolimits_{m\in\mathcal{A}} R^k_{m,CU}, \quad \forall \mathcal{A}. \tag{10}$$

According to (10), each cluster $k$ chooses a subset of CUs $\mathcal{A}$ that can maximize the achievable rate of a cluster. Similarly, the preference relation $\succ_k$ for any cluster $k$ can be given as follows:

$$(\mathcal{A}, \beta) \succ_k (\mathcal{A}', \beta') \Leftrightarrow U_k(\mathcal{A}, \beta) > U_k(\mathcal{A}', \beta'). \tag{11}$$

Next, for the proposed game, we aim to find a CU clustering scheme. However, we need to handle the challenge of externalities which are evident from (8) and (10). We can see that the preference functions are a function of the existing matching $\beta$. Moreover, it is evident from (3) that the CUs affect each other's performance due to the interference produced by comparatively high channel gain CUs. Thus, it is of key interest to devise a novel approach that can handle the challenge of externalities.

#### 2) PREFERENCES AND EXTERNALITIES

In the formulated game, if a CU $m$ is matched to a cluster $k$, it will interfere with the incumbent CUs of the cluster $k$ only if its channel gain is higher than the other CUs of that cluster. Consequently, this may force a CU $m$ to change its preference towards a cluster $k$ in response to the action of other players, i.e., CUs $m'$, which have been assigned to the same cluster $k$. Thus, in such a case, the player may never reach a final clustering or solution.

Therefore, we devise a new approach through which externalities can be handled. In this approach, the initial network information (i.e., channel gains of all CUs) is broadcast to the CUs by the MBS after collecting it from each individual CUs. This information is used by the CU in order to find the set of CUs that have a higher channel gain with the MBS. Note that in NOMA, we aim to schedule CUs into the same cluster that has significant differences in channel gain. Through the classification scheme presented in Algorithm 1, same class CUs should not be scheduled on the same cluster, as they will cause significant interference and degrade the network performance. Then, we devise an approach in which CUs only care about other CUs that are in the same class. Moreover, each CU would have a different set of CUs affecting itself. We name this set as an externality set for CU $m$, and represent it by $\mathcal{E}_m$ as follows:

$$\mathcal{E}_m = \left\{ m' \in \mathcal{M} : \frac{|h_{m'}|^2}{z_{m'}} > \frac{|h_m|^2}{z_m}, m, m' \in \mathcal{B} \right\}, \quad (12)$$

where $\mathcal{B}$ represents the set of CUs that are in the same class. From (12), each CU identifies all the CUs that have a higher channel gain compared to itself and are a member of the same class. The idea is to restrict the CUs that belong to the same class to be scheduled together on the same cluster.

#### 3) CLUSTERING ALGORITHM FOR CELLULAR USERS

Next, we present a novel clustering scheme for the formulated game. In our game, we also address the challenge of externalities, thus, we cannot use the traditional solutions designed for one-to-many games based on Gale-Shapley. Therefore, first, we have to define the blocking pair of the game and then present our novel CU clustering scheme. Formally, the blocking pair is defined as:

*Definition 2: A matching $\beta$ is blocked by a pair of players $(m, k)$ if there exists a pair $(m, k)$ with $m \notin \beta(k)$ and $k \notin \beta(m)$ such that $m \succ_k \beta(k)$, $k \succ_m \beta(m)$, and $\beta(k) \notin \mathcal{C}_m$.*

Definition 2 states that whenever a CU $m$ finds a cluster $k$ move preferable compared to its current assigned cluster $\beta(m)$ that does not contain a CU that is a member of its externality set (i.e., $\beta(k) \notin \mathcal{E}_m$), and cluster $k$ also prefers to accommodate CU $m$ (i.e., $k \succ_k \beta(k)$) by rejecting some accepted CUs in $\beta(k)$ which is ranked lower than CU $m$, then CU $m$ and cluster $k$ can deviate from their assigned matching to form a blocking pair. A matching can be stable only if there exist no blocking pairs. In our solution, the concept of stability ensures that after matching, no player (i.e., CUs and clusters) can benefit by replacing their current matched partners with any better partner [24].

Next, we present an efficient clustering algorithm for CUs that can achieve a stable solution. Initially, the MBS decides the order of proposal based on the set of available classes. The reason for choosing a proposing order stems from the fact that in NOMA, CUs belonging to the same class would have indistinguishable channel gains, thus, they should be restricted to be scheduled on the same cluster. Consequently, by allowing a sequential proposing order in terms of the classes, we would like CUs belonging to the same class to compete with each other. In our proposed algorithm, the proposing order starts by the strongest class A to the weakest class B. This order guarantees that any CU from a specific class does not affect the CUs of other class. The algorithm starts by building the preference profiles of both sides (lines 1-3). Then, each CU that belongs to a particular class updates its preference profiles based on the previous round of matching $\beta(k)^{(t-1)}$ (line 5). After updating, each CU $m$ from a particular class proposes to its most preferred cluster $k$ (line 6). A cluster $k$ upon receiving the proposal from a CU $m$, checks if there exists a CU $m' \in \beta(k)$ that is also a member of the externality set of the proposing CU $m$. This can result in either of the following two cases. The first case occurs when there exists CUs from the externality set $E_k$ in the current matching (line 8). This results in cluster $k$ removing lower ranked CUs from its current matching (lines 9-12). Once all lower ranked CUs are removed the externality set is checked again (line 13). The proposing CU $m$ is also rejected if there still exists any CU in the externality set. Then the proposing CU $m$ is rejected and considered to be the least preferred CU $m_{lp}$ (line 14). The second case occurs if the externality set is empty. The quota $q_k$ of cluster $k$ is checked in this case, if enough quota is available, then CU $m$ is accepted, otherwise rejected and set as the least preferred CU (lines 17-21). Finally, we update the preference profiles of all players by removing all the rejected CUs from the preference list of clusters and vice-versa (lines 22-24). The next class starts the proposing process once all CUs of the previous class ends its proposal process. Furthermore, if the matching results of two consecutive iterations $t$ remain unchanged, the matching for that class terminates (line 25). Moreover, the matching converges in limited iterations, as the numbers of CUs is finite in each class and the CUs rejected by a cluster do not propose to the same cluster once they are rejected.

