Resource Allocation for Device-to-Device Communications with Rate Guarantee

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***Abstract*—Fifth-generation (5G) mobile networks are expected to support vast numbers of connected devices and device-to-device (D2D) communication is expected to play a key role in 5G mobile networks. This paper studies the optimization problem of resource allocation that provides rate guarantee by fewest resource blocks. To solve it efficiently, we combine several optimization techniques such as relaxation and the block successive upper bound minimization (BSUM) method and derive a closed-form formula for each iteration in BSUM. Simulation results show that our method outperforms existing algorithms.**

***Index Terms*—D2D communication, mobile network, power control, resource allocation.**

I. Introduction

Fifth-generation (5G) mobile networks, compared to the fourth generation, are expected to support higher numbers of simultaneously connected devices and achieve higher system throughput at lower power consumption. It is forcast in [1] that 5G mobile networks will have 10X connection density, 5X spectrum efficiency, and 100X energy efficiency.

D2D communication is one of the key technologies to attain these goals. In particular, *multi-sharing* device-to-device (D2D) communication is expected to play a key role [2] in 5G mobile networks. Whereas *single-sharing* D2D communication restricts the resource blocks (RBs) allocated to a cellular user equipment (CUE) to be reused by at most one D2D user equipment (DUE), multi-sharing D2D communication allows reuse of each RB by multiple DUEs. This results in a frequency reuse factor of far greater than one.

Although D2D communication [3] can reuse either uplink or downlink RBs of CUEs, the major research trend is on the uplink side. This is because asymmetric Internet traffic results in spectrum underutilization of uplink spectrum. In the single-sharing D2D communication scenario, Han et al. [4] in 2012 maximized the number of DUE pairs permitted to access uplink RBs, with the assumption that all transmit power values at user equipments are given or pre-computed.

Maximizing system throughput (instead of the number of DUE pairs permitted) is studied in [5] for the single-sharing D2D communication scenario. In [5], Feng et al. considered both RB reuse and power control. They developed the Optimal Resource Allocation (ORA) algorithm consisting of admission control, transmit power allocation, and DUEs-to-CUEs maximum weight matching. Wang et al. [6] also studied single-sharing D2D communication with joint consideration of RB reuse and power control. Their proposed method is based on a Stackelberg game, in which CUEs and DUEs attempt to maximize their utility values.

As to the multi-sharing D2D communication scenario, a number of related works have existed in the literature. To increase the number of DUE pairs granted to access uplink RBs, Sun et al. [7] developed the Greedy Resource Allocation (GRA) algorithm. Based on conflict graphs, GRA allocates RBs to DUEs in the order of smallest degree first.

Given transmit power values at all CUEs and DUEs, the multi-sharing resource allocation problem aiming to maximize sum rate has been proven a NP-hard problem in [2]. In [2], Ciou et al. developed a heuristic algorithm called GTM+, which considers the rate requirements of CUEs and DUEs. GTM+ exploits both conflict graph and maximal weight independent set to improve system throughput.

Although GRA and GTM+ works well in the RB allocation issue for the multi-sharing D2D communication scenario, they both lack the ability of power control. To solve this problem, Kao et al. [8] considered RB reuse and power control jointly and developed a new scheme called MiSo. MiSo is composed of two parts—RB reuse and power control. The RB reuse part exploits maximum independent set. The power control part essentially computes the derived Stackelberg power.

All of the above schemes that are designed for multi-sharing D2D communication do not guarantee to meet all rate requirements even though there exist feasible solutions. In addition, they do not minimize the number of RBs reused by DUEs. Similar to [9] (which studies resource allocation for non-orthogonal multiple access), the primary goal in this paper is to provide the requested rates for all user equipments by fewest RBs. Under the precondition that the primary goal is attained, the secondary goal is to maximum system throughout. To find an optimal/suboptimal solution, this paper formulates the optimization problem behind and develops a new method for satisfying rate requirements by fewest RBs and for maximizing sum rate in the multi-sharing D2D communication scenario.

Our proposed method consists of two parts—RB allocation and power allocation. In the RB allocation part, we first formulate the optimization problem corresponding to the primary goal as a mixed integer non-linear program, which is NP-hard. To solve it efficiently, we approximate the original problem by a geometric program, which is equivalent to a convex optimization problem and can be solved quickly by off-the-shelf solvers. The solution of the geometric program determines which RB to reuse for each DUE pair.

