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Resource Allocation and Power Control for D2D Communications to Prolong the Overall System Survival Time of Mobile Cells

ZITIAN ZHANG[1], YUE WU[1], XIAOLI CHU[1,2], AND JIE ZHANG[1,2]
[1]School of Information Science and Engineering, East China University of Science and Technology, Shanghai 200237, China
[2]Department of Electronic and Electrical Engineering, The University of Sheffield, Sheffield S1 4ET, U.K.

Corresponding author: Yue Wu (yuewu@ecust.edu.cn)

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ABSTRACT Device-to-device (D2D) communications as an underlay to cellular networks can potentially improve the system throughput and reduce transmission delays between users, which, however, are largely limited by the battery lifetime of user equipment (UE). In this paper, we define the overall system survival time of a mobile cell and maximize it by jointly optimizing the resource allocation and power control (RAPC) for D2D and conventional cellular links. Considering that the UEs may have different levels of residual battery energy, we define the overall system survival time as the minimally expected battery lifetime among all transmitting UEs in a cell. Subject to the transmission rate requirement of each link, we formulate the joint optimization of RAPC as a non-linear programming problem, which is NP-hard. To solve it, we devise a game theory based distributed approach, where the links are considered as non-cooperative players with the overall system survival time as their utility function. We prove the existence of the Nash equilibrium in our RAPC game and propose a low-complexity algorithm to calculate each individual player's best response, given the strategies of other players. Numerical results show that our game theory based approach can significantly prolong the overall system survival time as compared with existing RAPC schemes.

INDEX TERMS D2D communication, resource allocation and power control, overall system survival time, game theory.

I. INTRODUCTION

With the drastic growth of multimedia applications such as video sharing, tele-presence, and 3D holography, user demands for mobile services are undergoing an unprecedented rise. Device-to-device (D2D) communications underlaying cellular networks [1] has recently emerged as a promising technology to offload traffic from base stations (BSs), enhance the spectrum efficiency, and reduce the transmission delay to user equipment (UE) [14].

The third generation partnership project (3GPP) long term evolution (LTE) Advanced systems have employed D2D communication for proximity services [2]. The use cases of D2D communication were defined in [3], and the required architectural enhancements to accommodate these use cases were investigated in [4]. Furthermore, D2D communication is expected to be an indispensable technology in the fifth generation (5G) mobile networks [5].

One of the critical problems of D2D underlaying cellular networks is the mutual interference between D2D and conventional cellular (CC) links, as they share the same radio resources [1]. Without a proper resource allocation and power control (RAPC) mechanism, such mutual interference may jeopardise both D2D and CC links. To address the interference between D2D and CC links, there have been many RAPC schemes proposed for D2D communications underlaying cellular networks recently [10]–[48]. However, most of these previous works focused on how to maximize the spatial reuse of radio resources [11]–[13], system throughput [14]–[25], or energy efficiency [26]–[36], which are pivotal concerns in conventional mobile networks mainly serving human users [6].

Besides human users, it is forecasted that 5G mobile networks will also provide communication services for massive non-human terminal devices with very limited energy and battery lifetime [7]. For many future mobile communication scenarios like smart home network, smart power grid, or wireless sensor network, the timeout of only a few devices shall depress the system's quality-of-service (QoS) drastically [8]. Moreover, the success of some practical D2D enabled or assisted applications, such as D2D content sharing, personal hotspot, and multihop communication, relies on the sufficiently long survival time of all cooperative devices in the system [9]. With these new characteristics of 5G mobile networks, there is an emerging need for D2D communication RAPC mechanisms to reduce the transmission power of the UEs with low residual energy so that the overall system survival time can be prolonged. Nevertheless, this problem has not been well investigated in the literature.

To fill the gap mentioned above, this paper proposes to maximize the overall system survival time per cell by jointly optimizing the RAPC for CC links and D2D links, which may reuse the radio resources of multiple CC links simultaneously. Considering that UEs may have different levels of residual energy, we define the overall system survival time of a mobile cell as the minimal expected battery lifetime of all transmitting UEs (including both the D2D UEs and the CC UEs) in the cell. As the BS usually has a greater capability in interference management than UEs, we assume that D2D links only reuse the uplink (UL) radio resources [10]. To the best of our knowledge, this work is an early attempt to address the specific topic of prolonging the overall system survival time in D2D communication RAPC scheme design. The main contributions of this paper are summarized as follows:

- We study the RAPC problem for D2D links and UL CC links to maximize the overall system survival time per cell, which is an emerging concern in mobile networks but has not been well investigated previously. Assuming that a D2D link can reuse the radio resources of more than one UL CC link, we formulate the RAPC problem into a non-convex non-linear programming (NLP) problem subject to the transmission rate requirement of each link.
- We develop a game theory based distributed approach to solve the RAPC problem. Unlike existing works that use the transmission rate or transmission power as the competing objective for each player (link), our RAPC game defines the overall system survival time as the players' utility function. Through theoretical analyses, we prove the existence of the Nash equilibrium in our RAPC game. We also present how our RAPC game can be established in practical cells.
- For an arbitrary D2D link or UL CC link in the cell, we provide the relationship between its transmission rate distribution among the multiple UL subchannels and the minimum transmission power needed of itself or all the other links mathematically. Based on this mathematical relationship, we propose a low complexity algorithm for our RAPC game, which can calculate each individual player's best response given the strategies of other players. The relationship identified and the algorithm proposed in this work not only are applicable for the D2D communications underlaying cellular networks but also can be used in more general RAPC scenarios where multiple links share the same radio resources.
- We theoretically analyze the computational complexity of the proposed algorithm and examine the performance of our game theory based approach through extensive numerical experiments. Experimental results verify that the approach developed in this paper will considerably improve the system performance in terms of overall system survival time. We also investigate the convergence speed of our RAPC game, which can provide a theoretical guidance to the protocol design for real mobile networks.

The reminder of this paper is organized as follows. In Section II, we briefly review the related work. In Section III, we illustrate the system model of D2D communications underlaying a cellular network and formulate the RAPC problem. We construct the RAPC game in Section IV, and present the algorithm to calculate each individual player's best response in Section V. Simulation results are presented in Section VI. Finally, we conclude the paper in Section VII.

II. RELATED WORK

RAPC for D2D communications underlaying cellular networks is a critical issue and deserves a thorough investigation to coordinate the interference between D2D and CC links efficiently. Numerous studies have been done to address this problem. Focusing on different kinds of system performance improvement, most of these works formulate the D2D communication RAPC problem from an optimization perspective.

In order to maximize the spatial reuse of radio resources, authors in [11] proposed a centralized resource allocation algorithm for D2D communications underlaying cellular networks. With the same objective, the joint mode selection and resource allocation scheme, joint antenna direction selection and resource allocation scheme were proposed in [12] and [13], respectively. To maximize the system throughput, a three-stage joint optimization of transmission admission, resource selection, and power control for D2D links was investigated in [14], centralized suboptimal greedy RAPC algorithms were proposed in [15], [16], [17], and [18]. Also considering to enhance the system throughput, the semi-distributed, distributed RAPC mechanisms for D2D communications were studied in [19] and [20], respectively. A coalition formation game based throughput-optimal D2D communication RAPC mechanism was proposed in [21]. Throughput-optimal RAPC mechanisms have also been proposed to address special mobile network scenarios such as D2D communications with caching [22], relay-aided transmission [23], energy harvesting networks [24], or inter-cell resource allocation [25]. Although high spatial reuse of radio resources or system throughput can be achieved using the mechanisms in these above works, none of them has studied the energy consumption of UEs, which are typically with a limited battery capacity and require a proper management of energy consumption.

Some initial efforts have been made in developing system energy efficiency, which is defined as the radio between the system spectrum efficiency and the sum transmission power of both D2D and CC transmitters. Using exhaustive research or conjecture based multi-agent Q-learning method, the joint mode selection and power control for D2D communications to enhance the energy efficiency were proposed in [26] and [27], respectively. In [28]–[30], the energy efficient joint RAPC schemes were proposed based on branch-and-bound, Lagrange dual decomposition, or adaptive genetic algorithm. Authors in [31] decomposed the original energy efficient joint RAPC problem into the resource allocation subproblem and the power control subproblem, and then designed heuristic algorithms to solve the two subproblems one by one. With the same objective, game theory based RAPC mechanisms were studied in [10], and [32]–[34]. Energy-efficient RAPC mechanism for device-cluster communication scenario was studied in [35], while energy-efficient mechanism for device-to-multi-device communication scenario was investigated in [36]. The authors in [37] investigated the trade-off between the system energy efficiency and the spectrum efficiency and showed that when the average transmission power of D2D links reaches a certain level, any further increase in spectrum efficiency will degrade the system energy efficiency. Similar work was extended to relay-aided D2D communication scenarios in [38]. However, these works have not considered the necessity of energy saving for UEs with low residual energy. Thus, the system's Qos may decline seriously due to the rapid depletion of a few UEs.

In addition to spatial reuse of radio resources, system throughput, and energy efficiency, there are some other interesting works considering to enhance system fairness [39], cellular coverage [40], and link reliability [41], [42]. Comprehensive surveys and overviews of RAPC management for D2D communications were provided in [43] and [44]. Also, these works have not involved how to prolong the overall system survival time.