*Theorem 1: The proposed Algorithm 2 is guaranteed to reach a two-sided stable matching $\beta$ between CUs and clusters.*

*Proof:* We adopt the proof from [35] to prove this theorem by contradiction. Suppose that Algorithm 2 produces a matching $\beta$ with a blocking pair $(m, k)$. Since CU $m$ prefers cluster $k$ ($k \succ_m \beta(m)$), it would have sent a proposal to cluster $k$ and must have been rejected due to lower priority on ranking of cluster $k$ than $\beta(k)$ (lines 13-14). Furthermore,

**Algorithm 2** CUs Clustering Algorithm

1: **input**: $\mathcal{P}_m^{(t)}$, $\mathcal{P}_k^{(t)}$, $\mathcal{E}_m$, $\forall k \in \mathcal{S}$, $\forall m \in \mathcal{M}$.
2: **initialize**: $t = 0$, $\beta^{(1)} \triangleq \{\beta(m)^{(1)}, \beta(k)^{(1)}\}_{m \in \mathcal{M}, k \in \mathcal{S}} = \emptyset$, $\mathcal{R}_k{}^{(1)} = \emptyset$, $E_k^{(1)} = \emptyset$, $q_k^{(1)} = |\mathcal{U}|$, $\forall k, m$.
3: **repeat**
4: $\quad t \leftarrow t + 1$.
5: $\quad$ Update $\forall m$, $\mathcal{P}_m{}^{(t)}$ for given $\beta(k)^{(t-1)}$.
6: $\quad$ $\forall m \in$ same class such that cluster $k$ as most preferred in $\mathcal{P}_m^{(t)}$.
7: $\quad$ **while** $m \notin \beta(k)^{(t)}$ and $\mathcal{P}_m^{(t)} \neq \emptyset$ **do**
8: $\quad\quad$ **if** $E_k^{(t)} = \{m' \in \beta(k)^{(t)} \cup \mathcal{E}_m\} \neq \emptyset$ **then**
9: $\quad\quad\quad$ $\mathcal{X}'^{(t)}_k = \{m' \in \beta(k)^{(t)}, k' \in \mathcal{E}_m | m \succ_k m'\}$.
10: $\quad\quad\quad$ $m_{lp} \leftarrow$ the least preferred $m' \in \mathcal{X}'^{(t)}_k$.
11: $\quad\quad\quad$ **for** $m_{lp} \in \mathcal{X}'^{(t)}_k$ **do**
12: $\quad\quad\quad\quad$ $\beta(k)^{(t)} \leftarrow \beta(k)^{(t)} \setminus m_{lp}$, $q_k{}^{(t)} \leftarrow q_k{}^{(t)} + 1$.
13: $\quad\quad\quad$ **if** $E_k^{(t)} = \{m' \in \beta(k)^{(t)} \cup \mathcal{E}_m\} \neq \emptyset$ **then**
14: $\quad\quad\quad\quad$ $m_{lp} \leftarrow m$.
15: $\quad\quad\quad$ **else**
16: $\quad\quad\quad\quad$ $\beta(k)^{(t)} \leftarrow \beta(k)^{(t)} \cup m$, $q_k{}^{(t)} \leftarrow q_k{}^{(t)} - 1$.
17: $\quad\quad$ **else**
18: $\quad\quad\quad$ **if** Check $q_k{}^{(t)} > 0$ **then**
19: $\quad\quad\quad\quad$ $\beta(k)^{(t)} \leftarrow \beta(k)^{(t)} \cup m$, $q_k{}^{(t)} \leftarrow q_k{}^{(t)} - 1$.
20: $\quad\quad\quad$ **else**
21: $\quad\quad\quad\quad$ $m_{lp} \leftarrow m$.
22: $\quad\quad$ $\mathcal{R}_k{}^{(t)} = \{m \in \mathcal{X}'_k{}^{(t)} | m_{lp} \succ_k m\} \cup \{k_{lp}\}$.
23: $\quad\quad$ **for** $m \in \mathcal{R}_k{}^{(t)}$ **do**
24: $\quad\quad\quad$ $\mathcal{P}_m{}^{(t)} \leftarrow \mathcal{P}_m{}^{(t)} \setminus k$, $\mathcal{P}_k{}^{(t)} \leftarrow \mathcal{P}_k{}^{(t)} \setminus m$.
25: $\quad$ **Check**: $\beta^{(t-1)} = \beta^{(t)}$.
26: **until** $\forall$ classes, i.e., A, B.

any lower ranked CU $m'$ was also rejected either before CU $m$ (lines 9-12) or was made unable to propose because cluster $k$ is removed from CU $m'$ preference list (lines 22-24). Thus, any lower ranked CU $m'$ cannot be matched by cluster $k$, i.e., $m' \notin \beta(k)$, a contradiction. □

### *B. D2D USERS MATCHING GAME*

Once the CU matching game is completed, we obtain the set of CUs that are matched to the set of subchannels, i.e., $\boldsymbol{\beta}$. To further improve the network performance, we allow a set of D2D users to be scheduled with the subchannels only if the interference protection can be guaranteed for the CUs, i.e., $C_2$ of (7) is not violated. However, we need to first calculate the interference threshold for each cluster, denoted $\theta^k$. Note that for each cluster, we can have up to two CUs. Thus, we choose $\theta^k$ for each cluster such that it meets the minimum interference tolerance among the two CUs on the cluster, i.e., $\theta^k = \min_{j \in \beta(k)} I^k_{j,th}$. From (2), we can calculate the interference tolerance of each CU $j$, i.e., $I^k_{j,th} = \frac{P_j |h_j|^2}{2^{R_j^{\max}} - 1} - z_j - I^k_{j,CU}$, where $I^k_{j,CU}$ is the interference from the other CU in the same cluster and $R_j^{\max}$ represents the quality of service for CU $j$.

#### 1) MATCHING GAME FORMULATION

Similar to our previous formulated game, here, also we have two sets of players, the set of clusters, $\mathcal{S}$, and the set of D2D users, $\mathcal{N}$. Moreover, it is evident from $C_4$ that each D2D user can be assigned to a single subchannel or a cluster. However, a cluster can accommodate multiple different D2D users. Moreover, the D2D users operating on the same subchannel or cluster will cause interference to the CUs and other D2D users. This can be observed from (4), the rate of a D2D user $n$. Similar to the previous proposed game, here, the *matching* $\alpha$ is defined on the set $\mathcal{N} \cup \mathcal{S}$.

The matching conditions in this game are in-line with the Definition 1 presented for the CU game. Here, the first two conditions represent the constraints given by $C_4$ and $C_2$ of (7), respectively. However, the quota $q_k$ here denotes the interference threshold ($\theta^k$) of cluster $k$ obtained after the CU matching game. Note that the quota $q_k$ of a cluster $k$ can represent the tolerable interference ($\theta^k$) level of the cluster. Through this, a decision can be made on the number of allowed D2D users on a cluster $k$ without violating constraint $C_2$.