In the power allocation part, we formulate the sum rate in each RB as a non-convex optimization problem. To speed up finding a stationary solution, we exploit the block successive upper bound minimization (BSUM) method [10], which runs iteratively until convergence. Each iteration merely computes the value of a closed-form formula we derive.

The remainder of this paper is organized as follows. Section II describes the system model. Section III presents our proposed method. Performance evaluation is shown in Section IV. Concluding remarks are presented in Section V.

II. System Model

Same as [8], [11], we consider a cell shown in Fig. 1, in which there are N DUE pairs and M CUEs scheduled for transmission during a transmission interval. The CUEs and DUE pairs are denoted by $C_1, C_2, \ldots, C_M$ and $D_1, D_2, \ldots, D_N$, respectively. For simplicity of exposition, when there is no ambiguity, m and n are also used to denote C_m and D_n, respectively. We denote the sender side of the DUE pair n by $D_{n,\text{Tx}}$ and the receiver side by $D_{n,\text{Rx}}$.

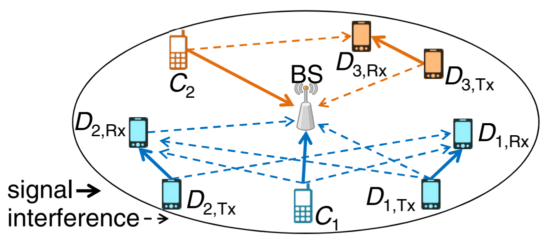

Fig. 1. CUEs share RBs with DUEs (C_1 shares with D_1 and D_2; C_2 shares with D_3 in this figure), causing mutual interference.

All CUEs are orthogonally pre-allocated *uplink* RBs. For exposition purpose, the RB allocated to CUE m is called RB m. Each RB is allowed to be reused by multiple DUE pairs in order to support as many simultaneously connected DUE pairs as possible. To specify the reuse of RBs, we define b_{nm} as a binary variable that indicates whether or not DUE pair n reuses RB m. More precisely, $b_{nm} = 1$ if DUE pair n reuses RB m; otherwise, $b_{nm} = 0$. A DUE pair may reuse one or multiple RBs; however, for management complexity and cost reasons, this paper focuses on the case where each DUE pair reuses up to one RB concurrently.

Transmit power, noise power, and channel gain are denoted as follows. The transmit power at CUE m is denoted by P_m. The transmit power at DUE n in RB m is denoted by P_{nm}. P_m and P_{nm} cannot exceed the maximum allowable value $P_{\max}$. The noise power is denoted by σ^2. G_{mB} is the channel gain between CUE m and the serving base station. G_{nB} is the channel gain between the sender of the DUE pair n and the base station. G_{nn} is the channel gain between the two ends of DUE pair n. G_{mn} is the channel gain from CUE m to DUE pair n. And G_{in} is the channel gain from $D_{i,\text{Tx}}$ to $D_{n,\text{Rx}}$.

All user equipments have rate demands, denoted by r_m^C for CUE m and r_n^D for DUE pair n. The primary goal of this paper is to minimize the number of RBs reused by DUE pairs such that all CUEs and DUE pairs meet their rate demands. The primary goal is equivalent to minimizing a L_0 norm[1] (which is a NP-hard problem) and can be well approximated by a L_1 norm (according to [12]). This leads to the following optimization problem:

$$\text{PR1:} \quad \min_{\{b_{nm}\},\{P_{nm}\},\{P_m\}} \sum_{n=1}^{N}\sum_{m=1}^{M} b_{nm} \tag{1}$$

subject to

$$\text{C1.1:} \; \sum_{m=1}^{M} \log_2\left(1+\frac{b_{nm}P_{nm}G_{nn}}{P_m G_{mn} + \sum_{i\neq n} b_{im}P_{im}G_{in} + \sigma^2}\right) \geq r_n^D, \quad \forall n \in \{1,2,\ldots,N\}$$

$$\text{C1.2:} \; \log_2\left(1+\frac{P_m G_{mB}}{\sum_{n=1}^{N} b_{nm}P_{nm}G_{nB} + \sigma^2}\right) \geq r_m^C, \quad \forall m \in \{1,2,\ldots,M\}$$