As mentioned above briefly, utilizing game theory to solve the D2D communication RAPC problem has become an active research topic because the game theory can provide a variety of mathematical tools to effectively analyze the individual or group behaviors of D2D and CC users. Game models can be generally divided into two categories: the non-cooperative games, and the cooperative games. In the former type, D2D and CC users are usually viewed as players competing to optimize their own utility function. Authors in [10] presented a distributed RAPC game where each D2D link tries to minimize its own transmission power given the strategies of other links. Auction game based RAPC schemes were proposed in [33], [34], [39], and [45]. In these auction game based RAPC schemes, spectrum resources were viewed as a set of resource units which are auctioned off by the D2D and CC links. In [46], authors developed a Stackelberg game based RAPC approach, where a CC link and a D2D link form a pair of leader and follower, and the follower will buy spectrum resources from its leader to improve its performance. In [47], authors modeled the RAPC problem as a multi-player multi-armed bandit game and leveraged a reinforcement learning method to acquire each D2D link's best strategy, which will maximize the link's transmission rate. Besides the non-cooperative games, cooperative game based D2D communication RAPC schemes have also been explored. In [21], [32], and [48], the RAPC problem was proposed to be solved by coalitional games, in which each link not only tries to optimize its own utility function but has the incentive to cooperate with other links as well. As such, each link will has a larger opportunity to acquire its preferred resources. Different from aforementioned game theory based approaches where the players competing for the optimization of transmission rate or energy efficiency, each individual player in our RAPC game will adjust its strategy to maximize the overall system survival time given the strategies of other players.

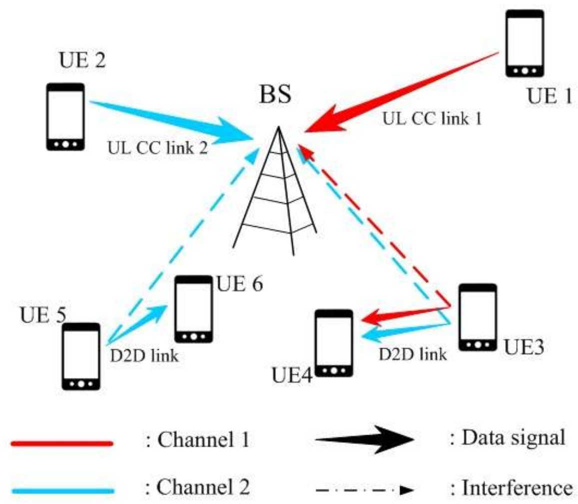

FIGURE 1. A demonstration of D2D communications underlaying a cellular network.

III. SYSTEM MODEL AND PROBLEM FORMULATION

The system model of D2D links underlaying a cellular network is illustrated in Fig. 1. We assume that the interference from other cells is well controlled via inter-cell interference coordination [49]. A BS is located at the center of the cell, where only the UL radio resources can be reused by D2D links. We assume that the cell has one control channel and K orthogonal frequency division multiple access (OFDMA) UL subchannels. The control channel is used to send management information, service advertisement, and control massages. The K UL subchannels are used for data transmission. Each UL subchannel has the same bandwidth of B_{SC}.

We investigate the RAPC problem in every scheduling period. We denote the sets of D2D links and UL CC links considered in a scheduling period as Γ (Γ has the cardinality of N) and Λ (Λ has the cardinality of M, where $M \leq K$), respectively. Each D2D link in set Γ consists of a D2D transmitter and a D2D receiver. Each UL CC link in set Λ has one CC UE acting as the transmitter. Specifically, each UE in the cell belongs to at most one D2D or UL CC link.

The D2D peer discovery and mode selection are out of our scope.

We assume that each UL CC link transmits in only one UL subchannel, and the M subchannels allocated to the M UL CC links are fixed within a scheduling period. A D2D link can transmit in one or more UL subchannels while an UL subchannel can be shared by multiple D2D links. The expected battery lifetime of the ith transmitting UE is given by (1) considering that its energy consumption includes two parts: the circuit power, and the transmission power which may be distributed in multiple UL subchannels [50].

$$L_i = \frac{Q_i}{P_i + P_{i,c}}, \quad i \in \Gamma \cup \Lambda \tag{1}$$

where Q_i represents the residual battery energy of the ith transmitting UE, P_i, $P_{i,c}$ are the transmission power and circuit power of the ith transmitting UE, respectively. The overall system survival time of all transmitting UEs in the cell is given by:

$$OS_{sys} = \min_i L_i, \quad i \in \Gamma \cup \Lambda \tag{2}$$

For link i, its signal to interference plus noise ratio (SINR) at the receiving UE in subchannel k is calculated as:

$$SINR_i^k = \frac{g_{ii} \cdot p_i^k}{N_0 + \sum_{(j \in \Gamma \cup \Lambda) \cap (j \neq i)} g_{ji} \cdot p_j^k}, \quad \forall i \in (\Gamma \cup \Lambda), \quad \forall k = 1, 2, \ldots, K \tag{3}$$

where g_{ii} is the channel power gain of link i ($i \in \Gamma \cup \Lambda$), g_{ji} is the interference channel power gain from the transmitter of link j to the receiver of link i, N_0 is the additive noise power to the receivers in arbitrary subchannel, variable p_i^k is defined as the transmission power of link i distributed on subchannel k. We consider a slow fading channel model. In each scheduling period, channel power gain and interference channel power gain for D2D links are calculated as $d^{-2} \cdot |h|^2$, where d is the distance between the transmitter and the receiver, h is the complex Gaussian channel coefficient that satisfies $h \sim CN(0, 1)$. While for UL CC links, channel power gain and interference channel power gain are calculated as $g_{BS} \cdot d^{-2} \cdot |h|^2$. g_{BS} is a constant representing the BS's signal receiving gain.

We define a binary indicator $\delta_i^k = 1$ indicates that the UL CC link i ($i \in \Lambda$) is allocated in subchannel k, $\delta_i^k = 0$ otherwise. We use C_w to represent a large enough positive constant and use R_i to represent the transmission rate requirement of link i ($i \in \Gamma \cup \Lambda$). We define variable r_i^k as link i's transmission rate on subchannel k. Uniformly, If $i \in \Lambda$ and $\delta_i^k = 0$, r_i^k will also be zero.

We maximize the OS_{sys} in (2) by optimizing the transmission rate and transmission power level for each link in Γ and Λ. The optimization problem is formulated as follows:

OPT :

$$\arg \max_{p_i^k, r_i^k, i \in \Gamma \cup \Lambda, k=1,\ldots,K} OS_{sys} \tag{4}$$

$$\textbf{\textit{s.t.}}: \; B_{sc} \cdot \log_2(1 + SINR_i^k) \geq r_i^k, \quad \forall i \in \Gamma \cup \Lambda, \quad \forall k = 1, 2, \ldots, K \tag{5}$$

$$\sum_{k=1}^{K} r_i^k \geq R_i, \quad \forall i \in \Gamma \cup \Lambda \tag{6}$$

$$\sum_{k=1}^{K} p_i^k = P_i, \quad \forall i \in \Gamma \cup \Lambda \tag{7}$$

$$r_i^k \leq \delta_i^k \cdot C_w, \quad \forall i \in \Lambda, \; \forall k = 1, 2, \ldots, K \tag{8}$$

$$r_i^k \geq 0, \quad \forall i \in \Gamma \cup \Lambda, \; \forall k = 1, 2, \ldots, K \tag{9}$$

$$p_i^k \geq 0, \quad \forall i \in \Gamma \cup \Lambda, \; \forall k = 1, 2, \ldots, K \tag{10}$$

where constraint (5) presents that, to guarantee link i's transmission rate, the SINR in each subchannel should exceed a certain level according to Shannon's theory. Constraint (6) is the transmission rate constraint for links belonging to $\Gamma \cup \Lambda$. Constraints (6), (7) and (8) imply that a D2D link may distribute its transmission rate into multiple subchannels, while an UL CC link only uses a single subchannel. Finally, constraints (9) and (10) represent that the transmission rate and transmission power must be non-negative.

IV. THE RAPC GAME

We note that the optimization problem ***OPT*** in (4) is a non-convex NLP problem, which is NP-hard. In the following, we develop a game theory based distributed approach to solve it.

Considering the UL CC links and D2D links as non-cooperative players, we define vector $\boldsymbol{r}_{i^*} = (r_{i^*}^1, r_{i^*}^2, \ldots, r_{i^*}^K)$ as the transmission rate of link i^* distributed in each subchannel, which is also seen as the strategy of play i^*. Each player tries to maximize the overall system survival time by adjusting its own strategy under the assumption that an arbitrary player i^* has the knowledge of other players' strategies, $\boldsymbol{r}_{-i^*}$. Obviously, $(\boldsymbol{r}_{i^*}, \boldsymbol{r}_{-i^*})$ should satisfy the constraints in (6), (8), and (9). Thus, player i^*'s utility function, $u_{i^*}(\boldsymbol{r}_{i^*}, \boldsymbol{r}_{-i^*})$, is defined as the optimal value of ***OPT*** in (4) where each r_i^k in constraint (5) is given by $(\boldsymbol{r}_{i^*}, \boldsymbol{r}_{-i^*})$.

Definition 1: The utility function of player i^* is defined as follows:

$$u_{i^*}(\boldsymbol{r}_{i^*}, \boldsymbol{r}_{-i^*}) = \max_{p_i^k, i \in \Gamma \cup \Lambda, k=1,\ldots,K} OS_{sys} \tag{11}$$

$$\textbf{\textit{s.t.}}: \; (5), \; (7), \; and \; (10) \tag{12}$$

$$r_i^k \; is \; given \; by \; (\boldsymbol{r}_{i^*}, \boldsymbol{r}_{-i^*}), \quad i \in \Gamma \cup \Lambda, \quad k = 1, \ldots, K \tag{13}$$

We divide every scheduling period into the following three phases.

In the first phase, all the UL CC links and D2D links are set to work in the control channel. The transmitting UEs broadcast their heartbeat messages successively, so that each receiving UE is able to calculate its desired channel power gain and the interference channel power gains by measuring the signal-to-noise ratio through the received signals. Moreover, the receiving UEs of D2D links or the BS will broadcast these channel power gains and interference channel power gains. Via the exchange of such messages, each link in the cell can have a global knowledge about all active UL CC and D2D links.