Similarly, in this game, the players rank each other through the preference profiles. To build the preference profiles of D2D users, each D2D user calculates the achievable data rate (i.e., the second term of the objective function in (7)) for each cluster and ranks them in descending order. The following preference function is used by each D2D user $n$:

$$U_n(k, \alpha) = R^k_{n,D2D}, \quad \forall k. \tag{13}$$

Similarly, the preference relation $\succ_n$ for any D2D user $n$ defined over the set of clusters $\mathcal{S}$ can be given as follows:

$$(k, \alpha) \succ_n (k', \alpha') \Leftrightarrow U_n(k, \alpha) > U_n(k', \alpha') \quad \forall k, k' \in \mathcal{S}. \tag{14}$$

Each cluster $k$ also builds its preference profile by the following preference function:

$$U_k(\mathcal{L}, \alpha) = \max_n \{|\mathcal{L}_n| : I^k_{\mathcal{L}_n} \leq \theta^k\}. \tag{15}$$

According to (15), the goal of each cluster $k$ is to choose a set of D2D users $\mathcal{L}$ subject to the tolerable interference threshold, $\theta^k$. This function maximizes the number of D2D users in the set $\mathcal{L}$. Thus, the D2D users that cause the smallest interference to the cluster $k$ are to preferred by cluster $k$. In the preference profile of cluster $k$, the subset with the largest number of members is considered the most preferred and ranked as the highest in the preference. The preference relation $\succ_k$ for any cluster $k$ towards any two subsets of D2D users, i.e., $\mathcal{L}', \mathcal{L} \subset \mathcal{S}$ can be defined as follows:

$$(\mathcal{L}, \alpha) \succ_k (\mathcal{L}', \alpha') \Leftrightarrow U_k(\mathcal{L}, \alpha) > U_k(\mathcal{L}', \alpha'). \tag{16}$$

Next, for the proposed game, we aim to find a find a stable cluster allocation scheme. However, similar to the previous game, here also we need to handle the challenge of externalities which are evident from (4) in which a D2D user affects other's performance through co-tier interference. Thus, we aim to devise a novel approach to handle such externalities.

#### 2) PREFERENCES AND EXTERNALITIES

Similar to the previous proposed game, a D2D user $n$ apart from causing interference to CU, also affects the neighboring D2D users using the same cluster $k$. This can cause the D2D users to change their preference with respect to the other players matched to the cluster and thus may never reach a final allocation. Therefore, we adopt an approach to handle such externalities similar to the works proposed in [24]. To handle such a situation, we use the concept of interference graph in which the initial network is represented as a graph. Nodes in this graph represent the D2D users in the network while the edges represent an interfering link between two D2D users. Each D2D user evaluates its neighbors by calculating the ratio of the required signal to the interference signal from the neighboring D2D node. If the result is above a predefined threshold $\zeta_n$, then, an edge exists between two neighboring D2D nodes:

$$\frac{P_n g_n^k}{P'_n g_{n',n}^k} \leq \zeta_n.$$

Through $\zeta_n$ we can define and adjust the severity of the interference for any D2D user $n$. The aim is to restrict two D2D users to be scheduled on the same cluster that is connected by an edge in the interference graph. Each D2D user then sends this set of the conflicting user to the MBS and we call this a conflict set for a D2D user $n$:

$$\mathcal{C}_n = \left\{ n' \in \mathcal{N} : \frac{P_n g_n^k}{P'_n g_{n',n}^k} \leq \zeta_n \right\}. \tag{17}$$

The aim here is to stop D2D users which are very close to each other to be scheduled on the same clusters, as this will cause instability in the preferences of D2D users and will degrade the performance of the network [24].

#### 3) CLUSTERING ALGORITHM FOR D2D USERS

Similar to the CU matching game, first, we need to define the blocking pair. However, in this game opposed to the CU matching game, we have to handle the challenge of dynamic quota apart from externalities. In dynamic quota, a cluster allows a different number of D2D users based on its interference threshold. Moreover, each D2D user can cause heterogeneous interference based on its location and channel dynamics. This heterogeneous interference of D2D users and dynamic quota of clusters introduce new challenges into the game, similar to [24] and [35]. Moreover, our game has two additional challenges, externalities and heterogeneous interference tolerance threshold for each cluster $k$, which are not addressed in [35] and [24], respectively. Therefore, first, we define the blocking pair of this game as follows:

*Definition 3: A matching $\alpha$ is said to be* stable *if there exists no* blocking pair $(n, k)$ *such that [24]:*

a) $q_{res}^k \geq q_n^k$, $n \succ_k \emptyset$, $k \succ_n \alpha(n)$, *and* $\alpha(k) \notin \mathcal{C}_n$,
b) $q_{res}^k < q_n^k$, $q_{res}^k + \sum_{n' \in \alpha(k)} q_{n'}^k \geq q_n^k$, $n \succ_k n'$, $k \succ_n \alpha(n)$, *and* $\alpha(k) \notin \mathcal{C}_n$,

where $q_{res}^k = \theta^k - \sum_{n \in \alpha(k)} q_n^k$ represents the residual quota, i.e., tolerance threshold on cluster $k$. *The quota of a cluster $k \in \mathcal{S}$ is filled for a D2D user $n \in \mathcal{N}$ when the condition $q_{res}^k < q_n^k$ is met.* Consider the case where a D2D user $n$ prefers a cluster $k$ over its assigned cluster $\alpha(n)$ and no conflicting D2D user exists in the currently matched set (i.e., $\alpha(k) \notin \mathcal{C}_n$), which occurs if either: i) cluster $k$ has enough quota $q_{res}^k$ to accommodate D2D user $n$ (i.e., $n \succ_k \emptyset$), or ii) it can accept D2D user $n$ by rejecting some of existing matched D2D users that ranked lower than D2D user $n$, if quota is filled. Then, both players have an incentive to deviate from their existing matching and form a blocking pair. In our solution, the concept of stability ensures that after matching, no player (i.e., CUs and clusters) can benefit by replacing their current matched partners with any better partner [24].

Next, we propose the D2D clustering algorithm which is similar to [24]. However, in the proposed algorithm, each cluster has different interference tolerance opposed to the works in [24] in which homogeneous interference threshold was proposed for the resources. First, local information is used to build the preferences for both sides (lines 1-2). Then, each D2D user re-calculates its utility at each iteration and reorders its ranking based on the previous matching $\alpha(k)^{(t-1)}$ (line 4). Next, each D2D user proposes to the most preferred cluster $k$ and the following two cases can occur. In the first case, the quota ${q_{res}^k}^{(t)}$ of cluster $k$ may not be sufficient to accommodate the proposing D2D user $n$. Thus, cluster $k$ will find all lower ranked matched D2D users than D2D user $n$ according to ${\mathcal{P}_k}^{(t)}$ (lines 7-9). These D2D users are then sequentially rejected until either enough quota is created to accommodate D2D user $n$ or there are no lower ranked D2D users to reject (lines 10-12). If enough quota is not created to accommodate D2D user $n$, then, D2D user $n$ is also rejected and considered as the least preferred D2D user represented by $n_{lp}$ (lines 13-14). In the second case, cluster $k$ has enough quota to accommodate D2D user $n$. In this case, the conflict set $\mathcal{C}_n$ is first checked by the cluster $k$. If empty, the proposal is accepted (lines 15-17), otherwise, all lower ranked D2D users that are currently matched are removed from the current matching (lines 18-22). If the conflict set is still non-empty, the D2D user $k$ is rejected and is considered to be the least preferred $n_{lp}$ (lines 23-26). Finally, we update the preference profiles of all players by removing all the rejected D2D users from the preference list of clusters and vice-versa (lines 27-29). This process will terminate when the matching converges, i.e., the same matching outcome for two consecutive iterations $t$.