$$\text{C1.3:} \; 0 \leq P_m, P_{nm} \leq P_{\max}, \; \forall m,n$$

$$\text{C1.4:} \; \sum_{m=1}^{M} b_{nm}P_{nm} \leq P_{\max}, \; \forall n \in \{1,2,\ldots,N\}$$

$$\text{C1.5:} \; b_{nm} \in \{0,1\}, \; \forall m,n$$

$$\text{C1.6:} \; \sum_{m=1}^{M} b_{nm} \leq 1, \; \forall n \in \{1,2,\ldots,N\}$$

where constraints C1.1 and C1.2 represent the rate requirements for DUE pairs and CUEs, constraints C1.3 and C1.4 represent the power budget for all devices, and Constraint C1.6 limits the reuse of RBs to (at most) one RB per DUE pair.

If the primary goal has multiple optimal solutions, among these solutions we will choose the one that maximize the sum rate, which is our secondary goal.

III. Resource Allocation Strategy

We propose a resource allocation strategy consisting of two parts—RB allocation and power allocation. The RB allocation part converts Problem PR1 into a geometric program, which can be easily transformed into a convex optimization problem and solved quickly by using any off-the-shelf solver such as CVX. The power allocation part exploits an iterative method called BSUM to speed up finding out a stationary solution. Each iteration computes the closed-form formula we derive.

A. Part I: RB allocation

Because the binary variables in $\{b_{nm}\}$ make PR1 a NP-hard problem [2], we adopt a relaxation technique to reduce computational complexity: We replace the constraint that each variable in $\{b_{nm}\}$ must be 0 or 1 by a weaker constraint, that each variable belongs to the interval $[0,1]$. In addition to this relaxation technique, we reduce the number of variables by

[1] That is, min $\|(b_{11}+b_{21}+\ldots+b_{N1}, b_{12}+b_{22}+\ldots+b_{N2}, \ldots, b_{1M}+b_{2M}+\ldots+b_{NM})\|_0$.

exploiting the fact that b_{nm} in Problem PR1 often appears with P_{nm} together: This fact allows us to replace $b_{nm}P_{nm}$ by P_{nm} and simplify PR1 into PR2 (shown later). Consequently, none of the variables in $\{b_{nm}\}$ appears in PR2 and the number of variables decreases by NM.

Let the matrix $\mathbf{P}$ be the matrix containing all the variables to be solved in PR2:

$$\mathbf{P} = \begin{bmatrix} P_1 & P_2 & \dots & P_M \\ P_{11} & P_{12} & \dots & P_{1M} \\ P_{21} & P_{22} & \dots & P_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ P_{N1} & P_{N2} & \dots & P_{NM} \end{bmatrix}$$

With some mathematical manipulations, PR1 can be simplified into the following optimization problem:

$$\text{PR2: } \min_{\mathbf{P}} \sum_{n=1}^{N} \sum_{m=1}^{M} P_{nm} \tag{2}$$

subject to

$$\text{C2.1: } \prod_{m=1}^{M} \frac{P_m G_{mn} + \sum_{i \neq n} P_{im} G_{in} + \sigma^2}{g_m(\mathbf{P})} \leq \frac{1}{2^{r_n^D}}, \ \forall n \in \{1, 2, \dots, N\}$$

$$\text{C2.2: } \frac{\sum_{n=1}^{N} P_{nm} G_{nB} + \sigma^2}{P_m G_{mB}} \leq \frac{1}{2^{r_m^C} - 1}, \ \forall m \in \{1, 2, \dots, M\}$$

$$\text{C2.3: } 0 \leq P_m, P_{nm} \leq P_{\max}, \ \forall m, n$$

$$\text{C2.4: } \sum_{m=1}^{M} P_{nm} \leq P_{\max}, \ \forall n \in \{1, 2, \dots, N\}$$

where $g_m(\mathbf{P}) = P_m G_{mn} + \sum_{i=1}^{N} P_{im} G_{in} + \sigma^2$. The four constraints C2.1 to C2.4 correspond to constraints C1.1 to C1.4, respectively.