In the second phase, UL CC and D2D links remain working in the control channel and participate in an RAPC game as non-cooperative players. In each iteration, the transmitting UEs broadcast their residual battery energy and circuit power as well as their current strategies. Each player calculates its best response, which will maximize its own utility function, given the strategies of other players. This response will be set as the player's new strategy and be broadcast in the next iteration. The RAPC game will keep running until it reaches a **Nash equilibrium** or its iteration number exceeds a certain threshold.

Definition 2: A set of strategies $\boldsymbol{r}$ for all the players participating in a game is a Nash equilibrium if no player can improve its utility function by unilaterally changing its own strategy, i. e.,

$$u_i(\boldsymbol{r_i}, \boldsymbol{r_{-i}}) \geq u_i(\boldsymbol{r'_i}, \boldsymbol{r_{-i}}), \quad \text{for } \forall \boldsymbol{r'_i} \neq \boldsymbol{r_i}, \quad \forall i \in \Gamma \cup \Lambda \tag{14}$$

The Nash equilibrium offers a stable outcome of a non-cooperative game where multiple players adjust their own strategies through self-optimization and reach a condition from which no player wishes to deviate.

Proposition 1: Nash equilibrium exists in the constructed RAPC game. Moreover, the optimal solution of ***OPT*** in (4) is a Nash equilibrium.

Proof: See Appendix A. ■

Proposition 1 establishes the existence of a Nash equilibrium of the constructed RAPC game, which guarantees the feasibility of our proposed game theory based approach.

Finally, in the third phase, each D2D link allocates its transmission rates as well as transmission power on the K UL subchannels while each UL CC link adjusts its transmission power on a system assigned subchannel based on the optimized output from the RAPC game in the previous phase.

V. BEST RESPONSE OF A PLAYER

In this section, we investigate the best response of player i^* that maximizes its own utility function given the strategies of other players, $\boldsymbol{r_{-i^*}}$. We first study the impact of player i^*'s transmission rate allocated in subchannel k, $r_{i^*}^k$, on the minimum transmission power needed in subchannel k of player i^* and other players. Then, we present a low complexity algorithm for player i^* to calculate its best response, $\boldsymbol{r_{i^*,opt}}$, which satisfies $\boldsymbol{r_{i^*,opt}} = \arg\max_{\boldsymbol{r_{i^*}}} u_{i^*}(\boldsymbol{r_{i^*}}, \boldsymbol{r_{-i^*}})$. We also analyze the computational complexity of the proposed algorithm.

A. POWER CONTROL ON SUBCHANNEL K

Based on constraint (5), we can find that the transmission power needed in subchannel k of each link is determined by the transmission rates distributed in subchannel k of all the links in $\Gamma \cup \Lambda$. Assuming that r_i^k is constant ($\forall i \in \Gamma \cup \Lambda$), we have the following **Lemma**.

Lemma 1: For an arbitrary link i^* in $\Gamma \cup \Lambda$, under the constraints of (5) and (10), its minimum feasible transmission power in subchannel k, $p_{i^*,min}^k$, can be achieved only when all the inequalities in constraint (5) become equality at the same time, i. e.,

$$B_{SC} \cdot \log_2\left(1 + \frac{g_{ii} \cdot p_i^k}{N_0 + \sum\limits_{(j \in \Gamma \cup \Lambda) \cap (j \neq i)} g_{ji} \cdot p_j^k}\right) = r_i^k, \quad \forall i \in \Gamma \cup \Lambda \tag{15}$$

Proof: See Appendix B. ■

Leveraging **Lemma 1**, we can get the minimum transmission power needed in subchannel k for all the links in $\Gamma \cup \Lambda$ by simultaneously solving the equations in (15), where each r_i^k, $i \in \Gamma \cup \Lambda$, is given. Moreover, if we order the links in $\Gamma \cup \Lambda$ from 1 to $(N + M)$, and construct an $(N + M) \times (N + M)$ matrix A as well as an $(N + M) \times 1$ column vector T as:

$$A(i,j) = \begin{cases} g_{ii}, & i = j \\ (1 - 2^{r_i^k/B_{SC}}) \cdot g_{ji}, & i \neq j \end{cases} \tag{16}$$

$$T(i) = (2^{r_i^k/B_{SC}} - 1) \cdot N_0 \tag{17}$$

we obtain the following **Lemma 2**.

Lemma 2: If the equations in (15) have feasible solutions, then the minimum transmission power allocated in subchannel k of all the links in $\Gamma \cup \Lambda$, $(p_{1,min}^k, p_{2,min}^k, \ldots, p_{(N+M),min}^k)^T$, can be calculated as:

$$(p_{1,min}^k, p_{2,min}^k, \ldots, p_{(N+M),min}^k)^T = A^{-1} \cdot T \tag{18}$$

where A^{-1} is the inverse matrix of A.

Proof: See Appendix C. ■

B. RESPONSE ALGORITHM FOR EACH INDIVIDUAL PLAYER

In this sub-section, we present an algorithm for player i^* to calculate its best response, which will maximize the utility function of player i^* given the other players' strategies, $\boldsymbol{r_{-i^*}}$.

The strategy of each UL CC player is fixed no matter what the strategies of other players are. If player i^* is an UL CC link, its best strategy is given by:

$$\boldsymbol{r_{i^*,opt}} = (\delta_{i^*}^1 \cdot R_{i^*}, \delta_{i^*}^2 \cdot R_{i^*}, \ldots, \delta_{i^*}^K \cdot R_{i^*}), \quad i^* \in \Lambda \tag{19}$$

Then, we focus on the best response of a D2D player, which can distribute its transmission rate into the K subchannels. For subchannel k, when r_i^k $(i \in \Gamma \cup \Lambda, \; i \neq i^*)$ is given by $\boldsymbol{r_{-i^*}}$, we can conclude from **Lemma 2** that the minimum transmission power allocated in subchannel k of link i^* and all the other links in $\Gamma \cup \Lambda$ is determined by link i^*'s transmission rate in subchannel k, $r_{i^*}^k$. Specifically, we have the following **Proposition**.

Proposition 2: If the transmission rates of all the other players in subchannel k are fixed while $r_{i^*}^k$ is considered as a variable, the minimum transmission power needed in subchannel k of player i^* and all the other players in $\Gamma \cup \Lambda$ is determined by $r_{i^*}^k$ as follows:

$$\begin{cases} p_{i^*,min}^k(r_{i^*}^k) = \dfrac{\beta_{i^*}^k \cdot (2^{r_{i^*}^k/B_{SC}} - 1)}{1 + \gamma_{i^*}^k \cdot (2^{r_{i^*}^k/B_{SC}} - 1)} \\ p_{i,min}^k(r_{i^*}^k) = \dfrac{\alpha_{ii^*}^k + \beta_{ii^*}^k \cdot (2^{r_{i^*}^k/B_{SC}} - 1)}{1 + \gamma_{i^*}^k \cdot (2^{r_{i^*}^k/B_{SC}} - 1)}, \quad i \neq i^* \end{cases} \tag{20}$$

where $\alpha_{ii^*}^k$ and $\beta_{i^*}^k$ are non-negative constants, $\gamma_{i^*}^k$ is a non-positive constant, and $\beta_{ii^*}^k$ for each $i \in \Gamma \cup \Lambda, i \neq i^*$, is a constant that satisfies $\beta_{ii^*}^k - \alpha_{ii^*}^k \cdot \gamma_{i^*}^k \geq 0$.

Proof: See Appendix D. ∎

Moreover, if we give two test values, c_1 and c_2, to $r_{i^*}^k$ and calculate the corresponding $p_{i^*,min}^k(r_{i^*}^k = c_1)$, $p_{i^*,min}^k(r_{i^*}^k = c_2)$, and $p_{i,min}^k(r_{i^*}^k = c_1)$, $p_{i,min}^k(r_{i^*}^k = c_2)$ for $i \neq i^*$ using (18), we can obtain the numerical values of $\beta_{i^*}^k$, $\gamma_{i^*}^k$, $\alpha_{ii^*}^k$, $\beta_{ii^*}^k$ $(i \neq i^*)$ in (20), respectively. The derivatives of $p_{i^*,min}^k(r_{i^*}^k)$ and $p_{i,min}^k(r_{i^*}^k)$, $i \in \Gamma \cup \Lambda$, $i \neq i^*$, with respect to $r_{i^*}^k$ have the following closed-form expressions:

$$\begin{cases} \dfrac{d(p_{i^*,min}^k(r_{i^*}^k))}{d(r_{i^*}^k)} = \dfrac{\ln 2 \cdot \beta_{i^*}^k \cdot 2^{r_{i^*}^k/B_{SC}}}{B_{SC} \cdot \left[1 + \gamma_{i^*}^k \cdot (2^{r_{i^*}^k/B_{SC}} - 1)\right]^2} \\ \dfrac{d(p_{i,min}^k(r_{i^*}^k))}{d(r_{i^*}^k)} = \dfrac{\ln 2 \cdot (\beta_{ii^*}^k - \alpha_{ii^*}^k \cdot \gamma_{i^*}^k) \cdot 2^{r_{i^*}^k/B_{SC}}}{B_{SC} \cdot \left[1 + \gamma_{i^*}^k \cdot (2^{r_{i^*}^k/B_{SC}} - 1)\right]^2}, \quad i \neq i^* \end{cases} \tag{21}$$

Based on **Lemmas 1, 2** and **Proposition 2**, we obtain $u_{i^*}(\boldsymbol{r_{i^*}}, \boldsymbol{r_{-i^*}})$ for given $\boldsymbol{r_{-i^*}}$ as follows:

$$L_i(\boldsymbol{r_{i^*}}, \boldsymbol{r_{-i^*}}) = \frac{Q_i}{P_{c,i} + \sum_{k=1}^{K} p_{i,min}^k(r_{i^*}^k)}, \quad \forall i \in \Gamma \cup \Lambda \tag{22}$$

$$u_{i^*}(\boldsymbol{r_{i^*}}, \boldsymbol{r_{-i^*}}) = \min_i \frac{Q_i}{P_{c,i} + \sum_{k=1}^{K} p_{i,min}^k(r_{i^*}^k)}, \quad i \in \Gamma \cup \Lambda \tag{23}$$

We use $\vartheta_{i^*}(\boldsymbol{r_{i^*}}, \boldsymbol{r_{-i^*}})$ to represent the set of links in $\Gamma \cup \Lambda$ whose transmitting UEs have the minimal expected battery lifetime among the $(N + M)$ links when player i^*'s strategy is set to be $\boldsymbol{r_{i^*}}$. We have **Proposition 3**.