*Theorem 2: Algorithm 3 converges to a stable allocation.*

*Proof:* The proof is similar to that of [24, Th. 2]. □

Moreover, we can also analyze the optimality property of the stable matching by using the definition of weak Pareto optimality [24], [38].

## IV. POWER ASSIGNMENT

In this section, first, we discuss the power assignment subproblem and propose the solution for its non-convexity

**Algorithm 3** D2D Clustering Algorithm

**input**: $\boldsymbol{\alpha}$, $\mathcal{P}_k^{(t)}$, $\mathcal{P}_n^{(t)}$, $\mathcal{C}_n$, $\forall n, k$.
**initialize**: $t = 0$, $\alpha^{(1)} \triangleq \{\alpha(n)^{(1)}, \alpha(k)^{(1)}\}_{n\in\mathcal{N},k\in\mathcal{S}} = \emptyset$, ${q_{res}^k}^{(1)} = \theta^k$, ${\mathcal{N}_k}^{(1)} = \emptyset$, $C_k^{(1)} = \emptyset$, $\forall n, k$.
$t \leftarrow t + 1$.
Update $\forall n$, ${\mathcal{P}_n}^{(t)}$ for given $\alpha(n)^{(t-1)}$.
$\forall n \in \mathcal{N}$ with cluster $k$ as its most preferred in $\mathcal{P}_n^{(t)}$.
**while** $n \notin \alpha(k)^{(t)}$ and $\mathcal{P}_n^{(t)} \neq \emptyset$ **do**
  **if** ${q_{res}^k}^{(t)} < q_n^k$, **then**
    ${\mathcal{P}'}_k^{(t)} = \{n' \in \alpha(k)^{(t)} | n \succ_k n'\}$.
    $n_{lp} \leftarrow$ the least preferred $n' \in {\mathcal{P}'}_k^{(t)}$.
    **while** $({\mathcal{P}'}_k^{(t)} \neq \emptyset) \cup ({q_{res}^k}^{(t)} < q_n^k)$ **do**
      $\alpha(k)^{(t)} \leftarrow \alpha(k)^{(t)} \setminus n_{lp}$, ${\mathcal{P}'}_k^{(t)} \leftarrow {\mathcal{P}'}_k^{(t)} \setminus n_{lp}$.
      ${q_{res}^k}^{(t)} \leftarrow {q_{res}^k}^{(t)} + q_{n_{lp}}^k$.
      **if** ${q_{res}^k}^{(t)} < q_n^k$ **then**
        $n_{lp} \leftarrow n$.
  **else**
    **if** $C_k^{(t)} = \{n' \in \alpha(k)^{(t)} \cup C_n\} = \emptyset$ **then**
      $\alpha(k)^{(t)} \leftarrow \alpha(k)^{(t)} \cup n$, ${q_{res}^k}^{(t)} \leftarrow {q_{res}^k}^{(t)} - q_n^k$.
    **else**
      $D_k^{(t)} = \{n' \in C_k^{(t)} | n \succ_k n'\}$.
      **for** $n_{lp} \in D_k^{(t)}$ **do**
        $\alpha(k)^{(t)} \leftarrow \alpha(k)^{(t)} \setminus n_{lp}$.
        ${q_{res}^k}^{(t)} \leftarrow {q_{res}^k}^{(t)} + q_{n_{lp}}^k$.
      **if** $C_k^{(t)} = \{n' \in \alpha(k)^{(t)} \cup C_n\} = \emptyset$ **then**
        $\alpha(k)^{(t)} \leftarrow \alpha(k)^{(t)} \cup n$, ${q_{res}^k}^{(t)} \leftarrow {q_{res}^k}^{(t)} - q_n^k$.
      **else**
        $n_{lp} \leftarrow n$.
  ${\mathcal{N}_k}^{(t)} = \{n \in {\mathcal{P}_k}^{(t)} | n_{lp} \succ_k n\} \cup \{n_{lp}\}$.
  **for** $n \in {\mathcal{N}_k}^{(t)}$ **do**
    ${\mathcal{P}_n}^{(t)} \leftarrow {\mathcal{P}_n}^{(t)} \setminus k$, ${\mathcal{P}_k}^{(t)} \leftarrow {\mathcal{P}_k}^{(t)} \setminus n$.
**output**: $\alpha^{(t)}$.

similar to the work in [39]. An efficient power assignment algorithm is provided both for the CUs and the D2D users based on the arithmetic-geometric mean approximation. Arithmetic-geometric mean approximation is one efficient method to solve the power assignment problem. However, the approaches presented in recent works such as [39] cannot be directly applied to our work. The main reason is that in our work, we need to identify the subset of all CUs or D2Ds in the same cluster which have higher channel gain. Thus, at each iteration, after users clustering (CUs or D2Ds) is done, power assignment is performed with the interference part only consisting of higher channel gain users (CUs or D2Ds). Algorithms such as sequential convex programming [31], gradient descent [28] can also be tailored to solve such problems. Finally in the following subsections, a joint algorithm is presented for user clustering and power assignment.

### *A. CELLULAR USER POWER ASSIGNMENT*

Given the user clustering $\boldsymbol{\beta}$, $\boldsymbol{\alpha}$ and power assignment of D2D $P_n$, the problem of power assignment for CUs is formulated as follows:

$$\begin{aligned}
&\mathbf{PA1}_{\mathbf{CU}}:\\
&\max_{P} \sum_{k\in\mathcal{S}} \sum_{m\in\mathcal{M}_k} \log_2\left(1 + \frac{P_m|h_m|^2}{I_m^k + \sum_{n\in\mathcal{N}_k} |h_{n,m}|^2 P_n^d + z_m}\right)\\
&\text{s.t.: } C_1: \sum_{k\in\mathcal{S}} \sum_{m\in\mathcal{M}_k} P_m \le P_T,\\
&\qquad C_2: P_m \ge 0, \quad \forall m \in \mathcal{M}.
\end{aligned} \tag{18}$$

The problem (18) is a non convex problem due to the rate function in (2) which is (highly) non-concave. To handle this challenge, we adopt the approach of successive convex approximation (SCA) [40], [41] and find the optimal power allocation.