PR2 is not a geometric program, because $g_m(\mathbf{P})$, which is posynomial, is not a monomial function. To approximate PR2 by a geometric program, we utilize the condensation method: Given an initial feasible solution $\mathbf{P_0}$, $g_m(\mathbf{P})$ is approximated by the monomial lower bound

$$\widetilde{g_m}(\mathbf{P}|\mathbf{P_0}) = \prod_{k=1}^{K} \left(\frac{u_k(\mathbf{P})}{\alpha_k} \right)^{\alpha_k}$$

where $u_k(\mathbf{P})$ are the k-th monomial terms in the posynomial $g_m(\mathbf{P})$, K is the total number of these terms, and $\alpha_k = \frac{u_k(\mathbf{P_0})}{g_m(\mathbf{P_0})}$. In practice, the third term in $g_m(\mathbf{P})$, σ^2, often can be ignored because it is typically much smaller than other terms in $g_m(\mathbf{P})$.

After replacing $g_m(\mathbf{P})$ by $\widetilde{g_m}(\mathbf{P}|\mathbf{P_0})$ in Constraint C2.1, PR2 becomes a geometric program, which can be transformed into a convex optimization problem. Therefore, the optimal values of all variables in $\mathbf{P}$ can be solved quickly by using any off-the-shelf solver such as CVX. With these optimal values, b_{nm}, which indicates whether DUE pair n reuses RB m, is obtained as:

$$b_{nm} = \begin{cases} 1, & \text{if } m = \underset{c \in \{1,2,\dots,M\}}{\arg\max} \dfrac{P_{nc}}{\sum_{j=1}^{M} P_{nj}}, \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

In summary, our RB allocation method starts with relaxing each DUE pair to *partially* reuse all RBs with the weights $\frac{P_{nc}}{\sum_j P_{nj}}$ in $[0, 1]$, where the optimal values of $\{P_{nm}\}$ are solved by a convex optimization solver such as CVX. After the weights are computed, each DUE pair is granted to reuse only the RB with the maximum weight, as shown in (3).

B. Part II: Power Allocation

After the RB allocation part aforementioned, each DUE pair has been granted to reuse one RB. Because no DUE pair is granted two or more RBs, power allocation for DUE pairs that are assigned different RBs are handled separately. In the following, we explain our power allocation method by taking RB m as an example. The goal of power allocation is to maximize the sum rate, while satisfying all rate requirements.

For simplicity of exposition, let us re-numerate all DUE pairs and CUE m: The DUE pairs that reuse RB m are re-numerated as $1, 2, \dots, N_m$; other DUE pairs are not considered because they do not access RB m. The pair consisting of CUE m and the serving base station is re-numerated as the 0-th DUE pair. Corresponding to this re-numeration, $P_{0m} = P_m, G_{00} = G_{mB}, G_{n0} = G_{nB}$, and $G_{0n} = G_{mn}$. Let $\vec{P}$ denote the vector $(P_{0m}, P_{1m}, \dots, P_{N_m m})$. Maximizing the sum rate in RB m with all rate requirements satisfied is equivalent to the following minimization problem:

$$\text{PR3: } \min_{\vec{P}} \sum_{n=0}^{N_m} -\ln \left(1 + \frac{P_{nm} G_{nn}}{\sum_{i=0, i \neq n}^{N_m} P_{im} G_{in} + \sigma^2} \right) \tag{4}$$

subject to

$$\text{C3.1: } \frac{P_{nm} G_{nn}}{\sum_{i=0, i \neq n}^{N_m} P_{im} G_{in} + \sigma^2} \geq \gamma_n, \ \forall n \in \{0, 1, \dots, N_m\}$$

$$\text{C3.2: } 0 \leq P_{nm} \leq P_{\max}, \ \forall n \in \{0, 1, \dots, N_m\}$$

where $\gamma_0 = 2^{r_m^C} - 1$ and $\gamma_n = 2^{r_n^D} - 1, \forall n \in \{1, 2, \dots, N_m\}$, are the signal-to-interference-plus-noise ratio (SINR) corresponding to the rate requirements. Constraint C3.1 represents the SINR requirements of CUE m and the DUE pairs that reuse RB m. Constraint C3.2 represents the power budget of these user equipments.

Although all the constraints of PR3 are equivalently to linear constraints, PR3 is not a convex optimization problem because its objective function contains non-convex terms. For acceleration purpose, we exploit the block successive upper bound minimization (BSUM) [10] method to find a stationary solution for PR3. The main ideas behind BSUM are *i)* choosing one variable at an iteration in a round-robin manner, *ii)* dealing with the chosen variable at the iteration whereas other variables are temporarily treated as constants, and *iii)* approximating each non-convex term in the objective function by an affine function (around a given feasible point).