Proposition 3: Assume $\boldsymbol{r_{i^*,opt}} = (r_{i^*,\,opt}^1, \ldots, r_{i^*,\,opt}^K)$ is the best strategy of D2D player i^* when link i^*'s transmission rate requirement equals R_{i^*} and the strategies of other players are given by $\boldsymbol{r_{-i^*}}$. If $\Delta \boldsymbol{r_{i^*,\,opt}} = (\Delta r_{i^*,\,opt}^1, \ldots, \Delta r_{i^*,\,opt}^K)$ is the optimal solution of the following linear programming (LP) problem in (24):

$$\arg \min_{\Delta r_{i^*}^k, k=1,\ldots,K} \Delta l_{i^*} \tag{24}$$

$$s.t.: \sum_{k=1}^{K} \frac{d(p_{i,min}^k(r_{i^*,\,opt}^k))}{d(r_{i^*}^k)} \cdot \frac{\Delta r_{i^*}^k}{Q_i} \leq \Delta l_{i^*}, \quad i \in \vartheta_{i^*}(\boldsymbol{r_{i^*,opt}}, \boldsymbol{r_{-i^*}}) \tag{25}$$

$$\sum_{k=1}^{K} \Delta r_{i^*}^k = \Delta R \tag{26}$$

$$\Delta r_{i^*}^k + r_{i^*,\,opt}^k \geq 0, \quad k = 1, \ldots, K \tag{27}$$

$\boldsymbol{r_{i^*,\,opt}} + \Delta \boldsymbol{r_{i^*,\,opt}}$ will also be the best strategy of player i^* when this player's transmission rate requirement equals $R_{i^*} + \Delta R$. ΔR is a positive real number which is small enough.

Proof: See Appendix E. ∎

Proposition 3 provides a method to achieve a D2D player i^*'s best strategy by gradually increasing the player's transmission rate requirement from zero to R_{i^*}. Following **Proposition 3**, the proposed response algorithm will divide a D2D player i^*'s transmission rate requirement into multiple ΔRs and handle these ΔRs step by step. In each step, the algorithm first finds the links in $\Gamma \cup \Lambda$ whose transmitting UEs have the minimal expected battery lifetime and constructs the set, $\vartheta_{i^*}(\boldsymbol{r_{i^*}}, \boldsymbol{r_{-i^*}})$, according to player i^*'s current strategy. Then, the algorithm calculates the derivative of $p_{i,min}^k$ with respect to $r_{i^*}^k$ for each subchannel k and each link i in the set of $\vartheta_{i^*}(\boldsymbol{r_{i^*}}, \boldsymbol{r_{-i^*}})$. Finally, the algorithm solves the LP problem in (24) and updates the transmission rates in the K UL subchannels for player i^*. According to **Proposition 3**, if ΔR is small enough, our proposed algorithm will achieve the best response for each D2D player.

The proposed algorithm is given in **Algorithm 1**.

C. COMPUTATIONAL COMPLEXITY

In the proposed **Algorithm 1**, calculating the matrix A with $r_{i^*}^k = c_1$ or c_2 in line 7 has the complexity of $O((N + M)^2)$, where N and M are the numbers of D2D links and UL CC links, respectively; calculating the inverse matrix of A has the complexity of $O((N + M)^3)$ [51]; calculating $p_{i^*,min}^k(r_{i^*}^k = c_1)$, $p_{i^*,min}^k(r_{i^*}^k = c_2)$, and $p_{i,min}^k(r_{i^*}^k = c_1)$, $p_{i,min}^k(r_{i^*}^k = c_2)$ for $i \in \Gamma \cup \Lambda$, $i \neq i^*$ using (18) has the complexity of $O((N + M)^2)$. In lines 9-11, solving $\alpha_{ii^*}^k$ and $\beta_{ii^*}^k$ in (20) for $i \in \Gamma \cup \Lambda$, $i \neq i^*$ has the complexity of $O((N + M))$. So the overall complexity of lines 6-12 is bounded by $O(K(N + M)^3)$.

In line 15, calculating $p_{i,min}^k(r_{i^*}^k)$ for all the links in $\Gamma \cup \Lambda$ and all the K subchannels using (20) has the complexity of $O(K(N + M))$. In line 16, calculating the expected battery lifetime of the transmitting UEs for all the links in $\Gamma \cup \Lambda$ also has the complexity of $O(K(N + M))$. Constructing the set of $\vartheta_{i^*}(\boldsymbol{r_{i^*}}, \boldsymbol{r_{-i^*}})$ in line 17 has the complexity of $O((N + M))$. In line 18, the complexity of calculating the derivative of $p_{i,min}^k$ with respect to $r_{i^*}^k$ for each subchannel k and each link in $\vartheta_{i^*}(\boldsymbol{r_{i^*}}, \boldsymbol{r_{-i^*}})$ is bounded by $O(K(N + M))$. Finally, solving the LP problem in line 19 has the maximum computational complexity of $O(K^4)$ [52]. So the overall complexity of lines 14 to 21 is bounded by $O(SK(N + M) + SK^4)$, where S is the number of ΔRs.

Algorithm 1 Response Algorithm for a Single Player, i^*

```
input the strategies of other players, r_{-i*}, player i*'s transmission rate requirement, R_{i*}, and the K UL subchannels;
generate an vector r_{i*} = zeros(1, K) to record the strategy of player i*;
if player i* is an UL CC link then
    r_{i*} = (δ^1_{i*} · R_{i*}, δ^2_{i*} · R_{i*}, ..., δ^K_{i*} · R_{i*});
else
    for k = 1, ..., K do
        set two test values, c_1 and c_2, to r^k_{i*}, respectively and calculate relevant p^k_{i*,min}(c_1), p^k_{i*,min}(c_2), p^k_{i,min}(c_1), p^k_{i,min}(c_2) for i ∈ Γ ∪ Λ, i ≠ i* using (18);
        solve β^k_{i*} and γ^k_{i*} in (20);
        for i ∈ Γ ∪ Λ, i ≠ i* do
            solve α^k_{ii*} and β^k_{ii*} in (20);
        end for
    end for
    divide R_{i*} into S ΔRs, each ΔR has the value of ΔR/S;

    for step = 1, ..., S do
        with current r_{i*}, calculate p^k_{i,min}(r^k_{i*}) for i ∈ Γ ∪ Λ and k = 1, ..., K using (20);
        with p^k_{i,min}(r^k_{i*}) for i ∈ Γ ∪ Λ and k = 1, ..., K, calculate the expected battery lifetime of the transmitting UE for each link i using (22);
        find the links in Γ ∪ Λ whose transmitting UEs have the minimal expected battery lifetime and constructs the set, ϑ_{i*}(r_{i*}, r_{-i*});
        calculates the derivative of p^k_{i,min} about r^k_{i*} for each subchannel k and each link i belonging to the set of ϑ_{i*}(r_{i*}, r_{-i*}) using (21);
        solve the LP problem in (24) and get the optimal solution Δr_{i*, opt} = (Δr^1_{i*, opt}, Δr^2_{i*, opt}, ..., Δr^K_{i*, opt});
        update player i*'s strategy: r_{i*} = r_{i*} + Δr_{i*, opt};
    end for
end if
output player i*'s response, r_{i*};
```

Thus, the overall complexity of **Algorithm 1** is bounded by $O(K(N+M)^3 + SK(N+M) + SK^4)$.

VI. SIMULATION RESULTS

We evaluate the performances of the proposed game theory based RAPC approach through Monte Carlo simulations. All the results are averaged over 1000 random tests. In each test, the UL CC UEs and D2D pairs are randomly distributed in the cell. The residual energy of each transmitting UE is uniformly distributed in $[Q_m \cdot \alpha, \ Q_m]$, where α denotes how different the residual energy of transmitting UEs will be. In the tests, transmission rate requirement of UL CC and D2D links are randomly distributed in $[0, R_{max}]$, where R_{max} is the maximum possible transmission rate requirement of links.

TABLE 1. Simulation parameters.

Parameter	Value
Cell radius	300m
K	10
B_{SC}	$200MHz$
N	10
M	10
R_{max}	1Gbps
Max D2D communication distance	10m
g_{BS}	1000
N_0	1e-6W
P_c	0.01W
Q_m	0.8J
α	0.2
Step number in **Algorithm 1**, S	100
Iteration number in game-based approaches	10

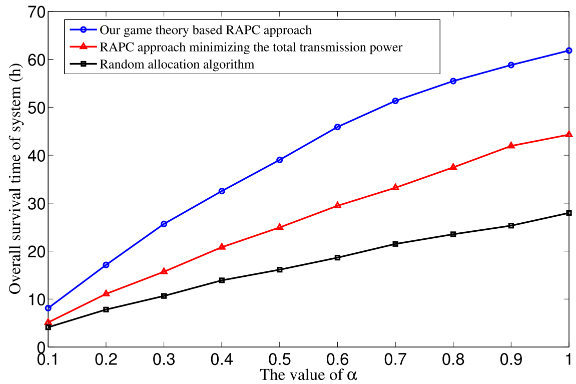

FIGURE 2. Overall system survival time achieved by the three approaches under different values of α when $R_{max} = 1Gbps$.