#### 1) ARITHMETIC-GEOMETRIC MEAN APPROXIMATION

Defining subset $\bar{\mathcal{M}}_k(m) \triangleq \left\{m' \in \mathcal{M}_k | \frac{|h_{m'}|^2}{z_{m'}} > \frac{|h_m|^2}{z_m}\right\}$ and $\tilde{z}_m = \sum_{n\in\mathcal{N}_k} |h_{n,m}|^2 P_n^d + z_m$ (the transmit powers of D2D users are fixed and thus can be treated as noise), then the achievable throughput of CU $m \in \mathcal{M}_k$ can be rewritten as follows:

$$R_{m,CU}^k = \log_2\left(\frac{\sum_{m'\in\bar{\mathcal{M}}_k(m)} P_{m'}|h_m|^2 + \tilde{z}_m + P_m|h_m|^2}{\sum_{m\in\bar{\mathcal{M}}_k(m)} P_{m'}|h_m|^2 + \tilde{z}_m}\right). \tag{19}$$

It can be shown that problem (18) is equivalent to

$$\begin{aligned}
&\mathbf{PA2}_{\mathbf{CU}}:\\
&\min_{P} \prod_{k\in\mathcal{S}} \prod_{m\in\mathcal{M}_k} \left(\frac{\sum_{m'\in\bar{\mathcal{M}}_k(m)} P_{m'}|h_m|^2 + \tilde{z}_m}{\sum_{m'\in\bar{\mathcal{M}}_k(m)} P_{m'}|h_m|^2 + \tilde{z}_m + P_m|h_m|^2}\right)\\
&\text{s.t.: } C_1: \sum_{m\in\mathcal{M}} P_m \le P_T,\\
&\qquad C_2: P_m \ge 0, \quad \forall m \in \mathcal{M}.
\end{aligned} \tag{20}$$

Defining $u_m^k(P) = \sum_{m'\in\bar{\mathcal{M}}_k(m)} P_{m'}|h_m|^2 + \tilde{z}_m + P_m|h_m|^2$, the arithmetic-geometric mean (AGM) inequality states that

$$\begin{aligned}
&u_m^k(P) \ge \underline{u}_m^k(P)\\
&= \prod_{m'\in\bar{\mathcal{M}}_k(m)} \left(\frac{P_{m'}|h_m|^2}{\kappa_m}\right)^{\kappa_m} \left(\frac{\tilde{z}_m}{\lambda_m}\right)^{\lambda_m} \left(\frac{P_m|h_m|^2}{\gamma_m}\right)^{\gamma_m},
\end{aligned} \tag{21}$$

where for all $m \in \mathcal{M}_k$, $m' \in \bar{\mathcal{M}}_k(m)$, $\kappa_m = P_{m'}|h_m|^2/u_m^k(P)$, $\lambda_m = \tilde{z}_m/u_m^k(P)$, and $\gamma_m = P_m|h_m|^2/u_m^k(P)$. The following approximate problem can be classified as a geometric program:

$$\mathbf{PA3_{CU}}:\ \min_{P} \prod_{k\in\mathcal{S}}\prod_{m\in\mathcal{M}_k}\left(\frac{\sum_{m'\in\bar{\mathcal{M}}_k(m)} P_{m'}|h_m|^2+\tilde{z}_m}{\underline{u}_m^k(P)}\right)$$
$$\text{s.t.: } C_1: \sum_{m\in\mathcal{M}} P_m \le P_T,$$
$$C_2: P_m \ge 0,\quad \forall m\in\mathcal{M}. \tag{22}$$

We can transform a geometric program as in (22) into a convex problem through a logarithmic change of variables [34]. Approximation parameters are updated by using the solution of current iteration $P(t)$ given by (21). Moreover, it can be stated that the accuracy increases in each iteration as we solve (22).

#### 2) CENTRALIZED SCA-BASED POWER ALLOCATION WITH AGM APPROXIMATION

Algorithm 4 summarizes our discussion for power assignment in which the power allocation scheme to solve (18) is presented based on the SCA approach with the AGM approximation. Moreover, Algorithm 4 converges to a locally optimal solution that satisfies the Karush-Kuhn-Tucker (KKT) conditions of the original problem in (18). The proof of locally optimal solution is similar to that of Proposition 3 in [39].

**Algorithm 4** SCA-Based Power Assignment With Arithmetic-Geometric Mean Approximation

1: Initialize: $t=1$;
2: **repeat**
3: Compute each coefficient

$$\kappa_m[t]=\frac{P_{m'}[t-1]|h_m|^2}{u_m^k(P[t-1])},\quad \lambda_m[t]=\frac{\tilde{z}_m}{u_m^k(P[t-1])},$$
$$\gamma_m[t]=\frac{P_m[t-1]|h_m|^2}{u_m^k(P[t-1])}.$$

4: Compute monomial

$$\underline{u}_m^k(P)[t]=\prod_{m\in\bar{\mathcal{M}}_k(m)}\left(\frac{P_{m'}[t-1]|h_m|^2}{\kappa_m[t]}\right)^{\kappa_m[t]} \times\left(\frac{\tilde{z}_m}{\lambda_m[t]}\right)^{\lambda_m[t]}\left(\frac{P_m[t-1]|h_m|^2}{\gamma_m[t]}\right)^{\gamma_m[t]}. \tag{23}$$

5: With $\underline{u}_m^k(P)[t]$, solve geometric program (22), e.g., by an interior-point method, for an optimal power $P[t]$.
6: Set $t:=t+1$;
7: **until** $P$ converge;

### B. D2D POWER ASSIGNMENT

Given the user clustering $\boldsymbol{\beta}$, $\boldsymbol{\alpha}$ and power assignment of CU $P_m$, the problem of power assignment for D2D users is formulated as follows:

$$\mathbf{PA1_{D2D}}:$$
$$\max_{P}\sum_{k\in\mathcal{S}}\sum_{n\in\mathcal{N}_k}\log_2\left(1+\frac{P_n^d|h_n|^2}{\sum_{n'\in\mathcal{N}_k\setminus\{n\}}|h_{n',n}|^2P_{n'}^d+\tilde{z}_n}\right)$$
$$\text{s.t.: } C_2: \sum_{n\in\mathcal{N}_k}\sum_{m\in\mathcal{M}_k}|h_{n,m}|^2P_n^d\le\theta^k,\quad\forall k\in\mathcal{S},$$
$$C_5: P_n^d\ge 0,\quad\forall n\in\mathcal{N}, \tag{24}$$

where $\tilde{z}_n \triangleq \sum_{m\in\mathcal{M}_k}|h_{BS,n}|^2P_m,+z_n$.

Apparently, problem (24) is not convex because the rate function in (4) is (highly) non-concave. To overcome such a major difficulty, we adopt the same SCA approach as discussed in the previous subsection.