Suppose a feasible point $\vec{P_0} = (P_{0m}^0, P_{1m}^0, \dots, P_{N_m m}^0)$ is given at the beginning of an iteration that deals with the k-th variable P_{km}. The objective function of PR3 (around the given feasible point $\vec{P_0}$) is bounded above and approximated by the sum of a convex function and an affine function of P_{km}:

$$\tilde{f}(P_{km}|\vec{P_0}) = -\ln\Big(1 + \frac{P_{km}G_{kk}}{\sum_{i\neq k} P^0_{im}G_{ik} + \sigma^2}\Big) + \sum_{n\neq k}\Big(-\ln\big(1 + \frac{P^0_{nm}G_{nn}}{\sum_{i\neq n} P^0_{im}G_{in}+\sigma^2}\big) + \frac{P^0_{nm}G_{nn}G_{kn}\ (P_{km}-P^0_{km})}{(\sum_{i=0}^{N_m} P^0_{im}G_{in}+\sigma^2)(\sum_{i\neq n} P^0_{im}G_{in}+\sigma^2)}\Big) \quad (5)$$

So the problem to solve at this iteration becomes

$$\text{PR4: } \min_{P_{km}} \tilde{f}(P_{km}|\vec{P_0}) \quad (6)$$

subject to

$$\text{C4.1-1: } \frac{P_{km}G_{kk}}{\sum_{i\neq k} P^0_{im}G_{ik} + \sigma^2} \geq \gamma_k$$

$$\text{C4.1-2: } \frac{P^0_{nm}G_{nn}}{P_{km}G_{kn} + \sum_{i\neq n,k} P^0_{im}G_{in} + \sigma^2} \geq \gamma_n,\ \forall n \neq k$$

$$\text{C4.2: } 0 \leq P_{km} \leq P_{\max}$$

where constraints C4.1-1 and C4.1-2 represent the SINR requirements of the k-th DUE pair and other DUE pairs, respectively. Constraint C4.2 represents the power budget of the k-th DUE pair.

PR4 is a convex optimization problem with a single variable because the objective function $\tilde{f}(P_{km}|\vec{P_0})$ is convex and all the constraints are (equivalent to) linear constraints. By Karush-Kuhn-Tucker (KKT) optimality conditions, we derive the closed-form formula for the minimum point of PR4:

$$P^*_{km} = \begin{cases} \hat{P}_{km}, & \text{if } L_{km} < \hat{P}_{km} < U_{km} \\ U_{km}, & \text{if } \hat{P}_{km} \geq U_{km} \\ L_{km}, & \text{if } \hat{P}_{km} \leq L_{km} \end{cases} \quad (7)$$

where

$$L_{km} = \frac{\gamma_k}{G_{kk}}\Big(\sum_{i\neq k} P^0_{im}G_{ik} + \sigma^2\Big)$$

$$U_{km} = \min\Bigg(\min_{n\neq k}\Big(\frac{P^0_{nm}G_{nn}}{G_{kn}\gamma_n} - \sum_{i\neq n,k}\frac{P^0_{im}G_{in}}{G_{kn}} - \frac{\sigma^2}{G_{kn}}\Big), P_{\max}\Bigg)$$

$$\hat{P}_{km} = \frac{1}{\sum_{n\neq k}\frac{P^0_{nm}G_{nn}G_{kn}}{(\sum_i P^0_{im}G_{in}+\sigma^2)(\sum_{i\neq n} P^0_{im}G_{in}+\sigma^2)}} - \frac{\sum_{i\neq k} P^0_{im}G_{ik}+\sigma^2}{G_{kk}}$$

In summary, after each DUE pair is granted to access one RB, power allocations in different RBs are handled separately. For RB m, the transmit power values at CUE m and at the DUE pairs that are granted to access RB m are determined in a round-robin, iterative manner until convergence. Each iteration decides the transmit power value at one user equipment by using a closed-form formula we derive. More precisely, the n-th iteration ($n = 0, 1, \dots$) computes the transmit power value at the k-th user equipment by the closed-form formula in (7), where $k = n \mod N$.