We compare our RAPC approach with another game theory based approach aiming at minimizing the total transmission power of the links [10], and a centralized random allocation algorithm, which distributes the transmission rates of D2D links to the K UL subchannels randomly. The values of major simulation parameters are summarized in **Table 1**.

In order to validate the solutions generated by our RAPC game, we evaluate the system performance including overall system survival time and average transmission power of considered links under different scenarios. The average transmission power is specified by the following equation:

$$Average\ transmission\ power = \frac{\sum_{i\in\Gamma\cup\Lambda} P_i}{N+M} \tag{28}$$

Fig. 2 shows the overall system survival time achieved by the three approaches under different values of α when $R_{max} = 1Gbps$. From Fig. 2, we can find that the performance of the three approaches increase as α gets large. Our game theory based RAPC approach always achieves the best overall system survival time. This can be explained as in our approach, each link focuses on prolonging the battery life for UEs with little residual energy. As α is small, transmitting UEs in the cell have greater residual energy variance, the advantage of our approach becomes more significant. When α equals 0.1, our RAPC approach outperforms the approach proposed in [10] by about 90%, and outperforms the centralized random allocation algorithm by about 100%.

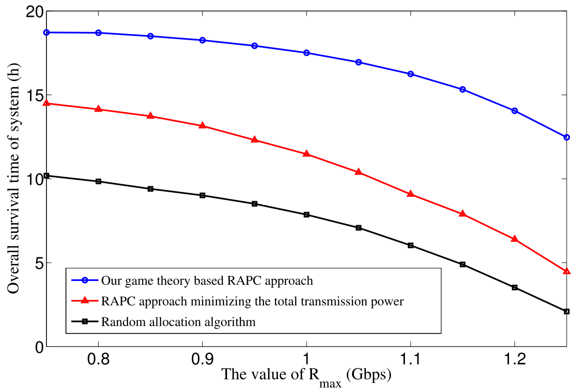

FIGURE 3. Overall system survival time versus R_{max} with $\alpha = 0.2$.

Fig. 3 plots the overall system survival time versus the maximum possible transmission rate requirement of links, R_{max}, with $\alpha = 0.2$. From Fig. 3, we can see the overall system survival time achieved by the three approaches descends rapidly when R_{max} increases. This is because according to Shannon's theory, in order to achieve a higher SINR at the receiver, the transmitting UE of each link must utilize larger transmission power. This, in turn, will introduce greater interference to other links and force them to increase their transmission power. Similar with Fig. 2, results in Fig. 3 also indicate that our game theory based RAPC approach always achieves the longest overall system survival time among the three approaches. When $R_{max} = 1.25Gbps$, our approach can prolong the overall system survival time by 160% and 400%, if it is compared with the approach proposed in [10] and the centralized random allocation algorithm, respectively.

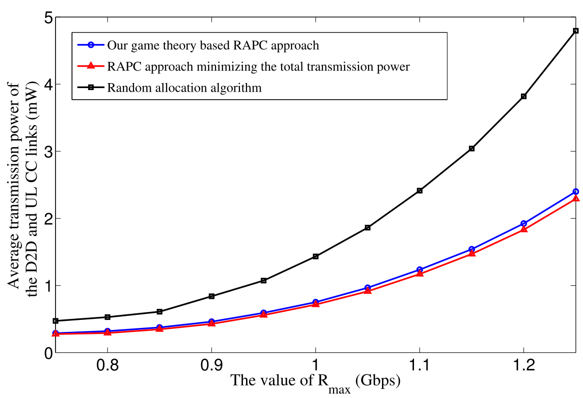

FIGURE 4. Average transmission power of the three approaches under different values of R_{max}.

Fig. 4 demonstrates the average transmission power of the three approaches under different values of R_{max} when α equals 0.2. The centralized random allocation algorithm always requires the largest transmission power under different conditions. When R_{max} increases, the centralized random allocation algorithm's average transmission power increases significantly. This is because assigning D2D links' transmission rates into the K subchannls randomly may produce severe mutual interference between D2D and UL CC links. We also see that the our RAPC approach needs a little more average transmission power than the approach proposed in [10], which aims at minimizing the total transmission power of links in the cell. This is due to our approach tries to protect the UEs with less residual energy. Thus, the UEs with sufficient residual energy may consume more transmission power. Nevertheless, we note that the increment in average transmission power is very limited (less than 5%).

We further investigate the convergence speed of our game theory based RAPC approach. When $\alpha = 0.2$ and R_{max} equals $0.75Gbps$, $1Gbps$, or $1.25Gbps$, respectively, the influence of iteration number in the presented game theory based approach is exhibited in Fig. 5.

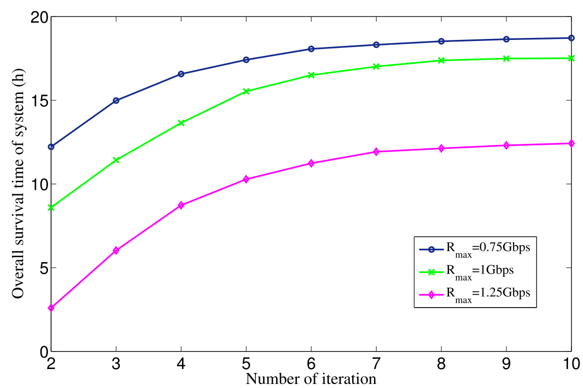

FIGURE 5. Overall system survival time versus iteration number in our game theory based approach.

From Fig. 5, it can be found that with the increase of iteration number in our game theory based approach (from 3 to 10), overall system survival time achieved by our approach extends distinctly. Theoretically, if the iteration number tends to infinity, our game theory based approach will finally reach a **Nash equilibrium** according to **Proposition 1**. However, Fig. 5 reveals that when the iteration number exceeds 6, performance achieved by our approach is very similar to that of larger iteration number cases. This is a meaningful phenomenon. It not only confirms the practicability of the proposed game theory based approach, but provides a guidance to the network protocol design as well.

VII. CONCLUSION

In this paper, we have investigated the RAPC problem for D2D communications as an underlay to UL CC communications with the goal of optimizing the overall system survival time, where each D2D link can reuse the resources of multiple UL CC links. We formulate the RAPC problem into a non-convex NLP problem, devise a non-cooperative game theory based distributed approach to solve it, and prove the existence of Nash equilibrium. We also propose an algorithm to calculate each individual player's best response given the strategies of other players. The computational complexity of the proposed algorithm is proved to be bounded in polynomial calculation time. Numerical results demonstrate that, when the transmitting UEs in a cell have quite different amounts of residual battery energy, our game theory based approach can prolong the overall system survival time by 90%-400% with comparison to existing schemes. Moreover, the proposed game theory based approach converges within around 7 iterations.

It is worthwhile noting that in our current simulations, the initial strategies of all the D2D players are randomly generated. In our future work, we will investigate the influence of the players' initial strategies on system performance and optimize the initial strategies for the considered RAPC problem.

APPENDIX A
PROOF OF PROPOSITION 1

Assume the optimal solution of **OPT** in (4) is $(r^k_{i,opt},\ p^k_{i,opt})$ for $\forall i \in \Gamma \cup \Lambda$ and $k = 1, \ldots, K$, the optimal value of **OPT** is L_{opt}. We first prove the set of strategies, $\boldsymbol{r_{i,opt}} = (r^1_{i,opt},\ r^2_{i,opt}, \ldots, r^K_{i,opt})$ $(\forall i \in \Gamma \cup \Lambda)$, is a Nash equilibrium of the constructed RAPC game.

We adopt the method of reduction to absurdity. If each player i in $\Gamma \cup \Lambda$ has the strategy of $\boldsymbol{r_{i,opt}}$ and there is a player i^* wanting to unilaterally adjust its strategy from $\boldsymbol{r_{i^*,opt}}$ to $\boldsymbol{r_{i^*,opt'}}$, then we have:

$$\boldsymbol{r_{i^*,opt'}} \neq \boldsymbol{r_{i^*,opt}} \tag{A–1}$$

$$u_{i^*}(\boldsymbol{r_{i^*,opt'}}, \boldsymbol{r_{-i^*,opt}}) > u_{i^*}(\boldsymbol{r_{i^*,opt}}, \boldsymbol{r_{-i^*,opt}}) \tag{A–2}$$

According to the definition of a player's utility function in (11), we have:

$$u_{i^*}(\boldsymbol{r_{i^*,opt}}, \boldsymbol{r_{-i^*,opt}}) \geq L_{opt} \tag{A–3}$$

Also, when players i^*'s strategy equals $\boldsymbol{r_{i^*,opt'}}$, we assume the solution of (11) which achieves $u_{i^*}(\boldsymbol{r_{i^*,opt'}}, \boldsymbol{r_{-i^*,opt}})$ is $p^k_{i,opt'}$ for $\forall i \in \Gamma \cup \Lambda$ and $k = 1, \ldots, K$. Obviously, $(p^k_{i,opt'},\ \boldsymbol{r_{i^*,opt'}},\ \boldsymbol{r_{-i^*,opt}})$ is a feasible solution of **OPT** in (4) and its corresponding value of the objective function is larger than L_{opt}. This contradicts the assumption that $(r^k_{i,opt},\ p^k_{i,opt})$ is the optimal solution of **OPT**. So the set of strategies, $\boldsymbol{r_{i,opt}}$, $\forall i \in \Gamma \cup \Lambda$, is a Nash equilibrium of the constructed RAPC game.

Moreover, as each variable of p^k_i for $\forall i \in \Gamma \cup \Lambda$ and $k = 1, \ldots, K$ has lower limit, **OPT** in (4) at least has one optimal solution. Thus, we can arrive at **Proposition 1**.