The achievable data rate of D2D $n\in\mathcal{N}_k$ can be rewritten as follows:

$$R_{n,D2D}^k=\log_2\left(\frac{\sum_{n\in\mathcal{N}_k}P_n^d|h_n|^2+\tilde{z}_n}{\sum_{n'\in\mathcal{N}_k\setminus\{n\}}|h_{n',n}|^2P_{n'}^d+\tilde{z}_n}\right). \tag{25}$$

It can be show that problem (24) is equivalent to

$$\mathbf{PA2_{D2D}}:\ \min_{P}\prod_{k\in\mathcal{S}}\prod_{n\in\mathcal{N}_k}\left(\frac{\sum_{n'\in\mathcal{N}_k\setminus\{n\}}|h_{n',n}|^2P_{n'}^d+\tilde{z}_n}{\sum_{n\in\mathcal{N}_k}P_n^d|h_n|^2+\tilde{z}_n}\right)$$
$$\text{s.t.: } C_2: \sum_{n\in\mathcal{N}_k}\sum_{m\in\mathcal{M}_k}|h_{n,m}|^2P_n^d\le\theta^k,\quad\forall k\in\mathcal{S},$$
$$C_5: P_n^d\ge 0,\quad\forall n\in\mathcal{N}. \tag{26}$$

Defining $u_n^k(P)=\sum_{n\in\mathcal{N}_k}P_n^d|h_n|^2+\tilde{z}_n$, the arithmetic-geometric mean (AGM) inequality states that

$$u_n^k(P)\ge\underline{u}_n^k(P)=\prod_{n\in\mathcal{N}_k}\left(\frac{P_n^d|h_n|^2}{\kappa_n}\right)^{\kappa_n}\left(\frac{\tilde{z}_n}{\lambda_n}\right)^{\lambda_n}, \tag{27}$$

where for all $\kappa_n=P_n^d|h_n|^2/u_n^k(P)$, and $\lambda_n=\tilde{z}_n/u_n^k(P)$. The following approximate problem can be classified as a geometric program:

$$\mathbf{PA3_{D2D}}:\ \min_{P}\prod_{k\in\mathcal{S}}\prod_{n\in\mathcal{N}_k}\left(\frac{\sum_{n'\in\mathcal{N}_k\setminus\{n\}}|h_{n',n}|^2P_{n'}^d+\tilde{z}_n}{\underline{u}_n^k(P)}\right)$$
$$\text{s.t.: } C_2: \sum_{n\in\mathcal{N}_k}\sum_{m\in\mathcal{M}_k}|h_{n,m}|^2P_n^d\le\theta^k,\quad\forall k\in\mathcal{S},$$
$$C_5: P_n^d\ge 0,\quad\forall n\in\mathcal{N}. \tag{28}$$

An algorithm similar to Algorithm 4 is used to solve the D2D power assignment problem in (24).

### C. JOINT USER CLUSTERING AND POWER ASSIGNMENT ALGORITHM

In this section, we discuss the overall joint user clustering and resource allocation algorithm for our proposed problem (JUCPA). We call it the coordinated NOMA (C-NOMA) algorithm, shown in Algorithm 5. In the initialization phase, the MBS collects all users' CSI information, classifies the CUs using Algorithm 1, and initializes equal transmit power to each CU. Next, in the joint phase, both the user clustering and power assignment algorithms are executed in an iterative manner to obtain a joint solution.

*Theorem 3: C-NOMA Algorithm achieves a suboptimal solution of the original problem in* (6).

**Algorithm 5** Coordinated NOMA (C-NOMA)

**Initialization Phase**
1: The MBS obtains the CSI of all CUs and D2D users.
2: Classify CUs using Algorithm 1.
3: Allocate equal transmit power to each CU.
**Joint Phase**
4: **repeat**
5: Update the CUs clustering $\boldsymbol{\beta}$ using Algorithm 2.
6: Update the D2D users clustering $\boldsymbol{\alpha}$ using Algorithm 3.
7: Update PA $P$ using Algorithm 4 for CUs and D2D users.
8: **until** convergence;

*Proof:* This joint algorithm is based on an alternative maximization approach. Since at each iteration, each sub-problem does not decrease the common objective function in a compact set, Algorithm 5 will finally converge to a sub-optimal solution of the original problem in (6). □

## V. SIMULATION RESULTS

In our simulation, the MBS is assumed to be deployed at a fixed location, and $M$ cellular users and $N$ D2D users are deployed following a homogeneous Poisson point process (PPP). The main parameters used in our simulations follow the guidelines in [42]–[44] and are shown in Table 1 unless stated otherwise. Note that, all statistical results are averaged over a large number of simulation runs of random location of CUs, D2D users and resource block gains.

**TABLE 1.** Default simulation parameters [24], [42].

| Simulation Parameters | Values |
|---|---|
| Radius of MBS | 500 m |
| Carrier frequency ($f$) | 2 GHz |
| Frame structure | Type 1 (FDD) |
| Transmission Time Interval (TTI) | 1 ms |
| Total transmit power of BS | 46 dBm |
| Total transmit power of D2D users | 23 dBm |
| System bandwidth | 1.4 MHz |
| Bandwidth of each RB ($W$) | 180 kHz |
| Number of subcarriers per RB | 12 |
| Neighboring subcarrier spacing | 15 kHz |
| Modulation and coding scheme (MCS) [43] | QPSK: $1/12, 1/9, 1/6, 1/3, 1/2, 3/5$<br>16QAM: $1/3, 1/2, 3/5$ |
| Path loss (cellular link) | $128.1 + 37.6 \log(\mathrm{d})$, d[km] |
| Path loss (D2D links) [44] | $32.45 + 20 \log(\mathrm{f}) + 20 \log(\mathrm{d})$, f[MHz] |
| Shadow fading standard deviation [44] | 3 dB |
| Proximity of D2D user ($R2$) | random $\{20 \sim 30\}$ m |
| Thermal noise for 1 Hz at 20 °C | $-174$ dBm |

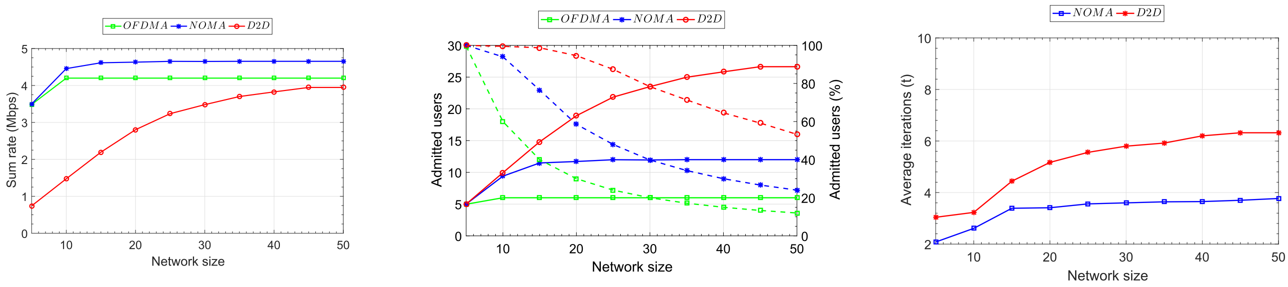
### A. SIMULATION RESULTS FOR NOMA, OFDMA AND D2D

In this subsection, first, we present the joint resource and power allocation performance for three schemes in terms of the average number of admitted users in the network,[3] average sum-rate, and average number of iterations. The first scheme is the NOMA scheme, in which multiple users (i.e., two users in this case) are allowed to transmit simultaneously on each RB. In this scheme, CUs are classified and then selected using Algorithms 1 and 2, respectively. Then, power assignment is performed for the CUs using Algorithm 4 to further improve the performance. The second type of scheme consists of the orthogonal frequency-division multiple access (OFDMA) scheme, in which only one CU is scheduled on each RB. For RB allocation, we apply the well-known Hungarian assignment method [45] and then used Algorithm 4 for power allocation. Note that to simulate both of these aforementioned schemes, we only consider CUs in our network. Finally, in the last scheme, we assumed that the network consists of only D2D users and then evaluate the performance of the proposed D2D scheme presented in Section III-B (Algorithm 3). In our simulations for all D2D users, we set the co-tier interference threshold to $\zeta_n = 10$ dB (i.e., the interference between two D2D users) and the cross-tier interference to $\theta^k = \infty$ (i.e., we consider no CU protection, as no CU is available in the network). For RB allocation, we applied Algorithm 3, followed by the power allocation scheme presented in Section IV-B.