IV. Performance Evaluation

We evaluate the performance of our proposed method by simulation and compare its performance with existing algorithms including ORA, GTM+ and MiSo. Among these algorithms, our purposed algorithm, GTM+, and MiSo allow multiple DUE pairs to reuse the same RB; whereas ORA is restricted to at most one DUE pair per RB. From the power control aspect, our method and ORA can adjust transmit power of both CUEs and DUE pairs. MiSo can adjust transmit power of DUE pairs only. GTM+ has no power control mechanism and thus transmits at a fixed and predefined power.

The simulation setting is as follows. The BS is located at the center of a cell with a radius of 500 meters. All CUEs and DUE pairs are uniformly distributed in the cell. The distance from a DUE transmitter to a DUE receiver is set to 15 meters. All CUEs have the same rate requirement of 3 bps/Hz; meanwhile, the rate requirements of all DUE pairs are set to 2 bps/Hz. The number of the DUE pairs is set to three times larger than the number of CUEs. For the algorithms with power control capability, the transmit power at each device ranges from 0 Watt to 23 dBm. For the algorithms without power control, all CUEs transmit at 23 dBm and DUE pairs transmit at 10 dBm. Other simulation parameters are set according to [8]. Some of them are listed in Table I.

TABLE I
A part of simulation parameters.

Parameters	Values
CUE transmit power	0W to 23dBm (23dBm if fixed)
DUE transmit power	0W to 23dBm (10dBm if fixed)
radius of a cell	500 m
path loss model for CUE and DUE	$128.1 + 37.6\log_{10}(d\text{ [km]})$
path loss model for DUE pairs	$148 + 40\log_{10}(d\text{ [km]})$
noise power, σ^2	-121.45 dBm
CUE's SINR threshold	7 (or equivalently 8.45 dB)
DUE's SINR threshold	3 (or equivalently 4.77 dB)

Note that because CUEs and DUEs are randomly deployed over a cell in our simulation, it is inevitable that a part of user equipment deployments generated randomly have no feasible solution under the rate and power constraints aforementioned. To cope with this problem, our simulation checks out the feasibility for each user equipment deployment. The user equipment deployments failing to pass the feasibility test are skipped and are not fed into any resource allocation method.

In terms of the ratio that DUE pairs are granted/permitted to reuse RBs, our method perform best, as shown in Fig. 2. MiSo is the second place, which permits more DUE pairs than GTM+. ORA does not result in a high permitted ratio. Our method performs very well in the permitted ratio because it exploits optimization techniques to support minimum rate guaranteed service by few RBs. MiSo and GTM+ are heuristic algorithms in nature; therefore, none of them guarantee optimality or close to optimality. ORA does not allow any RB to be reused by multiple DUE pairs; therefore, ORA permits fewer DUE pairs than the other algorithms.

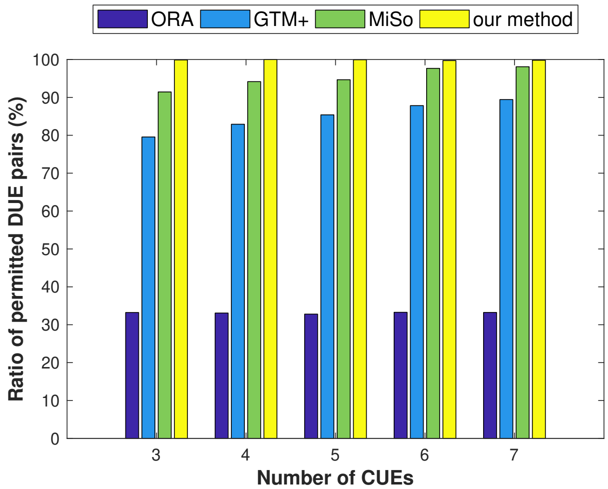

Fig. 2. The ratio of permitted DUE pairs.

In terms of the number of RBs reused by DUE pairs (for which a smaller value means better), our method performs best, MiSo is the runner-up, GTM+ is the third place, and ORA performs worst, as shown in Fig. 3. The reason why our method results in reuse of fewest RBs in most cases is because our method utilizes optimization techniques that aims to minimize the number of RBs reused by DUE pairs under rate and power constraints. In rare cases, our method takes slightly more RBs than MiSo does, merely because our method permits more DUE pairs which is shown previously in Fig. 2.