APPENDIX B
PROOF OF LEMMA 1

We also adopt the method of reduction to absurdity. We note the total number of D2D and UL CC links as $(N+M)$. For an arbitrary link i^* belonging to $\Gamma \cup \Lambda$, we assume the optimal solution of the following optimization problem:

$$\min\ p^k_{i^*} \tag{B–1}$$

$$\textbf{s.t.}:\ (5)\ and\ (10) \tag{B–2}$$

is $p^k_{i^*,min}$, and when $p^k_{i^*}$ achieves $p^k_{i^*,min}$ in (B–1), amounts of the variables $(p^k_i,\ i \in \Gamma \cup \Lambda)$ are expressed as $(p^k_{1,min},\ p^k_{2,min}, \ldots, p^k_{i^*,min}, \ldots, p^k_{(N+M),min})$.

Obviously:

$$B_{SC} \cdot \log_2\Big(1 + \frac{g_{ii} \cdot p^k_{i,min}}{N_0 + \sum\limits_{(j \in \Gamma \cup \Lambda) \cap (j \neq i)} g_{ji} \cdot p^k_{j,min}}\Big) \geq r^k_i, \quad \forall i \in \Gamma \cup \Lambda \tag{B–3}$$

If:

$$B_{SC} \cdot \log_2\Big(1 + \frac{g_{i^*i^*} \cdot p^k_{i^*,min}}{N_0 + \sum\limits_{(j \in \Gamma \cup \Lambda) \cap (j \neq i^*)} g_{ji^*} \cdot p^k_{j,min}}\Big) > r^k_{i^*} \tag{B–4}$$

we set

$$p^k_{i^*,min'} = (2^{r^k_{i^*}/B_{SC}} - 1)\Big(N_0 + \sum_{(j \in \Gamma \cup \Lambda) \cap (j \neq i^*)} g_{ji^*} \cdot p^k_{j,min}\Big)/g_{i^*i^*}.$$

Obviously, we have $0 \leq p^k_{i^*,min'} < p^k_{i^*,min}$. Because:

$$B_{SC} \cdot \log_2\Big(1 + \frac{g_{i^*i^*} \cdot p^k_{i^*,min'}}{N_0 + \sum\limits_{(j \in \Gamma \cup \Lambda) \cap (j \neq i^*)} g_{ji^*} \cdot p^k_{j,min}}\Big) = r^k_{i^*} \tag{B–5}$$

and

$$\begin{aligned} &B_{SC} \cdot \log_2\Big(1 \\ &\quad + \frac{g_{ii} \cdot p^k_{i,min}}{N_0 + \sum\limits_{(j \in \Gamma \cup \Lambda) \cap (j \neq i) \cap (j \neq i^*)} g_{ji} \cdot p^k_{j,min} + g_{i^*i} \cdot p^k_{i^*,min'}}\Big) \\ &> B_{SC} \cdot \log_2\Big(1 + \frac{g_{ii} \cdot p^k_{i,min}}{N_0 + \sum\limits_{(j \in \Gamma \cup \Lambda) \cap (j \neq i)} g_{ji} \cdot p^k_{j,min}}\Big) \geq r^k_i, \\ &\qquad \forall (i \in \Gamma \cup \Lambda) \cap (i \neq i^*) \end{aligned} \tag{B–6}$$

so $(p^k_{1,min},\ p^k_{2,min}, \ldots, p^k_{i^*,min'}, \ldots, p^k_{(N+M),min})$ is also a feasible solution to the optimization problem of (B–1). This contradicts with the assumption that $p^k_{i^*,min}$ is the optimal solution.

If:

$$B_{SC} \cdot \log_2\Big(1 + \frac{g_{i^*i^*} \cdot p^k_{i^*,min}}{N_0 + \sum\limits_{(j \in \Gamma \cup \Lambda) \cap (j \neq i^*)} g_{ji^*} \cdot p^k_{j,min}}\Big) = r^k_{i^*} \tag{B–7}$$

and there is a link $i^\dagger \neq i^*$ in set $\Gamma \cup \Lambda$ that satisfies the following inequality:

$$B_{SC} \cdot \log_2\Big(1 + \frac{g_{i^\dagger i^\dagger} \cdot p^k_{i^\dagger,min}}{N_0 + \sum\limits_{(j \in \Gamma \cup \Lambda) \cap (j \neq i^\dagger)} g_{ji^\dagger} \cdot p^k_{j,min}}\Big) > r^k_{i^\dagger} \tag{B–8}$$

we set

$$p^k_{i^\dagger,min'} = (2^{r^k_{i^\dagger}/B_{SC}} - 1) \cdot (N_0 + \sum_{(j\in\Gamma\cup\Lambda)\cap(j\neq i^\dagger)} g_{ji^\dagger} \cdot p^k_{j,min})/g_{i^\dagger i^\dagger}$$

and $p^k_{i^*,min'} = (2^{r^k_{i^*}/B_{SC}} - 1) \cdot (N_0 + g_{i^\dagger i^*} \cdot p^k_{i^\dagger,min'} + \sum_{(j\in\Gamma\cup\Lambda)\cap(j\neq i^*)\cap(j\neq i^\dagger)} g_{ji^*} \cdot p^k_{j,min})/g_{i^* i^*}$. Similarly, we can get $(p^k_{1,min}, \ldots, p^k_{i^\dagger,min'}, \ldots, p^k_{i^*,min'}, \ldots, p^k_{(N+M),min})$ is a feasible solution to (B–1) as well as $0 \leq p^k_{i^*,min'} < p^k_{i^*,min}$. This also contradicts with the assumption that $p^k_{i^*,min}$ is the optimal solution to (B–1).

Thus, we arrive at **Lemma 1**.

APPENDIX C
PROOF OF LEMMA 2

Leveraging **Lemma 1**, the amounts of minimum transmission power distributed on subchannel k for all the links in $\Gamma \cup \Lambda$, $(p^k_{1,min}, p^k_{2,min}, \ldots, p^k_{(N+M),min})^T$, can be achieved simultaneously by solving the equation set of (15).

Through equivalent transformation, (15) can be transformed into the following linear equations:

$$g_{ii} \cdot p^k_i + \sum_{(j\in\Gamma\cup\Lambda)\cap(j\neq i)} (1 - 2^{r^k_i/B_{SC}}) \cdot g_{ji} \cdot p^k_j = (2^{r^k_i/B} - 1) \cdot N_0, \quad \forall i \in \Gamma \cup \Lambda \tag{C–1}$$

which can be further transformed into:

$$A \cdot (p^k_1, p^k_2, \ldots, p^k_{(N+M)})^T = T \tag{C–2}$$

According to matrix theory, the solution of (C–2) can be calculated as:

$$(p^k_{1,min}, p^k_{2,min}, \ldots, p^k_{(N+M),min})^T = A^{-1} \cdot T \tag{C–3}$$

We can arrive at **Lemma 2**.

APPENDIX D
PROOF OF PROPOSITION 2

With **Lemma 2**, the minimum transmission power distributed on subchannel k of all the links in $\Gamma \cup \Lambda$ can be calculated as $A^{-1} \cdot T$, where the matrix A and the column vector T are defined in (16) and (17), respectively. Obviously, we have (D–1), as shown at the top of the next page.

According to matrix theory, inverse matrix of B, B^{-1}, can be calculated by the following equation:

$$B^{-1} = \frac{1}{|B|} \cdot B^* \tag{D–2}$$

where $|B|$ and B^* are the determinant and adjoint matrix of B, respectively.

If we see $r^k_{i^*}$ as a variable and see each r^k_i ($i \in \Gamma \cup \Lambda$, $i \neq i^*$) as a given number, $|B|$ and B^* will have the following expressions depicted in (D–3) and (D–4), respectively.

$$|B| = C^1 + \frac{C^2}{2^{r^k_{i^*}/B_{SC}} - 1} \tag{D–3}$$

In (D–3) or (D–4), as shown at the top of the next page, C^1, C^2, c^1_{ij} and c^2_{ij} for $i, j \in \Gamma \cup \Lambda$ are constants, which can be calculated via basic matrix operation. Thus, the minimum transmission power distributed on subchannel k of an arbitrary link belonging to $\Gamma \cup \Lambda$ can be calculated by (D–5), as shown at the top of the next page, and (D–6), as shown at the top of the page 12.

If we set

$$\beta^k_{i^*} = \left[c^1_{i^*i^*} \cdot N_0 + \sum_{(i\in\Gamma\cup\Lambda)\cap(i\neq i^*)} c^1_{i^*i} \cdot (2^{r^k_i/B_{SC}} - 1) \cdot N_0\right] / C^2 \tag{D–7}$$

$$\alpha^k_{ii^*} = \sum_{(j\in\Gamma\cup\Lambda)\cap(j\neq i^*)} c^2_{ij} \cdot (2^{r^k_j/B_{SC}} - 1) \cdot N_0/C^2 \tag{D–8}$$

$$\beta^k_{ii^*} = \left[c^1_{ii^*} \cdot N_0 + \sum_{(j\in\Gamma\cup\Lambda)\cap(j\neq i^*)} c^1_{ij} \cdot (2^{r^k_j/B_{SC}} - 1) \cdot N_0\right] / C^2 \tag{D–9}$$

$$\gamma^k_{i^*} = C^1/C^2 \tag{D–10}$$

we will get (20). Moreover, as $p^k_{i^*,min}(0) \geq 0$, $p^k_{i,min}(0) \geq 0$, $\frac{d(p^k_{i,min}(0^+))}{d(r^k_{i^*})} \geq 0$ and when $r^k_{i^*} \to +\infty$, $p^k_{i^*,min}(r^k_{i^*})$ hasn't solution of finite positive real number based on common sense, we have:

$$\beta^k_{i^*} \geq 0, \quad \gamma^k_{i^*} \leq 0 \tag{D–11}$$

$$\alpha^k_{ii^*} \geq 0, \quad \beta^k_{ii^*} - \alpha^k_{ii^*} \cdot \gamma^k_{i^*} \geq 0, \ \forall i \in \Gamma \cup \Lambda, \ i \neq i^* \tag{D–12}$$

Thus, we arrive at **Proposition 2**.