Fig. 2a compares the average sum-rates of the aforementioned schemes. In this simulation, we observe the average sum-rate when the network size (i.e., number of users in the network) is increased. First, we find that for all schemes, the average sum-rate increases as network size grows. However, for the OFDMA scheme, the sum-rate saturates as soon as the network size exceeds six users. The reason for this is that in the OFDMA scheme only six users (1.4 MHz) are allocated RBs whereas, in the NOMA scheme, twelve users are allocated RBs. Thus, performance improvement of 10% can be observed by using the traditional NOMA scheme for a sufficiently large network (12 users and higher). Second, we observe that the sum-rate of the D2D scheme increases gradually with the network size. The main reason behind this gradual increase is that as the network size increases (only D2D users), the number of admitted D2D users also increases. However, not all D2D users can be admitted due to the increase in inter-D2D interference with the growth in network size resulting from being in a close vicinity. Thus, only a few D2D users are allocated RBs, as seen in Fig. 2b. Moreover, we see that the D2D scheme admits the largest number of users (26 D2D users) compared to the NOMA (12 CUs) and OFDMA (6 CUs) schemes for a network size of 50 users. In Fig. 2c, we compare the average number of iterations[4] required for two schemes, i.e., the NOMA and D2D schemes. We observe that both schemes require only a few numbers of average iterations to converge to a stable solution, i.e., less than 4 iterations for the NOMA scheme and less

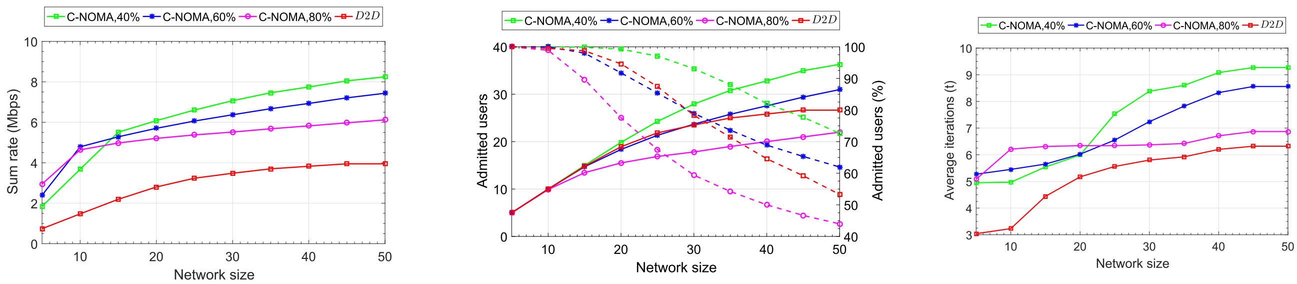
[3]The numbers of admitted users are per RB.

[4]The average number of iterations here represents the required iterations for the matching based schemes (i.e., Algorithms 2 and 3) to reach a stable solution.




(a) (b) (c)

**FIGURE 2.** Performance comparison of the OFDMA, NOMA and D2D schemes under various network sizes. (a) Average sum-rate. (b) Average number of admitted users. (c) Average number of iterations.




(a) (b) (c)

**FIGURE 3.** Performance comparison of different Coordinated NOMA and D2D schemes under various network sizes. (a) Average sum-rate. (b) Average number of admitted users. (c) Average number of iterations.

than 7 iterations for the D2D scheme. Moreover, we observe that the average number of iterations for the D2D scheme is significantly higher compared to the NOMA scheme. The main reason for this large number of iterations is that in the D2D scheme, as the network size grows, the conflict set also grows due to co-tier interference. Moreover, the quota of this scheme is dynamic, which requires more reject-accept operations compared to the fixed quota NOMA scheme.

### *B. SIMULATION RESULTS FOR COORDINATED NOMA*

In this subsection, we present the results of our proposed coordinated approach, i.e., coordinating NOMA-based CUs and D2D users. In coordinated NOMA, the goal is to allow both CUs and D2D users to operate on the same RBs in order to improve the overall network performance. In this simulation, we evaluate the average sum-rate, average number of admitted users and the average number of iterations of the proposed coordinated NOMA scheme by varying the network size. Moreover, we compare the performance of our scheme under three settings by dividing the network size into different proportions of CUs and D2D users: the first setting represents the case in which the network size is composed of 40% of CUs while the rest are the D2D users. We denote this setting by 'C-NOMA, 40%'. The second case represents the situation in which the network contains 60% of CUs and 40% of D2D users and is denoted by 'C-NOMA, 60%'. The final setting 'C-NOMA, 80%' represents the situation in which 80% of users are CUs while the remaining are D2D users. Additionally, we compare with a network comprised of only D2D users.

In Fig. 3a, we evaluate the average sum-rate of the aforementioned schemes by varying the network size. We observe that the average sum-rate for the C-NOMA, 40% setting is significantly higher compared to all other settings. The reason for this high sum-rate is that in the C-NOMA, 40% setting, the ratio of CUs to D2D users ($\frac{M}{N} = 0.6$, i.e., 20 CUs and 30 D2D users for a network size of 50 users) is lower than that of the other settings, and thus, a larger number of users (CUs and D2D users) is admitted in the network. Performance gains in terms of the average sum-rate up to 9%, 34% and 105% can be observed compared to the C-NOMA, 60%, C-NOMA, 80% and traditional D2D settings, respectively. Moreover, to reduce the SIC complexity in our system, we set the quota ($q_k$ in Algorithm 2) for each RB equal to two (i.e., only 2 CUs are allowed to use the same RB), and thus, for a system bandwidth of 1.4 MHz, a maximum of twelve CUs can be admitted (i.e., the ratio of RBs to admitted CUs ($A_M$) is $\frac{K}{A_M} \leq 0.5$) in the system for a sufficiently large network size. From Fig. 3a, we observe that as the network size increases, the ratio of RBs to admitted CUs approaches 0.5 (i.e., $\frac{K}{A_M} \approx 0.5$). Once the value of this ratio reaches $\frac{K}{A_M} = 0.5$, any further increase in the number of CUs does not affect the sum-rate of the C-NOMA scheme. Fig. 3b compares the average number of admitted users in the network for various network sizes. We see that as the network size increases, the number of admitted users in the network decreases due to the limited number of RBs in the network. Moreover, we find that the C-NOMA, 40% setting admits the maximum number of users (i.e., 72%, as shown by the dotted line in Fig. 3b) when compared to the C-NOMA, 60% (64%), C-NOMA, 80% (44%) and D2D (52%) settings.