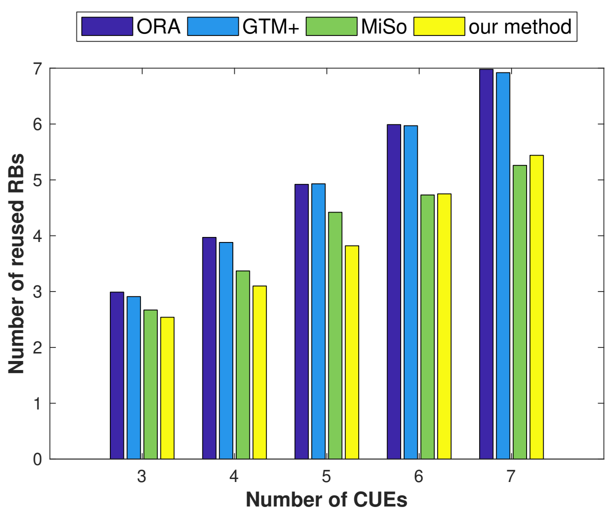

Fig. 3. The number of RBs reused by DUE pairs.

In terms of sum rate, our method ties with MiSo and GTM+ for the first place, as shown in Fig. 4. Although sum rate is the secondary goal of our method, the reason why our method does not significantly outperform MiSo and GTM+ in sum rate is because our method uses fewer RBs than MiSo and GTM+ (which is caused by the primary goal of our method). ORA performs worst because it is restricted to one DUE pair per RB.

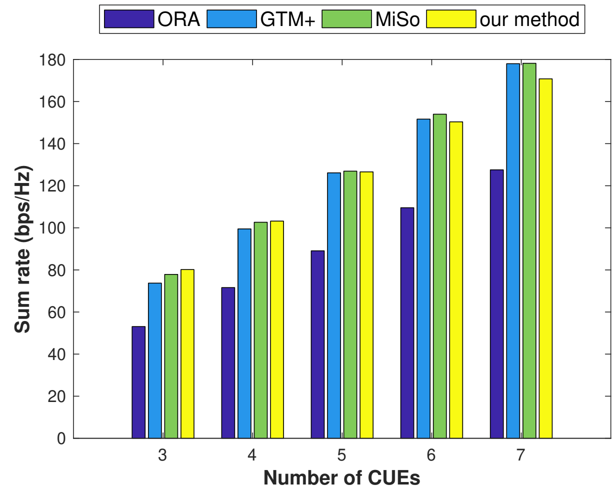

Fig. 4. The sum rate.

In terms of total power consumption, as shown in Fig. 5, our method performs best. The reason for its outperformance is because an intermediate step of our method, which has the objective function shown in (2), attempts to minimize total power consumed by DUEs. Both MiSo and GTM+ result in lower power consumption than ORA does. Compared with ORA, MiSo and GTM+ result in better power efficiency because both of them allow a RB to be reused by multiple DUE pairs (which improves frequency reuse and thus improves power efficiency indirectly) but ORA is restricted to one DUE pair per RB.

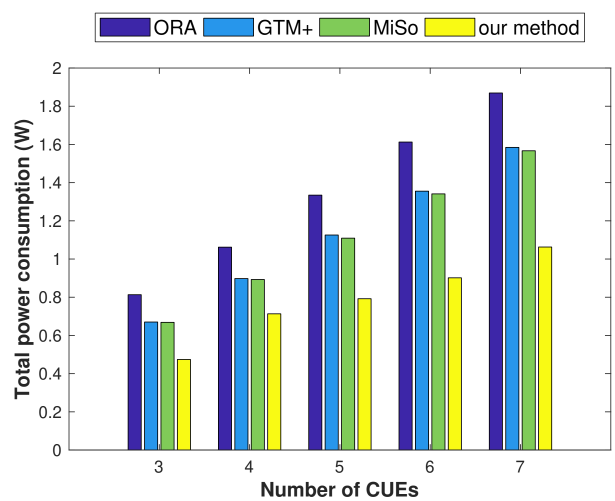

Fig. 5. Total power consumption.

V. Conclusion

5G mobile networks are expected to support vast numbers of cellular user equipments (CUEs) and device-to-device user equipments (DUEs) with a limited number of available resource blocks (RBs). To this end, we have studied the optimization problem whose primary goal is to support rate guarantee service provision by fewest RBs and whose secondary goal is to maximize sum rate. We have proposed an efficient method for such a problem. Simulation results show that our proposed method outperforms existing algorithms in terms of sum rate, power consumption, permitted ratio, and the number of RBs needed to be reused by DUEs.

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