APPENDIX E
PROOF OF PROPOSITION 3

In this paper, we only consider the conditions that $\boldsymbol{r_{i^*}}$ has feasible solutions and transmission power distributed on each subchannel of all the links have positive values. Given the strategies of other players, $\boldsymbol{r_{-i^*}}$, we define function $F_i(\boldsymbol{r_{i^*}})$ as the reciprocal of link i's expected battery lifetime if player i^*'s strategy is set to be $\boldsymbol{r_{i^*}}$. Obvious, link i's expected battery lifetime declines monotonously as the amount of $F_i(\boldsymbol{r_{i^*}})$ increases.

$$F_i(\boldsymbol{r_{i^*}}) = \frac{P_{c,i} + \sum_{k=1}^{K} p^k_{i,\min}(r^k_{i^*})}{Q_i} \tag{E–1}$$

$$A^{-1}\cdot T=\begin{bmatrix} g_{11} & \cdots & (1-2^{r_1^k/B_{SC}})\cdot g_{i^*1} & \cdots & (1-2^{r_1^k/B_{SC}})\cdot g_{(N+M)1} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ (1-2^{r_{i^*}^k/B_{SC}})\cdot g_{1i^*} & \cdots & g_{i^*i^*} & \cdots & (1-2^{r_{i^*}^k/B_{SC}})\cdot g_{(N+M)i^*} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ (1-2^{r_{(N+M)}^k/B_{SC}})\cdot g_{1(N+M)} & \cdots & (1-2^{r_{(N+M)}^k/B_{SC}})\cdot g_{i^*(N+M)} & \cdots & g_{(N+M)(N+M)} \end{bmatrix}^{-1}$$
$$\cdot\begin{bmatrix} (2^{r_1^k/B_{SC}}-1)\cdot N_0 \\ \vdots \\ (2^{r_{i^*}^k/B_{SC}}-1)\cdot N_0 \\ \vdots \\ (2^{r_{(N+M)}^k/B_{SC}}-1)\cdot N_0 \end{bmatrix}$$
$$=\begin{bmatrix} g_{11} & \cdots & (1-2^{r_1^k/B_{SC}})\cdot g_{i^*1} & \cdots & (1-2^{r_1^k/B_{SC}})\cdot g_{(N+M)1} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ -g_{1i^*} & \cdots & \dfrac{g_{i^*i^*}}{2^{r_{i^*}^k/B_{SC}}-1} & \cdots & -g_{(N+M)i^*} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ (1-2^{r_{(N+M)}^k/B_{SC}})\cdot g_{1(N+M)} & \cdots & (1-2^{r_{(N+M)}^k/B_{SC}})\cdot g_{i^*(N+M)} & \cdots & g_{(N+M)(N+M)} \end{bmatrix}^{-1}$$
$$\cdot\begin{bmatrix} (2^{r_1^k/B_{SC}}-1)\cdot N_0 \\ \vdots \\ N_0 \\ \vdots \\ (2^{r_{(N+M)}^k/B_{SC}}-1)\cdot N_0 \end{bmatrix}=B^{-1}\cdot\begin{bmatrix} (2^{r_1^k/B_{SC}}-1)\cdot N_0 \\ \vdots \\ N_0 \\ \vdots \\ (2^{r_{(N+M)}^k/B_{SC}}-1)\cdot N_0 \end{bmatrix} \tag{D–1}$$

$$B^*=\begin{bmatrix} c_{11}^1+\dfrac{c_{11}^2}{2^{r_{i^*}^k/B_{SC}}-1} & \cdots & c_{1i^*}^1 & \cdots & c_{1(N+M)}^1+\dfrac{c_{1(N+M)}^2}{2^{r_{i^*}^k/B_{SC}}-1} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ c_{i^*1}^1 & \cdots & c_{i^*i^*}^1 & \cdots & c_{i^*(N+M)}^1 \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ c_{(N+M)1}^1+\dfrac{c_{(N+M)1}^2}{2^{r_{i^*}^k/B_{SC}}-1} & \cdots & c_{(N+M)i^*}^1 & \cdots & c_{(N+M)(N+M)}^1+\dfrac{c_{(N+M)(N+M)}^2}{2^{r_{i^*}^k/B_{SC}}-1} \end{bmatrix} \tag{D–4}$$

$$p_{i^*,min}^k=\frac{1}{C^1+\frac{C^2}{2^{r_{i^*}^k/B_{SC}}-1}}\cdot\left[c_{i^*i^*}^1\cdot N_0+\sum_{(i\in\Gamma\cup\Lambda)\cap(i\neq i^*)}c_{i^*i}^1\cdot(2^{r_i^k/B_{SC}}-1)\cdot N_0\right]$$
$$=\frac{\left[c_{i^*i^*}^1\cdot N_0+\sum_{(i\in\Gamma\cup\Lambda)\cap(i\neq i^*)}c_{i^*i}^1\cdot(2^{r_i^k/B_{SC}}-1)\cdot N_0\right]\cdot(2^{r_{i^*}^k/B_{SC}}-1)}{C^1\cdot(2^{r_{i^*}^k/B_{SC}}-1)+C^2} \tag{D–5}$$

When link i^*'s transmission rate requirement equals R_{i^*}, we assume its best strategy is $\boldsymbol{r_{i^*,opt}}=(r_{i^*,opt}^1,\ r_{i^*,opt}^2,\dots,\ r_{i^*,opt}^K)$. When player i^* sets its strategy as $\boldsymbol{r_{i^*,opt}}$, we use $\vartheta_{i^*}(\boldsymbol{r_{i^*,opt}},\boldsymbol{r_{-i^*}})$ to represent the set of links in $\Gamma\cup\Lambda$ whose transmitting UEs have the minimal expected battery lifetime. According to the definition of player i^*'s utility function,

$$p^k_{i,min} = \frac{1}{C^1 + \frac{C^2}{2^{r^k_{i^*}/B_{SC}}-1}} \cdot \left[c^1_{ii^*} \cdot N_0 + \sum_{(j\in\Gamma\cup\Lambda)\cap(j\neq i^*)} c^1_{ij} \cdot (2^{r^k_j/B_{SC}} - 1) \cdot N_0 + \sum_{(j\in\Gamma\cup\Lambda)\cap(j\neq i^*)} \frac{c^2_{ij} \cdot (2^{r^k_j/B_{SC}} - 1) \cdot N_0}{2^{r^k_{i^*}/B_{SC}} - 1} \right]$$
$$= \frac{\left[c^1_{ii^*} \cdot N_0 + \sum_{(j\in\Gamma\cup\Lambda)\cap(j\neq i^*)} c^1_{ij} \cdot (2^{r^k_j/B_{SC}} - 1) \cdot N_0 \right] \cdot (2^{r^k_{i^*}/B_{SC}} - 1) + \sum_{(j\in\Gamma\cup\Lambda)\cap(j\neq i^*)} c^2_{ij} \cdot (2^{r^k_j/B_{SC}} - 1) \cdot N_0}{C^1 \cdot (2^{r^k_{i^*}/B_{SC}} - 1) + C^2},$$
$$i \in \Gamma \cup \Lambda, \quad i \neq i^* \qquad \text{(D–6)}$$

we have:

$$F_i(\boldsymbol{r_{i^*,opt}}) = \frac{1}{u_{i^*}(\boldsymbol{r_{i^*,opt}}, \boldsymbol{r_{-i^*}})}, \quad i \in \vartheta_{i^*}(\boldsymbol{r_{i^*,opt}}, \boldsymbol{r_{-i^*}}) \qquad \text{(E–2)}$$

$$F_i(\boldsymbol{r_{i^*,opt}}) < \frac{1}{u_{i^*}(\boldsymbol{r_{i^*,opt}}, \boldsymbol{r_{-i^*}})}, \quad i \notin \vartheta_{i^*}(\boldsymbol{r_{i^*,opt}}, \boldsymbol{r_{-i^*}}) \qquad \text{(E–3)}$$

We adopt the method of reduction to absurdity. We assume the optimal solution of the LP problem in (24) is $\Delta\boldsymbol{r_{i^*,\,opt}} = (\Delta r^1_{i^*,\,opt}, \ldots, \Delta r^K_{i^*,\,opt})$. As ΔR is a small positive number and $\boldsymbol{r_{i^*,opt}}$ is player i^*'s best strategy when the link's transmission rate requirement equals R_{i^*}, the absolute value of each element in $\Delta\boldsymbol{r_{i^*,\,opt}}$ is small enough. Thus, we have:

$$\begin{aligned} &F_i(\boldsymbol{r_{i^*,opt}} + \Delta\boldsymbol{r_{i^*,\,opt}}) \\ &\quad\approx F_i(\boldsymbol{r_{i^*,opt}}) \\ &\quad< \frac{1}{u_{i^*}(\boldsymbol{r_{i^*,opt}}, \boldsymbol{r_{-i^*}})}, \quad i \notin \vartheta_{i^*}(\boldsymbol{r_{i^*,opt}}, \boldsymbol{r_{-i^*}}) \end{aligned} \qquad \text{(E–4)}$$

$$\begin{aligned} &F_i(\boldsymbol{r_{i^*,opt}} + \Delta\boldsymbol{r_{i^*,\,opt}}) \\ &\quad= F_i(\boldsymbol{r_{i^*,opt}}) + \sum_{k=1}^{K} \frac{d(p^k_{i,min}(r^k_{i^*,\,opt}))}{d(r^k_{i^*})} \cdot \frac{\Delta r^k_{i^*,opt}}{Q_i} \\ &\quad= \frac{1}{u_{i^*}(\boldsymbol{r_{i^*,opt}}, \boldsymbol{r_{-i^*}})} + \sum_{k=1}^{K} \frac{d(p^k_{i,min}(r^k_{i^*,\,opt}))}{d(r^k_{i^*})} \cdot \frac{\Delta r^k_{i^*,opt}}{Q_i}, \\ &\qquad i \in \vartheta_{i^*}(\boldsymbol{r_{i^*,opt}}, \boldsymbol{r_{-i^*}}) \end{aligned} \qquad \text{(E–5)}$$