In Fig. 3c, we compare the average number of iterations required by varying the network size for different settings of C-NOMA scheme and the D2D scheme. It can be observed that the average number of iterations for each scheme increases as the network size grows. We see that the C-NOMA, 40% setting has the highest average number of iterations (less than 10 iterations) for a large network size (network size $\geq$ 25). The main reason for this is that as the network size grows, the number of D2D users in this setting grow with a higher proportion compared to the other settings. Consequently, there is more inter-D2D interference due to relatively larger conflict set that requires more reject-accept operations (i.e., lines 18-26 of Algorithm 3). Hence, a higher number of iterations. However, for a small network size (i.e., 20 or fewer users), most of the users are accepted at their initial proposals, and thus, a fewer number of iterations is required. We also infer from Fig. 3c that the C-NOMA, 80% setting has almost an indistinguishable average number of iterations (around 6.5 iterations) for a network size of 35 or fewer users. The main reason for this trend is that for a network size of 35 or fewer users, the number of D2D users in the network is almost insignificant (i.e., 7 D2D users for 35 users), and thus, the number of reject-accept operations in Algorithm 3 is very small. However, as the network size grows, the inter D2D interference also grows which slightly increases the average number of iterations. A similar trend is also seen in the C-NOMA, 60% setting for a network size of 25 or more users. Fig. 4 presents the comparison for the C-NOMA,[5] NOMA and OFDMA schemes in terms of the average sum-rate versus the network size. We can see that the C-NOMA scheme significantly outperforms both the NOMA and OFDMA schemes for a network size of 50 users by achieving a performance gain of up to 70% and 92% in terms of the average sum-rate, respectively. This shows that

[5] We consider the C-NOMA, 40% scheme for comparison as it results in the maximum performance gain.

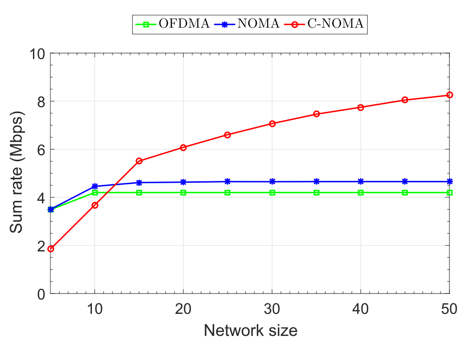



**FIGURE 4.** Average sum-rate vs. network size for the OFDMA, NOMA and Coordinated NOMA schemes.

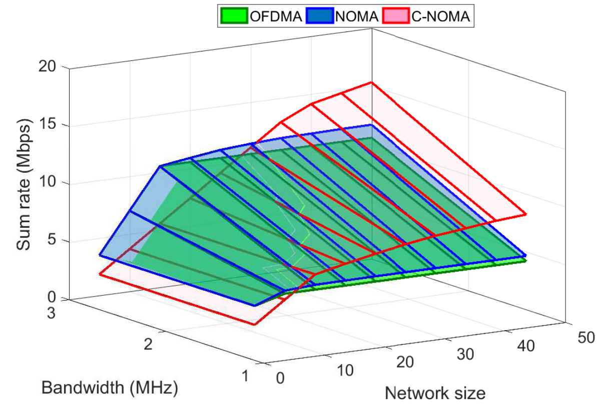



**FIGURE 5.** Average sum-rate of different schemes under various system bandwidth.

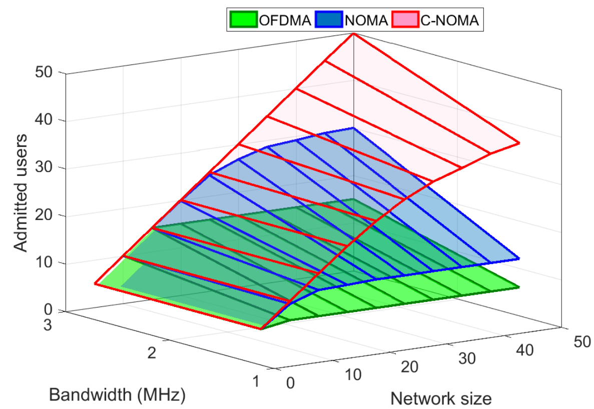



**FIGURE 6.** Average admitted users in different schemes under various system bandwidth.

for a dense setting, the C-NOMA scheme can play a significant role in enhancing the system sum-rate and increasing the number of admitted users in the network.

Next, we perform simulations to evaluate the performances of the OFDMA, NOMA and C-NOMA schemes under two different system bandwidth, 1.4 MHz (6 RBs) and 3 MHz (15 RBs). Fig. 5 presents the average sum-rate comparison for different system bandwidth values. The sum-rate for all schemes increases for a larger system bandwidth because the unassigned users are able to actually acquire RBs as the RBs available in the system increase. In Fig. 6, we compare the average number of admitted users in the system. We infer that the number of admitted users in the C-NOMA scheme increases linearly with respect to the network size for a bandwidth of 3 MHz. Moreover, the number of admitted number of users for the traditional NOMA and OFDMA schemes also increase for larger bandwidth due to more RB availability.

## VI. CONCLUSION

In this paper, we designed an efficient user clustering and power assignment framework for cellular and underlay D2D users by using matching-game and complementary

Geometric programming approaches. We considered the aspects of user clustering and power assignment, for analyzing the performance with respect to network users (i.e., cellular and D2D users). To solve the user clustering problem, we proposed a novel scheme based on the matching theory that can be operated sequentially to obtain a stable user cluster consisting of both cellular and D2D users. These user clustering algorithms help us to obtain a stable cluster that is a locally optimal solution of an NP-hard user clustering problem at each time slot. We applied complementary geometric programming and the arithmetic-geometric mean inequality to solve the non-convex power assignment problem. Finally, we proposed a joint computationally tractable iterative algorithm to obtain a suboptimal solution for the joint user clustering and power assignment problem. Our framework achieved a stable, distributed and scalable solution for the network. Simulation results have shown that the proposed framework convergence, achieved interference protection and enhanced network connectivity, which is crucial for future wireless networks.

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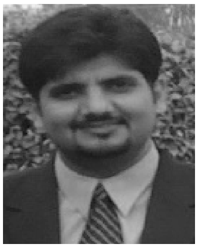

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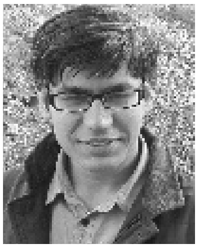

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