Thus, the optimal value of the LP problem in (24), $\Delta l_{i^*,opt}$, equals:

$$\Delta l_{i^*,opt} = \max_{i\in\vartheta_{i^*}(\boldsymbol{r_{i^*,opt}},\boldsymbol{r_{-i^*}})} F_i(\boldsymbol{r_{i^*,opt}} + \Delta\boldsymbol{r_{i^*,\,opt}}) - \frac{1}{u_{i^*}(\boldsymbol{r_{i^*,opt}}, \boldsymbol{r_{-i^*}})} \qquad \text{(E–6)}$$

As $\boldsymbol{r_{i^*,opt}}$ is player i^*'s best strategy when the link's transmission rate requirement equals R_{i^*}, $\Delta l_{i^*,opt}$ is not less than 0. If $\boldsymbol{r_{i^*,opt}} + \Delta\boldsymbol{r_{i^*,\,opt}}$ is not player i^*'s best strategy when the link's transmission rate requirement equals $R_{i^*} + \Delta R$, there is a feasible strategy $\boldsymbol{r_{i^*,fsb}}$ for player i^* which satisfies:

$$F_i(\boldsymbol{r_{i^*,fsb}}) < \Delta l_{i^*,opt} + \frac{1}{u_{i^*}(\boldsymbol{r_{i^*,opt}}, \boldsymbol{r_{-i^*}})}, \quad i \in \Gamma \cup \Lambda \qquad \text{(E–7)}$$

$$\sum_{k=1}^{K} r^k_{i^*,fsb} = R_{i^*} + \Delta R_{i^*} \qquad \text{(E–8)}$$

According to **Proposition 2** and (21), we can directly achieve the conclusion that the derived function of $p^k_{i,min}(r^k_{i^*})$ about $r^k_{i^*}$ for each link i is a monotonic increasing function. We have the following inequality:

$$\begin{aligned} &\frac{d(p^k_{i,min}(r^k_{i^*,opt}))}{d(r^k_{i^*})} \cdot [r^k_{i^*,fsb} - (r^k_{i^*,opt} + \Delta r^k_{i^*,opt})] \\ &\approx \frac{d(p^k_{i,min}(r^k_{i^*,opt} + \Delta r^k_{i^*,opt}))}{d(r^k_{i^*})} \cdot [r^k_{i^*,fsb} - (r^k_{i^*,opt} + \Delta r^k_{i^*,opt})] \\ &\leq p^k_{i,min}(r^k_{i^*,fsb}) - p^k_{i,min}(r^k_{i^*,opt} + \Delta r^k_{i^*,opt}), \\ &\quad \forall i \in \vartheta_{i^*}(\boldsymbol{r_{i^*,opt}}, \boldsymbol{r_{-i^*}}), \quad \forall k = 1, \ldots, K \end{aligned} \qquad \text{(E–9)}$$

Based on (E–5), (E–7) and (E–9), we have:

$$\begin{aligned} &\sum_{k=1}^{K} \frac{d(p^k_{i,\min}(r^k_{i^*,opt}))}{d(r^k_{i^*})} \cdot [r^k_{i^*,fsb} - (r^k_{i^*,opt} + \Delta r^k_{i^*,opt})] \\ &\quad\leq \sum_{k=1}^{K} p^k_{i,min}(r^k_{i^*,fsb}) - \sum_{k=1}^{K} p^k_{i,min}(r^k_{i^*,opt} + \Delta r^k_{i^*,opt}) \\ &\quad= [F_i(\boldsymbol{r_{i^*,fsb}}) \cdot Q_i - P_{c,i}] \\ &\qquad - [F_i(\boldsymbol{r_{i^*,opt}} + \Delta\boldsymbol{r_{i^*,\,opt}}) \cdot Q_i - P_{c,i}] \\ &\quad< \Delta l_{i^*,opt} \cdot Q_i - \sum_{k=1}^{K} \frac{d(p^k_{i,min}(r^k_{i^*,\,opt}))}{d(r^k_{i^*})} \cdot \Delta r^k_{i^*,opt}, \\ &\qquad \forall i \in \vartheta_{i^*}(\boldsymbol{r_{i^*,opt}}, \boldsymbol{r_{-i^*}}) \end{aligned} \qquad \text{(E–10)}$$

We construct an auxiliary vector $\Delta\boldsymbol{r_{i^*,aux}}$ as:

$$\Delta\boldsymbol{r_{i^*,aux}} = \Delta\boldsymbol{r_{i^*,\,opt}} + \delta \cdot [\boldsymbol{r_{i^*,fsb}} - (\boldsymbol{r_{i^*,opt}} + \Delta\boldsymbol{r_{i^*,\,opt}})] \qquad \text{(E–11)}$$

where δ is a positive real number whose absolute value is small enough. And we have the following relations:

$$\begin{aligned} &\sum_{k=1}^{K} \frac{d(p^k_{i,min}(r^k_{i^*,\,opt}))}{d(r^k_{i^*})} \cdot \frac{\Delta r^k_{i^*,aux}}{Q_i} \\ &= \sum_{k=1}^{K} \frac{d(p^k_{i,min}(r^k_{i^*,\,opt}))}{d(r^k_{i^*})} \cdot \frac{\Delta r^k_{i^*,opt}}{Q_i} \\ &\quad + \delta \cdot \sum_{k=1}^{K} \frac{d(p^k_{i,\min}(r^k_{i^*,opt}))}{d(r^k_{i^*})} \cdot \frac{[r^k_{i^*,fsb} - (r^k_{i^*,opt} + \Delta r^k_{i^*,opt})]}{Q_i} \end{aligned}$$

$$
\begin{aligned}
&< \sum_{k=1}^{K} \frac{d(p_{i,min}^{k}(r_{i^*,\,opt}^{k}))}{d(r_{i^*}^{k})} \cdot \frac{\Delta r_{i^*,opt}^{k}}{Q_i} \\
&\quad + \frac{\delta}{Q_i} \cdot [\Delta l_{i^*,opt} \cdot Q_i - \sum_{k=1}^{K} \frac{d(p_{i,min}^{k}(r_{i^*,\,opt}^{k}))}{d(r_{i^*}^{k})} \cdot \Delta r_{i^*,opt}^{k}] \\
&= (1-\delta) \cdot \sum_{k=1}^{K} \frac{d(p_{i,min}^{k}(r_{i^*,\,opt}^{k}))}{d(r_{i^*}^{k})} \cdot \frac{\Delta r_{i^*,opt}^{k}}{Q_i} + \delta \cdot \Delta l_{i^*,opt} \\
&\leq (1-\delta) \cdot \Delta l_{i^*,opt} + \delta \cdot \Delta l_{i^*,opt} \\
&= \Delta l_{i^*,opt}, \ \forall i \in \vartheta_{i^*}(\boldsymbol{r}_{i^*,opt}, \boldsymbol{r}_{-i^*}) \qquad \text{(E–12)}
\end{aligned}
$$

As $\Delta \boldsymbol{r}_{i^*,aux}$ is obviously a feasible solution of the LP problem in (24), (E–12) contradicts with the assumption that $\Delta \boldsymbol{r}_{i^*,\,opt}$ is the LP problem's optimal solution.

Thus, we arrive at **Proposition 3**.

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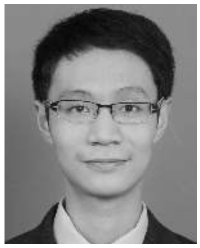
ZITIAN ZHANG received the B.S. and Ph.D. degrees from Shanghai Jiao Tong University, in 2010 and 2016, respectively. He was as a Research Engineer with the China Aeronautical Radio Electronics Research Institute, from 2016 to 2017, and has led three research projects. He is currently a Lecturer with the East China University of Science and Technology. His research interests include device-to-device communications, deep learning, and fog radio access networks.



YUE WU received the Ph.D. degree from The University of Sheffield, in 2016. He was a Research Fellow with Alibaba Inc., from 2010 to 2011. He is currently a Lecturer with the East China University of Science and Technology. He is a Co-Inventor of three patents. His research interests include device-to-device communications, radio resource management, optimization, peer-to-peer systems, machine learning, and mobile data analysis. He received the IEEE Best Conference Paper Award. He received the Shanghai Sailing Program Young Scholarship, in 2017.

XIAOLI CHU received the Ph.D. degree from The Hong Kong University of Science and Technology, in 2005. From 2005 to 2012, she was with King's College London. She is currently a Lecturer with The University of Sheffield. She has published more than 80 peer-reviewed journal and conference papers. She is a Leading Editor/Author of the book *Heterogeneous Cellular Networks* (CUP, 2013). She was a Co-Chair of the Wireless Communications Symposium for the IEEE ICC 2015 and a Guest Editor of the IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY and the *ACM/Springer Journal of Mobile Networks and Applications*.

JIE ZHANG has been holding the Chair in wireless systems at the University of Sheffield, since 2011. He and his students/colleagues have pioneered research in femto/small cell and HetNets and have published some highly cited publications. He has published more than 200 peer-reviewed journal or conference papers and received more than 6000 citations. He co-founded RANPLAN that produces a suite of world leading in-building DAS, indoor–outdoor small cell/HetNet network design, and optimization tools. Since 2005, he has been awarded over 20 grants by the EPSRC, the EC FP6/FP7/H2020, and industry.